The Informational Role of CDS in Stock Market Efficiency*

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Abstract

This paper extends econometric tests developed in the market efficiency literature to firms subject to corporate default risk by exploring the information contained in credit default swaps (CDS) at-market spreads. Using a large dataset of S&P 500 firms and an extended time frame (2008–2020), we find that stock market efficiency improves along with financial leverage for individual firms. By contrast, aggregate default risk produces lower efficiency scores in US stock indices. Multiple robustness tests confirm that an active CDS market for single names improves informational efficiency of stock prices and helps them align with their fundamentals.

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1. Introduction

A substantial body of empirical evidence has emerged over the last decades suggesting a lack of efficiency in aggregate stock market returns. At the same time, returns on individual firms seem to be more closely tied to changes in fundamentals such as earnings and dividends. This distinction led Samuelson (1998) to hypothesize that stock markets may be more efficient at the firm level (*micro* efficiency) than at the aggregate level (*macro* inefficiency), a proposition that has found recent support from a theoretical perspective (e.g., Gârleanu and Pedersen, 2022; Glasserman and Mamaysky, 2023). Meanwhile, the emergence of an active market for single-name credit default swaps (CDS) has significantly expanded the available firm-specific information on default risk. The prominent role of CDS in information transmission to the stock market prompts us to investigate if an active CDS market improves the informational efficiency of individual stock prices.

The linkage between single-name CDS and stocks has been extensively documented in the literature. Recent studies show that the CDS market contains unique, firm-specific information that is not captured by the prices of other related securities, such as stocks and bonds. At the most fundamental level, the CDS market reflects corporate disclosure quality through accounting transparency (e.g., Bhat, Callen, and Segal, 2016) and asset reliability (e.g., Arora, Richardson, and Tuna, 2014). The CDS market is also faster than credit rating events to reflect changes in firm creditworthiness (e.g., Chava, Ganduri, and Ornthanalai, 2019). In addition, the CDS market provides important information to equity analysts that is not aggregated into stock prices and useful to improve the accuracy of their forecasts (e.g., Batta, Qiu, and Yu, 2016; Kim et al., 2018; Zhao et al., 2022). Finally, because of the asymmetric payoff of CDS contracts, an active CDS market significantly reduces the likelihood of future stock price crashes by facilitating the incorporation of bad news into stock prices and preventing firms from hoarding negative information (Liu et al., 2024).

In this perspective, a typical channel of cross-market transmission might be the capital structure arbitrage (CSA) strategies routinely used by rational and sophisticated arbitrageurs, such as hedge funds, private equity funds, or investment banks.[1] Because the CDS market provides valuable hedging instruments and stimulates price discovery, the literature suggests that CSA activity at the firm level may provide an active channel for incorporating information about an individual firm's default risk into the stock market. In contrast, the impact of aggregate default risk on stock market informational efficiency seems less clear.

In this paper, we investigate the role of CDS in stock market informational efficiency, both at the individual firm level as well as in the aggregate. For this purpose, we extend several econometric tests developed in the market efficiency literature to a context in which default risk information is available to the market and accounted for in the optimal forecast produced by the stock market. Our theoretical approach starts with expanding the description of the stock's fundamental value by incorporating rational expectations of default risk on top of expected future cash flows. This approach leads to a richer description of the stock's fundamentals than the traditional present value of the rationally expected dividend stream. For this purpose, we rely on the log-linear dividend-ratio model (Campbell and Shiller, 1988) to extend the notion of *perfect-foresight* equilibrium price to firms subject to default risk.[2] Under perfect foresight, we use realized CDS returns and elasticities of CDS premiums with respect to stock prices to calculate an ex-post rational price. The paper's fundamental premise is that the more informative CDS returns are, the closer the market price will track this ex-post rational price and the higher the stock market efficiency will be. *Ceteris paribus*, we expect CDS trading to be more active and informative for firms with higher default risk

[1]See, for example, Yu (2006), Duarte, Longstaff, and Yu (2007), Das and Hanouna (2009), Kapadia and Pu (2012), Boehmer, Chava, and Tookes (2015), Augustin et al. (2020). These market participants exploit mispricings between a company's equity, corporate bonds, and single-name credit derivatives like CDS. In practice, CSA may come under various forms. A typical strategy consists of selling (buying) CDS contracts to bet on the convergence of the CDS market while simultaneously hedging in the equity market with a short (long) position in stocks to hedge a short (long) position in CDS contracts (e.g., Yu, 2006; Das and Hanouna, 2009).

[2]Perfect foresight assumes investors know the right equilibrium price conditional on the future state of nature. The perfect-foresight price is thus the hypothetical price that would prevail if all market participants had perfect knowledge of future events. It has been widely used in the volatility tests literature (e.g., Shiller, 1981; Grossman and Shiller, 1981).

(i.e., higher leverage or CDS levels), potentially leading to more efficient stock markets.

We then derive testable predictions by investigating deviations between perfect-foresight and market prices. We first compare the market price volatility to the perfect-foresight price volatility through variance ratios (Shiller, 1981; LeRoy and Porter, 1981). If CDS trading improves market efficiency, we expect lower excess volatility and variance ratios closer to one for firms with higher levels of leverage or CDS spreads. Second, as variance ratios do not allow for definitive hypothesis testing, we extend Mankiw, Romer, and Shapiro's (1985, 1991) orthogonality test. This testing strategy is based on the fact that, under the null hypothesis of market efficiency, the market price is the best predictor of the ex-post rational price. In particular, it has a lower forecast error compared to any other forecast. We expect the variance spread to decrease when the CDS market becomes more informative. Finally, we extend West's (1988) variance-bound test, which exploits the entire information set available to the market. We propose a new efficiency score, which ranges from -100 (no efficiency) to 100 (full efficiency), to assess market efficiency. We expect higher efficiency scores when the CDS market becomes more informative.

We test our predictions using a large and representative sample of U.S. firms. Our main results are obtained for the universe of S&P 500 constituents over the period from 2008 to 2020. After filtering for the companies whose 5-year senior unsecured CDS contract is actively traded, our universe comprises 339 single names. In line with the recent literature (e.g., Collin-Dufresne, Junge, and Trolle, 2020), we consider liquid and representative credit indices to proxy for aggregate credit risk information, including broad U.S. CDS indices, such as the CDX Investment Grade and CDX High Yield credit indices, and value-weighted CDS spreads.

Our preliminary findings, based on credit-augmented variance ratios, indicate a significant excess volatility of market prices compared to ex-post rational prices. However, we find that excess volatility declines with firm leverage, a key finding that is robust to the sampling period. Most importantly, this preliminary result is robust to the choice of an observable proxy for equity-credit elasticity. In line with our first prediction, this pattern suggests a significant rise in micro-efficiency when the single-name CDS market becomes more informative.

To confirm our preliminary findings, we run an extensive battery of orthogonality and variance-bound tests augmented by default risk. Using our new metric ranging from -100 (no efficiency) to 100 (full efficiency), we document significant excess volatility of stock prices compared to the stock's fundamentals augmented by default risk information. We also find a relatively low level of excess volatility for highly leveraged firms. To illustrate this point, it is not uncommon for highly leveraged firms to display an efficiency score as high as 20 over 2008-2020, while all-equity firms typically display negative scores. This key finding is robust to the sampling period and the firm's economic sector. In other words, an active CDS market for single names significantly improves *micro* efficiency. This result contrasts with Boehmer, Chava, and Tookes (2015), who find that the introduction of a CDS market can reduce stock market efficiency. They show that CDS initiation reduces liquidity on the fim's stock price in "bad" states by driving out uninformed investors from the stock market. However, their definition of price efficiency is based on the deviations of actual transaction prices relative to an implicit random walk. Furthermore, Boehmer, Chava, and Tookes (2015) control for firm-specific characteristics, such as the distance to default, to capture the dynamic effect of CDS introduction. By contrast, our measures of price efficiency are based on deviations from the explicit stock fundamentals. Moreover, they reflect the impact of firm leverage in the cross-section of firms.

In addition to these results obtained at the firm level, we investigate to what extent credit risk information impacts the aggregate equity market by running similar tests on various U.S. stock indices, including broad indices such as the S&P 500 or sector indices. In contrast to the results with individual firms, the aggregate analysis reveals low efficiency scores for large-cap U.S. stock indices. This latter finding obtains for high-leverage industries such as Banks, Financials, or Utilities. Contrary to the firm-level case, we find highly significant variance ratios well above one, positive variance spread statistics, and negative efficiency scores (well below -50), indicating a high level of excess volatility or low level of efficiency. However, sectoral indices such as the Banks, Financials, and Utility industry sectors exhibit higher efficiency scores due to their heavy reliance on financial leverage above 0.40 and the presence of firms with prominent credit information.

1.1 Related literature.

The asset pricing literature has recently started to revisit Samuelson's dictum that "the efficient markets hypothesis works better for individual stocks than for the stock market as a whole" (Jung and Shiller, 2005). Gârleanu and Pedersen (2022) provide a theoretical foundation for Samuelson's dictum with an asymmetric-information equilibrium model where investors choose between active management, passive management, or direct holdings. In their setting, portfolios with the most systematic risk maximize inefficiency while long-short portfolios eliminating factor risk are the least inefficient ones. They find that Samuelson's dictum holds when the number of securities is large because active investors "have stronger incentives to correct (micro) inefficiencies in relative prices than to correct the overall (macro) price level." Glasserman and Mamaysky (2023) develop a model of information and portfolio choice in which investors specialize in either macro or micro information because of fixed attention costs. In line with Samuelson's dictum, they find an equilibrium characterized by micro- rather than macro-efficiency. Although our empirical findings are limited by design to the role of single-name CDS in stock market efficiency, they are aligned with the predictions offered by these two theoretical approaches.

The recent literature provides ample evidence about the informational role of CDS markets. Acharya and Johnson (2007) show that insider information flows into the stock market through CDS trading in case of negative credit news. Batta, Qiu, and Yu (2016) show that the CDS market conveys private information ahead of earnings announcements. Similarly, Kim et al. (2018) show that the managers of a firm with traded CDSs are more prone to issue earnings forecasts and disclose voluntarily. Zhao et al. (2022) find that CDS trading curbs equity analysts' excessive optimism. These studies collectively suggest that equity analyst forecasts become more accurate after the introduction of CDS trading. Kryzanowski, Perrakis, and Zhong (2017) document that informed trading of negative firm-specific events, such as earning surprises, takes place primarily in the CDS market, whose specialized participants have greater ability to process both private and public information. As a result, CDS trading generates information about a firm's credit quality and lowers the informativeness of a credit rating downgrade announcement (Chava, Ganduri, and Ornthanalai, 2019). Han, Subrahmanyam, and Zhou (2017) find that the CDS term structure contains information about the future financial health of firms that diffuses to the stock market. Forte and Lovreta (2023) show that CDS spreads significantly predict future asset volatility, a key component of structural models of the firm for the determination of the optimal capital structure.

Our paper draws on the literature examining information transmission and synchronicity between the CDS and stock markets. Kapadia and Pu (2012) find a lack of market integration, which they attribute to firm-specific limits to credit-equity arbitrage. Lee, Naranjo, and Velioglu (2018) show that while CDS spreads may react sluggishly to aggregate stock market news, the CDS market plays a leading role in conveying firm-specific credit risk information around credit rating events, in contrast with the early literature.[3] Augustin et al. (2020) find that credit-equity integration and CDS-stock synchronicity improve with cross-listings as they draw institutional investors' attention, trigger the production of firm-specific information, and allow for more credit-equity arbitrage activity. Lee, Naranjo, and Sirmans (2021) document CDS-to-equity spillover effects related to future credit rating changes that are well anticipated by quick-moving CDS spreads.

Finally, our paper relates more specifically to the burgeoning literature examining the impact of CDS on stock market efficiency. Qiu and Yu (2012) show that the CDS market

[3]See, for example, Narayan, Sharma, and Thuraisamy (2014), Hilscher, Pollet, and Wilson (2015), and Marsh and Wagner (2016).

facilitates the price discovery process in the stock market. In a paper closely related to ours, Boehmer, Chava, and Tookes (2015) examine the effect of single-name CDS markets on equity market quality and find that equity prices become less efficient when CDS contracts are introduced. Chava, Ganduri, and Ornthanalai (2019) find that CDS trading mutes by 44 to 52% the reaction of stock prices to firms' rating downgrades by reducing the informativeness of credit rating downgrades. Liu et al. (2024) show that CDS markets facilitate the incorporation of bad news into equity prices via cross-market information spillover. They find that the informational role of CDS reduces stock price crash risk.

The remainder of the paper proceeds as follows. Section 2 develops our theoretical approach and derives testable hypotheses. Section 3 describes the data used in the empirical analysis. Section 4 details our main results. Section 5 proposes a battery of robustness tests. Finally, Section 6 concludes the article.

2. Modeling informational efficiency in the presence of default risk

2.1 Incorporating default risk into the stock's fundamental value

To motivate the incorporation of default risk into the stock price fundamental value, we focus on the elasticity of CDS spreads with respect to stock prices. Figure 1 plots weekly CDS par spreads against weekly closing stock prices for two highly leveraged firms: Ford Motor Co. (median debt-to-asset ratio 0.90) and United Airlines (median debt-to-asset ratio 0.58). Here, the trendlines underscore the typical "hockey-stick" pattern in CDS-stock scatter plots. Notice how increases in CDS spread represent bad news for the stock's fundamental value, pushing the stock price downward. Conversely, a decline in the CDS spread represents positive information about the firm's financial health, pushing the stock price upward. In other words, the trendline can be seen as the locus of the credit-equity market equilibrium.

Figure 1. Elasticity of CDS spreads against stock prices

This figure shows scatter plots of weekly CDS par spreads (5-year, senior unsecured contract) against weekly closing stock prices (triangles). Trendlines have been fitted with power functions. Data source: Thomson Reuters.

