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Credit default swaps, the leverage effect, and cross-sectional predictability of equity and firm asset volatility[☆]

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ABSTRACT

Leverage represents both a fundamental component of equity volatility and a long-run selection variable. Based on this premise, we investigate the influence of leverage on the long-run cross-sectional predictability of future realized equity volatility. Leverage makes equity volatility significantly less predictable than underlying firm asset volatility, a result that is robust to different predictors of future realized volatility: credit default swap implied, historical, and option implied volatility. A simple model of optimal capital structure, wherein companies maximize tax benefits subject to a common maximum default probability (minimum credit rating) target, helps explain this finding.

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1. Introduction

An important implication of structural credit risk models (Merton, 1974) is the decomposition of equity volatility into a (firm) asset volatility component and leverage effect component.[1] While the influence of leverage on the predictability of future equity volatility has been investigated before, the ordinary approach consists of analyzing the mechanical effect of equity price movements: other things being equal, a downturn in equity price increases the leverage ratio, and this, in turn, amplifies the expected equity volatility.[2] Focusing on this mechanical effect makes full sense when interest is in the short-run, time-serial variation in equity volatility. However, it is also reasonable to consider many situations in which the main interest is in its long-run, cross-sectional variation (e.g., long-run management of equity portfolios). In such situations, the role of leverage as a choice variable is particularly relevant.

This study investigates the interconnection between the capital structure selection problem and the predictability of future (long-run, cross-sectional variation in) equity volatilities. At first glance, this question might seem relatively easy to address. "Because equity volatility is the composition of asset volatility and the leverage effect, the predictability of equity volatility will be directly related to the weight and predictability of those two components." However, it may be argued that this problem is much more complicated. Previous empirical evidence demonstrates that, in the cross-section, leverage and asset volatility have a very significant negative correlation (Choi and Richardson, 2016; Im et al., 2020). Additionally, we can reasonably presume that this is because leverage (endogenous selection variable) responds to asset volatility (exogenous variable), which ultimately determines equity volatility (endogenous resultant variable). Another reasonable assumption is that as a choice variable, leverage will not move instantaneously to accommodate changes in short-run asset volatility. In contrast, leverage is thought to be a persistent variable that adjusts slowly to its optimal target (De Miguel and Pindado, 2001; Cook and Tang, 2010). Therefore, unraveling the knot between the assessment of future asset volatility, the corresponding optimal leverage, the speed of adjustment to such an optimal capital structure, and the resulting implications for the predictability of future equity volatility may be far from a simple problem to address.

Our analysis proceeds as follows. First, we focus on *how* and *to what extent*. Namely, we evaluate and compare the predictability of future realized equity volatility vis-à-vis the underlying asset volatility. This exercise allows us to quantify, in the first place, the actual influence of leverage on the predictability of future equity volatility. We address this question by primarily examining the informational content of credit default swap (CDS) spreads. The election of this type of contract is motivated by its long maturity, which makes it a perfect candidate for the purposes of the present study. Our database consists of 52 European companies with highly liquid 5-year CDS spreads for the period 2004–2017.[3] From the informational content of both CDS implied and historical volatilities, we conclude that the influence of leverage is indeed remarkable. While CDS implied (historical) asset volatilities explain as much as 69.37% (53.45%) of the variation in future realized asset volatilities, the predictive power of CDS implied (historical) equity volatilities for future realized equity volatilities is only 22.19% (19.35%). Such striking results lead us to address the question of *why* next. More precisely, we explore whether the divergence in the predictability of equity and asset volatility provides indirect evidence on companies' leverage policy, its dependence on the assessment of future asset volatility, and/or the speed of adjustment of leverage to its optimal target. As a preliminary step, we verify that our modest results in the prediction of future equity volatility are not just a reflection of: a) good results in the prediction of future asset volatility, and b) poor results in the prediction of the future leverage effect. We explore this possibility because, according to structural credit risk models, a CDS is an option-like contract on *firm asset value*; therefore, its value is also dependent on *asset volatility*. Consequently, CDS spreads allow for direct estimates of implied asset volatility rather than equity volatility. For the estimation of such CDS implied equity volatilities, we can hardly proceed in a different way than by adding the *current* leverage effect to the *forward-looking* CDS implied asset volatility. Thus, if the current leverage effect is a poor predictor of the future realized leverage effect, then CDS implied equity volatility will also be affected as a predictor for future equity volatility. Although reasonable, our empirical analysis unambiguously rejects this explanation. In numbers, the predicting power of the current leverage effect for the future realized leverage effect is 77.37%, that is, higher than that of CDS implied asset volatility for future realized asset volatility (also, the predicting power of the historical leverage effect is 61.60%). Evidently, this additional finding makes the initial finding even more puzzling. We also test whether a more flexible model for future realized equity volatility, where CDS implied asset volatility and the current leverage effect are considered as two separate explanatory variables, could increase their explanatory power. We find only marginal support for this hypothesis. Certainly, higher flexibility in the model's coefficients increases its explanatory power: from 22.19% to 28.50%. However, the final result is still far from the predictability of future asset volatility.

Having rejected the most obvious explanations, we finally explore the implications of a simple (actually naïve) model of optimal capital structure. The model is built on a set of stylized facts. First, credit ratings play a central role in the selection of the capital

[1] We notice that the term 'asset volatility' may be rather ambiguous. In fact, it can refer to either the volatility of the firm *unlevered* assets (underlying financial variable in most structural credit risk models; e.g., Merton, 1974; Leland and Toft, 1996; Du et al., 2019), or the volatility of the firm *levered* assets (total market value of equity and debt; e.g., Choi and Richardson, 2016; Im et al., 2020). While those two measures will be exactly the same only in the absence of taxes and (all forms of) bankruptcy costs (e.g., Merton, 1974), we can expect them to be very closely related. In any case, for the sake of clarity, unless otherwise stated asset volatility refers in this study to the volatility of the firm *unlevered* assets.

[2] See for example Engle and Siriwardane (2018).

[3] Our selection criterion is similar to that in Du et al. (2019), who analyze a final sample of 49 companies with highly liquid CDS spreads for 2001–2013.

structure. In a survey of 392 CFOs, Graham and Harvey (2001) find that the most important determinants of capital structure are financial flexibility and credit ratings. Kisgen (2006, 2009, 2019) provides a detailed discussion on the reasons for credit ratings, especially an investment-grade rating, to represent, in fact, a sensible target. These include regulations based on ratings, rating triggers, and relationship with third parties (customers, suppliers, and employees). Kisgen (2006, 2009, 2019) documents capital structure decisions consistent with such credit rating targets. Similarly, Elkamhi et al. (2012) find that the traditional comparison between tax benefits and bankruptcy costs leads to the conclusion that firms are generally under-levered. However, this apparent puzzle disappears when the costs associated with a non-investment grade rating (referred to as pre-bankruptcy costs) are accounted for. Specifically, a 1–2% annual loss of unlevered asset value due to a non-investment grade rating is sufficient to reconcile the predicted and observed leverage ratios. The second stylized fact is the negative cross-sectional correlation between asset volatility and leverage, and its final effect on the cross-sectional variation in equity volatility. As previously noted, this negative correlation has been documented by Choi and Richardson (2016) and Im et al. (2020), and is also corroborated by our own data. Both Choi and Richardson (2016) and our study confirm that, in the cross-section, the aforementioned relationship between asset volatility and leverage causes equity volatility to have no apparent connection with any of these two variables. As a closely related result, Chen et al. (2014) and Borochin and Yang (2017) find that companies reduce leverage when equity volatility is, or is expected to be higher.

The model we propose provides a unified theoretical framework for all these stylized facts and our novel results. In the strongest version of the model, every company observes its expected asset volatility before choosing its level of debt. This debt is finally chosen so that the company maximizes its tax benefits subject to a maximum default probability (minimum credit rating) target that, without loss of generality, is assumed to be identical for all companies. The effective underlying assumption is that for any default probability higher than that (for any lower credit rating), the present value of bankruptcy and pre-bankruptcy costs would exceed the present value of tax benefits. In our simple model, said identical default probability target translates, in turn, into an identical equity volatility target. The basic implication is as follows: because all companies select their leverage so that their expected equity volatility equals the same target, future (cross-sectional differences in) realized equity volatilities are, by construction, unpredictable. More importantly, this implication holds no matter how predictable future realized asset volatilities are.[4] We also consider a weaker and more realistic version of the model, in which the actual debt levels can deviate from their optimal values. We argue that to the extent that such deviations are persistent in time, this new element makes future realized equity volatilities somewhat predictable but not necessarily as predictable as future realized asset volatilities. We find clear empirical support for both versions of the model in different time periods. To begin, the cross-sectional variation in implied asset volatilities is much higher than that of implied equity volatilities, reflecting the properties of realized asset and equity volatilities. Also, the informational content of implied asset volatilities is relatively stable throughout the whole sample period 2004–2017. In contrast, the informational content of implied equity volatilities is close to zero during the calm period preceding the subprime crisis and only becomes clearly positive afterward. We associate these findings with an initial calm period in which companies had the opportunity to select their optimal debt levels (strongest version of the model). When the subprime crisis occurred, followed by the sovereign debt crisis, the leverage ratios began to deviate significantly from their optimal values (weakest version). It was only at that moment that significant (and non-random) cross-sectional differences in equity volatilities, partially anticipated by implied equity volatilities, finally appeared. Our evidence on the informational content of historical volatilities indicates that they evolved in a fashion similar to implied volatilities, a result that can be equally explained on the basis of our simple model.

We conduct several robustness tests and extensions. First, we address the possibility that our results are driven by poor estimation of the underlying firm asset value. This is an unobservable variable; thus, any estimate of CDS implied (or realized) asset volatility will depend on how firm asset value is originally estimated. Our base case estimation approach consists of two main steps. In the first step, we use Leland and Toft (1996) structural credit risk model to derive the time series of firm asset values and other relevant information (i.e., the default barrier) from the time series of equity values. In the second step, we use the estimated values to derive a sample of CDS implied and realized asset volatilities. It is important to stress that, once we have estimated the time series of firm asset values from the equity market *alone* (first step), our procedure for estimating CDS implied and future realized asset volatilities (second step) is similar to the procedure regularly used to estimate option implied and future realized equity volatilities. Another important remark is that Leland and Toft's model *allows* to determine the optimal capital structure following the conventional trade-off between tax benefits and bankruptcy costs. However, their pricing equations—those used in our estimations—do not presume *per se* that such an optimal capital structure has been selected. In contrast, our results rely on *observed* equity prices and accounting debt values, and these values do not need to be (and, in general, they will not be) optimal according to Leland and Toft's model. All of the above been said, we verify the robustness of our results to other estimation approaches. Among these, we include a naïve model in which the firm asset value is simply the equity value plus the book value of total liabilities. In this particular case, we not only differentiate the databases used in each step of the estimation (equity values vs. CDS spreads) but also the underlying model (naïve vs. structural). The results, which are

[4] In what follows, and to ease the exposition, we will usually refer to an "equity volatility target". However, it should be stressed that it is not assumed that companies actually have a target in terms of equity volatility. Such an expression will just reflect the indirect consequence of a maximum default probability target.

presented in an Internet Appendix, corroborate our main findings.[5] Second, we relate model-dependent (Leland and Toft) implied asset volatilities to model-free (naïve) measures of realized asset volatility and confirm that the high explanatory power of implied asset volatility for future realized asset volatility is not the product of a common measurement error. Third, we explore the cross-sectional predictability of *levered* asset volatility and verify that the results are similar to those obtained for *unlevered* asset volatility. Fourth, we confirm that our main conclusions are also robust to either an in-sample or out-of-sample analysis. Fifth, because our simple model provides estimates of the optimal leverage effects, we explore the speed of adjustment to such optimal values. Our results prove to be consistent with extant studies on the adjustment of leverage ratios to their optimal targets (De Miguel and Pindado, 2001; Cook and Tang, 2010). Sixth, we extend our investigation to the informational content of equity options.[6] With this final extension, we aim to address some additional questions. On the one hand, while our simple model of the interconnection between leverage and asset volatility is motivated by the empirical evidence on the informational content of CDS implied and historical volatilities, the bottom line of the model—and of this study—is the existence of a fundamental difference in the cross-sectional predictability of asset and equity volatility that goes above and beyond the information provided by either CDS implied or historical volatilities. Hence, if such a fundamental difference truly exists, it should also be reflected in the informational content of equity options. On the other hand, we must remember 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 (where the real input is asset volatility). In other words, it could be argued that our results would be different if we used equity options instead of CDS spreads. Finally, an important question to explore is the relative informational content of CDS spreads and equity options for future realized volatilities. We address all these questions simultaneously by evaluating and comparing the informational content of one-year CDS spreads and one-year equity options. Our results confirm that such informational content is clearly superior for future realized asset volatility than it is for future realized equity volatility. Further, once we control for the information provided by historical volatilities, irrespective of whether we deal with either asset or equity volatilities, the additional informational content of CDS spreads is higher and almost subsumes any additional informational content of equity options.

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 bond yield spreads and equity volatility. In these regressions, either an option implied or historical measure of equity volatility is used as a proxy for equity volatility. 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 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 about 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 regarding the future volatility of firm asset value: the actual underlying financial variable in CDS spreads. Our study is also the first to analyze whether CDS spreads (as well as historical data on equity prices and accounting figures; and equity options prices) are significantly more/less informative about future realized equity volatility than about future realized asset volatility, and why.

The remainder of this paper is organized as follows. Section 2 describes our methodology for estimating implied and realized volatilities. Section 3 introduces the sample. Section 4 presents the analysis of implied versus realized asset volatilities, and Section 5 is devoted to the subsequent analysis of implied versus realized equity volatilities. Section 6 explores the reasons behind the different results for asset and equity volatilities. Section 7 presents the robustness tests and extensions. Section 8 summarizes the main findings

[5] Another possibility would be to follow Choi and Richardson (2016), and use actual market returns for equity and debt. Despite its appeal, such an approach would not necessarily be the most efficient one in our case. To begin, it would provide estimates of *levered* asset volatility, and, therefore, just another (although quite interesting) proxy for *unlevered* asset volatility, which is the focus of our investigation. Alternatively, we could follow Davydenko (2012): estimate the levered asset value from actual market data (as in Choi and Richardson, 2016), and then correct this value to account for the present value of tax benefits (zero in his case) and bankruptcy costs. However, this possibility would imply again the introduction of a more or less elaborate model. It is finally worth noting that restricting the analysis to those companies with highly liquid CDS spreads, and the same market information as in Choi and Richardson (2016) and Davydenko (2012), would probably result in a very limited sample. The next quote illustrates this point (Davydenko, 2012; page 29): *"Following the standard approach to implementing structural models […], in my calculations I use the market value of equity plus the book value of debt to proxy for the total market value of assets […]. Thus, I disregard my more accurate estimates […] based on debt prices, because such estimates are rarely available in implementations."* The *standard approach* described by Davydenko (2012) reflects precisely the naïve approach that we include in our robustness tests.

[6] We notice that, following Geske (1977), it is actually possible to describe an equity option as a contingent claim (compound option) on firm asset value, whose price also depends on asset volatility. However, we do not account for this possibility here. Instead, option implied asset volatilities will be just the result of deleveraging option implied equity volatilities. We also notice that, in principle, our analysis could be equally extended to explore the informational content of corporate bonds; however, such an extension would be more problematic. While the CDS and options markets provide periodic quotes for standardized instruments with given maturities, this is not the case in the corporate bond market. In most cases, corporate bonds are infrequently traded, can include specific covenants (e.g., convertible bonds), and can differ significantly in maturity. As a result, it would certainly be difficult to collect a homogenous sample of implied asset and equity volatilities in corporate bond prices.

and concludes the paper.