(a) Ford Motor (2008-2020) (b) United Airlines (2011-2019)

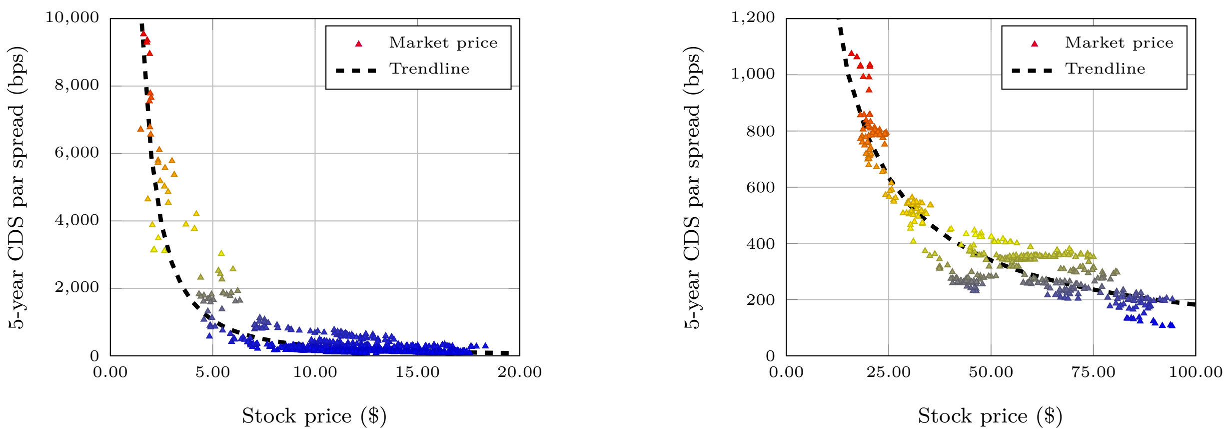


Figure 1 suggests that the firm's CDS spread should be a strictly decreasing function of the firm's stock price. Most importantly, the elasticity of CDS spreads with respect to stock prices appears to play a pivotal role in capturing information transmissibility between the two markets, especially for distressed companies. This paper uses a simple linear function of firm leverage as an observable proxy for the CDS-stock elasticity. This modeling choice is not arbitrary but based on a theoretical justification provided in Appendix A, which is grounded in structural models of the firm (e.g., Merton, 1974). Section 3.3 provides further details on the implementation of our proxy.[4]

We posit $P_t = f(\lambda_t)$, where P_t is the stock price, λ_t is the CDS par spread, and f is a deterministic and monotonic function. A parameterization often used in the literature (e.g., Frey and Schmidt, 2009; Zimmermann, 2021) is the power function $f(\lambda_t) := \lambda_t^{-\varepsilon_t}$, where $\varepsilon_t \geqslant 0$ is the equity-credit elasticity. This parameterization captures the empirical CDS-

[4]Most CDS-stock studies do not take a time-varying equity-credit elasticity into account, with the notable exceptions of Acharya and Johnson (2007), Qiu and Yu (2012), and Batta, Qiu, and Yu (2016), who use the CDS spread. In Section **??** we consider two alternative approaches to proxy for the credit-equity elasticity, including the CDS spread.

stock pattern observed in Figure 1 and documented in the literature (e.g., Kapadia and Pu, 2012).

2.2 The perfect-foresight price under default risk

We can now generalize the notion of perfect foresight to firms subject to default risk. Recall that the perfect-foresight price is the ex-post present value of all future cash flows, i.e., the hypothetical price that would prevail if all market participants had perfect knowledge of future events. The previous approach of the equity-credit elasticity leads to the following extension.[5]

Definition 1. *The default-risk augmented perfect-foresight price p_t^* is the (log) stock price that would prevail if equity investors had perfect knowledge of (i) future dividends, (ii) future changes in the firm's default intensity (which we assume can be proxied by changes in the CDS par spread), and (iii) future equity-credit elasticities of the firm.*[6]

Perfect foresight constrains investors to agree on equilibrium prices conditional on future realized states of nature. Let I_t denote the public information set at a given point in time. As no information in I_t other than the market price p_t can improve the forecast of p_t^*, we have:

$$p_t = \mathbb{E}[p_t^* \mid I_t], \tag{1}$$

which says that the actual stock price p_t is an optimal predictor of the ex-post rational price p_t^*.

In Appendix B, we derive a procedure to determine the perfect-foresight price under default risk. Our procedure is based on the log-linearization of returns (Campbell and Shiller, 1988), which can be extended to firms subject to default risk by using the fact that, under the power parameterization described in Section 2.1, the log-price is given by $p_t = -\varepsilon_t \lambda_t$. The

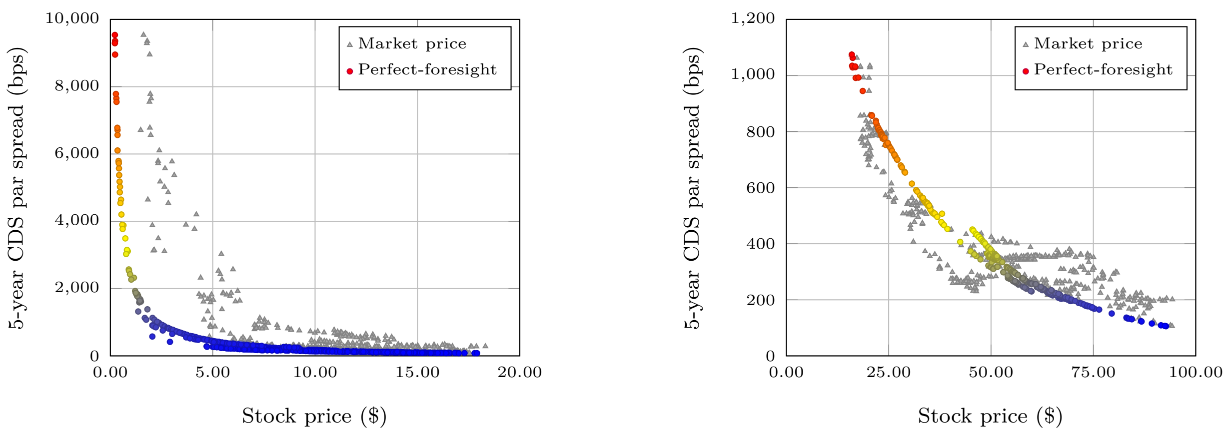
[5] In the rest of the paper, lowercase letters (e.g., log-price p, log-dividend d) denote natural logarithms of the corresponding uppercase letters (e.g., cash price P, cash dividend D).

[6] Henceforth, we refer to the default-risk augmented perfect-foresight price simply as "perfect-foresight price."

Figure 2. The perfect-foresight price

This figure plots weekly CDS par spreads (5-year, senior unsecured contract) against weekly closing stock prices (grey triangles), and weekly perfect-foresight prices (see Section C.1 for implementation details) against weekly closing stock prices (colored marks). Time period: 2008:06 to 2020:12. Data source: Thomson Reuters.

(a) Ford Motor (2008-2020) (b) United Airlines (2011-2019)



log-return is therefore expressed as a function of the CDS log-return, namely, $-\varepsilon\Delta\ln(\lambda_t)$. We exploit this insight in the following result, which provides a recursive construction of the perfect-foresight price under default risk.

Proposition 1 (**Perfect-foresight price**)**.** *The firm's perfect-foresight log stock price is a solution of the following recursive equation:*

$$p_t^* = \rho^{\mathbf{1}_{\mathcal{D}}(t)} p_{t+1}^* - r_{t+1} + \varepsilon_{t+1}\Delta\ln(\lambda_{t+1}) + (1-\rho)\tilde{d}_{t+1} + k\mathbf{1}_{\mathcal{D}}(t), \tag{2}$$

where:

- $\mathcal{D}$ *denote the set of cum-dividend dates* t *such that the firm pays a discrete dividend* $D_{t+1} > 0$ *over the period* $]t; t+1]$*;*
- $\tilde{d}_t := d_t$ *if* $t \in \mathcal{D}$ *and 0 otherwise;*
- r_{t+i} *refers to the risk-free rate of interest over the* $(t+i)$*-th period;*
- ε_{t+i} *denotes the firm's equity-credit elasticity over the* $(t+i)$*-th period;*

- λ_{t+i} *denotes the firm's log default intensity over the* $(t+i)$*-th period;*
- $\rho := 1/(+\exp(\bar{\delta}) \leqslant 1$ *is a discount factor determined by the historical average* $\bar{\delta}$ *of the log dividend-price ratio*
- $k := \ln(1+e^{\bar{\delta}}) - (1-\rho)\bar{\delta}$ *is a constant.*

Proof. See Appendix B. □

Figure 2 illustrates our perfect-foresight calculations for two highly leveraged firms: Ford Motor Co. (median debt-to-asset ratio 0.90) and United Airlines (median debt-to-asset ratio 0.58). The figure plots weekly CDS par spreads against weekly closing stock prices and perfect-foresight prices. We observe typical clusters of stock price-CDS points (grey triangles) scattered on both sides of the perfect-foresight price-CDS curve, indicating potential deviations from stock market efficiency.

2.3 Extending variance ratios

Inspired by the volatility tests literature (e.g., Shiller, 1981; LeRoy and Porter, 1981), we now build on the previous insight to devise a credit-augmented efficiency test based on variance comparisons. From rational expectations and Equation (1), we know that the forecast error $\eta_t := p_t^* - p_t$ must be unforecastable based on I_t. Since η_t must be uncorrelated with p_t, it follows that $\text{Var}[p_t^*] = \text{Var}[\eta_t] + \text{Var}[p_t] \geqslant \text{Var}[p_t]$, which leads to the following variance ratio bound:

$$\upsilon := \frac{\text{Var}[p_t]}{\text{Var}[p_t^*]} \leqslant 1. \tag{3}$$

Equation (3) says that the variance of the perfect-foresight (log) price p_t^* provides an upper bound to the variance of the market (log) price p_t. As a result, Equation (3) represents a testable restriction on the time series p_t that extends variance bounds (Shiller, 1981; LeRoy and Porter, 1981) to a context in which default risk information belongs to the public information set I_t.

In Figure 2, close visual inspection reveals more dispersion around the perfect-foresight-

CDS curve in United Airlines' scatterplot (Panel b) than in Ford's scatterplot (Panel a). This observation suggests a variance approach to assess market efficiency by comparing the actual stock price variance against the perfect-foresight price variance. Unsurprisingly, our calculations show that Ford's variance ratio (0.28) over 2008-2020 was much lower than United Airlines's (1.62).

2.4 Extending tests of stock market efficiency

At this stage, we recognize that variance ratios do not allow for definitive hypothesis testing (e.g., Gilles and LeRoy, 1991). We pursue our approach by borrowing from Mankiw, Romer, and Shapiro (1985, 1991, hereafter MRS), who propose a valid orthogonality test.[7] Recall from Equation (1) that, under the null hypothesis of market efficiency, the stock price at time t is the conditional expectation of the perfect-foresight price. The critical insight of MRS is that, under the null, the forecast error of any alternative forecast based on information available at time t is uncorrelated with the error in forecasting p_t^* using p_t. MRS then introduce a *naive* forecast p_t^o based on a limited information set, such as future dividend forecasts. Using the independence of the two forecast errors, they write a variance inequality that leads to a statistical test of market efficiency.

The following proposition extends Mankiw, Romer, and Shapiro's (1991) variance inequality to a context in which default risk information is accounted for in the rational expectations produced by the market (see online Appendix D.1 for a proof).

Proposition 2 (MRS orthogonality test). *Let the naive forecast p_t^o denote a linear*

[7] The variance ratio based on Equation (3) implicitly assumes weak stationarity of the dividend process to ensure the existence of the population variances of log prices and dividends. However, the dividend process is likely to be a persistent integrated process, so de-trending may not be sufficient to compensate for a unit root and the absence of a well-defined second moment. By contrast, Mankiw, Romer, and Shapiro's (1985, 1991) test remains valid even when there is a unit root in the dividend process. See Gilles and LeRoy (1991) for a survey of variance-bounds tests.

function of the current log dividend d_t, and let define the variance spread:

$$q := \mathbb{E}\left[\left(\frac{p_t^* - p_t^o}{p_t}\right)^2\right] - \left(\mathbb{E}\left[\left(\frac{p_t^* - p_t}{p_t}\right)^2\right] + \mathbb{E}\left[\left(\frac{p_t - p_t^o}{p_t}\right)^2\right]\right). \tag{4}$$

We have the variance identity $q \equiv 0$, as well as the following variance inequality:

$$\mathbb{E}\left[\left(\frac{p_t^* - p_t^o}{p_t}\right)^2\right] \geqslant \max\left(\mathbb{E}\left[\left(\frac{p_t^* - p_t}{p_t}\right)^2\right], \mathbb{E}\left[\left(\frac{p_t - p_t^o}{p_t}\right)^2\right]\right). \tag{5}$$

Proposition 2 tells us that the market (p_t) does a better job of forecasting the fundamental value (p_t^*) than any other forecast (p_t^o). It implies that significant violations in the variance inequality (5) suggest a lack of stock market efficiency. It provides grounds for a statistical test of the role of default risk information in stock market efficiency. Section C.2 describes the implementation of our testing strategy based on Equation (5).

Another testing strategy based on the perfect-foresight price is inspired by West's (1988, hereafter W88) variance-bound test. Following West's (1998) approach, we distinguish between the public information set I_t available to the market and a subset H_t of I_t. We then compare the typical size of a revision in the sub-optimal forecast made from H_t with the typical size of the revision in the optimal market forecast. As the information set H_t is smaller than I_t, the typical error made from H_t should be higher than the prediction error committed by the market.

The following proposition formalizes this insight and generalizes West's variance inequality (1988, Proposition 1) to a context in which default risk information is factored into the rational expectations produced by the market (see online Appendix D.2 for a proof).

Proposition 3 (W88 variance-bound test). *Let $H_t := \{1, r_{t-j}, \varepsilon_{t-j}\Delta\ln(\lambda_{t-j}), \tilde{d}_{t-j} \mid j \geqslant 0\}$ denote a subset of the public information set available to the market (i.e., $H_t \subset I_t$). Let $\check{p}_t := \mathbb{E}[p_t^* \mid H_t]$ denote the credit risk forecast of the perfect-foresight price obtained by projection onto H_t. Assuming the transversality condition $\lim_{T\to\infty} \rho^T p_{t+T}^* = 0$ to exclude the* *existence of rational bubbles, we have the following variance inequality at any time t:*

$$\mathbb{E}\left[(\check{p}_t - \mathbb{E}[\check{p}_t \mid H_{t-1}])^2\right] \geqslant \mathbb{E}\left[(p_t - \mathbb{E}[p_t \mid I_{t-1}])^2\right]. \tag{6}$$

Proposition 3 says that the error in a partially-informed forecast, such as the one generated using only credit risk information, will be higher on average than the revision in the forecast produced from the whole information set available to the market. In other words, a sub-optimal forecast must be noisier than the market's optimal forecast, placing a bound on the volatility produced by the market price. Section C.3 implements a testing strategy based on Equation (6).