2. Methodology

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, naturally referred to as the default barrier. As shown by Ericsson et al. (2015), this general setting implies a closed-form solution for the spread that equates the premium-leg and protection-leg of a CDS contract:

$$CDS_t = v(V_t, V_b, \sigma) = \frac{r(1-\theta)G_t(\tau)}{[1 - H_t(\tau) - G_t(\tau)]}, \tag{2}$$

where r represents the risk-free interest rate, θ the recovery rate, and τ the contract maturity. Specific expressions for $G_t(\tau)$ and $H_t(\tau)$ as a function of V_t, V_b, and σ are provided in Appendix A.[7]

Expression (2) 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 2.3. Subsection 2.2 deals with the fundamental problem of determining the underlying firm asset value, V_t, and the default barrier, V_b.

2.2. Structural credit risk model and estimation method

So far, we have omitted any reference to a particular structural credit risk model. This is important to stress because it implies that Expression (2) should not be associated with any specific model, but with the general setting described in subsection 2.1. That said, implied asset volatility will still depend on how firm asset value and the default barrier are defined, that is, on the particular model and estimation method selected.[8] The common element of all models that fall into our general setting is the representation of the equity value, S_t, as a function of V_t, V_b, and σ:

$$S_t = g(V_t, V_b, \sigma). \tag{3}$$

Ericsson et al. (2015) find that Leland and Toft (1996) model (LT hereafter) produces the most accurate CDS spread predictions when compared to alternative models; namely, Leland (1994) and Fan and Sundaresan (2000). Accordingly, we use LT as our base case model. The exact representation of Expression (3) in LT, including the optimal default barrier, is provided in Appendix B1. We use this expression to derive the time series of firm asset values from the time series of observed equity values. Because the default barrier is an endogenous result in LT, we do not need to specify an estimation method for this value. However, it is worth noting that while the model implies a constant default barrier, the actual model implementation will cause this value to change in the time series. This is because some of the determinants of the default barrier (e.g., total debt principal, interest payments, risk-free interest rate) will change. Note also that, while our interest at this point is only in the time series of firm asset values, $\boldsymbol{V} = (V_1, \dots, V_T)$, and time series of default barriers, $\boldsymbol{V_b} = (V_{b,1}, \dots, V_{b,T})$, both the optimal default barrier equation and equity pricing equation are also dependent on σ; therefore, we need to specify a value for this parameter as well. We apply the following recursive scheme to estimate the full set of values $\{\boldsymbol{V}; \boldsymbol{V_b}; \sigma\}$[9]:

Inversion—Correction (*IC*) Algorithm

Let σ_0 denote some initial value for σ, and let $\{\boldsymbol{V}_{k-1}; \boldsymbol{V}_{\boldsymbol{b},k-1}; \sigma_{k-1}\}$ denote the $\{\boldsymbol{V}; \boldsymbol{V_b}; \sigma\}$ values resulting from iteration $k-1$. Iteration k implies the following steps:

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

[7] Please note that, in effect, short-hand notation is used that omits the dependence of $G_t(\tau)$ and $H_t(\tau)$ on V_t, V_b, and σ (and other parameter values). This dependence is clearly described in Appendix A. Please also note that Expression (2) relies on specific assumptions on the CDS contract. We refer the interested reader to Ericsson et al. (2015) for details.

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

[9] This procedure was first introduced by Crosbie and Bohn (2003) in the context of Merton's (1974) model, and subsequently employed by Vassalou and Xing (2004), Bharath and Shumway (2008), and Forte (2011), among others.

$$V_{b,k,t} = V_{b,t}(\sigma_{k-1}); \quad (4a)$$

$$V_{k,t} = g^{-1}(S_t | V_{b,k,t}, \sigma_{k-1}). \quad (4b)$$

Correction (C). *Estimate the volatility of the $\mathbf{V}_k$ series, σ_k, and proceed as follows:*

- *If $\sigma_k \neq \sigma_{k-1}$, assume σ_k and return to Step I.*
- *If $\sigma_k = \sigma_{k-1}$, conclude.*

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

a) $\{\mathbf{V}^*; \mathbf{V}_b^*; \sigma^*\}$ fulfill both the optimal default barrier equation and equity pricing equation for all t, given $\mathbf{S}$ (Step *I*).

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

Condition a) implies that the set of values $\{\mathbf{V}^*; \mathbf{V}_b^*; \sigma^*\}$ is consistent with LT.[10] By ensuring condition b), we actually assume that the "implied asset volatility in equity prices" 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 (constant, infinite horizon) asset volatility.

2.3. Estimation of implied and realized asset volatilities

The standard implementation of a structural credit risk model consists of using $\{\mathbf{V}^*; \mathbf{V}_b^*; \sigma^*\}$ values and Expression (2) 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,

$$\sigma_{i,t} = v^{-1}\left(CDS_t | V_t^*, V_{b,t}^*\right), \quad (5)$$

and then compute the corresponding log implied asset volatility, $i_t = log(\sigma_{i,t})$.[11]

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 1260 trading days (1259 return observations).[12] If we define $R_{t,m} = log(V^*_{t-1259+m}/V^*_{t-1260+m})$ and $\bar{R}_t = (1259)^{-1}\sum_{m=1}^{1259} R_{t,m}$, then:

$$\sigma_{h,t} = \sqrt{\frac{252}{1258}\sum_{m=1}^{1259}\left(R_{t,m} - \bar{R}_t\right)^2}. \quad (6)$$

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

2.4. 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:

$$\sigma_{S,t} = \left(\frac{\partial S_t}{\partial V_t}\cdot\frac{V_t}{S_t}\right)\cdot\sigma, \quad (7)$$

or

$$log(\sigma_{S,t}) = log\left(\frac{\partial S_t}{\partial V_t}\cdot\frac{V_t}{S_t}\right) + log(\sigma). \quad (8)$$

The first term on the right-hand side of Expression (8) 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 LT is provided in Appendix B2.

Let $le_{c,t}$ denote the current leverage effect at time t, as estimated from $(V_t^*, V_{b,t}^*, \sigma^*)$:

[10] As described in Appendix B1, in the LT model both the optimal default barrier equation and equity pricing equation are a function of the effective tax rate and bankruptcy costs. Consequently, the final estimation of $\{\mathbf{V}^*; \mathbf{V}_b^*; \sigma^*\}$ and the associated values for $G_t(\tau)$ and $H_t(\tau)$ at any time t will be too.

[11] 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.

[12] The election of 1260 trading days is made to fit the 5-year maturity of the CDS contracts.

$$le_{c,t} = \left[\frac{\partial g\left(V_t^*, V_{b,t}^*, \sigma^*\right)}{\partial V_t^*} \cdot \frac{V_t^*}{g\left(V_t^*, V_{b,t}^*, \sigma^*\right)} \right]. \tag{9}$$

Expression (9) can be used to derive implied equity volatility at time t:

$$\sigma_{S,i,t} = le_{c,t} \cdot \sigma_{i,t}. \tag{10}$$

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, $c_{le,t} = log\ (le_{c,t})$, to log implied asset volatility:

$$i_{S,t} = c_{le,t} + i_t. \tag{11}$$

Realized equity volatility at time t, $\sigma_{S,h,t}$, is estimated using the available information about equity values in the same way we estimate realized asset volatility. If we define $R_{S,t,m} = log\ (S_{t-1259+m}/S_{t-1260+m})$ and $\bar{R}_{S,t} = (1259)^{-1} \sum_{m=1}^{1259} R_{S,t,m}$, then:

$$\sigma_{S,h,t} = \sqrt{\frac{252}{1258} \sum_{m=1}^{1259} \left(R_{S,t,m} - \bar{R}_{S,t}\right)^2}. \tag{12}$$

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

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

$$le_{h,t} = \frac{\sigma_{S,h,t}}{\sigma_{h,t}}. \tag{13}$$

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

Expression (13) implies decomposition of log realized equity volatility into a leverage effect component and an asset volatility component; in particular,

$$h_{S,t} = h_{le,t} + h_t. \tag{14}$$

This decomposition can naturally be interpreted as the historical counterpart of the log implied equity volatility decomposition in Expression (11).

In what follows, and to simplify the exposition, it will be understood that volatility and the leverage effect refer to log volatility and the 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 greater liquidity.[13] For those companies, we use Datastream (Thomson Reuters) and the existing literature to define the necessary inputs to implement LT following the IC algorithm (LT/IC hereafter). The period considered is 1999–2017:

a) *Equity value:* Daily data on equity values correspond to daily data on market capitalization.
b) *Total debt principal:* Daily data on the principal value of debt is obtained using a linear interpolation of yearly total liability data.[14]
c) *Debt maturity:* Following Ericsson et al. (2015), we assume a debt maturity of 6.76 years.[15]
d) *Total coupon payment:* The total coupon payment is assumed to be equal to total interest expense. As before, we perform a linear interpolation of annual data to derive the daily data.
e) *Tax rate:* Following Leland (1998), Ericsson et al. (2015), and Doshi et al. (2019), we assume the effective tax is 20%.
f) *Bankruptcy costs:* Once again, in line with the empirical analysis of Ericsson et al. (2015) and Doshi et al. (2019), bankruptcy costs are set at 15%. This value is within the range found by Andrade and Kaplan (1998).

[13] This selection criterion is, indeed, similar to that in Du et al. (2019), whose initial sample is composed of those companies that constituted the CDX index from January 2001 to December 2013.

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

[15] This maturity for newly issued debt reflects the average debt maturity of 3.38 years reported by Stohs and Mauer (1996). Ericsson et al. (2015) find that, when compared to other alternatives for debt maturity in LT (i.e., 5 and 10 years), this value generates the lowest mean CDS pricing errors. Doshi et al. (2019) assume the same average debt maturity.

g) *Payout rate:* For each year, we compute the ratio of interest expense 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 for each company by computing the average of these annual values during the whole sample period.[16]

h) *Risk-free interest rate:* The risk-free rate at time t is estimated by performing a linear interpolation between the 6-year and 7-year swap rates. The interpolation is made so that we fit the assumed maturity of 6.76 years.[17]

Previous information is all we need to implement LT/IC. For the subsequent estimation of CDS implied volatilities, we also collect daily data from Datastream on 5-year Euro-denominated CDS spreads and swap rates for 2004–2017. Again following Ericsson et al. (2015) and standard practice, we assume a recovery rate of 40%.[18]

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 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).[19] Table 1 contains the final sample of 52 companies that are considered in further analyses. The main descriptive statistics, along with the results from implementing LT/IC, are provided in Table 2.

4. Implied vs. realized asset volatilities

We estimate implied and realized asset volatilities as described in subsection 2.3. Implied and realized asset volatilities are computed 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.[20] On average, implied asset volatility is higher, more disperse, less asymmetric, and less leptokurtic than realized asset volatility. Using logs actually makes implied asset volatility slightly more leptokurtic; however, the realized asset volatility distribution is now more like the implied asset volatility distribution, and significantly closer to a normal distribution.

Before we proceed with our empirical analysis, note that time t will be a constant in each of the 114 consecutive cross-sectional regressions 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 ($h_j \equiv h_{j,t}$), and f_j its future realized asset volatility ($f_j \equiv h_{j,t+1260}$). With this notation, the three models we estimate at any particular time t can be expressed as follows:

$$\text{Model 1}: f_j = \alpha_0 + \alpha_i i_j + \varepsilon_j, \tag{15}$$

$$\text{Model 2}: f_j = \alpha_0 + \alpha_h h_j + \varepsilon_j, \tag{16}$$

$$\text{Model 3}: f_j = \alpha_0 + \alpha_i i_j + \alpha_h h_j + \varepsilon_j, \tag{17}$$

where $j = 1, \ldots, 52$. 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). These and all following models are 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: 0.785 and 0.732, respectively. However, the mean explanatory power of Model 1 is 69.37%, clearly above that of Model 2 at 53.45%. When 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: 0.693 vs. 0.118, and 100% vs. 18%, respectively. Moreover, the explanatory power of Model 3 is 70.68%, a modest difference of 1.31% from Model 1. In other words, the additional informational content of historical asset volatility is not zero, but rather small. Complementary results from likelihood ratio (LR) tests point in the same direction. While the null hypothesis of equivalence between the restricted Model 1 and the unrestricted Model 3 is rejected at the 5% level in only 31% of the regressions, the equivalence between Model 2 and Model 3 is rejected in each of

[16] Our estimation of the payout rate is, thus, similar to that in Ericsson et al. (2015), being worth mentioning that we obtain an almost identical mean value: 2.65% in their case, and 2.68% in our sample.

[17] 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%.

[18] It is worth noting that our implementation of LT/IC starts in 1999; that is, five years before the first CDS spread is available. This makes it possible to compare the informational content of implied and historical volatilities for future realized volatilities starting January 2004.

[19] In 2008, the short squeeze in Volkswagen's stock made it the most valuable listed company in the world. See Allen et al. (2021) for a detailed analysis of this case.

[20] 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).

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

This table contains the list of companies included in the final sample.

Table 2
Main descriptive statistics of the final sample and results of implementing Leland and Toft/Inversion—Correction.

	Panel A: Main descriptive statistics			Panel B: Results of implementing LT/IC		
	MC	*Eq. vol.*	*CDS*	V	V_b	σ
Mean	25,601.84	0.32	101.81	52,658.94	23,462.52	0.15
Median	16,570.36	0.33	81.93	35,875.66	14,280.30	0.15
SD	23,666.58	0.05	62.25	46,986.72	23,924.03	0.05
Min.	4739.57	0.23	30.78	10,329.07	2091.92	0.07
Max.	138,695.00	0.46	378.07	237,045.93	118,579.16	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 of implementing LT/IC (Panel B). *MC* is the average market capitalization in millions of euros. *Eq.Vol.* indicates equity volatility. *CDS* is the average mid bid-ask quote in basis points for 2004–2017. V and V_b refer to the average estimated firm asset values and default barriers in millions of euros, respectively. σ is asset volatility.

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	0.19	0.13	−1.72	−2.10
Median	0.18	0.13	−1.70	−2.06
SD	0.06	0.04	0.36	0.33
Skewness	0.49	1.11	−0.48	−0.21
Kurtosis	3.12	5.87	3.23	3.42

This table provides the main descriptive statistics for implied and (future) realized asset volatilities. Reported numbers represent the time-series averages of the cross-sectional mean, median, standard deviation, skewness, and kurtosis across 114 monthly observations.

the 114 regressions. To put it differently, LR tests suggest that in 69% of the cases implied asset volatilities subsume all the informational content of historical asset volatilities, while the opposite is never true. 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 tends to subsume the informational content of historical asset volatility.

5. Implied vs. realized equity volatilities

Does the informational content of CDS spreads about future realized asset volatility translate into equivalent informational content

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, explanatory power, and likelihood ratio test						
		Intercept	i_j	h_j	*Adj.* R^2	*LR Test*
Model 1	Mean / [Rej.]	−0.756	0.785		69.37%	[31%]
	(Signif.)	*(100%)*	*(100%)*			
Model 2	Mean / [Rej.]	−0.637		0.732	53.45%	[100%]
	(Signif.)	*(80%)*		*(100%)*		
Model 3	Mean	−0.647	0.693	0.118	70.68%	
	(Signif.)	*(86%)*	*(100%)*	*(18%)*		

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 (f_j), is related to its implied asset volatility (i_j; Model 1), its historical asset volatility (h_j; Model 2), and the two explanatory variables (i_j and h_j; Model 3). 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 each independent variable's coefficient, the number of times this coefficient is significant at the 5% level, the mean *Adj.* R^2 for each model, and the number of times the *LR Test* rejects at the 5% level the null hypothesis of equivalence between a particular restricted model (Models 1 and 2) and the unrestricted model (Model 3).

for future realized equity volatility? To answer this question, we estimate implied and realized equity volatilities as described in subsection 2.4. The main descriptive statistics for implied and realized equity volatilities are presented in Table 5. On average, implied equity volatility is more disperse, more asymmetric, and more leptokurtic than realized equity volatility. Using logs reduces the asymmetry and leptokurtosis of both distributions, and the leptokurtosis of equity volatility is actually eliminated.