2.5 Hypotheses development

The literature on the CDS market's informational advantage emphasizes its role in producing and aggregating negative firm-specific information (e.g., Acharya and Johnson, 2007; Batta, Qiu, and Yu, 2016; Kim et al., 2018). In particular, the CDS market is a preferred venue for informed trading and price discovery prior to earnings announcements, especially large negative earnings surprises (Batta, Qiu, and Yu, 2016). The dampening effect of CDS trading on analyst forecasts optimism is stronger for firms with negative news, poorer financial performance, or higher leverage (Zhao et al., 2022). CDS trading reduces the informativeness of credit rating downgrades and mutes the equity market reaction to rating downgrades (Chava, Ganduri, and Ornthanalai, 2019). In addition, CDS trading facilitates the incorporation of negative information into stock prices (e.g., Qiu and Yu, 2012; Liu et al., 2024). As a result, we hypothesize that stock market efficiency will increase with firm-specific determinants of CDS spreads, such as firm leverage or firm volatility (e.g., Zhang, Zhou, and Zhu, 2009; Ericsson, Jacobs, and Oviedo, 2009).

The precise mechanism we model and test in this paper is as follows. First, we assume that the higher the firm's default risk, the higher the prevalence of negative information, and the higher the elasticity of stock prices relative to CDS spreads (see Appendix A for the theoretical rationale). Second, as the equity-credit elasticity is related to information transmission between the two markets, CDS trading should be more informational and impound more firm-specific information into stock prices as default risk increases. We now summarize the main hypotheses in our paper, which exploit the results in Propositions 2 and 3.

Hypotheses. *The higher the firm's leverage, the more we expect:*

- **H1** *the variance ratio v to be closer to 1, i.e., the variance of the ex-post rational price p_t^* to be closer to the variance of the market price p_t.*
- **H2** *the MRS variance spread q to be closer to 0, i.e., the market price p_t to be a better forecast of the ex-post rational price p_t^* compared to the naive forecast p_t^o;*
- **H3** *innovations in the imperfect forecast $\check{p}_t$ based on limited credit risk information to be more volatile than innovations in the actual market price p_t, i.e., the spread between the variance in the innovations in $\check{p}_t$ and p_t to increase.*

Hypotheses **H1** to **H3** follow directly from the market efficiency tests discussed in Section 2.4. The implementation of hypothesis **H1-H3** is discussed in Appendix C and empirically tested in Section 4.

3. Data

3.1 Selection of the firm sample

In this paper, we choose to focus on CDS rather than corporate bonds.[8] We thus consider the daily CDS closing (mid) par spreads of the most widely traded North American reference entities. In addition, we impose three requirements to build a large and representative universe of CDS-referenced firms. The first requirement is for bid-ask CDS quotes to be

[8]Three main reasons justify our choice. First, the CDS market is more standardized than the fragmented bond market. As a result, bond trading is more expensive than CDS trading (Oehmke and Zawadowski, 2017). Second, CDS introduction reduces bond market efficiency and liquidity while CDSs lead the price discovery process (Das, Kalimipalli, and Nayak, 2014). Finally, CDS prices contain unique information that is not captured by other securities (Lee, Naranjo, and Velioglu, 2018). See also Lee, Naranjo, and Sirmans (2024).

available in Thomson Reuters (TR) over an extended 13-year sample period running from January 01, 2008, to December 31, 2020.[9] The second requirement is for the corresponding common stocks to have been constituent companies of the S&P 500 stock index at some point during the 2008-2020 sampling period. Finally, the historical debt-to-asset ratio has to be available in the TR database over the entire sampling period. The coverage universe of reference entities satisfying the previous three requirements comprises 339 single names. While we have been careful to design a sample selection strategy using data from TR, we recognize that other data sources may include additional CDS data for dates prior to 2008.

3.2 Credit market data

For consistency, we consider only CDS par spreads corresponding to U.S.-dollar denominated contracts on the most liquid tenor (5 years), the lowest seniority (Senior Unsecured Debt), and the same restructuring clause (No Restructuring, 2014 Protocol). TR provides end-of-day prices by collecting daily single-name CDS quotes from over 30 contributors worldwide and applying a rigorous screening procedure to eliminate outliers or doubtful data.[10] Final CDS quotes are thus composite mid spreads calculated by TR and expressed in basis points.[11]

3.3 Construction of a proxy variable for the equity-credit elasticity ϵ

Following Zimmermann (2021), we use a linear function of corporate leverage as a time-varying proxy for the firm's equity-credit elasticity, ϵ. To measure the firm's financial leverage, we use the debt-to-asset leverage ratio, that is, the ratio of total debt book value to

[9] Some firms in the sample experienced major credit events, such as defaults, mergers, or acquisitions, leading to their early exit from the S&P 500 during the 2008-2020 period (e.g., Eastman Kodak, Dean Foods). Conversely, other firms joined the index later in the sample period.

[10] Mayordomo et al. (2014) offer an in-depth comparative study of the TR database and five other public sources of corporate CDS prices.

[11] The timing for the end-of-day composite calculation is in T+1 (5:00 am GMT). As this last update takes place after the end of trading for U.S. stocks, there is no bias in detecting information flows from stock markets to credit markets.

enterprise value:[12]

$$\frac{\text{Short-term Debt} + \text{Long-term Debt}}{\text{Market Capitalization} + \text{Total Debt} + \text{Minority Interest} + \text{Preferred Stock} - \text{Cash}}. \tag{7}$$

We gather daily estimates of the debt-to-asset ratio over 2008-2020 for each sample firm. Notice that the fluctuations in the firm's market capitalization on top of the changes in total debt book value entail daily variations in corporate leverage.

3.4 Firm-level sample overview

Merging all data sets and applying the appropriate data filters leaves us with 853,766 joint observations of CDS spreads, stock prices, and firm characteristics over the period 2008:01 to 2020:12. Our final sample consists of 339 U.S. firms, with 279 obligors having an average Standard and Poor's (S&P) credit rating of investment grade (AAA, AA, A, and BBB) and the remaining 60 obligors below investment grade (BB, B, and CCC) or non rated. Our coverage is similar to comparable studies on U.S. public firms with traded CDS, such as Kapadia and Pu (2012), Lee, Naranjo, and Velioglu (2018), or Chava, Ganduri, and Ornthanalai (2019).

Table 1 provides detailed descriptive statistics of the firm-level dataset. Panel A provides summary statistics for firm characteristics such as size, total debt, dividend yield, leverage, CDS level, and idiosyncratic volatility.[13] The mean CDS spread (resp. leverage) across the entire sample is 148 basis points (resp. 0.32). These metrics are close to the ones reported by Lee, Naranjo, and Velioglu (2018) for public firms.

Panel B reports correlations. As already documented in the literature (e.g., Lee, Naranjo,

[12] A conservative approach to the financial leverage of financial institutions is in order. In the case of banks, for example, TR includes due from other banks into cash on hands and customer deposits should not appear in total debt. For insurance companies, policyholders' liabilities should not appear in total debt.

[13] Idiosyncratic equity volatility is a key determinant of default risk (e.g., Campbell and Taksler, 2003) and shows slightly higher correlation with firm fundamentals such as CDS level (0.54 vs. 0.49) or firm leverage (0.44 vs. 0.43) than realized volatility. We estimate 1-year idiosyncratic volatility as the (annualized) standard residual error in the regression of daily stock returns against daily S&P 500 market returns over one year.

Table 1. Firm-level descriptive statistics

The table reports summary statistics for firm characteristics (Panel A), correlations (Panel B), and business sectors (Panel C). The sample consists of 339 U.S. firms over the period 2008:01 to 2020:12. Sample statistics are computed across all observations. Data source: Thomson Reuters.

	5^{th} perc.	25^{th} perc.	Median	Mean	75^{th} perc.	95^{th} perc.	SD	Observations	
			Panel A: firm-level statistics						
Size (mkt. cap., $bn)	2.17	8.01	17.17	39.55	39.02	163.90	75.50	853,766	*100.0%*
Dividend yield (%)	0.00	1.02	2.12	2.50	3.24	5.94	3.68	853,766	*100.0%*
Total debt (book value, $bn)	0.70	2.69	5.48	21.96	11.99	58.57	73.75	853,766	*100.0%*
Leverage (debt to assets)	0.07	0.16	0.26	0.32	0.42	0.78	0.23	853,766	*100.0%*
CDS level (mid-price, bps)	27	50	82	148	154	475	252	853,766	*100.0%*
Idiosyncratic stock volatility	0.12	0.16	0.21	0.26	0.30	0.56	0.16	853,766	*100.0%*
Daily observations by firm	420	2,096	3,027	2,518	3,099	3,210	877	853,766	*100.0%*
	Size ($bn)	Div. yield (%)	Tot. Debt ($bn)	Leverage	CDS (bps)	Volatility	♯ Firms	Observations	
			Panel C: correlation matrix						
Size ($bn)	1								
Dividend yield (%)	−0.02	1							
Total debt ($bn)	0.32	0.02	1						
Leverage	−0.11	0.11	0.47	1					
CDS level (bps)	−0.16	0.04	−0.02	0.46	1				
Idiosyncratic stock volatility	−0.20	0.09	0.01	0.44	0.54	1			
			Panel C: business sector-level average statistics						
Academic & Educ. Services	3.66	2.50	0.49	0.16	129	0.24	1	3,138	*0.4%*
Basic Materials	15.82	2.29	4.82	0.28	149	0.28	24	54,891	*6.4%*
Consumer Cyclicals	22.49	2.32	8.99	0.31	213	0.30	66	185,549	*21.7%*
Consumer Non-Cyclicals	61.57	2.62	19.27	0.25	97	0.20	41	111,580	*13.1%*
Energy	43.10	2.41	9.13	0.29	144	0.32	30	72,549	*8.5%*
Financials	49.88	2.25	110.54	0.51	147	0.27	39	93,420	*10.9%*
Healthcare	50.38	1.39	8.86	0.23	101	0.23	25	60,657	*7.1%*
Industrials	30.41	2.34	8.69	0.28	117	0.22	41	100,862	*11.8%*
Real Estate	19.30	4.64	8.14	0.34	145	0.24	15	38,241	*4.5%*
Technology	85.94	2.24	15.07	0.27	180	0.28	32	70,698	*8.3%*
Utilities	18.30	3.81	14.16	0.47	110	0.19	25	62,181	*7.3%*

and Velioglu, 2018), firm leverage correlates with CDS spread levels (0.46) but shows weak correlation with firm size (−0.11) or dividend yield (−0.04). The CDS spread is negatively correlated with firm size (−0.16) and thus slightly increases for smaller firms, in line with Lee, Naranjo, and Sirmans (2021). Idiosyncratic volatility is significantly correlated with leverage (0.44) and CDS (0.54).

Panel C breaks down the sample into business sectors listed in the Thomson Reuters Business Classification (TRBC). We notice that the two most leveraged industries are the Financials (0.51) and Utilities (0.47) business sectors. However, with only 10.9% of the overall observations, the Financials sector's weight in the sample remains limited.

3.5 Aggregate-level sample overview

We test the implications of our model at an aggregate level using a variety of value-weighted portfolios of U.S. stocks belonging to our firm-level dataset. We use U.S. equity indices provided by Standard & Poor's. To capture the dynamics of large-cap U.S. companies endowed with an active CDS market, we first consider the S&P 100 and the S&P 500 stock indices. Covering approximately 80% of all U.S. market capitalizations, this last index provides a representative gauge of the overall U.S. equity market. Second, to better understand the role of classic asset pricing factors such as Value and Growth, we consider the S&P 500 Value and the S&P 500 Growth indices. Third, to capture the role of industry sectors more specifically, we also consider the ten sub-indices of the S&P 500 corresponding to the ten main economic sectors. Fourth, to allow for a more refined focus on highly-leveraged firms in the Financials sector, we also include the S&P 500 sub-index of Banks. Finally, we complement our sample with the S&P 400 Mid Cap stock index, an index of mid-sized companies that do not overlap with the S&P 500 constituents.

Table 2 reports the fundamental metrics of each index. To reconstitute these metrics, we follow the methodology of S&P U.S. Indices by weighing indices with float-adjusted market

Table 2. Descriptive statistics of value-weighted stock portfolios

This table reports summary statistics for the various U.S. stock indices used as valued-weighted stock portfolios in this paper. Sample statistics are computed across all observations. The sample period is 2008:01 to 2020:12. Data source: Thomson Reuters.

	Avg. ♯ firms	Avg. size ($trn)	Avg. firm size ($bn)	Avg. div. yield (%)	Weighted leverage	Weighted CDS (bps)	Isoweight CDS (bps)	Obs.
Panel A: large-cap portfolios								
S&P 100	102	10.16	101.1	2.40	0.23	59	77	3,189
S&P 500	499	18.11	36.7	2.04	0.23	72	121	3,189
Panel B: global portfolios								
S&P 500 Value	359	12.11	34.5	2.76	0.30	78	131	3,189
S&P 500 Growth	301	11.71	40.2	1.58	0.16	61	97	3,189
S&P 400 Mid Cap	400	0.54	5.5	1.78	0.22	206	287	3,189
Panel C: sector portfolios								
S&P Banks	17	0.78	45.7	2.62	0.68	87	101	2,943
S&P Financials	78	2.45	32.3	2.23	0.56	97	124	3,189
S&P Utilities	30	0.49	17.3	3.93	0.43	99	119	3,189
S&P Real Estate	22	0.37	15.1	3.77	0.31	153	151	2,953
S&P Communic. Serv.	9	0.79	86.7	5.18	0.31	125	222	2,953
S&P Industrials	63	1.51	24.1	2.28	0.26	70	88	3,189
S&P Materials	29	0.47	17.3	2.29	0.23	109	133	2,815
S&P Consumer Discr.	79	1.75	23.8	1.51	0.19	99	162	3,189
S&P Consumer Staples	38	1.47	39.7	2.82	0.17	48	77	3,121
S&P Healthcare	54	2.14	39.4	1.91	0.16	46	80	3,189
S&P Energy	36	3.38	91.2	2.84	0.17	73	159	3,189
S&P Technology	70	3.07	44.9	1.33	0.09	50	109	3,189

capitalizations.[14] Additions and deletions of constituent companies are thus reflected on a daily basis. In addition, to obtain the exact timeline of dividend flows paid out by the index, we compare its price return version without adjustment for regular cash dividends to its total return version with reinvested dividends.[15] From the daily composition of each index, we can thus reconstitute its log-dividend price ratio, its aggregate debt-to-asset ratio, and its aggregated CDS par spread. This aggregate measure of financial leverage serves as a proxy for the index's credit-equity elasticity.

[14]The share counts used to calculate sector indices are based on the free-floating shares available to investors instead of the total outstanding shares. For more details on the float adjustment methodology of S&P U.S. equity indices, we refer to the supporting document published by S&P Dow Jones Indices.

[15]Index levels are calculated by dividing the market capitalization with a divisor keeping track of any change in the overall market capitalization that should not alter individual stock prices (e.g., corporate actions of constituent companies, addition or deletions of constituents, changes in free-floating share counts). For more details on the S&P U.S. equity indices calculation, we refer to the supporting document published by S&P Dow Jones Indices.

4. Results

4.1 Efficiency tests at the firm level

4.1.1 Preliminary results on variance ratios

To convey the gist of our efficiency results, we first provide a preliminary assessment of the distribution of the default-augmented variance ratio, υ. Recall that a variance ratio above one can be interpreted as a sign of market inefficiency. This is because the market price, p_t, exhibits significant excess volatility compared to the perfect-foresight price, p_t^*.

Figure 3 summarizes our story. Panel (a) shows the distribution of variance ratios estimated using individual firms. At first sight, the right-most boxplot in Panel (a) suggests a lack of market efficiency since the median variance ratio across all firms is well above one in the 2008-2020 sample period (median 6.23). However, an important finding emerges from the granular sort by leverage quintile. Excess volatility decreases with financial leverage and tends to disappear in the most leveraged quintiles (Q_3-Q_5). This preliminary finding is robust to the sample period. We obtain similar results for the credit crisis (2008-2009) and post-crisis (2010-2020) periods (unreported).

One concern with firm full samples is the potential look-ahead bias caused by sorting firms based on their full-sample leverage mean. In addition, our results might be driven by some specific year or company since not all firms' historical samples have the same length. To address these concerns, we repeat the analysis by firm-years as follows. First, every year we sort firms by leverage into quintiles. Next, we require at least 100 observations in each firm-year sample to avoid small-sample issues due to missing data. We thus obtain 3,606 valid firm-year samples, for each of which we estimate variance ratio. Finally, we collect the variance ratios for each leverage quintile. This approach enables us to run numerous variance ratios and obtain a more granular view of the results. Additionally, since all tests now apply to one-year samples, we treat all firms of the universe on the same footing and assign the same weight to all years in the period 2008-2020.

Figure 3. Default-risk-augmented variance ratios

These boxplots compare distributions of the default-risk-augmented variance ratio υ across leverage percentiles of firms. In the first stage, we sort the 339 firms (resp. 3,608 firm-years) into quintiles based on the firm's (resp. firm-year's) average annual leverage, Q_1 being the quintile with the smallest leverage. In the second stage, we compute for each firm i (resp. firm-year (i,t)) the variance ratio $\hat{\upsilon}^i$ (resp. $\hat{\upsilon}^{i,t}$). The sample period is 2008:01 to 2020:12. Data source: Thomson Reuters.

(a) By individual firms (2008-2020) (b) By firm-years (2008-2020)

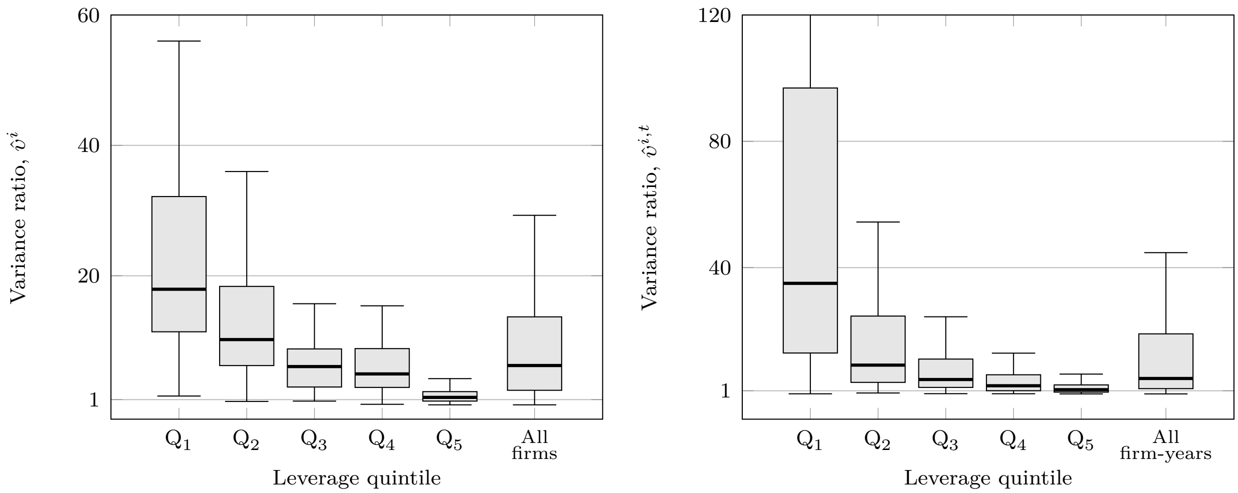


Table 3. Determinants of the default-risk-augmented variance ratio

This table reports the default-risk-augmented variance ratio υ across leverage percentiles of firm-years. In the first stage, we sort the 3,606 firm-years into quintiles based on the firm-year's average annual leverage, Q_1 being the quintile with the smallest leverage. In the second stage, we compute for each firm-year (i,t) the variance ratio $\hat{\upsilon}^{i,t}$. Summary statistics for each quintile are the medians across firm-years of the time-series means of the characteristics for each firm. Within each quintile, meta p-values are combined across firm-years via Fisher's sum of logarithms method (e.g., Heard and Rubin-Delanchy, 2018). ***, ** and * denote statistical significance at the 0.1%, 1%, and 5% levels, respectively. The sample period is 2008:01 to 2020:12. Data source: Thomson Reuters.

	Q_1 (low)	Q_2	Q_3	Q_4	Q_5 (high)	All firm-years
Panel A: simple sort by firm leverage						
Avg. firm leverage	0.10	0.19	0.27	0.39	0.67	0.32
♯ firm-years	726	723	722	720	715	3,606
Median $\hat{\upsilon}$	35.02***	9.12***	4.56***	2.59***	1.34***	4.89***
Panel B: simple sort by firm CDS spread						
Avg. CDS spread (bps)	37.6	61.1	91.8	141.8	415.2	148.8
Median $\hat{\upsilon}$	8.46***	5.76***	5.81***	4.20***	2.91***	4.89***
Panel C: double sort by firm leverage and firm size						
Q_1 (low size)	35.97***	11.13***	6.81***	3.81***	1.94***	4.04***
Q_2	32.32**	9.62***	5.32***	3.16***	1.57***	4.28***
Q_3	38.20***	10.23***	4.00***	1.90***	1.98***	5.02***
Q_4	37.33***	9.31***	3.96***	2.80***	1.21***	5.94***
Q_5 (high size)	28.68***	6.12***	3.60***	1.77***	0.52***	6.00***
Panel D: double sort by firm leverage and idiosyncratic volatility						
Q_1 (low vol)	20.25***	7.16***	3.80***	1.96***	0.76***	5.02***
Q_2	37.81	7.99***	4.32***	2.32***	0.89***	5.87***
Q_3	40.97***	10.94***	5.32***	2.60***	1.52***	5.49***
Q_4	42.29***	11.92***	4.78***	2.82***	1.78***	5.32***
Q_5 (high vol)	34.83***	7.61***	4.50***	3.25***	1.81***	3.74***

Panel (b) of Figure 3 shows the distributions of variance ratios estimated using firm-years.The convergence to unity is sharper when υ is estimated by company-years (sample size: 3,606) rather than individual firms (sample size: 339). In other words, market efficiency seems to increase with firm leverage as default risk information ingrained in the fundamentals p_t^* becomes more and more reflected in the market's optimal forecast, p_t.

Table 3 investigates the impact of CDS determinants on the variance ratio $\hat{\upsilon}$ by reporting sorts across firm-year percentiles. We think of each firm-year estimation as an independent study and perform a meta-analysis of significance levels. We thus perform an F-test for variance equality on each firm-year estimation and combine the p-values within each quintile via Fisher's sum of logarithms method (e.g., Heard and Rubin-Delanchy, 2018).

Panel A reports a simple sort based on leverage and confirms the negative and monotonic relation between $\hat{\upsilon}$ and firm leverage, as predicted in Section 2.5 and illustrated in Figure 3. Panel B shows a decrease of $\hat{\upsilon}$ with CDS spread, which is unsurprising given the significant correlation between CDS spread and firm leverage (0.47). By contrast, the finer double sort by size and leverage shown in Panel C does not indicate any discernable relation between $\hat{\upsilon}$ and firm size. Finally, the double sort by leverage and volatility (Panel D) reveals a slightly increasing relation between $\hat{\upsilon}$ and idiosyncratic volatility. This is not surprising, given the high correlation between idiosyncratic volatility and leverage in Table 1.

As mentioned previously, variance ratios do not allow for definitive hypothesis testing. Therefore, we now turn on orthogonality and variance-bound tests to confirm this preliminary insight.

4.1.2 Efficiency tests by individual firms

Table 4 reports estimates for MRS orthogonality and W88 variance-bound tests. We consider different assumptions concerning the sample period. As our entire sample includes the 2008-2009 credit crisis, our empirical results might be driven by this specific period of high corporate leverage, intense stock market volatility, and turmoil in credit markets. Therefore, we repeat our efficiency tests on two distinct sub-sample periods to address this concern: the financial crisis (2008:01-2009:12) and the post-crisis period (2010:01-2020:12). We sort firms into quintile portfolios based on the average firm leverage over the considered sample period. Summary statistics by leverage quintiles are reported for the three sample periods. As expected, the (unreported) average CDS spread increases across quintiles. On the other hand, the average dividend yield across quintiles remains close to its whole sample mean of 2.47%, except for the two highest quintiles Q_4-Q_5 during the credit crisis (2008-2009).

We implement the MRS orthogonality test with an equity risk premium $\mathfrak{p} = 5\%$ over the long-term U.S. Treasury rate. This assumption seems reasonable for the U.S. stock market

Table 4. Efficiency tests by firm quintiles

This table reports orthogonality and variance-bound tests. We sort firms into quintile portfolios based on their average annual leverage, Q_1 being the smallest leverage quintile. The summary statistics reported for each quintile are the averages (across firms) of the time-series means of the characteristics for each firm. The absolute value of the MRS variance spread statistic q_T is given by Equation (C5), where the naive forecast is estimated with an equity risk premium $\mathfrak{p} = 0.05$. The $\chi^2(1)$ statistic for the null hypothesis $H_0 : \hat{q}_T = 0$ is calculated via robust standard errors corrected for heteroscedasticity and serial correlation (Newey and West, 1987). Estimates of the market efficiency score w are given by Equation (C6) and calculated with an AR lag order $q = 5$. Within each quintile, p-values are combined across firms via Fisher's sum of logarithms method (e.g., Heard and Rubin-Delanchy, 2018). ***, ** and * denote statistical significance at the 0.1%, 1%, and 5% levels, respectively. The sample period is 2008:01 to 2020:12. Data source: Thomson Reuters.

	Q_1 (low)	Q_2	Q_3	Q_4	Q_5 (high)	All firms
Panel A: full sample of firms (2008-2020)						
Avg. firm leverage	0.11	0.20	0.29	0.39	0.65	0.33
♯ firms	68	68	68	68	67	339
Observations	172,028	168,867	180,476	178,396	153,999	853,766
Med. variance spread, $\lvert q_T\rvert$	1.20***	0.83***	0.62***	0.45***	0.41***	0.64***
Med. efficiency score, w	−96.2***	−89.7***	−77.9***	−70.6***	−28.1***	−80.6***
Positive scores (%)	0.0	0.0	0.0	3.0	27.3	6.0
Avg. positive score, w^+	0.0	0.0	0.0	0.7	9.1	2.0
Panel B: credit crisis sample of firms (2008-2009)						
Avg. firm leverage	0.10	0.20	0.32	0.48	0.77	0.37
♯ firms	57	57	57	57	57	285
Observations	22,472	22,063	22,285	22,426	23,451	112,697
Med. variance spread, $\lvert q_T\rvert$	1.49***	1.52***	1.49***	0.78***	0.76***	1.25***
Med. efficiency score, w	−96.4***	−91.0***	−79.1***	−64.0***	−33.7***	−82.4***
Positive scores (%)	0.0	0.0	1.8	10.7	28.6	8.1
Avg. positive score, w^+	0.0	0.0	0.1	1.7	9.0	2.1
Panel C: post-crisis sample of firms (2010-2020)						
Avg. firm leverage	0.11	0.19	0.28	0.38	0.63	0.32
♯ firms	66	66	66	66	66	330
Observations	146,140	149,896	152,744	155,365	136,505	740,650
Med. variance spread, $\lvert q_T\rvert$	1.08***	0.81***	0.58***	0.52***	0.45***	0.60***
Med. efficiency score, w	−97.7***	−89.8***	−82.2***	−65.9***	−28.3***	−81.3***
Positive scores (%)	0.0	0.0	0.0	6.2	29.7	7.1
Avg. positive score, w^+	0.0	0.0	0.0	1.1	12.0	2.6
Panel D: full sample of firm-years (2008-2020)						
Avg. firm leverage	0.10	0.18	0.27	0.39	0.67	0.32
♯ firm-years	726	723	722	720	715	3,606
Observations	169,288	169,918	170,223	167,590	169,370	846,389
Med. variance spread, $\lvert q_T\rvert$	0.79***	0.62***	0.51***	0.49***	0.44***	0.55***
Med. efficiency score, w	−97.7***	−89.8***	−82.2***	−65.9***	−28.3***	−81.3***
Positive scores (%)	0.0	0.0	0.0	6.2	29.7	7.1
Avg. positive score, w^+	0.0	0.0	0.0	1.1	12.0	2.6

over the period 2008-2020. As explained in Section C.2, for each firm, the t-statistic of the sample mean $\hat{q}_T$ follows a $\chi^2(1)$-distribution. We combine the p-values of the $\chi^2(1)$-test within each quintile via Fisher's sum of logarithms method (e.g., Heard and Rubin-Delanchy, 2018). We interpret a variance spread q_T far from zero, either positively or negatively, as a sign of market inefficiency. Although we observe relatively high absolute values for $\hat{q}_T$ across all firms and over the three sample periods, the key takeaway of Table 4 is the inverse pattern of $|\hat{q}_T|$ with respect to financial leverage. That is, $\hat{q}_T$ decreases monotonically as leverage increases over the entire sample period (2008-2020). A similar pattern holds for the crisis (2008-2009) and post-crisis (2010-2020) periods. This provides reliable evidence of a significant relationship between market efficiency and firm financial leverage. In Section **??**, additional robustness tests show that this key finding is robust to the size of the equity risk premium $\mathfrak{p}$ and the time horizon T chosen to estimate the perfect-foresight price $P^*_{t\to T}$.