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 ($f_{S,j} \equiv h_{S,j,t+1260}$). The three models to be tested are, therefore, the following:

$$\text{Model 4}: f_{S,j} = \beta_0 + \beta_{S,i} i_{S,j} + \varepsilon_{S,j}, \tag{18}$$

$$\text{Model 5}: f_{S,j} = \beta_0 + \beta_{S,h} h_{S,j} + \varepsilon_{S,j}, \tag{19}$$

$$\text{Model 6}: f_{S,j} = \beta_0 + \beta_{S,i} i_{S,j} + \beta_{S,h} h_{S,j} + \varepsilon_{S,j}. \tag{20}$$

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).

According to the results in Table 6, the mean explanatory power of implied equity volatility in Model 4 is "only" 22.19%, quite far from the mean explanatory power of 69.37% for implied asset volatility in Model 1. Moreover, implied equity volatility does not seem to contain significantly more information than historical equity volatility. 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—0.639 vs. 0.499, and 92% vs. 63%, respectively—the mean explanatory power of Model 5 is 19.35%, only slightly lower than that of Model 4. The exact difference of 2.84% is, in effect, quite far from the gap of 15.92% between Models 1 and 2. Additional results from the comprehensive Model 6 indicate, however, that implied and historical equity volatility contain complementary information. Similar to what we observed for asset volatility in Model 3, the mean of the coefficient of implied equity volatility and the number of times this coefficient is significant are both higher than their historical equity volatility counterparts—0.493 vs. 0.286, and 82% vs. 46%, respectively; yet, these differences are not as remarkable as those in Model 3. Moreover, the mean explanatory power of 26.96% for Model 6 represents an increase of 4.77% with respect to Model 4, clearly above the improvement of moving from Model 1 to Model 3 (1.31%), and the equivalence between any of the restricted models and the unrestricted Model 6 is usually (and similarly) rejected: in 56% of the cases if we look at Model 4, and in 61% of the cases if we focus on Model 5. Finally, and although our main interest here is 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 (53.45%). The marked disagreement in our results for asset volatility and equity volatility is certainly puzzling. In Section 6, we explore three possible explanations.

6. Implied asset and equity volatility: exploring the differences

6.1. Current leverage effect could be a poor predictor of future realized leverage effect

According to Expression (11), 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 (14) 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 also be affected.

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	0.42	0.31	−0.91	−1.21
Median	0.39	0.29	−0.94	−1.23
SD	0.09	0.08	0.17	0.23
Skewness	1.49	1.11	0.81	0.51
Kurtosis	7.76	4.23	4.92	2.94

This table provides the main descriptive statistics for implied and (future) realized equity volatilities. Reported numbers represent the time-series averages of the cross-sectional mean, median, standard deviation, skewness, and kurtosis across 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, explanatory power, and likelihood ratio test						
		Intercept	$i_{S,j}$	$h_{S,j}$	*Adj.* R^2	*LR Test*
Model 4	Mean / [Rej.]	−0.645	0.639		22.19%	[56%]
	(Signif.)	*(91%)*	*(92%)*			
Model 5	Mean / [Rej.]	−0.608		0.499	19.35%	[61%]
	(Signif.)	*(80%)*		*(63%)*		
Model 6	Mean	−0.405	0.493	0.286	26.96%	
	(Signif.)	*(69%)*	*(82%)*	*(46%)*		

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 ($f_{S,j}$), is related to its implied equity volatility ($i_{S,j}$; Model 4), its historical equity volatility ($h_{S,j}$; Model 5), and the two explanatory variables ($i_{S,j}$ and $h_{S,j}$; Model 6). 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 each independent variable's coefficient, the number of times this coefficient is significant at the 5% level, the mean *Adj.* R^2 for each model, and the number of times the *LR Test* rejects at the 5% level the null hypothesis of equivalence between a particular restricted model (Models 4 and 5) and the unrestricted model (Model 6).

Finally, according to Expression (9), 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 significantly higher informational content of implied asset volatility vis-à-vis historical asset volatility, implied equity volatility is only slightly more informative than historical equity volatility.

To test these hypotheses, we estimate the current and realized leverage effects as described in subsection 2.4. 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 normal distributions.

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 ($f_{le,j} \equiv h_{le,j,t+1260}$). With this notation, the three models to be estimated are:

$$\text{Model 7}: f_{le,j} = \gamma_0 + \gamma_{le,c} c_{le,j} + \varepsilon_{le,j}, \tag{21}$$

$$\text{Model 8}: f_{le,j} = \gamma_0 + \gamma_{le,h} h_{le,j} + \varepsilon_{le,j}, \tag{22}$$

$$\text{Model 9}: f_{le,j} = \gamma_0 + \gamma_{le,c} c_{le,j} + \gamma_{le,h} h_{le,j} + \varepsilon_{le,j}. \tag{23}$$

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).

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 0.935. Moreover, its mean explanatory power of 77.37% 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 0.899. Moreover, its mean explanatory power of 61.60% is higher than the mean explanatory power of historical asset volatility in Model 4. Our last hypothesis—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, suggest that the additional informational content of the historical leverage effect is actually very small. On the one hand, its coefficient is significant in only 13% of the regressions, with a mean value that drops to 0.063. This is a clear contrast to the corresponding values for the current leverage effect: 96% and 0.880, respectively. On the other hand, incorporating the historical leverage effect only

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	2.49	2.65	0.81	0.89
Median	2.12	2.27	0.74	0.82
SD	1.31	1.27	0.37	0.39
Skewness	2.75	2.41	1.04	0.87
Kurtosis	13.59	11.12	4.47	3.79

This table provides the main descriptive statistics for the current and (future) realized leverage effects. Reported numbers represent the time-series averages of the cross-sectional mean, median, standard deviation, skewness, and kurtosis across 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, explanatory power, and likelihood ratio test						
		Intercept	$c_{le,j}$	$h_{le,j}$	*Adj.* R^2	*LR Test*
Model 7	Mean / [Rej.]	0.147	0.935		77.37%	[20%]
	(Signif.)	*(68%)*	*(100%)*			
Model 8	Mean / [Rej.]	0.165		0.899	61.60%	[96%]
	(Signif.)	*(56%)*		*(100%)*		
Model 9	Mean	0.143	0.880	0.063	77.98%	
	(Signif.)	*(63%)*	*(96%)*	*(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* ($f_{le,j}$), is related to its current leverage effect ($c_{le,j}$; Model 7), its historical leverage effect ($h_{le,j}$; Model 8), and the two explanatory variables ($c_{le,j}$ and $h_{le,j}$; Model 9). 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 each independent variable's coefficient, the number of times this coefficient is significant at the 5% level, the mean *Adj.* R^2 for each model, and the number of times the *LR Test* rejects at the 5% level the null hypothesis of equivalence between a particular restricted model (Models 7 and 8) and the unrestricted model (Model 9).

increases the mean explanatory power of Model 7 by 0.61% (total of 77.98%). Additional results from LR tests indicate that in 80% of the cases the current leverage effect subsumes all the informational content of the historical leverage effect, while the opposite is true in only 4% of the cases. 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.

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 for the future realized leverage effect and future realized asset volatility, respectively. This, however, does not imply that they are both unbiased estimates. As a clear example, it is reasonable to deduce from the results in Table 3 that implied asset volatility accounts not only for future expected asset volatility, but also for a volatility risk premium (Du et al., 2019). 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 in fact be different, it makes sense to evaluate the explanatory power of a more flexible model that allows their respective coefficients to be different.[21] The two new models that we will compare with Model 5 are:

$$\text{Model 10}: f_{S,j} = \beta_0 + \beta_{le,c} c_{le,j} + \beta_i i_j + \varepsilon_{S,j}, \tag{24}$$

$$\text{Model 11}: f_{S,j} = \beta_0 + \beta_{le,c} c_{le,j} + \beta_i i_j + \beta_{S,h} h_{S,j} + \varepsilon_{S,j}. \tag{25}$$

In these two models, the future realized equity volatility of company *j* is related to its current leverage effect and implied asset volatility (Model 10), and these two variables plus historical equity volatility (Model 11).

The results in Table 9 provide mixed evidence. On the one hand, they offer clear support to our new hypothesis. Coefficients for the current leverage effect and implied asset volatilities in Model 10 are certainly different from each other on average (0.780 vs. 0.591), and more often significant than the coefficient of implied equity volatility in Model 4 (98% and 97% vs. 92%, respectively). Also, contrary to the explanatory power of Model 4 (22.19%), the explanatory power of Model 10 (28.50%) represents a significant difference with respect to the explanatory power of historical equity volatility in Model 5 (19.35%). Besides, according to LR tests, historical equity volatility subsumes the joint informational content of the current leverage effect and implied asset volatility in only

[21] While a formal test of the precise value of the regression coefficients is beyond the purposes of this study, it is worth noting that the results in Tables 4 and 8 are, in effect, indicative of higher bias in implied asset volatility than in the current leverage effect.

Table 9
Future realized equity volatility as a function of current leverage effect, implied asset volatility, and historical equity volatility.

Dependent variable: future realized equity volatility, $f_{S,j}$							
Model, independent variables, explanatory power, and likelihood ratio test							
		Intercept	$c_{le,j}$	i_j	$h_{S,j}$	*Adj.* R^2	*LR Test*
Model 10	Mean / [Rej.]	−0.821	0.780	0.591		28.50%	[58%]
	(Signif.)	*(97%)*	*(98%)*	*(97%)*			
Model 5	Mean / [Rej.]	−0.608			0.499	19.35%	[98%]
	(Signif.)	*(80%)*			*(63%)*		
Model 11	Mean	−0.593	0.637	0.456	0.265	32.63%	
	(Signif.)	*(75%)*	*(98%)*	*(70%)*	*(43%)*		

This table summarizes the results of estimating Models 10, 5, and 11 using OLS with White standard errors. In these three models, the future realized equity volatility of company j ($f_{S,j}$), is related to its current leverage effect and implied asset volatility ($c_{le,j}$ and i_j; Model 10), its historical equity volatility ($h_{S,j}$; Model 5), and the three explanatory variables ($c_{le,j}$, i_j, and $h_{S,j}$; Model 11). 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 each independent variable's coefficient, the number of times this coefficient is significant at the 5% level, the mean *Adj.* R^2 for each model, and the number of times the *LR Test* rejects at the 5% level the null hypothesis of equivalence between a particular restricted model (Models 10 and 5) and the unrestricted model (Model 11).

2% of the cases (98% of rejections for the null hypothesis of equivalence between Models 5 and 11). This represents a clear drop with respect to the 39% of cases in which historical equity volatility subsumes the informational content of implied equity volatility (the equivalence between Models 5 and 6 is rejected in 61% of the cases). It seems, therefore, that in terms of explaining future realized equity volatility, it is indeed better to consider the current leverage effect and implied asset volatility as two separate explanatory variables.[22] On the other hand, 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 historical equity volatility in Model 5 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. To summarize, most of our puzzling results from Models 1 to 9 are so far unexplained. Consequently, we proceed with our third possible explanation.

6.3. The interconnection between leverage and asset volatility

6.3.1. Motivation

According to the results in Choi and Richardson (2016) and Im et al. (2020), there is a very significant negative correlation between asset volatility and leverage. Choi and Richardson (2016) also demonstrate that, following Expression (8), 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 may exhibit very similar equity volatilities. In light of those previous results, we address 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?

Fig. 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 across the whole period 1999–2017. It seems, in fact, that our estimations are fully consistent with those of 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 to leverage.[23]

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

The information in Figs. 1 and 2, along with the evidence from Models 1 to 11, 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

[22] It is worth noting that, although the decomposition of implied equity volatility has a clear positive effect on its own informational content, the *additional* informational content of historical equity volatility remains essentially the same. Looking again at the results of comprehensive Model 11, the coefficient of historical equity volatility is significant in 43% of the regressions, with a mean value of 0.265. These values are, in effect, similar to those in Model 6: 46% and 0.286, respectively. Also, incorporating historical equity volatility increases the explanatory power of Model 10 by 4.13% (total of 32.63%), close to the difference of 4.77% between Models 4 and 6. Finally, LR tests indicate that the current leverage effect and implied asset volatility subsume the informational content of historical equity volatility in 42% of the cases (the equivalence between Models 10 and 11 is rejected in 58% of these cases). This is also similar to the number of cases (44%) in which implied equity volatility subsumes the informational content of historical equity volatility (56% of rejections for the null hypothesis of equivalence between Models 4 and 6).

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

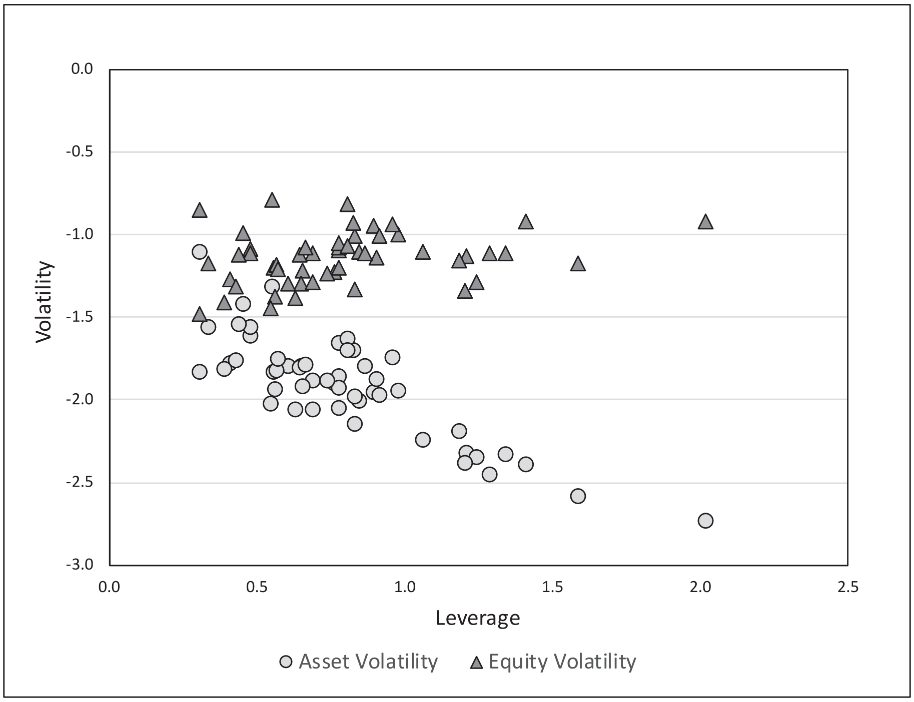

Fig. 1. Asset and equity volatility as a function of leverage.
This figure depicts asset and equity volatility as a function of leverage for each of the 52 companies. Leverage is defined as the log of the mean value of (V_t/S_t) over the period 1999–2017. Asset and equity volatility refer to the log of realized volatilities for the same sample period.

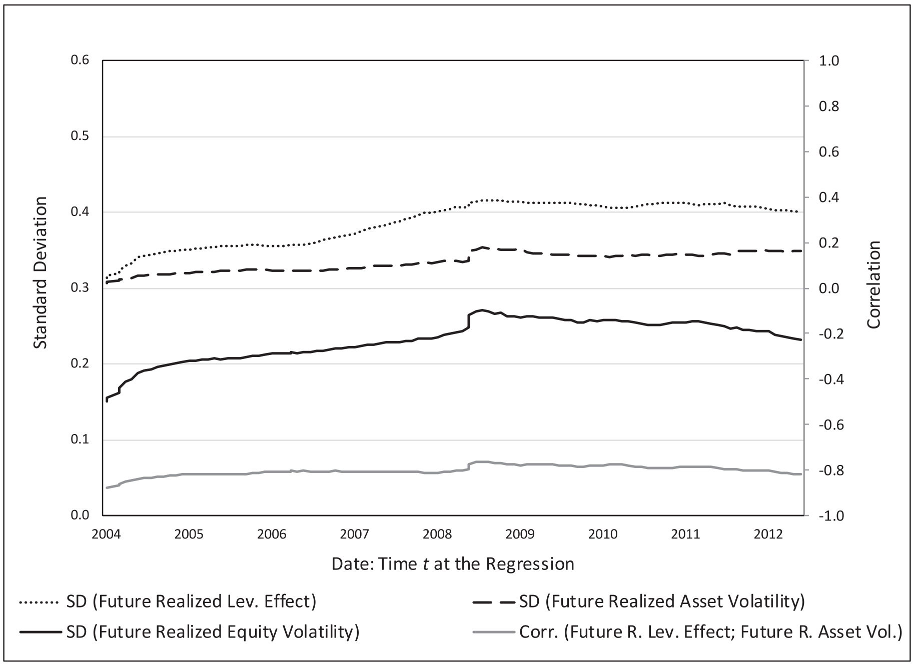

Fig. 2. Correlation between future realized leverage effect and future realized asset volatility, and standard deviation of future realized leverage effect, future realized asset volatility, and future realized equity volatility.
This figure plots the correlation between the future realized leverage 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).

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. It is also worth anticipating that, for the same sake of simplicity, the model will ignore the possibility of bias in implied asset volatility and/or the current leverage effect, and, therefore, any potential difference between the explanatory power of Model 4 and Model 10. However, extending our model to account for such biases would be a rather simple task.

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

$$f_j = i_j + \eta_j \tag{26}$$

and

$$f_{le,j} = c_{le,j} + \eta_{le,j}, \tag{27}$$

where η_j and $\eta_{le,j}$ represent white noise, uncorrelated with each other or with either i_j or $c_{le,j}$. Hence, we assume in effect that implied asset volatility and the current leverage effect represent the future expected asset volatility and leverage effect, respectively. Expressions (26) and (27) imply that future realized equity volatility is

$$f_{S,j} = i_{S,j} + \eta_{S,j}, \tag{28}$$

where $i_{S,j} = c_{le,j} + i_j$ is the implied (and future expected) equity volatility, and $\eta_{S,j} = \eta_{le,j} + \eta_j$.

We next assume that all companies aim to maximize their tax benefits while controlling for both bankruptcy and pre-bankruptcy costs. More specifically, we assume that they will choose the highest possible debt level under the restriction that their expected default probability not exceed a maximum threshold q^*. This simple but instrumental assumption lies on the empirical findings of Kisgen (2006, 2009, 2019) and Elkamhi et al. (2012), and can be associated to a minimum (investment grade) credit rating target. We further assume that such 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:

$$DD_{S_t} = \frac{S_t - 0}{\sigma_S S_t} = \frac{1}{\sigma_S}. \tag{29}$$

Accordingly, two companies will have the same default probability whenever they have the same equity volatility.[24]

Consider now that, while all companies have the same equity volatility target, their asset volatility is not the same, either in the cross-section or time-series. Because the prediction that company j makes about its future realized asset volatility is i_j, its optimal current leverage effect—that is, the one that makes its expected equity volatility equal to f_S^*— will be:

$$c_{le,j}^* = f_S^* - i_j. \tag{30}$$

Following this expression and previous results, if companies can select their debt level so $c_{le,j} = c_{le,j}^*$, then implied equity volatility will be:

$$i_{S,j} = f_S^*. \tag{31}$$

In other words, both the cross-sectional variation in implied equity volatility and its explanatory power in 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, unpredictable. Finally, it is worth noting that this will happen no matter what the explanatory power is of implied asset volatility (Model 1) and the current leverage effect (Model 7). On the contrary, the higher their explanatory power—that is, the higher the variance of i_j and $c_{le,j}$ relative to the variance of η_j and $\eta_{le,j}$ in Expressions (26) and (27)—the higher the alignment of the proposed model with the evidence provided in Fig. 2 (higher variance for the 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, that 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 Fig. 2). The model, however, is not consistent with our finding of strictly positive explanatory power for implied equity volatility.

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

[24] We could relate this assumption to the empirical results in Campbell and Taksler (2003), who find that equity volatility explains as much variation in corporate bond yield spreads as do credit ratings. It is also worth noting that, under the naïve model in the Internet Appendix, there is no actual 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: $DD_{V_t} = (V_t - V_b)/\sigma V_t = 1/\sigma_S$.

$$c_{le,j} = c^*_{le,j} + dc_{le,j}, \tag{32}$$

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.[25] This new assumption leads to a new value for implied equity volatility:

$$i_{S,j} = f^*_S + dc_{le,j}. \tag{33}$$

Following this expression, a relatively small cross-sectional variation in $dc_{le,j}$ would be enough to generate strictly positive explanatory power for implied equity volatility, but still lower than that of implied asset volatility and the current leverage effect. The introduction of this new factor does not necessarily make the model inconsistent with the evidence provided in Fig. 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.

Fig. 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 greatest capacity to adjust their debt levels to their optimal values. On the opposite side, the sub-prime crisis (2008–2009) and the peak of 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 deviated most from their optimal values.[26]

Fig. 4 represents the evolution of the explanatory power of the current leverage effect (Model 7), implied asset volatility (Model 1), and implied equity volatility (Model 4). For completeness, the figure also includes the explanatory power of the decomposed implied equity volatility (Model 10). Again, consistent with the implications of our simple model, the explanatory powers of the current leverage effect and implied asset volatility are always higher than that of implied equity volatility. Also consistent with the model's predictions, the higher the cross-sectional variation in implied equity volatility (Fig. 3), the higher the explanatory power of this variable (Fig. 4; Models 4 and 10). More precisely, the explanatory power of implied equity volatility is in the range of 0–15% during the calm period preceding the sub-prime crisis, starts to grow in 2007, and has settled in the range of 30–50% since mid-2008.

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

Following previous assumptions, future realized equity volatility is

$$f_{S,j} = f^*_S + dc_{le,j} + \eta_{S,j}, \tag{34}$$

while historical equity volatility could be expressed as

$$h_{S,j} = f^*_S + dc^h_{le,j} + \eta^h_{S,j}, \tag{35}$$

where $dc^h_{le,j}$ stands for the historical (current) leverage effect's deviation from its optimal value, and $\eta^h_{S,j}$ represents white noise, uncorrelated with $\eta_{S,j}$. Expression (35) is simply the historical counterpart to Expression (34).

We first consider the strongest version of our model, where companies have the capacity to select their optimal debt levels. If this is the case, then $dc^h_{le,j} = dc_{le,j} = 0$ and the explanatory power of historical equity volatility will be equal to zero, that is, equal to the explanatory power of $\eta^h_{S,j}$ 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.

We now assume that companies face restrictions when they attempt to choose their optimal debt level (weakest version of the model). In this instance, to the extent that $dc_{le,j}$ is correlated with $dc^h_{le,j}$, the explanatory power of historical equity volatility will be strictly positive. Such a correlation would again be the result of the slow adjustment of debt levels to changes in both 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 short, because the underlying explanatory factor in implied and historical equity volatility is the deviation of actual debt levels from their optimal values and its persistence over time, the explanatory power of these variables will be closely related to the presence (or not) of such deviations.

Fig. 5 provides evidence on the evolution of the explanatory power of the historical leverage effect (Model 8), historical asset

[25] See Choi and Richardson (2016).

[26] Still, the maximum correlation between the current leverage effect and implied asset volatility stays at a remarkable negative value of −0.74 (May 2012).

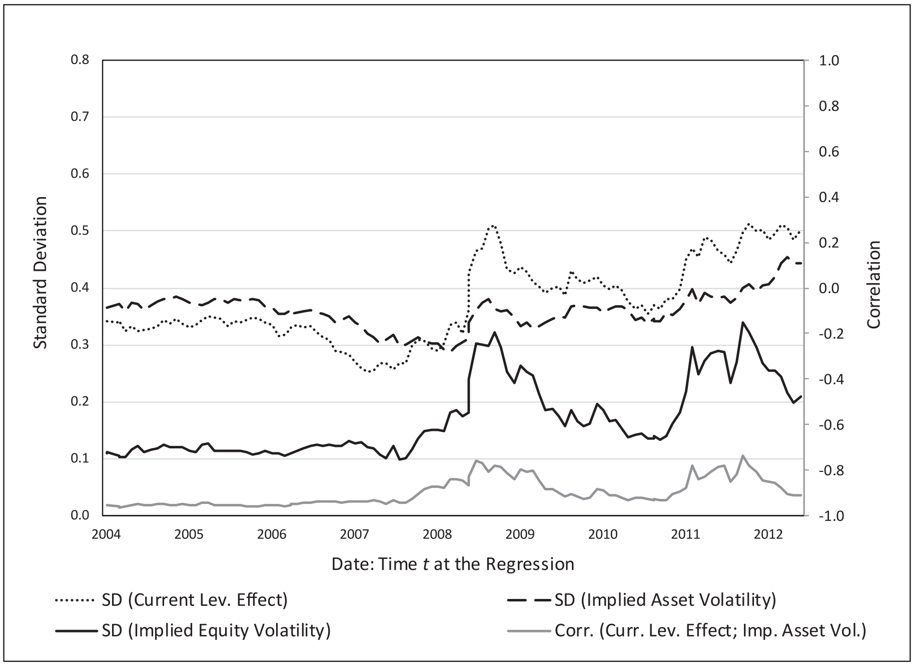

Fig. 3. Correlation between current leverage effect and implied asset volatility, and standard deviation of current leverage effect, implied asset volatility, and implied equity volatility.

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).

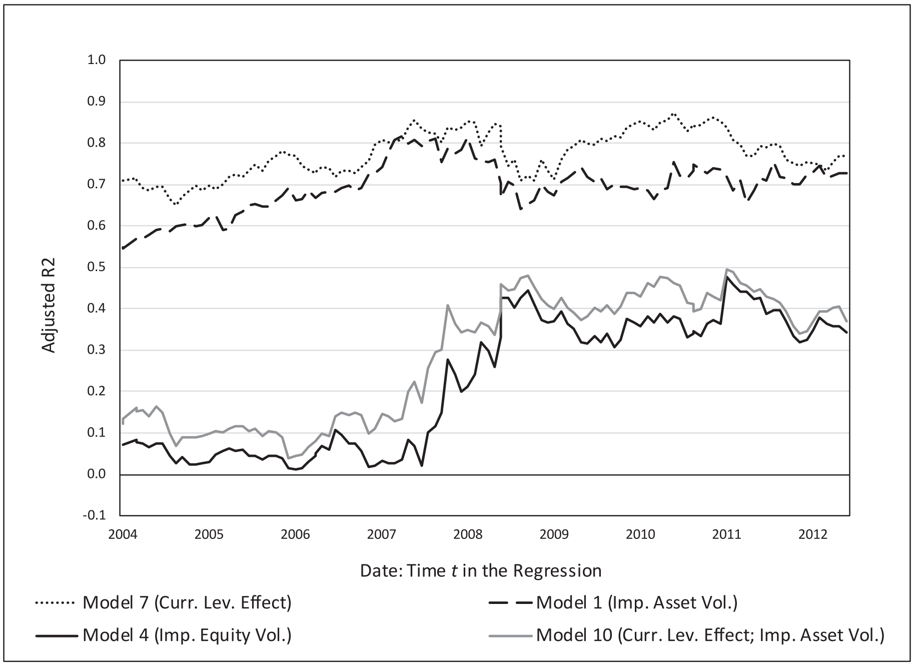

Fig. 4. Explanatory power of Models 7, 1, 4, and 10.

This figure plots the adjusted R^2 of Model 7 (future realized leverage effect as a function of current leverage effect; black dotted line), Model 1 (future realized asset volatility as a function of implied asset volatility; black dashed line), Model 4 (future realized equity volatility as a function of implied equity volatility; black solid line), and Model 10 (future realized equity volatility as a function of current leverage effect and implied asset volatility; grey solid line). The figure reflects the results for each of the 114 monthly regressions.

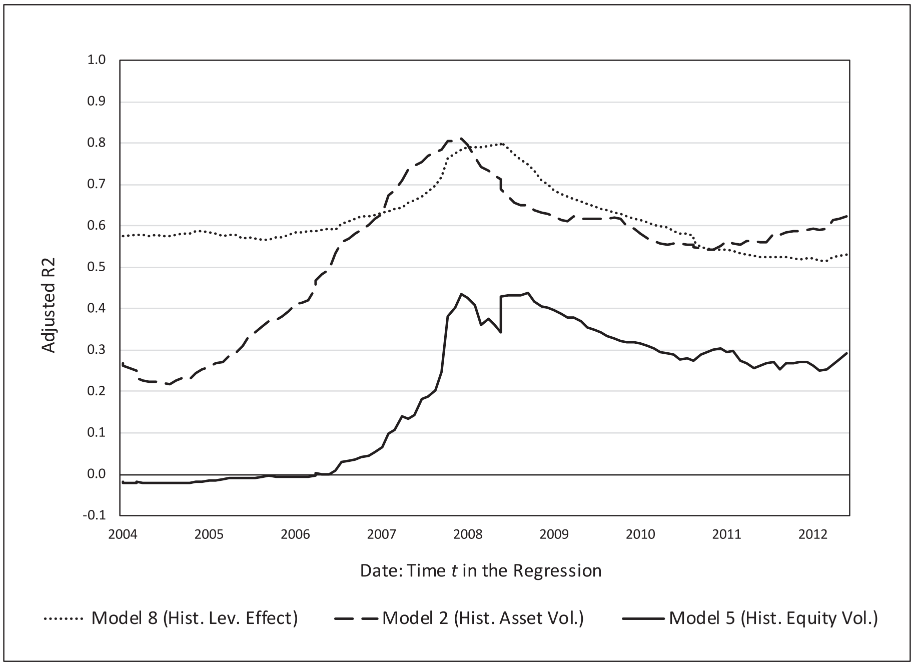

Fig. 5. Explanatory power of Models 8, 2, and 5.
This figure plots the adjusted R^2 of Model 8 (future realized leverage effect as a function of historical leverage effect; black dotted line), Model 2 (future realized asset volatility as a function of historical asset volatility; black dashed line), and 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.

volatility (Model 2), and historical equity volatility (Model 5). The figure reveals that the explanatory power of historical equity volatility is systematically lower than that of the historical leverage effect and historical asset volatility. Moreover, while the explanatory power of historical equity volatility is not exactly the same as the explanatory power of implied equity volatility in Fig. 4 (Models 4 and 10), consistent with our hypotheses, they exhibit a very similar pattern: rather small (or equal to zero) in the pre-crisis period, with sudden growth afterward. In conclusion, the overall results in Fig. 5 confirm that our simple model of the interconnection between leverage and asset volatility can also explain the different informational content of historical asset and equity volatility.