We implement the W88 variance-bound test with an AR lag order $q = 5$ for the credit risk variable of all firms in the sample. We have run the test for various values of the AR lag order $q \leqslant 5$ with similar results. For brevity, we do not report these results. As explained in Section C.3, for each firm, we obtain the (robust) standard error and t statistic of $\hat{W}$ by GMM. Once again, we combine p-values within each quintile via Fisher's sum of logarithms method (e.g., Heard and Rubin-Delanchy, 2018).

For each firm, we calculate the variances of market innovations ($\hat{\sigma}_u^2$) and credit risk innovations ($\hat{\sigma}_v^2$). The (unreported) standard deviation $\hat{\sigma}_u$ is relatively stable across quintiles. By contrast, the (unreported) standard deviation $\hat{\sigma}_v$ is close to zero in the lowest-leveraged quintile Q_1, suggesting, as expected, a low level of credit risk activity for all-equity firms. Then $\hat{\sigma}_v$ grows monotonically across leverage quintiles. The (unreported) variance spread statistic, W, which measures the rescaled difference between $\hat{\sigma}_v^2$ and $\hat{\sigma}_u$, reflects the excess variance produced by market prices relative to their fundamentals. It is negative and statistically significant in most quintiles for the three sample periods. This constant rejection of the null hypothesis confirms our preliminary finding of a lack of market efficiency for most firms.

For the sake of clarity, Table 4 reports the score $\hat{w}$ as defined in Equation (C6) instead of W. This efficiency score is comprised between -100 (no efficiency) and 100 (total efficiency). Although the overall score of market efficiency for the entire sample is relatively low at -80.6, it regularly increases along with firm leverage. It culminates at -28.1 in the last quintile, indicating that credit market activity strongly influences the stock market efficiency of highly-leveraged firms. We find qualitative results similar to our benchmark results for the two other sample periods. This finding alleviates the concern of an empirical bias induced by the 2008-2009 credit crisis period.

Finally, we consider the small sub-sample of firms with a positive score $\hat{w}^+ := \max(\hat{w}, 0)$. The key finding of our variance-bound test is thus located in the penultimate column of Table 4, where 27.3% of the firms exhibit positive scores for the period 2008-2020 with a mean at 9.1. This significant proportion of positive scores in Q_5 contrasts with the four other quintiles and suggests the actual efficiency of the stock market for highly-leveraged firms. Equally important, this finding is robust to the sample period and does not appear specific to the credit crisis (2008-2009).

4.2 Aggregate-level efficiency tests

We run variance ratios, orthogonality, and variance-bound tests on several value-weighted stock portfolios to test for stock market efficiency at the aggregate level. We consider different proxies to represent aggregate credit risk information. Our first two proxies are liquid and representative credit indices: the CDX Investment Grade (CDX.IG) and CDX High Yield (CDX.HY), which are benchmarks for the two main segments of the North-American corporate credit market (e.g., Collin-Dufresne, Junge, and Trolle, 2020). A third proxy is provided by the aggregated CDS spread of the considered stock index constituents.[16] This last approach can better reflect the specific default risk incorporated in each stock index.

[16] We first reconstitute the daily composition and weighting of each stock index. The aggregated CDS of the index is then calculated as the weighted average of the CDS par spreads of its constituents.

Table 5 reports efficiency test results at the aggregate level on the various U.S. stock indices described in Section 3.5. We implement the MRS orthogonality test identically to the firm-level case (see Section C.2 for implementation details) with an equity risk premium $\mathfrak{p} = 0.05$ over the risk-free rate to estimate the naive forecast. Again, we implement West's (1988) default-augmented variance-bound test identically to the firm-level case (see Section C.3 for implementation details). We use a weekly AR lag order $q = 5$ in the three credit risk scenarios.[17]

Panel A focuses on the two S&P flagship stock indices—the S&P 100 and S&P 500. At first sight, the surprisingly high variance ratios between 3.09 and 7.08 under every proxy of aggregated credit risk and every sample period suggest significant excess volatility for both indices. Although less statistically significant, the variance spread statistics q_T range between 0.89 and 2.35, reinforcing this preliminary assessment. This preliminary finding is then fully confirmed by the highly-significant, negative scores w of market efficiency achieved by these two indices. Again, the critical finding of Table 5 is the utmost lack of stock index efficiency for the two U.S. large-cap indices. The S&P 500 index achieves a paltry median score of -65.87 out of 100 under CDX.IG credit risk at best. This (negative) score should be contrasted with the (positive) scores of the highly-leveraged firms in Tables 4 and **??**, which quickly attain 10 out of 100.

Panel B focuses on mid- to large-cap, non-sectoral stock indices—the S&P 500 Value and Growth and the S&P 400 Mid Cap. Similarly to the two large-cap indices, we find highly-significant variance ratios well above one, positive variance spread statistics, and negative efficiency scores (well below -50) across the board, indicating a high level of excess volatility or low level of efficiency. This is especially true for the S&P 500 Growth index, which has a low level of aggregated leverage (0.16). It is noteworthy to mention the significant difference in market efficiency between the Value and Growth indices. The S&P Value index displays almost twice the aggregated level of leverage of the S&P Growth index (0.30 compared with

[17] Similarly to the firm level, we have run the test for various lag orders $q \leqslant 5$ with (unreported) results primarily unchanged.

Table 5. Aggregate-level tests of efficiency

This table reports efficiency tests for U.S. stock indices under three credit risk scenarios: (a) CDX Investment Grade (CDX IG), (b) CDX High Yield (CDX HY), and (c) value-weighted average of the index constituents' CDS (Index weighted CDS). The leverage and dividend yield reported for each index is the mean of the daily value-weighted averages of the index constituents' debt-to-asset ratios. Panels A, B, and C report estimates for the variance ratio υ, the MRS variance spread statistic $|q_T|$ given by (C5) and estimated with an equity risk premium $\mathfrak{p} = 0.05$, and the market efficiency score w given by (C6) and estimated with an AR lag order $q = 5$. Panel D reports correlations of efficiency statistics with the weighted leverage, the weighted dividend yield, the weighted CDS and the average market capitalization. ***, ** and * denote statistical significance at the 0.1%, 1%, and 5% levels, respectively. The sample period is 2008:01 to 2020:12. Data source: Thomson Reuters.

	Weighted Leverage	Div. Yield (%)	CDX IG υ	CDX IG $\lvert q_T \rvert$	CDX IG w	CDX HY υ	CDX HY $\lvert q_T \rvert$	CDX HY w	Index weighted CDS υ	Index weighted CDS $\lvert q_T \rvert$	Index weighted CDS w	Obs.
Panel A: large-cap portfolios												
Full sample (2008-2020)												
S&P 100	0.23	2.40	4.00***	1.29*	−73.99***	3.50***	1.32**	−78.19***	4.57***	1.46***	−82.23***	3,189
S&P 500	0.23	2.04	4.41***	1.26	−75.14***	3.89***	1.29*	−79.03***	5.32***	1.46***	−85.93***	3,189
Credit crisis sample (2008-2009)												
S&P 100	0.25	2.39	5.82***	1.86***	−78.43*	5.24***	1.71***	−86.69**	4.59***	2.19***	−84.16***	484
S&P 500	0.25	2.08	6.33***	1.96***	−82.03*	5.57***	1.84***	−86.21**	6.13***	2.35***	−87.24***	484
Post-crisis sample (2010-2020)												
S&P 100	0.23	2.40	5.79***	0.97	−70.37***	5.91***	1.02	−71.96***	6.01***	1.08***	−80.97***	2,705
S&P 500	0.23	2.03	6.24***	0.94	−71.20***	6.35***	1.00	−72.57***	7.08***	1.08***	−84.79***	2,705
Median of index-year samples (2008-2020)												
S&P 100	0.23	2.39	3.09***	0.89	−65.87***	4.29***	0.91	−71.09***	4.09***	1.01***	−81.43***	245
S&P 500	0.23	2.04	3.25***	0.93	−68.31***	4.44***	0.96	−71.10***	4.78***	1.09***	−86.44***	245
Panel B: global portfolios												
Full sample (2008-2020)												
S&P 500 Value	0.30	2.76	2.51***	0.41*	−61.66***	2.08***	0.44***	−67.47***	3.53***	0.68***	−67.39***	3,189
S&P 500 Growth	0.16	1.58	7.91***	2.23	−88.09***	7.51***	2.27	−89.82***	9.96***	2.37*	−93.17***	3,189
S&P 400 Mid Cap	0.22	1.78	5.23***	0.84*	−79.91***	4.95***	0.91**	−83.06***	19.15***	1.42**	−84.35***	3,189
Credit crisis sample (2008-2009)												
S&P 500 Value	0.36	3.16	5.23***	0.58	−73.88*	4.20***	0.44*	−78.67*	6.04***	1.11***	−69.94**	484
S&P 500 Growth	0.16	1.37	9.67***	3.80***	−89.88***	9.86***	3.72***	−93.18***	8.92***	4.18***	−92.57***	484
S&P 400 Mid Cap	0.23	1.92	8.49***	1.90***	−87.09***	6.76***	1.89***	−90.26***	7.38***	3.24***	−91.14***	484

(Continued)

Table 5. *(Continued)*

	Weighted Leverage	Div. Yield (%)	CDX IG v	CDX IG $\lvert q_T \rvert$	CDX IG w	CDX HY v	CDX HY $\lvert q_T \rvert$	CDX HY w	Index weighted CDS v	Index weighted CDS $\lvert q_T \rvert$	Index weighted CDS w	Obs.
Panel B: global portfolios *(Continued)*												
Post-crisis sample (2010-2020)												
S&P 500 Value	0.29	2.69	3.93***	0.29**	−52.91***	3.98***	0.33*	−55.73***	4.36***	0.46***	−71.29***	2,705
S&P 500 Growth	0.16	1.62	10.55***	1.72	−87.09***	11.09***	1.77	−87.44***	12.68***	1.80***	−93.56***	2,705
S&P 400 Mid Cap	0.22	1.75	5.75***	0.49**	−74.93***	6.22***	0.55*	−77.31***	25.87***	0.82***	−79.53***	2,705
Median of index-year samples (2008-2020)												
S&P 500 Value	0.30	2.76	2.05***	0.25**	−51.47***	2.54***	0.28*	−60.27***	2.78***	0.43***	−71.67***	245
S&P 500 Growth	0.16	1.58	7.38***	1.81**	−85.13***	9.89***	1.84*	−86.49***	15.76***	1.92***	−93.74***	245
S&P 400 Mid Cap	0.22	1.78	4.59***	0.65**	−76.43***	5.10***	0.70*	−80.28***	7.67***	1.10***	−82.41***	245
Panel C: sector portfolios (2008-2020)												
S&P Banks	0.68	2.62	1.87***	0.43**	−48.93***	1.62***	0.78***	−61.64***	1.93***	0.39**	29.01	2,943
S&P Financials	0.56	2.23	1.52***	0.07	−48.88**	1.26***	0.13	−56.70***	1.20***	0.15*	−26.43	3,189
S&P Utilities	0.43	3.93	1.09*	0.04	−9.35	0.89***	0.09	−21.10	1.30***	0.44***	−40.15**	3,189
S&P Real Estate	0.31	3.77	3.21***	0.37**	−83.09*	2.53***	0.40***	−86.68**	2.22***	0.52***	−74.96***	2,953
S&P Communications	0.31	5.18	0.68***	0.06	−58.51	0.55***	0.07	−63.52***	0.94	0.10	−49.68	2,953
S&P Industrials	0.26	2.28	3.63***	0.50	−72.50***	3.14***	0.79**	−76.34***	3.75***	1.17***	−66.97***	3,189
S&P Materials	0.23	2.29	2.57***	0.16**	−84.29***	2.18***	0.27***	−86.50***	3.06***	0.29***	−88.62***	2,815
S&P Cons. Discr.	0.19	1.51	8.94***	1.93	−84.13***	8.22***	2.48	−86.76***	8.79***	2.74*	−84.75***	3,189
S&P Cons. Staples	0.17	2.82	3.70***	0.26	−74.01***	3.38***	0.48*	−79.09***	5.08***	0.59*	−89.21***	2,121
S&P Energy	0.17	2.88	2.61***	0.71*	−94.33*	2.60***	1.05	−95.15	3.79***	0.91***	−87.84*	3,189
S&P Healthcare	0.16	1.91	7.23***	1.01	−87.45***	6.69***	1.42	−88.43***	11.44***	1.66	−91.93***	3,189
S&P Technology	0.09	1.33	13.69***	3.40	−97.05***	13.80***	4.19	−97.57***	16.04***	4.25	−98.54***	3,189
Panel D: correlations (index-year samples, 2008-2020)												
Weighted leverage	1.00***	0.36***	−0.36***	−0.34***	0.73***	−0.39***	−0.32***	0.70***	−0.30***	−0.36	0.80***	217
CDX IG	0.07	0.08	0.15*	0.28***	−0.17*	−0.03	0.27***	−0.08	−0.05	0.33***	0.04	217
CDX HY	0.09	0.17*	0.10	0.26***	−0.15*	−0.06	0.23***	−0.07	−0.05	0.29***	0.04	217
Weighted CDS	0.25***	0.26	−0.14*	−0.09	−0.02	−0.22**	−0.10	0.03	−0.17*	−0.06*	0.14*	217
Dividend yield	0.36***	1.00***	−0.30***	−0.40***	0.30***	−0.31***	−0.41***	0.33***	−0.24***	−0.40***	0.26***	217

0.16) and exhibits, to some extent, better index efficiency scores.