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 that 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 basic assumption in Expression (26) is that implied asset volatility represents an unbiased estimate of future realized asset volatility. Our results suggest, on the contrary, that implied asset volatility is a powerful but biased estimate of future realized asset volatility (see Section 4 and subsection 6.2). It does not seem, however, that the model's main predictions rely on the assumption that the constant term in Expression (26) equals 0, and the slope equals 1.

Expression (27) 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 (34) and (35), the actual implicit assumption is that decisions about debt levels are made once every five years. However, recognizing that companies could adjust their debt levels at any point in time would only reinforce the model's predictions. The higher the capacity of companies to modify their debt levels, the lower the deviation in their realized equity volatilities from the common target, and the lower the explanatory power of implied and historical equity volatility.

Another simplifying assumption of the model is that the trade-off between tax benefits on the one hand, and bankruptcy plus pre-bankruptcy costs on the other, 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 model's main predictions. In particular, we could consider the possibility that such a trade-off leads to much lower cross-sectional variation in optimal equity volatility than in expected asset volatility (that is exactly what the model aims to reflect), but not to the point where all companies have the same precise equity volatility target. In this instance, the strictly positive explanatory power of implied and historical equity volatility 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 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. Indeed, the evidence in Fig. 5 indicates 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 model's predictions is the product of its simplifying assumptions.

7. Robustness tests and extensions

7.1. Alternative models and estimation methods

We have selected a mainstream structural credit risk model (LT), and a relatively standard estimation method (IC algorithm). Even so, it could easily be argued that our main results rely on this particular choice. We consider three alternative approaches in the Internet Appendix (Appendix C). The first is based on Forte (2011), a relatively simple exogenous default barrier model that has already been shown to produce sensible CDS spread predictions.[27] The estimation method applied consists of an Inversion—Correction—Maximization (ICM) algorithm, an extended version of the IC algorithm described in subsection 2.2, which, following Forte and Lovreta (2012), allows us to "endogenize" the exogenous default barrier. The second approach is a naïve one, where the firm asset value is simply the equity value plus total liabilities, and the default barrier is equal to total liabilities.[28] Our main argument is that, while we could extend our analysis to a larger set of structural credit risk models and estimation methods, a more definite robustness test can probably be achieved by assuming this completely different, model-free approach. The third and last alternative approach consists of a pseudo-naïve implementation of Forte (2011), where the default barrier is again equal to total liabilities (i.e., debt principal). With this additional estimation, we aim to explore in more detail any potential difference between the endogenous and naïve approximations in the definition of the default barrier. To summarize, we use four different models and/or estimation methods to define the time series of firm asset values and the time series of default barriers: Leland and Toft/Inversion—Correction (LT/IC); Forte/Inversion—Correction—Maximization (F/ICM); Naïve Model (NM); and Forte/Inversion—Correction—Principal (F/ICP). In the core of the paper, we have concentrated on describing the results based on LT/IC. Details on the other approaches, and their corresponding results, can be found in the Internet Appendix.[29] The conclusions are as follows.[30] First, irrespective of the model (either parametric or non-parametric) and estimation method, the main empirical findings remain the same: CDS implied and historical volatilities are significantly more informative about future cross-sectional differences in asset volatilities than in equity volatilities, and, in all cases, the explanation can be found in the leverage effect component in equity volatility, and the interconnection between leverage and asset volatility. Second, numerical results from the two endogenous default barrier approaches (LT/IC and F/ICM) are roughly the same. Last, compared to the use of a naïve approach to defining the default barrier (NM and F/ICP), the use of an endogenous approach leads to higher informational content for CDS implied volatilities. This, however, seems to be a reasonable finding: the more precise the definition of the default barrier in Expression (2), the higher our expectations about the informational content of CDS implied volatilities.[31]

7.2. Model-free realized asset volatilities

Previous analysis confirms that our main conclusions are not the product of one particular model and estimation method. However, because we always use one specific model to estimate both implied and realized asset volatilities, it could be argued that the high explanatory power of implied asset volatility for future realized asset volatility is, at least to some extent, the reflection of a common measurement error. To address this potential problem, we repeat the estimation of Models 1, 2, and 3 by relating our model-dependent implied asset volatilities (LT/IC), to our model-free measures of future and historical asset volatilities (NM). The results in Table 10 indicate that the mean explanatory power of implied asset volatility remains almost the same (68.66% vs. 69.37% under the base case approach), and a similar conclusion arises when historical asset volatility (53.78% vs. 53.45%) and the comprehensive model (70.04% vs. 70.68%) are considered. In conclusion, we find no evidence that the high explanatory power of implied asset volatility for future realized asset volatility is the result of a common measurement error.

[27] See also Forte and Peña (2009) and Forte and Lovreta (2012).

[28] Charitou et al. (2013) use a similar approach to estimate the distance-to-default in Merton (1974).

[29] We could be tempted to also use Merton's model as an additional robustness test. However, this model assumes that default can only occur at the maturity of one particular zero coupon bond. Hence, it does not fall into the set of structural credit risk models described in subsection 2.1, and it is not consistent with Expression (2). Similarly, we could consider the possibility of using Geske's (1977) model, which allows for multiple defaults. However, this model is difficult to implement in practice, and, again, it does not fall into the category of constant default barrier models that lead to Expression (2).

[30] To ease the comparison, we use a simple correspondence between tables and figures in the core of the paper and in the Internet Appendix. By way of example, Table 3 in the core of the paper provides descriptive statistics for implied and realized asset volatilities from LT/IC, while Table IA 3 in the Internet Appendix offers the corresponding values from F/ICM, NM, and F/ICP.

[31] We must insist on the fact that, although the definition of the default barrier may or may not be model-dependent, in our estimations, the equity value and nominal debt are always the observed values.

Table 10
Future (model-free) realized asset volatility as a function of (model-dependent) implied asset volatility and historical (model-free) asset volatility.

Dependent variable: future realized asset volatility, f_j						
Model, independent variables, explanatory power, and likelihood ratio test						
		Intercept	i_j	h_j	*Adj.* R^2	*LR Test*
Model 1	Mean / [Rej.]	−0.746	0.783		68.66%	[27%]
	(Signif.)	*(100%)*	*(100%)*			
Model 2	Mean / [Rej.]	−0.606		0.734	53.78%	[100%]
	(Signif.)	*(74%)*		*(100%)*		
Model 3	Mean	−0.626	0.672	0.138	70.04%	
	(Signif.)	*(84%)*	*(100%)*	*(25%)*		

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 (model-free) asset volatility of company j (f_j), is related to its (model-dependent) implied asset volatility (i_j; Model 1), its historical (model-free) asset volatility (h_j; Model 2), and the two explanatory variables (i_j and h_j; Model 3). 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 each independent variable's coefficient, the number of times this coefficient is significant at the 5% level, the mean *Adj.* R^2 for each model, and the number of times the *LR Test* rejects at the 5% level the null hypothesis of equivalence between a particular restricted model (Models 1 and 2) and the unrestricted model (Model 3).

7.3. Levered asset volatilities

Our structural approach leads to a comparison between the predictability of equity and *unlevered* asset volatility.[32] However, it is also possible to analyze the predictability of *levered* asset volatility.[33] According to LT, the levered firm asset value is itself a contingent claim on the unlevered firm asset value:

$$LV_t = L(V_t, V_b, \sigma). \tag{36}$$

The exact analytic expression for $L(V_t, V_b, \sigma)$ is reproduced in Appendix B1. From this expression, and similar to equity volatility, levered asset volatility, $\sigma_{LV,t}$, can be related to unlevered asset volatility as follows (log values directly used):

$$log(\sigma_{LV,t}) = log\left(\frac{\partial LV_t}{\partial V_t}\cdot\frac{V_t}{LV_t}\right) + log(\sigma), \tag{37}$$

where the first term on the right-hand side accounts for the leverage effect component in levered asset volatility (Appendix B2 provides the precise expression for $\partial LV_t/\partial V_t$). With a slight abuse of notation, we can denote $c_{le,t}^{LV}$ the current value of the leverage effect at time t:

$$c_{le,t}^{LV} = log\left[\frac{\partial L\left(V_t^*, V_{b,t}^*, \sigma^*\right)}{\partial V_t^*}\cdot\frac{V_t^*}{L\left(V_t^*, V_{b,t}^*, \sigma^*\right)}\right]. \tag{38}$$

The implied levered asset volatility will be:

$$i_{LV,t} = c_{le,t}^{LV} + i_t. \tag{39}$$

The estimated levered firm asset values from Expression (36) also allow for the estimation of realized levered asset volatility at time t, $h_{LV,t}$.[34] More precisely, if we define $R_{LV,t,m} = log\ (LV_{t-1259+m}/LV_{t-1260+m})$ and $\bar{R}_{LV,t} = (1259)^{-1}\sum_{m=1}^{1259} R_{LV,t,m}$, then:

$$h_{LV,t} = log\sqrt{\frac{252}{1258}\sum_{m=1}^{1259}\left(R_{LV,t,m} - \bar{R}_{LV,t}\right)^2}. \tag{40}$$

Table 11 provides the main descriptive statistics for implied and realized levered asset volatilities. The results reveal that levered and unlevered asset volatilities (Table 11 vs. Table 3) exhibit very similar distributions. This reflects the minor influence of leverage in this case, at least in comparison with its influence on equity volatility.[35]

Following our simplified notation once again, we denote $c_{le,j}^{LV}$ as the current leverage effect in levered asset volatility of company j ($c_{le,j}^{LV} \equiv c_{le,j,t}^{LV}$), $i_{LV,j}$ its implied levered asset volatility ($i_{LV,j} \equiv i_{LV,j,t}$), $h_{LV,j}$ its historical levered asset volatility ($h_{LV,j} \equiv h_{LV,j,t}$), and $f_{LV,j}$ its future realized levered asset volatility ($f_{LV,j} \equiv h_{LV,j,t+1260}$). The four concrete models to be tested are as follows:

[32] Please refer to footnotes 1 and 5.

[33] We thank an anonymous referee for suggesting this extension.

[34] An important remark is that, in practice, and by construction, the estimated levered firm asset value at time t from Expression (36) will be equal to the observed market value of equity plus the estimated market value of total debt: $LV_t = L(V_t^*, V_{b,t}^*, \sigma^*) = S_t + D(V_t^*, V_{b,t}^*, \sigma^*)$.

[35] Our estimations provide a mean value for the (log) current and realized leverage effect in levered asset volatility of 0.04 and 0.05, respectively. The corresponding values for equity volatility are 0.81 and 0.89 (see Table 7).

Table 11
Main descriptive statistics for implied and realized levered asset volatilities.

	Implied levered asset volatility	Realized levered asset volatility	Log implied levered asset volatility	Log realized levered asset volatility
Mean	0.20	0.14	−1.68	−2.05
Median	0.19	0.13	−1.67	−2.01
SD	0.06	0.04	0.32	0.31
Skewness	0.60	1.18	−0.31	−0.09
Kurtosis	3.48	6.11	3.07	3.50

This table provides the main descriptive statistics for implied and (future) realized levered asset volatilities. Reported numbers represent the time-series averages of the cross-sectional mean, median, standard deviation, skewness, and kurtosis across 114 monthly observations.

$$\text{Model 12}: f_{LV,j} = \omega_0 + \omega_{LV,i} i_{LV,j} + \varepsilon_{LV,j}, \tag{41}$$

$$\text{Model 13}: f_{LV,j} = \omega_0 + \omega_{le,c} c_{le,j}^{LV} + \omega_i i_j + \varepsilon_{LV,j}, \tag{42}$$

$$\text{Model 14}: f_{LV,j} = \omega_0 + \omega_{LV,h} h_{LV,j} + \varepsilon_{LV,j}, \tag{43}$$

$$\text{Model 15}: f_{LV,j} = \omega_0 + \omega_{LV,i} i_{LV,j} + \omega_{LV,h} h_{LV,j} + \varepsilon_{LV,j}. \tag{44}$$

In these four models, the future realized levered asset volatility of company *j* is related to its implied levered asset volatility (Model 12), its current leverage effect in levered asset volatility and implied asset volatility (Model 13), its historical levered asset volatility (Model 14), and its implied and historical levered asset volatility (Model 15).

A comparison of the results in Table 12 with those in Table 4 for unlevered asset volatility confirms the moderate influence of the leverage effect. To begin, implied levered asset volatility explains 66.96% of the cross-sectional variation in future realized levered asset volatility (the corresponding result for unlevered asset volatility is 69.37%). In addition, considering the current leverage effect in levered asset volatility and unlevered asset volatility as two separate explanatory variables does not improve the results. As a matter of fact, the adjusted R^2 falls slightly to reach 66.75%. Also, the explanatory power of historical levered (unlevered) asset volatility is 53.79% (53.45%). Finally, similar to historical unlevered asset volatility, the additional informational content of historical levered asset volatility is relatively small. More precisely, the explanatory power of comprehensive Model 15 is 69.15%. This represents a modest increment of 2.19% with respect to Model 12 and is quite similar to the explanatory power of Model 3 in Table 4 (70.68%).

A noteworthy conclusion from our robustness tests is that the results are particularly robust to different estimation approaches and to the consideration of levered or unlevered asset volatilities. To provide some intuition on this finding, Fig. 6 plots the overall realized asset volatility offered by alternative estimation methods against that obtained from our base case approach. The figure is explicit in the sense that, regardless of the estimation method applied and whether we consider levered or unlevered assets, estimates of realized asset volatilities are relatively the same.

7.4. Out-of-sample estimation

Our empirical results rely on estimating the time series of firm asset values and default barriers using the information available for the whole period 1999–2017. Hence, it could also be argued that our conclusions about the informational content of CDS spreads at a given time *t* are driven by the use of information that is not fully available at that time *t*. To address this question, we perform an out-of-sample estimation based on two main building blocks. First, we presume that the actual time series of firm asset values for each company is the one we have already estimated using all the information available for 1999–2017. This implies that realized asset volatilities remain the same, and because realized equity volatilities do not change either, the realized leverage effects are also the same. Second, to estimate implied asset volatilities and the current leverage effects at a given time *t*, we restrict ourselves to the use of information that is fully available at that time *t*. Suppose, by way of example, that our interest is in a particular time *t* within 2004. In this case, we perform a new implementation of LT/IC exactly as described in subsection 2.2 but use only the information available for 1999–2003. We next apply the resulting value for the constant asset volatility (and payout rate), accounting figures at the close of 2003 (i.e., interest expense and total liabilities), and Expression (4), to estimate the default barrier and firm asset value at that specific time *t* within 2004. All these values are finally used as the necessary inputs to estimate implied asset volatility and the current leverage effect at time *t*. Moving to any particular date in 2005 implies a new implementation of LT/IC using the information available for 2000–2004, and the process is repeated for every year until 2017. It is worth stressing that, by following this strategy, we intentionally limit the informational content of implied volatilities vis-à-vis historical volatilities in two different ways. First, by updating core inputs to the estimation of implied volatilities only once per year (e.g., implied volatilities in December 2005 are based on model parameters estimated as of December 2004). Second, by comparing out-of-sample estimates of implied asset volatilities to (still) in-sample estimates of historical asset volatilities.

The results from this new analysis are provided in Table 13. While our restrictions certainly lead to a decrease in the mean explanatory power of CDS implied volatilities, the main empirical findings remain the same: this informational content is still higher than that of historical volatilities and, once again, CDS spreads are significantly more informative about future cross-sectional differences in realized asset than equity volatilities.

As a complementary analysis, Fig. 7 plots the evolution of the explanatory power of both the out-of-sample and in-sample

Table 12
Future realized levered asset volatility as a function of implied levered asset volatility, current leverage effect in levered asset volatility, implied asset volatility, and historical levered asset volatility.

Dependent variable: future realized levered asset volatility, $f_{LV,j}$								
Model, independent variables, explanatory power, and likelihood ratio test								
		Intercept	$i_{LV,j}$	$c_{le,j}^{LV}$	i_j	$h_{LV,j}$	*Adj.* R^2	*LR Test*
Model 12	Mean / [Rej.]	−0.724	0.791				66.96%	[51%]
	(Signif.)	*(100%)*	*(100%)*					
Model 13	Mean	−0.699		0.982	0.809		66.75%	
	(Signif.)	*(100%)*		*(34%)*	*(100%)*			
Model 14	Mean / [Rej.]	−0.608				0.713	53.79%	[100%]
	(Signif.)	*(80%)*				*(100%)*		
Model 15	Mean	−0.578	0.647			0.179	69.15%	
	(Signif.)	*(87%)*	*(100%)*			*(34%)*		

This table summarizes the results of estimating Models 12, 13, 14, and 15 using OLS with White standard errors. In these four models, the future realized levered asset volatility of company j ($f_{LV,j}$), is related to its implied levered asset volatility ($i_{LV,j}$; Model 12), its current leverage effect in levered asset volatility and implied asset volatility ($c_{le,j}^{LV}$ and i_j; Model 13), its historical levered asset volatility ($h_{LV,j}$; Model 14), and its implied and historical levered asset volatility ($i_{LV,j}$ and $h_{LV,j}$; Model 15). 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 each independent variable's coefficient, the number of times this coefficient is significant at the 5% level, the mean *Adj.* R^2 for each model, and the number of times the *LR Test* rejects at the 5% level the null hypothesis of equivalence between a particular restricted model (Models 12 and 14) and the unrestricted model (Model 15).

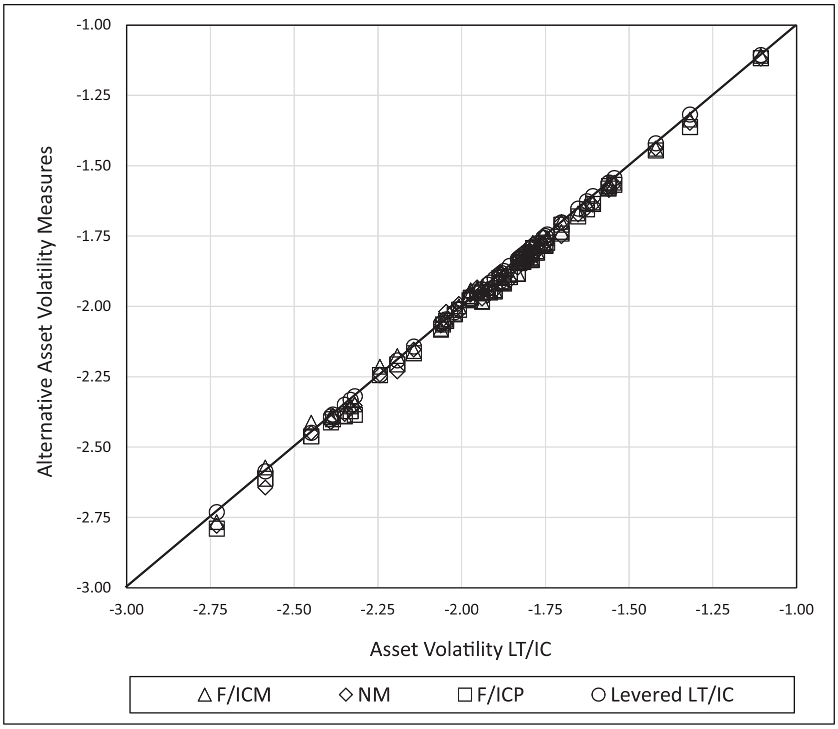

Fig. 6. Alternative asset volatility measures.
This figure plots different asset volatility measures versus that obtained using the Leland and Toft/Inversion–Correction method (LT/IC). The figure represents each of the 52 companies over the period 1999–2017. The alternative methods are Forte/Inversion—Correction—Maximization (F/ICM); Naïve Model (NM); and Forte/Inversion—Correction—Principal (F/ICP). The figure also incorporates levered asset volatility according to LT/IC.

estimation of Model 10, along with the evolution of the explanatory power of Model 5. The figure reveals that during the pre-crises period, the out-of-sample estimation of Model 10 leads to much lower explanatory power than the in-sample estimation. After this period, however, the explanatory power of the out-of-sample estimation is roughly the same as the in-sample estimation, and sometimes higher. Hence, the out-of-sample results provide, if anything, even greater support for the idea of an initial calm period

Table 13
Out-of-sample estimation. Main results.

Dependent variables: future realized asset volatility (f_j, Panel A), future realized leverage effect ($f_{le,j}$, Panel B), and future realized equity volatility ($f_{S,j}$, Panel C)

Model, independent variables, explanatory power, and likelihood ratio test

		Intercept	$c_{le,j}$	$h_{le,j}$	i_j	h_j	$h_{S,j}$	*Adj.* R^2	*LR Test*
Panel A: Future realized asset volatility, f_j									
Model 1	Mean / [Rej.]	−0.891			0.705			61.21%	[46%]
	(Signif.)	*(100%)*			*(100%)*				
Model 2	Mean / [Rej.]	−0.637				0.732		53.45%	[84%]
	(Signif.)	*(80%)*				*(100%)*			
Model 3	Mean	−0.702			0.564	0.199		63.86%	
	(Signif.)	*(82%)*			*(81%)*	*(28%)*			
Panel B: Future realized leverage effect, $f_{le,j}$									
Model 7	Mean / [Rej.]	0.176	0.911					74.76%	[19%]
	(Signif.)	*(76%)*	*(100%)*						
Model 8	Mean / [Rej.]	0.165		0.899				61.60%	[94%]
	(Signif.)	*(56%)*		*(100%)*					
Model 9	Mean	0.156	0.800	0.132				75.43%	
	(Signif.)	*(71%)*	*(93%)*	*(16%)*					
Panel C: Future realized equity volatility, $f_{S,j}$									
Model 10	Mean / [Rej.]	−0.978	0.636		0.432			25.65%	[58%]
	(Signif.)	*(96%)*	*(74%)*		*(72%)*				
Model 5	Mean / [Rej.]	−0.608					0.499	19.35%	[80%]
	(Signif.)	*(80%)*					*(63%)*		
Model 11	Mean	−0.745	0.441		0.248		0.316	29.46%	
	(Signif.)	*(79%)*	*(64%)*		*(28%)*		*(44%)*		

This table summarizes the results of estimating Models 1, 2, and 3 (Future Realized Asset Volatility, f_j; Panel A), Models 7, 8, and 9 (Future Realized Leverage Effect, $f_{le,j}$; Panel B), and Models 10, 5, and 11 (Future Realized Equity Volatility, $f_{S,j}$; Panel C), using OLS with White standard errors and out-of-sample estimates of the current leverage effect and implied asset volatility. i_j is (out-of-sample) implied asset volatility; h_j, historical asset volatility; $c_{le,j}$, (out-of-sample) current leverage effect; $h_{le,j}$, historical leverage effect; and $h_{S,j}$, historical equity volatility. 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 each independent variable's coefficient, the number of times this coefficient is significant at the 5% level, the mean *Adj.* R^2 for each model, and the number of times the *LR Test* rejects at the 5% level the null hypothesis of equivalence between a particular restricted model and the corresponding unrestricted model.

characterized by extremely low cross-sectional predictability of equity volatility (strongest version of the model), followed by a crisis period where such cross-sectional predictability becomes clearly positive (weakest version). It is also worth noting that the out-of-sample estimation of Model 10 still leads to systematically higher explanatory power than that of Model 5. Taken all these results together, we find no evidence that our main conclusions are the product of in-sample estimations.

7.5. Speed of adjustment to optimal leverage effects

The simple model presented in subsection 6.3.2 implies that the optimal leverage effect of company j is (see Expressions (32) and (33)):

$$c^*_{le,j} = c_{le,j} + f^*_S - i_{S,j}. \tag{45}$$

However, as discussed in subsection 6.3.3, Expression (45) relies on several simplifying assumptions. That is, all companies have exactly the same equity volatility target, and the implied equity volatility of company j provides an unbiased representation of its future expected equity volatility. Thus, a more general functional form of the optimal leverage effect would be:

$$c^*_{le,j,t} = c_{le,j,t} + f^*_{S,j} - E_t\left[f_{S,j}\right], \tag{46}$$

where $f^*_{S,j}$ accounts for the possibility of (minor) differences in the equity volatility target across companies, and $E_t[f_{S,j}]$ is the future expected equity volatility. Note also that for the purposes of the present analysis, the time index t has been reincorporated.

In principle, Expression (46) could be used to analyze the optimal leverage effect of company j at any time t, and the speed of adjustment to it.[36] The only difficulty seems to lie in the estimation of $f^*_{S,j}$ and $E_t[f_{S,j}]$. In what follows, we assume that the expected equity volatility of company j at time t is:

[36] We thank again our anonymous referee for proposing this additional extension.

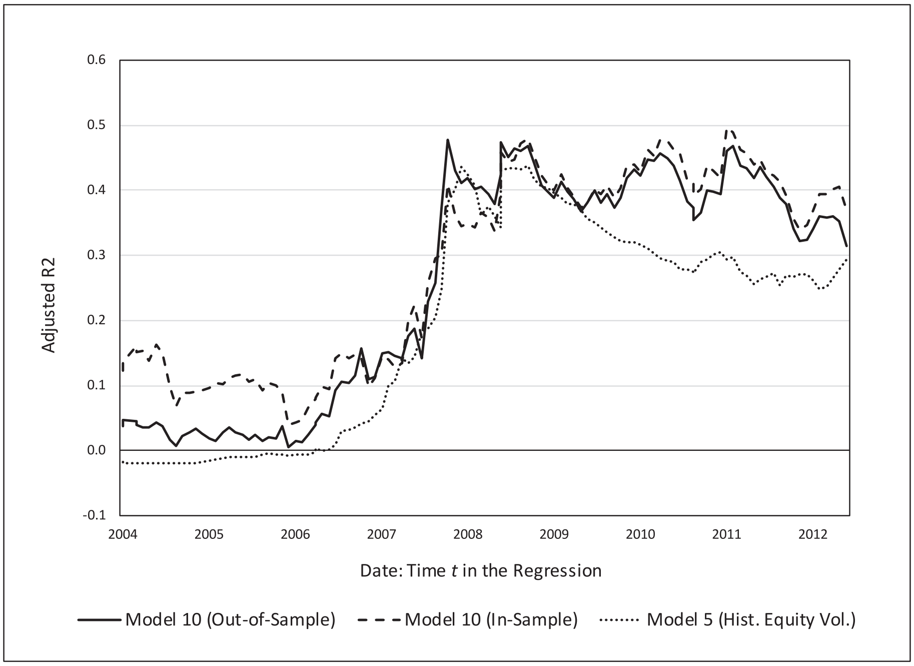

Fig. 7. Explanatory power of Model 10 (in-sample and out-of-sample), and Model 5.
This figure plots the adjusted R^2 of Model 10 (future realized equity volatility as a function of current leverage effect and implied asset volatility) using out-of-sample (solid line) and in-sample (dashed line) estimations. The adjusted R^2 of Model 5 (dotted line) is also drawn. This figure reflects the results for each of the 114 monthly regressions.

$$E_t\left[f_{S,j}\right] = i_{S,j,t} + \Omega_j, \tag{47}$$

where Ω_j represents a permanent, company specific bias in implied equity volatility as a predictor of future realized equity volatility. We also assume that a specific time t^* can be identified, where $E_{t^*}\left[f_{S,j}\right] = f^*_{S,j}$. In other words, we assume the possibility of identifying a moment in time wherein company j has selected its optimal leverage. If this is the case, then:

$$f^*_{S,j} = i_{S,j,t^*} + \Omega_j. \tag{48}$$

The previous assumptions imply that the optimal leverage effect of company j at time t is simply:

$$c^*_{le,j,t} = c_{le,j,t} + i_{S,j,t^*} - i_{S,j,t}. \tag{49}$$

In a nutshell, because our interest is not really on either $f^*_{S,j}$ or $E_t[f_{S,j}]$, but on the difference between the two, the permanent bias in implied equity volatility as a representation of the future expected equity volatility plays no role. The estimation of $c^*_{le,j,t}$ relies only of the existence and possible identification of t^*.

Let us consider again our results for the cross-sectional correlation between the current leverage effect and implied asset volatility. The time series of this correlation coefficient, extended to 2017, is reproduced in Fig. 8. As stated in the empirical analysis in subsection 6.3.2, we can see this correlation coefficient as an indicator of companies' capacity to determine their optimal leverage effect. In particular, a significant negative correlation would be indicative of a favorable period in that regard. Following this reasoning, we apply the multiple structural break test of Bai and Perron (1998) to endogenously determine both the number and date of structural breaks in the correlation between the current leverage effect and implied asset volatility. As shown in Fig. 8, the sequential breakpoint test identifies three structural breaks in the series and, therefore, four regimes during our sample period: January 2004 to January 2008 (Period 1), February 2008 to February 2010 (Period 2), March 2010 to December 2012 (Period 3), and January 2013 to December 2017 (Period 4).

Following our conclusions from subsection 6.3.2, we use Period 1 to approximate i_{S,j,t^*} for each company j by computing the mean implied equity volatility during that initial period. Based on these results, we estimate a two-stage dynamic partial adjustment capital structure model (De Miguel and Pindado, 2001; Cook and Tang, 2010). In the first stage, we estimate the optimal leverage effect according to Expression (49). In the second stage, we estimate the adjustment speed by running a pooled regression of the change in the leverage effect on the deviation from the target:

$$c_{le,j,t} - c_{le,j,t-1} = \phi_0 + \phi_1\left(c^*_{le,j,t} - c_{le,j,t-1}\right) + e_t, \tag{50}$$

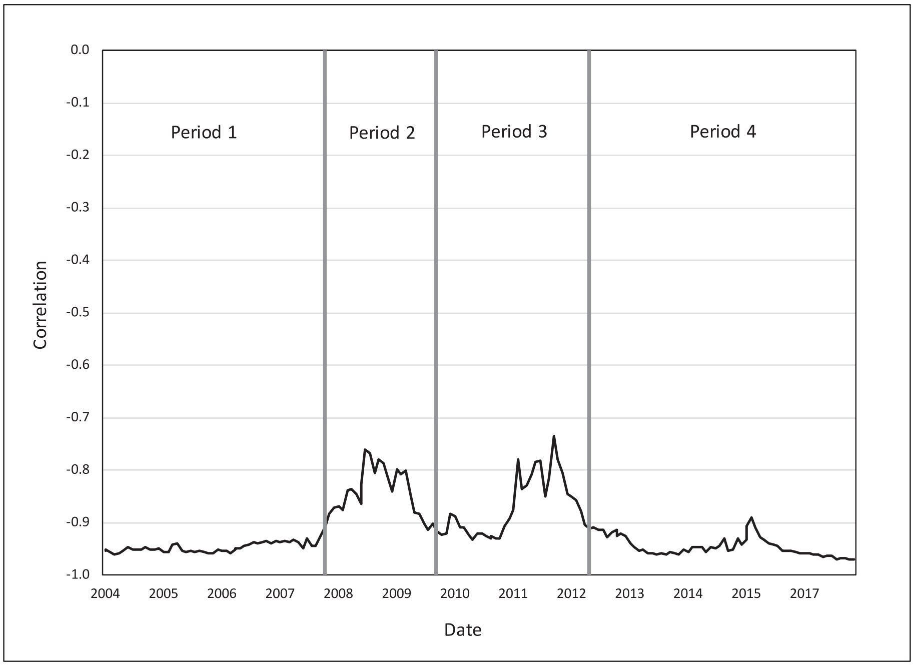

Fig. 8. Structural breaks in the correlation between current leverage effect and implied asset volatility.
This figure reflects the structural breaks in the correlation between the current leverage effect and implied asset volatility during the sample period 2004–2017.

where ϕ_1 reflects the speed of the adjustment of the leverage effect of company j to its optimal value. A coefficient ϕ_1 equal to 1 (along with a constant term ϕ_0 equal to 0) would indicate a perfect adjustment of the leverage effect to its target value at each point in time.