Panel C reports results for sector sub-indices of the S&P 500 sorted by aggregated leverage. Except for a few highly-leveraged sectors, the variance ratio estimates are well above unity and provide a picture similar to non-sectoral indices. The critical finding of Table 5 lies in the three columns reporting the MRS variance spread statistic. We observe a statistic decreasing with aggregated leverage that leads to striking contrasts between both ends of the leverage spectrum. For example, the average q_T stands as low as 0.08 for the Financials index (leverage 0.56) and as high as 14.51 for the Technology index (leverage 0.09). A similar decreasing pattern emerges with the score of market efficiency: the less leveraged a business sector is, the lower its efficiency score. Unsurprisingly, the most leveraged sectoral index (S&P Banks) is the only one to exhibit a positive score w at 29.01 under the value-weighted CDS flow of credit risk information. Overall, these low scores of index efficiency confirm our diagnosis of excess volatility in most sectors. However, due to their heavy reliance on financial leverage above 0.40, the Banks, Financials, and Utility industry sectors stand out with statistically significant scores above -50 out of 100 and MRS statistics close to zero. This finding seems robust and consistent across every aggregated flow of credit risk information.

Panel D reports correlations between our efficiency measures and the fundamentals of U.S. stock indices. We estimate correlations based on index-year samples to avoid small-sample issues due to the relatively low number of entire index samples. The first row shows a consistent negative (resp. positive) correlation around -0.3 (resp. 0.70) between the MRS statistic $|q_T|$ (resp. the efficiency score w) and index value-weighted leverage. As a result, this first row crystallizes a key finding of the paper: stock index efficiency correlates with aggregated leverage. To a lesser extent, we notice a similar effect of the dividend yield and the value-weighted CDS level on stock index efficiency.

5. Robustness tests

To ensure that our modeling choices do not condition our findings, we have run extensive robustness tests, which are detailed below.

5.1 Robustness to the equity-credit elasticity specification

We first address the concern that the economic proxy used for the equity-credit elasticity might bias the firm-level findings of Section 4. In Appendix A, our theoretical analysis shows that the equity-credit elasticity should be an increasing function of firm leverage. Thus, our baseline implementation of the perfect-foresight stock price p_t^* relies on the adimensional debt-to-asset ratio as a proxy for ε (see Section 3.3). However, because of the presence of the ε multiplier (leverage) in front of the CDS returns (see Equation (2) of Proposition 1), firm leverage is liable to inflate the variance of p_t^* and deflate variance ratios. To investigate the robustness of our results, we report two alternative specifications for ε.

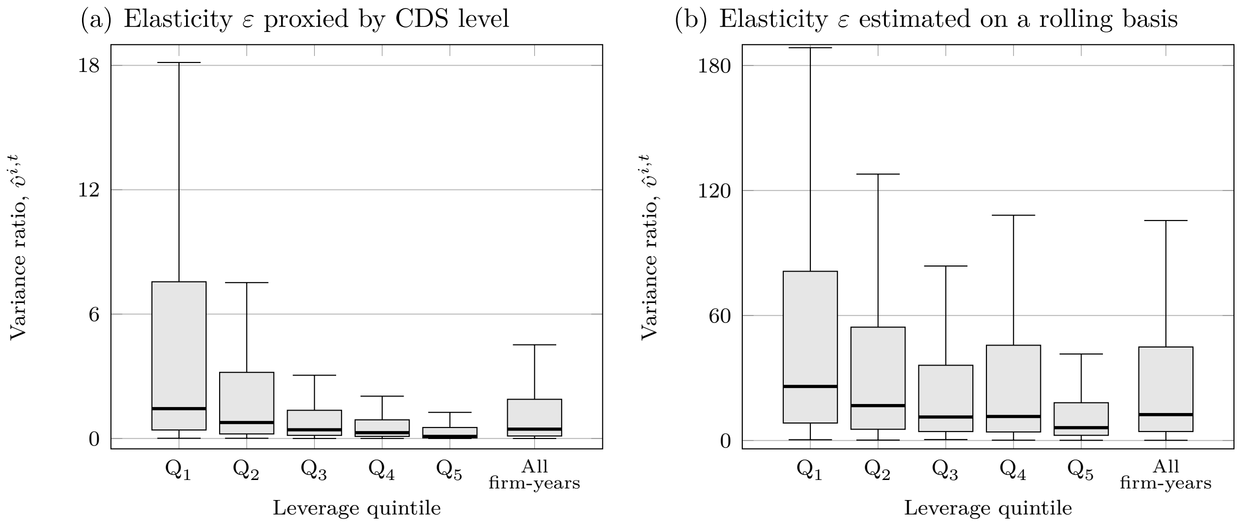
The first alternative proxy we consider is the firm's CDS level, as in Acharya and Johnson (2007). This proxy significantly correlates with the debt-to-asset ratio (correlation 0.46). The second alternative proxy we use is a model-free estimate of the realized equity-credit elasticity obtained by regressing log-CDS returns on log-equity returns on a 6-month rolling window. This proxy incurs sampling noise but has the benefit of remaining agnostic about the theoretical relation between percentage changes in stock prices and percentage changes in CDS spreads.

Figure 4 shows the distribution of the credit-augmented variance ratio $\hat{v}^{i,t}$ estimated by firm-years over 2008-2020. It should be compared to Panel (b) of Figure 3. Panel (a) uses the re-scaled CDS par spread as a proxy for ε (i.e., $\varepsilon_{i,t} = 100 \times \text{CDS}_{i,t}$). Similar to our baseline implementation, excess volatility tends to decrease with financial leverage and disappear in the most leveraged quintiles. Panel (b) uses a daily estimate for ε calculated using a rolling 6-month period.[18] Although the rolling estimate $\hat{\varepsilon}_{i,t}$ can be noisy, the decreasing pattern of

[18]The calculation is given by $\hat{\varepsilon}_{i,t} = \text{cov}[\Delta \ln(\text{CDS}_{i,t}), \Delta \ln(P_{i,t})]/\text{var}[\Delta \ln(P_{i,t})]$.

Figure 4. Variance ratios with alternative proxies of ε

These boxplots compare distributions of the default-risk-augmented variance ratio υ across leverage percentiles of firm-years, where $\varepsilon_{i,t}$ is proxied by $100 \times \text{CDS}_{i,t}$ (Panel a) or estimated using a rolling 6-month period as $\text{cov}[\Delta \ln(\text{CDS}_{i,t}), \Delta \ln(P_{i,t})]/\text{var}[\Delta \ln(P_{i,t})]$ (Panel b). In the first stage, we sort the 3,608 firm-years into quintiles based on the firm-year's average annual leverage, Q_1 being the quintile with the smallest leverage. In the second stage, we compute for each firm-year (i, t) the variance ratio $\hat{\upsilon}^{i,t}$. Sample period: 2008:01 to 2020:12. Data source: Thomson Reuters.



$\hat{\upsilon}^{i,t}$ with firm leverage is confirmed. Since $\hat{\varepsilon}_{i,t}$ has no built-in linkage with firm leverage, we consider the decline of $\hat{\upsilon}^{i,t}$ along with leverage as a confirmation of our findings.

5.2 Robustness to the business sector and credit rating changes

A potential concern with our results is that highly-leveraged firms in the financial industry might bias the empirical findings of Section 4. As a preliminary robustness analysis, we repeat our efficiency tests on the entire sample period (2008-2020) without the Financials sector. We find results that are qualitatively similar to those in Table 4, confirmed in the two sub-sample periods (2008-2009 and 2010-2020). We do not report these results for brevity, which suggest a limited impact from the Financials sector.

As a more general and rigorous robustness check, we investigate the determinants of the different metrics of market efficiency used previously (namely, the variance ratio υ, the MRS statistic $|q|$, and the efficiency score w) in the cross-section of firms through panel regressions.

For that purpose, we collect the statistics $\hat{v}_{i,t}$, $|\hat{q}_{i,t}|$ and $\hat{w}_{i,t}$ estimated in Table 4 for each firm i and each year t ($2008 \leqslant t \leqslant 2020$). We then estimate the three following panel regression models with firm- and year-fixed effects:

$$\begin{aligned}\hat{Y}_{i,t} = &\ \beta_1 \mathrm{LVG}_{i,t} + \beta_2 \mathrm{CDS}_{i,t} + \beta_3 \mathrm{LVG}_{i,t} \times \mathrm{CDS}_{i,t} + \beta_4 \mathrm{VOL}^{\mathrm{Stock}}_{i,t} + \beta_5 \mathrm{LVG}_{i,t} \times \mathrm{VOL}^{\mathrm{Stock}}_{i,t} \\ &+ \beta_6 \mathrm{LOGSIZE}_{i,t} + \beta_7 \mathrm{DIV}_{i,t} + \beta_8 \mathrm{VOL}^{\mathrm{CDS}}_{i,t} + \beta_9 \mathrm{VOL}^{\mathrm{S\&P}}_{t} + \beta_{10} \mathrm{VIX}_t + \beta_{11} \mathrm{RATE}^{(10)}_t \\ &+ \beta_{12} (\mathrm{RATE}^{(10)}_t - \mathrm{RATE}^{(2)}_t) + \beta_{13} \mathrm{NOTCH\ DOWN}_{i,t} + \beta_{14} \mathrm{NOTCH\ UP}_{i,t} \\ &+ \sum_{j=1}^{8} \gamma_j \mathrm{RATING}^{(j)}_{i,t} + \sum_{j=1}^{11} \delta_j \mathrm{SECTOR}^{(j)}_{i} + \sum_{i,t} \mathrm{FE}_{i,t} + \epsilon_{i,t},\end{aligned} \tag{8}$$

where $\hat{Y}_{i,t}$ is one of the three variables of interest (i.e., $\ln(\hat{v}_{i,t}), \ln(|\hat{q}_{i,t}|), \hat{w}_{i,t}$) described above for firm i and year t, $\mathrm{FE}_{i,t}$ denotes firm- and year-fixed effects and $\epsilon_{i,t}$ are i.i.d. disturbances. Here, $\mathrm{LVG}_{i,t}$ (resp. $\mathrm{CDS}_{i,t}$, $\mathrm{LOGSIZE}_{i,t}$, $\mathrm{DIV}_{i,t}$, $\mathrm{VOL}^{\mathrm{Stock}}_{i,t}$, $\mathrm{VOL}^{\mathrm{CDS}}_{i,t}$) is the average financial leverage (resp. CDS level, logarithm of market capitalization, dividend yield, 1-year idiosyncratic stock volatility, 1-year CDS volatility) of firm i over year t. In addition, $\mathrm{VOL}^{\mathrm{S\&P}}_{t}$ and VIX_t denote the standard deviation of the returns on the S&P 500 index and the average VIX level during the (i,t) firm-year sample, respectively. Finally, $\mathrm{RATE}^{(2)}_t$ (resp. $\mathrm{RATE}^{(10)}_t$) measures the 2-year (resp. 10-year) U.S. Treasury note rate and controls for the average short-term (resp. long-term) interest rate over year t. To control for the confounding effect of the firm's credit rating (resp. business sector), we include $\mathrm{RATING}^{(j)}_{i,t}$ (resp. $\mathrm{SECTOR}^{(j)}_{i}$) as dummy variables for the average S&P credit rating class (resp. business sectors) of firm i over year t.[19] The dummy variable $\mathrm{NOTCH\ DOWN}_{i,t}$ (resp. $\mathrm{NOTCH\ UP}_{i,t}$) captures the occurrence of any S&P rating notch downgrade (resp. upgrade) for firm i over year t.

The results of these regressions are reported in the Online Appendix E.1. Table 6 reports results using the log-variance ratio as the response variable. The results confirm that the negative relationship between the log variance ratio and firm leverage in Table 3

[19]To calculate the average credit rating class on each firm-year, we first convert prevailing rating notches on each trading day to a numerical scale between 0 and 20. Then, we compute the average and assign it to the closest S&P credit rating class.

are highly significant in all specifications, i.e., including macroeconomic control variables, dummy variables for business sectors, and credit rating change dummy variables. Specifically, the leverage coefficient $\hat{\beta}_1$ in Equation 8 is significant at the 0.1% threshold in every specification tested. The absolute CDS level is significant in some, but not all specifications, but the coefficient $\hat{\beta}_2$ is very close to zero, suggesting that the absolute CDS level has little influence on market efficiency. A similar result holds for the leverage-CDS cross-impact (measured by $\hat{\beta}_3$). Unsurprisingly, the coefficients of the idiosyncratic equity volatility and aggregate market volatility are significantly positive, suggesting efficiency deteriorates with excess volatility for the stock. Conversely, CDS volatility and VIX implied volatility appear to be associate with improved stock efficiency ($\hat{\beta}_7, \hat{\beta}_9 > 0$).

Table 7 reports regression results using the MRS log-variance spread. Firm leverage continues to be significantly negatively associated with market efficiency (i.e., an increase in firm leverage is associated with a decrease in the MRS variance spread). The CDS level and its interaction with firm leverage are no longer significant in any of the specifications. The impact of idiosyncratic stock volatility is negative and significant at the 5% level in three of the specifications tested, and insignificant in the most general specification that controls for business sectors. CDS volatility and the aggregate stock volatility are never significant, while implied volatility (VIX) is significant in the most general specification.