Following Cook and Tang (2010), we compare the speed of adjustment across two regimes: Good vs. Bad states. Given that we define the first Good period (i.e., Period 1) as an initial state, we estimate the second-stage regressions using the remaining sample period and define the Good period as Period 4, and the Bad period as the combination of Period 2 (sub-prime crisis) and Period 3 (sovereign debt crisis).[37] To differentiate between the two regimes, we follow Cook and Tang (2010) and include a Good dummy variable that takes the value of 1 if the firm-month observation belongs to the Good period and 0 otherwise, as well as an interaction term calculated as the product of the Good dummy variable multiplied by the deviation from the target (i.e., $c^*_{le,j,t} - c_{le,j,t-1}$). The results of the second-stage regressions of the change in the leverage effect on the deviation from the target are presented in Table 14. As expected, the difference in the speed of adjustment toward the target differs in the Good and Bad periods. This follows from comparing the sign and significance of the interaction term, which, being positive, indicates a higher speed of adjustment during Good periods. The signs and significance of the regressors are consistent with the results of Cook and Tang (2010).[38]

7.6. The informational content of equity options

In previous sections, we have investigated the informational content of 5-year CDS spreads for 5-year future realized asset and equity volatilities. While the long maturity and high liquidity of such contracts make them an ideal choice for the purposes of the present study, in this section we extend our analysis to the informational content of one-year CDS spreads and one-year equity options for one-year future realized volatilities. Our objective is twofold. First, we want to test whether our main conclusions are robust to the use of equity options to estimate implied asset and equity volatilities. Second, we want to investigate whether CDS are more/less informative about future realized asset and equity volatilities than equity options. It is precisely for this second objective—and for the goal of providing a sensible answer—that our analysis will focus on the informational content of CDS contracts and equity options with identical maturities.[39]

Data on one-year CDS spreads is again collected from Datastream. We use these data to derive one-year CDS implied asset and equity volatilities as described in Section 2. Information about one-year option implied equity volatilities is directly obtained from OptionMetrics. These are calculated as the average implied equity volatility in standardized at-the-money call and put options. The

[37] Results remain unchanged if the Period 1 is also included in the regression sample. These results are available upon request.
[38] It should be noted, however, that Cook and Tang (2010) use yearly data whereas our results are based on monthly data.
[39] To facilitate comparison with results from our base case analysis in Sections 4–6, results in this subsection rely again on in-sample estimates of CDS implied volatilities. However, results from using out-of-sample estimates (available upon request) are essentially the same.

Table 14
Two-regimes adjustment speed estimates.

	Good	Bad	G vs. B
Intercept	0.002	0.013	0.013
	(0.001) **	(0.002) ***	(0.002) ***
TargetDif.	0.072	0.035	0.035
	(0.008) ***	(0.008) ***	(0.008) ***
GoodD			−0.012
			(0.002) ***
*GoodD*TargetDif.*			0.038
			(0.011) ***
Obs.	3172	3224	6396
R^2	8.63%	1.80%	4.27%

This table summarizes the results of the second-stage regressions of the dynamic partial adjustment capital structure model using OLS with heteroskedasticity robust standard errors. *TargetDif.* is the deviation from the target leverage effect ($c^*_{le,j,t} - c_{le,j,t-1}$). *GoodD* is a dummy variable that takes the value of 1 if the firm-month observation belongs to a Good period (Period 4) and 0 otherwise (Periods 2 and 3). The table reports the coefficient estimates and the corresponding standard errors (in parentheses). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

corresponding option implied asset volatilities are derived by subtracting the leverage effect component in those option implied equity volatilities. The availability of data is, however, slightly lower than before. In particular, lack of data leads us to concentrate on 2007–2017. In addition, the number of companies with available information for our cross-sectional regressions is not constant this time, but increases steadily from a minimum of 41 in January 2007 to a maximum of 50 since October 2014.[40] Nevertheless, because our rolling window is now only one-year, the total number of monthly cross-sectional regressions is actually higher (124).

The main descriptive statistics for (one-year) CDS implied, option implied, and realized volatilities, are provided in Table 15. The table indicates that, contrary to option implied volatilities, CDS implied volatilities are, on average, considerably higher than realized volatilities. While we previously found that 5-year CDS implied volatilities overestimate realized volatilities (Tables 3 and 5), the gap is now certainly larger. Such a result is, however, consistent with previous empirical evidence. For instance, Du et al. (2019) find that medium and long-term CDS spreads can easily be replicated by incorporating a volatility risk premium; in contrast, one-year CDS spreads are also affected by a significant jump risk premium. The combination of a volatility risk premium and a jump risk premium is, however, not enough to replicate one-year CDS spreads, a result that Du et al. (2019) attribute to the also higher influence of illiquidity risk on one-year spreads. Moreover, in a study closely related to ours, Lovreta and Silaghi (2020) find a downward sloping term structure of CDS implied asset volatilities. In this term structure, the one-year maturity stands out for its very high level of implied volatilities. Lovreta and Silaghi (2020) find that this downward sloping term structure is associated with market and funding illiquidity, investors' risk aversion, informational frictions, demand/supply factors, and momentum.[41]

The results for the informational content of CDS implied, option implied, and historical asset volatilities are provided in Table 16.[42] Specific results from Models I-III suggest that historical asset volatilities (Model III, adjusted R^2 76.57%) are more informative for future realized asset volatilities than CDS implied asset volatilities (Model I, 67.75%), while these, in turn, are roughly equally informative as option implied asset volatilities (Model II, 67.56%). Looking at the results from Models IV-VII, two main conclusions emerge. First, the higher informational content of historical asset volatilities is confirmed. This is revealed by the fact that, when combined with either CDS implied asset volatilities (Model V), option implied asset volatilities (Model VI), or both of them (Model VII), the mean coefficient of historical asset volatility is always the highest and most often significant. Second, while results from the combination of CDS and option implied asset volatilities (Model IV) seem to suggest a higher informational content of equity options vis-à-vis CDS spreads, other results provide a slightly different picture. In particular, once we control for the informational content of historical asset volatilities, the additional informational content of CDS implied asset volatilities (Model V, 80.45%) is higher than that of option implied asset volatilities (Model VI, 78.18%). Results from the most comprehensive model (Model VII, 80.63%) corroborate that, if any, option implied asset volatilities have a very marginal contribution once historical and CDS implied asset volatilities are accounted for. This is also confirmed by LR tests. The null hypothesis of equivalence between Model V and Model VII is rejected in only 8% of the cases, suggesting that in 92% of these cases CDS implied and historical asset volatilities subsume all the informational content of option implied asset volatilities. In summary, our analysis based on one-year data indicates that historical asset volatilities are more informative for future realized asset volatilities than either CDS or option implied asset volatilities. Of these, CDS implied asset volatilities contain the most significant additional information.

The results regarding the informational content of CDS implied, option implied, and historical equity volatilities are provided in

[40] By way of comparison, in their analysis of implied volatilities from individual equity options, both Bakshi et al. (2003) and Duan and Wei (2009) consider a final sample of 30 companies.

[41] See also Kelly et al. (2019).

[42] From now on, and for the sake of brevity, we omit a formal description of the different regression models, which can be found in the different tables.

Table 15
Main descriptive statistics for one-year implied and realized volatilities.

Panel A: Asset volatility (one-year)	CDS implied asset volatility	Option implied asset volatility	Realized asset volatility	Log CDS implied asset volatility	Log option implied asset volatility	Log realized asset volatility
Mean	0.29	0.13	0.13	−1.32	−2.12	−2.16
Median	0.29	0.13	0.12	−1.25	−2.08	−2.14
SD	0.11	0.05	0.05	0.43	0.41	0.36
Skewness	0.25	0.95	1.06	−0.85	−0.41	−0.11
Kurtosis	2.61	4.69	4.96	3.91	3.66	3.08

Panel B: Equity volatility (one-year)	CDS implied equity volatility	Option implied equity volatility	Realized equity volatility	Log CDS implied equity volatility	Log option implied equity volatility	Log realized equity volatility
Mean	0.63	0.29	0.30	−0.48	−1.27	−1.27
Median	0.61	0.28	0.28	−0.49	−1.29	−1.29
SD	0.07	0.07	0.09	0.10	0.21	0.27
Skewness	1.06	1.02	1.38	0.67	0.44	0.49
Kurtosis	5.22	4.60	6.60	4.18	3.23	3.33

This table provides the main descriptive statistics for one-year implied and (future) realized volatilities. Reported numbers represent the time-series averages of the cross-sectional mean, median, standard deviation, skewness, and kurtosis across 124 monthly observations. Panel A contains the results for asset volatility, while Panel B reports the corresponding results for equity volatility.

Table 16
Future one-year realized asset volatility as a function of CDS implied, option implied, and historical asset volatility.

Dependent variable: future realized asset volatility (one-year), f_j

Model, independent variables, explanatory power, and likelihood ratio test

		Intercept	i_j	i_j^{op}	h_j	*Adj.* R^2	*LR Test*
Model I	Mean / [Rej.]	−1.232	0.701			67.75%	[99%]
	(Signif.)	*(100%)*	*(100%)*				
Model II	Mean / [Rej.]	−0.574		0.749		67.56%	[94%]
	(Signif.)	*(66%)*		*(100%)*			
Model III	Mean / [Rej.]	−0.244			0.897	76.57%	[58%]
	(Signif.)	*(48%)*			*(100%)*		
Model IV	Mean / [Rej.]	−0.780	0.340	0.433		72.03%	[94%]
	(Signif.)	*(79%)*	*(56%)*	*(64%)*			
Model V	Mean / [Rej.]	−0.443	0.258		0.645	80.45%	[8%]
	(Signif.)	*(67%)*	*(49%)*		*(99%)*		
Model VI	Mean / [Rej.]	−0.235		0.236	0.671	78.18%	[47%]
	(Signif.)	*(51%)*		*(25%)*	*(91%)*		
Model VII	Mean	−0.429	0.250	0.007	0.650	80.63%	
	(Signif.)	*(59%)*	*(47%)*	*(13%)*	*(93%)*		

This table summarizes the results of estimating seven different models for one-year future realized asset volatility (f_j), using OLS with White standard errors. A total of 124 consecutive cross-sectional regressions are implemented with a time interval of one month (21 trading days). i_j is CDS implied asset volatility; i_j^{op}, option implied asset volatility; and h_j, historical asset volatility. The table reports the mean of each independent variable's coefficient, the number of times this coefficient is significant at the 5% level, the mean *Adj.* R^2 for each model, and the number of times the *LR Test* rejects at the 5% level the null hypothesis of equivalence between a particular restricted model (Models I to VI) and the unrestricted model (Model VII).

Table 17. Because descriptive statistics in Table 15 are indicative of a significant bias in the one-year CDS implied asset volatilities, we start our analysis by comparing the informational content of CDS implied equity volatilities and that provided by its two constituents (see again subsection 6.2). The conclusions are as follows. First, we confirm once again that it makes more sense to consider the current leverage effect and CDS implied asset volatility as two separate explanatory variables (Model IX, 38.63%), than to merge them into a CDS implied equity volatility (Model VIII, 19.87%). Because the bias in CDS implied asset volatilities is significantly higher for one-year than for 5-year contracts, such a conclusion is now even more evident. Second, the informational content of the (decomposed) CDS implied equity volatilities is higher than that of option implied equity volatilities (Model X, 34.28%). However, in line with our results for asset volatility, the informational content of historical equity volatilities (Model XI, 53.97%) exceeds that of any implied equity volatility measure. Third, again consistent with our results for asset volatility, once we control for historical and CDS implied equity volatilities, the additional informational content of option implied equity volatilities is rather small (a difference of only 0.36% between Models XIII and XV). Besides, the null hypothesis of equivalence between Models XIII and XV is rejected in only 10% of the cases, leading to the conclusion that in 90% of these cases CDS implied and historical equity volatilities subsume all the informational content of option implied equity volatilities. Last but not least, irrespective of the volatility measure used (CDS implied, option implied, or historical), our new results corroborate the study's main conclusion. Namely, a fundamental difference exists in the cross-sectional predictability of asset and equity volatility.

Table 17
Future one-year realized equity volatility as a function of CDS implied, option implied, and historical equity volatility.

Dependent variable: future realized equity volatility (one-year), $f_{S,j}$

Model, independent variables, explanatory power, and likelihood ratio test

		Intercept	$i_{S,j}$	$c_{le,j}$	i_j	$i^{op}_{S,j}$	$h_{S,j}$	*Adj. R^2*	*LR Test*
Model VIII	Mean	−0.812	1.038					19.87%	
	(Signif.)	*(91%)*	*(64%)*						
Model IX	Mean / [Rej.]	−0.972		1.469	1.176			38.63%	[99%]
	(Signif.)	*(97%)*		*(90%)*	*(81%)*				
Model X	Mean / [Rej.]	−0.272				0.783		34.28%	[90%]
	(Signif.)	*(39%)*				*(94%)*			
Model XI	Mean / [Rej.]	−0.304					0.781	53.97%	[64%]
	(Signif.)	*(65%)*					*(100%)*		
Model XII	Mean / [Rej.]	−0.425		0.962	0.764	0.512		49.04%	[79%]
	(Signif.)	*(53%)*		*(71%)*	*(62%)*	*(65%)*			
Model XIII	Mean / [Rej.]	−0.383		0.672	0.539		0.597	60.00%	[10%]
	(Signif.)	*(66%)*		*(60%)*	*(52%)*		*(94%)*		
Model XIV	Mean / [Rej.]	−0.200				0.191	0.669	54.86%	[67%]
	(Signif.)	*(51%)*				*(12%)*	*(82%)*		
Model XV	Mean	−0.312		0.646	0.521	0.103	0.549	60.36%	
	(Signif.)	*(60%)*		*(56%)*	*(49%)*	*(6%)*	*(71%)*		

This table summarizes the results of estimating eight different models for one-year future realized equity volatility ($f_{S,j}$), using OLS with White standard errors. $i_{S,j}$ is CDS implied equity volatility; $c_{le,j}$, current leverage effect; i_j, CDS implied asset volatility; $i^{op}_{S,j}$, option implied equity volatility; and $h_{S,j}$, historical equity volatility. A total of 124 consecutive cross-sectional regressions are implemented with a time interval of one month (21 trading days). The table reports the mean of each independent variable's coefficient, the number of times this coefficient is significant at the 5% level, the mean *Adj.* R^2 for each model, and the number of times the *LR Test* rejects at the 5% level the null hypothesis of equivalence between a particular restricted model (Models IX to XIV) and the unrestricted model (Model XV).