5.3 Robustness of MRS orthogonality test specification

The baseline implementation of the orthogonality tests reported in Section 4 raises legitimate concerns regarding the specifications used for the perfect-foresight price and the naive forecast (see Section C.2). First, our implementation of the perfect-foresight $P^*_{t\to T}$ given by Equation (C2) might be highly dependent on the time horizon T. As a consequence, our orthogonality tests might be overly sensitive to the level of the terminal stock price P_T used to back out $P^*_{t\to T}$. Second, our orthogonality tests might also be sensitive to the equity risk premium $\mathfrak{p}$ and the dividend assumptions chosen to simulate the naive forecast P^o_t given by

Equation (E15). To investigate the robustness of our results regarding these two concerns, we report an alternative implementation of our orthogonality tests.

We run two robustness analyses to check if our results are conditioned by the specifications used in our MRS tests results. First, we consider a more robust specification of the naive forecast P_t^o based on the annual moving average over the last five years of dividends, that is, 20 quarterly dividend amounts. Second, we use a robust version of the variance spread statistic q_T to avoid being overly dependent on a single value of the market price at the time horizon T. Specifically, we consider multiple trajectories of the the perfect-foresight price originating at different terminal dates, and use an average trajectory using percentiles of the terminal distribution of realized stock prices. The results are discussed in Appendix E.2. The results using either of these approaches are qualitatively similar to our main results.

6. Conclusions

This paper extends econometric tests developed in the market efficiency literature to firms subject to default risk. This novel approach exploits the information contained in single-name CDS and credit indices, using a large dataset of S&P 500 firms over an extended time frame (2008–2020). We find that efficiency tests accounting for default risk suggest higher (lower) *micro*-efficiency for firms with high (low) leverage. In contrast, default-augmented tests show distinct *macro*-inefficiency for large-cap U.S. stock indices, i.e., low-efficiency scores except for highly leveraged sector indices such as Banks, Financials, or Utilities.

Our findings suggest that an active CDS market increases stock market efficiency at the firm level. We interpret this finding in the context of two key factors. First, the informational advantage of CDS markets is more pronounced for firms experiencing higher default risk or leverage for several reasons: CDS contracts are more informative about negative information because of their asymmetric payoff; initiation of CDS trading attracts relationship banks, informed lenders, and other insiders in the market; CDS trading conveys valuable information before earnings announcements; and CDS trading reduces equity analysts' optimism. Second, the transmission of information from CDS to equity is more efficient for leveraged firms. We conjecture that the CDS market becomes more conducive to equity-credit arbitrage as the elasticity of stock prices with respect to CDS spreads increases with default risk.

Our findings not only contribute to the empirical literature but also align with key insights from the recent theoretical literature on Samuelson's dictum, which suggests that active investors reduce micro-inefficiencies more than they do macro-inefficiencies (e.g., Garleanu and Pedersen, 2022; Glasserman and Mamaysky, 2023). Indeed, our findings support this notion, as specialized CDS market participants have stronger incentives to correct micro inefficiencies through single-name credit-equity arbitrage.

Appendix A. The equity-credit elasticity in Merton's (1974) model

In this appendix, we provide a theoretical justification for the choice of a simple linear function of firm leverage as a proxy for the elasticity ε of the stock price P with respect to the CDS par spread λ, defined by the relationship $P = \lambda^{-\varepsilon}$. Under Merton's (1974) model, the main state variable is the firm value, V. The equity-credit elasticity can be expressed as:

$$\varepsilon = -\frac{\lambda}{P}\frac{\partial P}{\partial \lambda} = -\left(\frac{1}{P}\frac{\partial P}{\partial V}\right) \Big/ \left(\frac{1}{\lambda}\frac{\partial \lambda}{\partial V}\right). \tag{A1}$$

First, we use the relation $\sigma P = \frac{\partial P}{\partial V}\sigma_v V$ (see equation 3.b in Merton, 1974), where σ_v is the firm value volatility and σ is the stock price volatility, to obtain:

$$\frac{1}{P}\frac{\partial P}{\partial V} = \frac{\sigma}{\sigma_v V}. \tag{A2}$$

Second, without loss of generality, we can assimilate the CDS par spread λ to Merton's (1974) default probability $N(-d_2)$ at horizon T. Here $N(\cdot)$ is the standard normal cumulative distribution function, d_2 is given by $(\ln(V/D) + rT - \sigma_v^2 T/2)/(\sigma_v\sqrt{T})$, and D is the firm's nominal amount of debt. Differentiating $N(-d_2)$ with respect to V, we obtain:

$$\frac{1}{\lambda}\frac{\partial \lambda}{\partial V} = \frac{-N'(-d_2)}{N(-d_2)\sigma_v V\sqrt{T}}. \tag{A3}$$

Substituting Equations (A2) and (A3) into Equation (A1) yields:

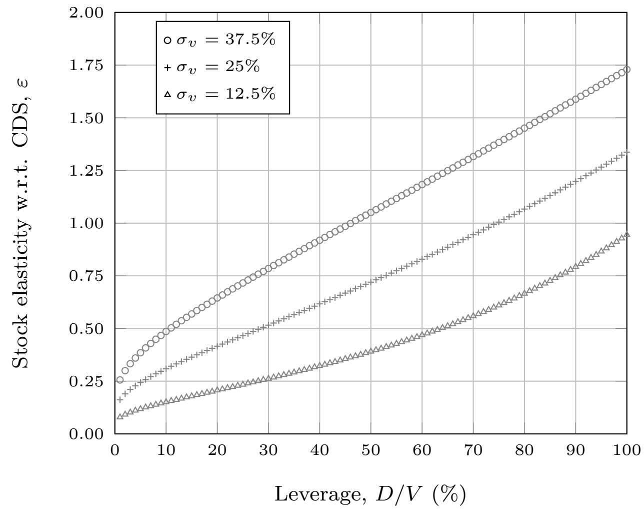
$$\varepsilon = \sigma\sqrt{T}\frac{N(-d_2)}{N'(-d_2)}. \tag{A4}$$

It is now easy to show that ε *increases* with firm leverage. Using $N'(x) = e^{-x^2/2}/\sqrt{2\pi}$ and $N''(x) = -xN'(x)$ to differentiate with respect to D yields:

$$\frac{\partial \varepsilon}{\partial D} = \sigma\sqrt{T} \times \left(-\frac{\partial d_2}{\partial D}\right) \times \frac{[N'(-d_2)]^2 - N(-d_2)d_2N'(-d_2)}{[N'(-d_2)]^2}. \tag{A5}$$

Figure 5. Equity-credit elasticity vs. firm leverage

The figure plots the elasticity ε of the equity value P with respect to the default probability λ under the Merton (1974) model. Three values for firm-value volatility σ_v are considered: 12.5%, 25% and 37.5%. The debt-to-asset ratio D/V is varied in order to generate different values of the default probability and equity value. Pricing assumptions: $T = 10$ years, $r = 2\%$, $\sigma = 30\%$.



Substituting $\frac{\partial d_2}{\partial D} = -1/(D\sigma_v\sqrt{T})$ and using the fact that $1 + xN(x)/N'(x) > 0$ for all x, we obtain finally:

$$\frac{\partial \varepsilon}{\partial D} = \frac{\sigma}{D\sigma_v}\left[1 - d_2\frac{N(-d_2)}{N'(-d_2)}\right] > 0. \tag{A6}$$

Figure 5 plots the equity-credit elasticity ε for different hypotheses of firm value volatility σ_v. It confirms that it is reasonable to proxy ε by a linear function of the debt-to-asset ratio, D/V, as we do in Section 3.3.

Appendix B. Proof of Proposition 1

We consider the stock price of a defaultable firm. Let $\mathcal{D}$ denote the set of cum-dividend dates t such that the firm pays a discrete dividend $D_{t+1} > 0$ over the period $]t; t+1]$. The one-period, gross return from time t to time $t+1$ is given by:

$$1 + R_{t+1} = \frac{P_{t+1} + D_{t+1}}{P_t}, \tag{B1}$$

where P_t and P_{t+1} denote start-of-period and end-of-period stock prices. Let $h_{t+1} := \ln(1 + R_{t+1})$ denote the ex-post, one-period log-return from time t to time $t+1$. Taking logarithms on both sides of (B1) gives:

$$h_{t+1} = p_{t+1} - p_t + \ln(1 + \exp(\delta_{t+1})), \tag{B2}$$

where $\delta_{t+1} := \ln(D_{t+1}/P_{t+1})$ is the log dividend-price ratio. As in Campbell and Shiller's (1988) log-dividend price model, we approximate (B2) by a first-order Taylor series expansion around the average $\bar{\delta}$ of the log dividend-price ratio:[20]

$$(\forall t \in \mathcal{D}) \qquad h_{t+1} \approx p_{t+1} - p_t + \ln(1 + \exp(\bar{\delta})) + \frac{\exp(\bar{\delta})}{1 + \exp(\bar{\delta})}(\delta_{t+1} - \bar{\delta}). \tag{B3}$$

Define $\rho := 1/(1 + \exp \bar{\delta})$ such that $\exp(\bar{\delta})/(1 + \exp \bar{\delta}) = 1 - \rho$. Let also k denote the quantity $\ln(1 + \exp \bar{\delta}) - (1 - \rho)\bar{\delta}$. With these new notations, the log-linear return approximation (B3) simplifies into:

$$(\forall t \in \mathcal{D}) \qquad p_t \approx \rho p_{t+1} - h_{t+1} + (1 - \rho) d_{t+1} + k. \tag{B4}$$

[20] See Engsted, Pedersen, and Tanggaard (2012) for the accuracy of Campbell and Shiller's (1988) Taylor expansion.

Solving forward for the log-price:

$$(\forall t \in \mathcal{D}) \qquad p_t \approx \rho^T p_{t+T} - \sum_{s>t,\, s\in\mathcal{D}}^{t+T} \rho^{s-t-1} \left(h_s - (1-\rho)d_s - k\right). \tag{B5}$$

We rule out rational bubbles by imposing $\lim_{T\to\infty} \rho^T p_{t+T} = 0$. We have the asymptotic expression which is valid only for cum-dividend dates in $\mathcal{D}$:

$$(\forall t \in \mathcal{D}) \qquad p_t \approx \sum_{t<s,\, s\in\mathcal{D}}^{\infty} \rho^{s-t-1} \left(-h_s + (1-\rho)d_s + k\right). \tag{B6}$$

Following the theoretical approach described in Section 2.1, we use the power parameterization to express the ex-post log-return as follows:

$$h_s = r_s - \varepsilon_s \Delta \ln(\lambda_s). \tag{B7}$$

where ε is the credit-equity elasticity, λ is the firm's default intensity (proxied by the firm's CDS par spread), and r is the risk-free rate. We can then substitute the ex-post theoretical return (B7) and re-index at a daily frequency:

$$p_t \approx \sum_{i=1}^{\infty} \rho^{n_i} \left(-r_{t+i} + \varepsilon_{t+i}\Delta \ln(\lambda_{t+i}) + (1-\rho)\tilde{d}_{t+i} + k\mathbf{1}_{\mathcal{D}}(t+i)\right), \tag{B8}$$

where n_i is the number of discrete dividend dates in $\mathcal{D}$ between t and $t+i$, and $\tilde{d}_t \equiv d_t$ if $t \in \mathcal{D}$ and 0 otherwise. Noticing that $\sum_{i=1}^{\infty} \rho^{n_i} \mathbf{1}_{\mathcal{D}}(t+i) = 1/(1-\rho)$, and assuming perfect knowledge of future dividends, future changes in log-default intensities, and future credit-equity elasticities, we obtain the perfect-foresight price on cum-dividend dates $t \in \mathcal{D}$:

$$p_t^* = \frac{1}{1-\rho} + \sum_{i=1}^{\infty} \rho^{n_i} \left(-r_{t+i} + \varepsilon_{t+i}\Delta \ln(\lambda_{t+i}) + (1-\rho)\tilde{d}_{t+i}\right). \tag{B9}$$

Finally, we can redefine the perfect-foresight price p_t^* outside $\mathcal{D}$ by extension of the formula (B9) for any regular date $t \in \mathbb{N}$.

Appendix C. Econometric Methodology

In this section, we describe the perfect-foresight-based univariate strategy used to implement the variance ratio, orthogonality, and variance-bound tests formalized in Propositions 2 and 3.

C.1 Implementing the perfect-foresight stock price

In this section, we derive a empirical proxy for the perfect-foresight stock price p_t^*. This variable remains unobservable in a finite sample. Following the literature on excess volatility tests (e.g., Shiller, 1981; Grossman and Shiller, 1981), we use the recursive property of p_t^*:

$$p_t^* = \sum_{i=1}^{T-1} p_{t,i}^* + \rho^{n_T} p_T^*, \tag{C1}$$

where $n_T := \sharp\{s \in \mathcal{D} \mid t \leqslant s < T\}$ denotes the number of discrete dividend dates between t and time horizon T. By truncating the infinite sum with a terminal price, the following proxy for p_t^* relies only on in-sample information:

$$p_{t\to T}^* := \sum_{i=1}^{T-1} p_{t,i}^* + \rho^{n_T} p_T, \tag{C2}$$

where p_t denotes the stock market (log) price. In our implementation of $p_{t\to T}^*$, we use for p_T the last closing stock price quoted (i.e., December 31, 2020) in our dataset. For each firm of the sample, the discount factor ρ is estimated from the historical dividend-price ratio. The typical S&P 500 firm has an annual dividend yield of 2% over the period 2008-2020, leading to a typical value of $\rho = 0.995$ for quarterly dividends.

C.2 Implementing orthogonality tests

Following Mankiw, Romer, and Shapiro (1985, 1991), we introduce a "naive forecast" P_t^o of the perfect-foresight price $P_{t\to T}^* := \exp(p_{t\to T}^*)$ that reflects the discounted value of the infinite stream of future dividends. P_t^o reflects the rational forecast obtained when actual dividends never deviate from a function of their recent realizations, D_{t-i}. Given the daily frequency of our dataset, we consider a simple specification based on the annual moving average over the last four quarterly dividend amounts:

$$P_t^o = \frac{1}{r_t + \mathfrak{p}} \sum_{i=1}^{4} D_{t-i}. \tag{C3}$$

We use a discounting rate equal to the long-term risk-free rate (r_t) plus an unobservable risk premium $\mathfrak{p}$. In the empirical tests, we use the 10-year Treasury Bill rate as proxy for r_t.