We close this section by discussing in more detail two particularly challenging conclusions from Tables 16 and 17. First, for the one-year maturity, the explanatory power of historical volatilities appears to be higher than that of either CDS or option implied volatilities. This finding is in clear contrast to previous empirical evidence based on one-month option prices, and our own results based on 5-year CDS spreads.[43] Thus, a reasonable hypothesis is that our poor results are related precisely to the low liquidity of one-year options and CDS contracts. Because our core analysis based on highly liquid 5-year CDS contracts (Tables 3-9) is already consistent with this hypothesis, we further confirm it by exploring the informational content of one-month equity options for exactly the same sample and time period analyzed in Tables 16 and 17.[44] Main descriptive statistics for one-month option implied and realized volatilities are provided in Table 18, while results on the explanatory power of option implied and historical volatilities for future realized asset and equity volatilities are summarized in Tables 19 and 20, respectively. The main conclusions that arise from this additional analysis are as follows. On the one hand, consistent with the extant literature, the informational content of one-month option implied volatilities is higher than that of historical volatilities. On the other hand, the higher cross-sectional predictability of asset volatility vis-à-vis equity volatility is once again verified.

The second challenging conclusion from Table 17 is that, for the one-year maturity, CDS implied asset volatilities and the current leverage effects are, together, more informative for future realized equity volatilities than option implied equity volatilities. It is worth noting that this result is in line with another study closely related to ours. In particular, Forte and Lovreta (2019) use one-year CDS spreads to create an equity volatility index for the Eurozone and show that it leads the one-year VSTOXX. It is also worth stressing that, as is evident, we are confident of both our own empirical results and those in Forte and Lovreta (2019). Having said all this, the conclusion that CDS spreads are more informative for future realized equity volatilities than equity options should be viewed with caution. While imposing a common maturity seems to be a reasonable approach for comparison purposes, we must stress once more that the one-year maturity is not the most liquid alternative either for CDS contracts or for equity options. Thus, a reasonable question to investigate would be the relative informational content of the full term structure of CDS spreads and that of equity options for future realized short-run/long-run asset/equity volatilities. Investigating the best combination of information provided by CDS spreads and option prices would also be an interesting question to address. Indeed, all these extensions represent a very promising line for further research, but clearly beyond the scope of the present study.

[43] See Poon and Granger (2003) for a review of the literature on option prices.

[44] Ideally, for comparison purposes, we would also like to repeat our analysis based on 5-year CDS spreads by considering the same restricted sample and time period as in Tables 16 and 17. However, this is not totally feasible. The informational content of 5-year CDS spreads necessarily concludes five years (rather than one year) before the end of our sample period, and, therefore, a maximum of 114 cross-sectional regressions (instead of 124) can be implemented. As an alternative, we repeat our core analysis (Tables 3-9) staring 2007 (rather than 2004), and imposing the same sample restrictions as in Tables 15 and 17. Results (available upon request) confirm once again the overall conclusions from our core analysis.

Table 18
Main descriptive statistics for one-month option implied and realized volatilities.

Panel A: Asset volatility (one-month)				
	Option implied asset volatility	Realized asset volatility	Log option implied asset volatility	Log realized asset volatility
Mean	0.13	0.12	−2.12	−2.23
Median	0.13	0.11	−2.08	−2.21
SD	0.05	0.05	0.38	0.42
Skewness	0.89	1.33	−0.46	−0.02
Kurtosis	5.04	5.90	3.85	3.11
B: Equity volatility (one-month)				
	Option implied equity volatility	Realized equity volatility	Log option implied equity volatility	Log realized equity volatility
Mean	0.30	0.28	−1.28	−1.37
Median	0.28	0.26	−1.30	−1.38
SD	0.08	0.11	0.24	0.34
Skewness	1.17	1.35	0.46	0.28
Kurtosis	5.34	6.47	3.24	3.23

This table reports the main descriptive statistics for one-month option implied and (future) realized volatilities. Reported numbers represent the time-series averages of the cross-sectional mean, median, standard deviation, skewness, and kurtosis across 124 monthly observations. Panel A contains the results for asset volatility, while Panel B reports the corresponding results for equity volatility.

Table 19
Future one-month realized asset volatility as a function of option implied and historical asset volatility.

Dependent variable: future realized asset volatility (one-month), f_j						
Model, independent variables, explanatory power, and likelihood ratio test						
		Intercept	i_j^{op}	h_j	*Adj.* R^2	*LR Test*
Model II	Mean / [Rej.]	−0.342	0.889		63.50%	[27%]
	(Signif.)	*(38%)*	*(100%)*			
Model III	Mean / [Rej.]	−0.581		0.742	53.68%	[82%]
	(Signif.)	*(60%)*		*(100%)*		
Model VI	Mean	−0.262	0.666	0.250	65.68%	
	(Signif.)	*(34%)*	*(90%)*	*(40%)*		

This table summarizes the results of estimating three different models for one-month future realized asset volatility (f_j), using OLS with White standard errors. i_j^{op} is option implied asset volatility; and h_j, historical asset volatility. A total of 124 consecutive cross-sectional regressions are implemented with a time interval of one month (21 trading days). The table reports the mean of each independent variable's coefficient, the number of times this coefficient is significant at the 5% level, the mean *Adj.* R^2 for each model, and the number of times the *LR Test* rejects at the 5% level the null hypothesis of equivalence between a particular restricted model (Models II and III) and the unrestricted model (Model VI).

Table 20
Future one-month realized equity volatility as a function of option implied and historical equity volatility.

Dependent variable: future realized equity volatility (one-month), $f_{S,j}$						
Model, independent variables, explanatory power, and likelihood ratio test						
		Intercept	$i_{S,j}^{op}$	$h_{S,j}$	*Adj.* R^2	*LR Test*
Model X	Mean / [Rej.]	−0.135	0.972		48.23%	[15%]
	(Signif.)	*(23%)*	*(98%)*			
Model XI	Mean / [Rej.]	−0.565		0.606	36.15%	[75%]
	(Signif.)	*(75%)*		*(95%)*		
Model XIV	Mean	−0.131	0.768	0.195	50.24%	
	(Signif.)	*(23%)*	*(85%)*	*(28%)*		

This table summarizes the results of estimating three different models for one-month future realized equity volatility ($f_{S,j}$), using OLS with White standard errors. $i_{S,j}^{op}$ is option implied equity volatility; and $h_{S,j}$, historical equity volatility. A total of 124 consecutive cross-sectional regressions are implemented with a time interval of one month (21 trading days). The table reports the mean of each independent variable's coefficient, the number of times this coefficient is significant at the 5% level, the mean *Adj.* R^2 for each model, and the number of times the *LR Test* rejects at the 5% level the null hypothesis of equivalence between a particular restricted model (Models X and XI) and the unrestricted model (Model XIV).

8. Conclusions

Equity volatility can be decomposed into asset volatility and leverage effect components. Based on this decomposition, the presents study explores the influence of leverage as a choice variable on the long-run cross-sectional predictability of equity volatility. We conduct this analysis by primarily investigating the different informational content of highly liquid 5-year CDS spreads for future realized asset and equity volatilities. The main conclusion we obtain from this analysis is that the influence of leverage is in fact remarkable. CDS implied asset volatilities have very significant informational content for future realized asset volatilities. In addition, this informational content is clearly superior and tends to subsume the informational content of historical asset volatilities. However, the results change considerably when we focus our attention on equity volatilities. Compared with their asset volatility counterparts, CDS implied equity volatilities have much lower informational content for future realized equity volatilities. Moreover, this informational content is only slightly higher and complementary to the informational content of historical equity volatilities. We argue that a simple model of optimal capital structure, wherein companies maximize tax benefits subject to a common maximum default probability (minimum credit rating) target, helps explain these findings. According to this model, the optimal leverage of a company is a decreasing function of its asset volatility, and this, in turn, leads to much lower cross-sectional variation in optimal equity volatility than in expected asset volatility. The final implication of the model is that the more successful companies are in achieving their optimal debt policy, the lower the cross-sectional predictability of equity volatility. Most importantly, this implication holds irrespective of the cross-sectional predictability of asset volatility. We show that our empirical results are, indeed, fully consistent with this prediction. Taken together, these findings provide important insights on the *when* and *why* of the cross-sectional predictability of equity volatility.

Data availability

The authors do not have permission to share data.

Appendix A. Expressions $G_t(\tau)$ and $H_t(\tau)$

Let us denote $N[\cdot]$ as the standard normal cumulative distribution function. The specific expressions for $G_t(\tau)$ and $H_t(\tau)$ are (see Leland and Toft, 1996):

$$H_t(\tau) = e^{-r\tau}[1 - F_t(\tau)], \tag{A1}$$

with

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

and

$$G_t(\tau) = \left(\frac{V_t}{V_b}\right)^{-a+z} N\left[y_{1,t}(\tau)\right] + \left(\frac{V_t}{V_b}\right)^{-a-z} N\left[y_{2,t}(\tau)\right]; \tag{A2}$$

where

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

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

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

In these expressions, V_t is the unlevered firm asset value, σ is asset volatility, r is the risk-free interest rate, δ is the payout rate, and V_b is the default barrier.

Appendix B. Leland and Toft (1996)

B.1. Endogenous default barrier and equity pricing equation in Leland and Toft (1996)

The endogenous default barrier in Leland and Toft (1996) is:

$$V_b = \frac{\left(\frac{C}{r}\right)\left(\frac{A}{rM} - B\right) - \left(\frac{AP}{rM}\right) - \left(\frac{\xi C\varphi}{r}\right)}{1 + \lambda\varphi - (1-\lambda)B}, \tag{B1}$$

where M represents the maturity of the bond that is continuously rolled over with the same annual coupon, C/M, and principal, P/M, and where ξ and λ denote the effective tax rate and bankruptcy costs, respectively. Also,

$$\varphi = a + z;$$

$$A = 2ae^{-rM}N\left(a\sigma\sqrt{M}\right) - 2zN\left(z\sigma\sqrt{M}\right) - \frac{2}{\sigma\sqrt{M}}n\left(z\sigma\sqrt{M}\right) + \frac{2e^{-rM}}{\sigma\sqrt{M}}n\left(a\sigma\sqrt{M}\right) + (z-a);$$

$$B = -\left(2z + \frac{2}{z\sigma^2 M}\right)N\left(z\sigma\sqrt{M}\right) - \frac{2}{\sigma\sqrt{M}}n\left(z\sigma\sqrt{M}\right) + (z-a) + \frac{1}{z\sigma^2 M};$$

with $n(\cdot)$ denoting the standard normal density function.

The equity pricing equation in this model is:

$$S_t = g(V_t, V_b, \sigma) = L(V_t, V_b, \sigma) - D(V_t, V_b, \sigma), \tag{B2}$$

where

$$L(V_t, V_b, \sigma) = V_t + \frac{\xi C}{r}\left[1 - \left(\frac{V_t}{V_b}\right)^{-\varphi}\right] - \lambda V_b\left(\frac{V_t}{V_b}\right)^{-\varphi}; \tag{B3}$$

$$D(V_t, V_b, \sigma) = \frac{C}{r} + \left(P - \frac{C}{r}\right)\left[\frac{1-e^{-rM}}{rM} - I_t(M)\right] + \left[(1-\lambda)V_b - \frac{C}{r}\right]J_t(M); \tag{B4}$$

with

$$I_t(M) = \frac{1}{rM}\left[G_t(M) - e^{-rM}F_t(M)\right];$$

$$J_t(M) = \frac{1}{z\sigma\sqrt{M}}\left[-\left(\frac{V_t}{V_b}\right)^{-a+z}N\left[y_{1,t}(M)\right]y_{1,t}(M) + \left(\frac{V_t}{V_b}\right)^{-a-z}N\left[y_{2,t}(M)\right]y_{2,t}(M)\right].$$

B.2. Expression $\partial S_t/\partial V_t$ in Leland and Toft (1996)

Following Expression (B2),

$$\frac{\partial S_t}{\partial V_t} = \frac{\partial L(V_t, V_b, \sigma)}{\partial V_t} - \frac{\partial D(V_t, V_b, \sigma)}{\partial V_t}.$$

The first term on the right-hand side of the previous expression is

$$\frac{\partial L(V_t, V_b, \sigma)}{\partial V_t} = 1 + \frac{\xi C\varphi}{rV_b}\left(\frac{V_t}{V_b}\right)^{-\varphi-1} + \lambda\varphi\left(\frac{V_t}{V_b}\right)^{-\varphi-1};$$

while the second term is

$$\frac{\partial D(V_t, V_b, \sigma)}{\partial V_t} = -\left(P - \frac{C}{r}\right)\frac{\partial I_t(M)}{\partial V_t} + \left[(1-\lambda)V_b - \frac{C}{r}\right]\frac{\partial J_t(M)}{\partial V_t},$$

where

$$\frac{\partial I_t(M)}{\partial V_t} = \frac{1}{rM}\left[\frac{\partial G_t(M)}{\partial V_t} - e^{-rM}\frac{\partial F_t(M)}{\partial V_t}\right],$$

with

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

$$\begin{aligned}\frac{\partial G_t(M)}{\partial V_t} = &\left[\left(\frac{-a+z}{V_b}\right)\left(\frac{V_t}{V_b}\right)^{-a+z-1}\right]N\left[y_{1,t}(M)\right] \\ &+ \left(\frac{V_t}{V_b}\right)^{-a+z}n\left(y_{1,t}(M)\right)\frac{\partial y_{1,t}(M)}{\partial V_t} - \left[\left(\frac{a+z}{V_b}\right)\left(\frac{V_t}{V_b}\right)^{-a-z-1}\right]N\left[y_{2,t}(M)\right] + \left(\frac{V_t}{V_b}\right)^{-a-z}n\left(y_{2,t}(M)\right)\frac{\partial y_{2,t}(M)}{\partial V_t};\end{aligned}$$

and

$$\frac{\partial x_{1,t}(M)}{\partial V_t} = \frac{\partial x_{2,t}(M)}{\partial V_t} = \frac{\partial y_{1,t}(M)}{\partial V_t} = \frac{\partial y_{2,t}(M)}{\partial V_t} = -\frac{1}{V_t\sigma\sqrt{M}}.$$

Finally,

$$\frac{\partial J_t(M)}{\partial V_t} = \frac{1}{z\sigma\sqrt{M}}\left[\left(\frac{a-z}{V_b}\right)\left(\frac{V_t}{V_b}\right)^{-a+z-1} N\left[y_{1,t}(M)\right]y_{1,t}(M) - \left(\frac{V_t}{V_b}\right)^{-a+z}\frac{\partial\left(N\left[y_{1,t}(M)\right]y_{1,t}(M)\right)}{\partial V_t}\right.$$
$$\left. -\left(\frac{a+z}{V_b}\right)\left(\frac{V_t}{V_b}\right)^{-a-z-1} N\left[y_{2,t}(M)\right]y_{2,t}(M) + \left(\frac{V_t}{V_b}\right)^{-a-z}\frac{\partial\left(N\left[y_{2,t}(M)\right]y_{2,t}(M)\right)}{\partial V_t}\right],$$

where

$$\frac{\partial\left(N\left[y_{1,t}(M)\right]y_{1,t}(M)\right)}{\partial V_t} = -\frac{n\left(y_{1,t}(M)\right)y_{1,t}(M) + N\left[y_{1,t}(M)\right]}{V_t\sigma\sqrt{M}};$$

$$\frac{\partial\left(N\left[y_{2,t}(M)\right]y_{2,t}(M)\right)}{\partial V_t} = -\frac{n\left(y_{2,t}(M)\right)y_{2,t}(M) + N\left[y_{2,t}(M)\right]}{V_t\sigma\sqrt{M}}.$$

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jcorpfin.2022.102347.

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