To test the null hypothesis of stock market efficiency, we introduce:

$$q_{t,T} := ((P^*_{t\to T} - P_t^o)/P_t)^2 - ((P^*_{t\to T} - P_t)/P_t)^2 - ((P_t - P_t^o)/P_t)^2. \tag{C4}$$

We then consider the sample counterpart of Equations (4-5):

$$q_T := T^{-1} \sum_{t=1}^{T} q_{t,T}. \tag{C5}$$

According to Proposition 2, the MRS statistic q_T cannot diverge from zero without generating market inefficiencies.[21] In other words, market efficiency should translate into $|\hat{q}_T| = 0$. To obtain a standard error for the sample mean $\hat{q}_T$, we run for each firm the linear regression $q_{t,T} = \alpha + \epsilon_t$, where ϵ_t are iid disturbances. This regression model yields robust asymptotic standard errors corrected for heteroscedasticity and serial correlation (Newey and West, 1987). We then compute the square of the t-statistic $\hat{\alpha}/\text{Var}(\hat{\alpha})$ for the null hypothesis of market efficiency $\mathbf{H}_0 :\ \hat{\alpha} = 0$. This two-sided Wald statistic follows a $\chi^2(1)$ distribution.

[21]If $q_T \uparrow +\infty$, the two forecast trajectories $P^*_{t\to T}$ and P_t^o must move away from each other. In this case, the market price path cannot uniformly converge toward one of these two forecast trajectories, otherwise q_T would tend to zero by construction. Conversely, if $q_T \downarrow -\infty$, the market price path must diverge from at least one of the two forecast trajectories, say P_t^o. In this case, the market price path cannot converge uniformly toward the other forecast trajectory $P^*_{t\to T}$, otherwise q_T would also tend to zero by construction.

C.3 Implementing variance-bound tests

Let $V_H := \mathbb{E}[(\check{p}_t - \mathbb{E}[\check{p}_t \mid H_{t-1}])^2]$ be the variance of revision in the credit risk forecast and $V_I := \mathbb{E}[(p_t - \mathbb{E}[p_t \mid I_{t-1}])^2]$ the variance of revision in the optimal forecast produced by the market. For each firm, we estimate the variance spread $V_H - V_I$ (see online Appendix E.1 for implementation details). Similarly to West (1988), it will be more convenient to compute and report the relative variance spread between -100 and 100:

$$w := 100 \times \frac{V_H - V_I}{\max(V_H; V_I)}. \tag{C6}$$

We interpret a negative value of w as revealing excess volatility in the stock market. Conversely, w close to 100 indicates a nearly-efficient stock market. In other words, the spread w can be interpreted as a market efficiency score.

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Internet Appendix

In this online appendix, we provide additional material for "The Informational Role of CDS in Stock Market Efficiency", not reported in the main text for brevity.

Appendix D. Mathematical Proofs

D.1 Proof of Proposition 2

The optimal and naive forecasts are both in the public information set, so that $p_t - p_t^o$ is measurable for I_t. By definition of conditional expectations:

$$\mathbb{E}\left[p_t^*(p_t - p_t^o)\right] = \mathbb{E}\left[\mathbb{E}[p_t^* \mid I_t](p_t - p_t^o)\right], \tag{D1}$$

which yields the following orthogonality restriction:

$$\mathbb{E}[(p_t^* - p_t)(p_t - p_t^o)] = 0. \tag{D2}$$

We obtain Equation (4) by squaring the identity $p_t^* - p_t^o = (p_t^* - p_t) + (p_t - p_t^o)$, taking expectations, and normalizing by the information available at time t.

D.2 Proof of Proposition 3

Following West's (1988) approach, we insert the recursive dynamics for the perfect-foresight stock price into the identity $\check{p}_t = \mathbb{E}[p_t^* \mid H_t]$:

$$\begin{aligned}
\check{p}_t &= \mathbb{E}\left[\rho^{\mathbf{1}_{\mathcal{D}}(t)} p_{t+1}^* - r_{t+1} + \varepsilon_{t+1} \Delta \ln(\lambda_{t+1}) + (1-\rho)\tilde{d}_{t+1} + k\mathbf{1}_{\mathcal{D}}(t) \mid H_t\right] \\
&= -r_{t+1} + \varepsilon_{t+1} \Delta \ln(\lambda_{t+1}) + (1-\rho)\tilde{d}_{t+1} + k\mathbf{1}_{\mathcal{D}}(t) + \rho^{\mathbf{1}_{\mathcal{D}}(t)} \mathbb{E}\left[p_{t+1}^* \mid H_t\right] \\
&= \rho^{\mathbf{1}_{\mathcal{D}}(t)} \check{p}_{t+1} - r_{t+1} + \varepsilon_{t+1} \Delta \ln(\lambda_{t+1}) + (1-\rho)\tilde{d}_{t+1} + k\mathbf{1}_{\mathcal{D}}(t) - \rho^{\mathbf{1}_{\mathcal{D}}(t)} \left(\check{p}_{t+1} - \mathbb{E}[p_{t+1}^* \mid H_t]\right),
\end{aligned} \tag{D3}$$

where we have used the fact the random variables $r_t, \varepsilon_t \Delta \ln(\lambda_t)$, and $\tilde{d}_t$ belong to the information set H_t. Let introduce the revision in the credit risk forecast produced by the arrival of new information during the period:

$$\check{e}_{t+1} \equiv \check{p}_{t+1} - \mathbb{E}[p^*_{t+1} \mid H_t] = p_{t+1} - \mathbb{E}\left[\mathbb{E}[p^*_{t+1} \mid H_{t+1}] \mid H_t\right] = \check{p}_{t+1} - \mathbb{E}[\check{p}_{t+1} \mid H_t], \tag{D4}$$

where we have used the tower property of conditional expectations. By recursive substitution up to order m we obtain:

$$\check{p}_t = \sum_{j=1}^{m} p^*_{t,j} - \sum_{j=1}^{m} \rho^{n_j \mathbf{1}_{\mathcal{D}}(t+j)} \check{e}_{t+j} + \rho^{n_m \mathbf{1}_{\mathcal{D}}(t+m)} \check{p}_{t+m}, \tag{D5}$$

where n_j is the number of discrete dividend dates between t and $t+j$. Once again, we rule out rational bubbles by imposing $\lim_{m\to\infty} \rho^{n_m \mathbf{1}_{\mathcal{D}}(t+m)} \check{p}_{t+m} = 0$. Letting $m \to \infty$, we obtain:

$$\check{p}_t = p^*_t - \sum_{j=1}^{\infty} \rho^{n_j \mathbf{1}_{\mathcal{D}}(t+j)} \check{e}_{t+j}. \tag{D6}$$

An analogous argument with the complete information set I_t yields :

$$p_t = p^*_t - \sum_{j=1}^{\infty} \rho^{n_j \mathbf{1}_{\mathcal{D}}(t+j)} e_{t+j}, \tag{D7}$$

where $e_t \equiv p_{t+1} - \mathbb{E}[p_{t+1} \mid H_t]$ is the revision in the market forecast due to the arrival of new information. Notice that the sequence of forecasting revisions $\{e_{t+j}\}_{j\geqslant 0}$ are orthogonal to the information set I_t by optimality of the market price (i.e., $\mathbb{E}[e_{t+j} \mid I_t] = 0$). As a result we have:

$$\begin{aligned}\operatorname{Var}\left[\sum_{j=1}^{\infty}\rho^{n_j \mathbf{1}_{\mathcal{D}}(t+j)}\check{e}_{t+j}\right] = \operatorname{Var}\left[\check{p}_t - p_t^*\right] &= \operatorname{Var}\left[\check{p}_t - p_t + p_t - p_t^*\right] \\ &= \operatorname{Var}\left[\check{p}_t - p_t\right] + \operatorname{Var}\left[\sum_{j=1}^{\infty}\rho^{n_j \mathbf{1}_{\mathcal{D}}(t+j)}e_{t+j}\right] \\ &\geqslant \operatorname{Var}\left[\sum_{j=1}^{\infty}\rho^{n_j \mathbf{1}_{\mathcal{D}}(t+j)}e_{t+j}\right]. \end{aligned} \tag{D8}$$

To calculate these two variances, we notice that *(i)* the sequence $\{\rho^{n_j \mathbf{1}_{\mathcal{D}}(t+j)}\}_{j\geqslant 0}$ is absolutely summable because $0 < \rho < 1$, and *(ii)* $\{\check{e}_{t+j}, e_{t+j}\}_{j\geqslant 0}$ are sequences of uncorrelated random variables. As a result, we can interchange the variance operator with the infinite summation to obtain:

$$\sum_{j=1}^{\infty}\rho^{2n_j \mathbf{1}_{\mathcal{D}}(t+j)}\operatorname{Var}\left[\check{e}_{t+j}\right] \geqslant \sum_{j=1}^{\infty}\rho^{2n_j \mathbf{1}_{\mathcal{D}}(t+j)}\operatorname{Var}\left[e_{t+j}\right]. \tag{D9}$$

This simplifies into $\operatorname{Var}\left[\check{e}_{t+j}\right] \geqslant \operatorname{Var}\left[e_{t+j}\right]$, which is Equation (6) of Proposition 3.

Appendix E. Econometric Appendix

E.1 Econometric implementation of the variance-bound test

To estimate the variance of the revision in the credit risk forecast, $\check{p}_t$, we assume that the credit risk factor $\varepsilon_t \Delta \ln(\lambda_t)$ follows a covariance-stationary AR(q) process. We thus fit the following model for each firm:

$$\varepsilon_{t+1}\Delta\ln(\lambda_{t+1}) = \phi_1 \varepsilon_t \Delta \ln(\lambda_t) + \cdots + \phi_q \varepsilon_{t-q}\Delta\ln(\lambda_{t-q}) + v_{t+1}, \tag{E1}$$

where $\Phi(L) \equiv I - \phi_1 L - \cdots - \phi_q L^q$ is the characteristic polynomial and L is the backshift operator. Since the perfect-foresight price p_t^* is an infinite geometrically declining sum of future variations in credit risk (see Proposition 1), its projection onto H_t is an infinite sum of conditional expectations. In Appendix E.2, it is shown how to calculate the sum of this convergent series explicitly as a function of past history (Hansen and Sargent, 1980). The credit risk forecast $\check{p}_t$ is thus given explicitly (see Equation (E14)) in terms of current and past values of variations in credit risk:

$$\check{p}_t = \frac{1}{\phi}\left(\varepsilon_t \Delta \ln(\lambda_t) + \sum_{k=1}^{q-1}\left(\sum_{j=k+1}^{q}\phi_j\right)\varepsilon_{t-k}\Delta\ln(\lambda_{t-k})\right), \tag{E2}$$

where $\phi := \Phi(1) = 1 - \phi_1 - \cdots - \phi_q$. The period-to-period revisions in the forecast $\check{p}_t$ are as follows:

$$\check{p}_t - \mathbb{E}[\check{p}_t \mid H_{t-1}] = \phi^{-1}\varepsilon_t \Delta \ln(\lambda_t), \tag{E3}$$

and they are those of the credit risk variable $\varepsilon_t \Delta \ln(\lambda_t)$. Note that by considering only the credit risk component in the innovations, we adopt a conservative approach which underestimates the variability of in the revisions of the forecast $\check{p}_t$. It is straightforward to take into account the interest rate and dividend components in Equation (E3) on top of the credit risk component.[1] An estimator of the variance of the credit risk innovations is the residual standard error σ_v^2 from regression (E1) weighted by the projection coefficient ϕ^{-1}, and a similar result holds for the interest rate variable. As a result, our estimate of this variance is given by $\sigma_v^2/\hat{\phi}^2$.

To estimate the variance in the revision of the optimal forecast produced by the market,

[1]The results of Appendix E.2 apply without modification to the interest rate variable, r_t, and the log-dividend, d_t. For example, assume that the interest rate r_t variable jointly follows a covariance-stationary ARIMA$(q; s; 0)$ process: $\Delta^s r_{t+1} = \psi_1 \Delta^s r_t + \cdots + \psi_q \Delta^s r_{t-q} + w_{t+1}$, where $\Psi(L) \equiv I - \psi_1 L - \cdots - \psi_q L^q$ is the characteristic polynomial and $\Delta^s \equiv (1-L)^s$. The conditional expectation of $\check{p}_t$ on current and past values of interest rate levels would be $\Psi^{-1}\left(r_t + \sum_{k=1}^{q-1}\left(\sum_{j=k+1}^{q}\psi_j\right)r_{t-k}\right)$, where $\Psi \equiv \Psi(1) = 1 - \psi_1 - \cdots - \psi_q$. The period-to-period revisions in $\check{p}_t$ would thus include an interest rate component, and Equation (E3) would be extended as: $\check{p}_t - \mathbb{E}[\check{p}_t \mid H_{t-1}] = \Phi^{-1}\varepsilon_t \Delta \ln(\lambda_t) + \Psi^{-1} r_t$. The West statistic would be calculated as $W \equiv \sigma_v^2 \hat{\Phi}^{-2} + \sigma_w^2 \hat{\Psi}^{-2} - \hat{\sigma}_u^2 \hat{\beta}^{-2}$, leading to a higher probability of rejecting the null hypothesis $\mathbf{H}_0 : \hat{W} > 0$. As a result, it is more conservative not to include interest rate and dividend variability in the basic implementation of our variance-bound test.

we follow the theory (see Equation (B4)) and run for each firm the regression:

$$p_t = \alpha + \beta p_{t+1} + \gamma \tilde{d}_{t+1} + u_{t+1}, \tag{E4}$$

where u_{t+1} are iid disturbances. The inclusion of the log-dividend $\tilde{d}_t$ has the effect of adjusting market price innovations due to dividend decreases. The correlation of p_{t+1} with the error term u_{t+1} precludes the use of OLS estimation. Consequently, we estimate Equation (E4) by instrumental variables using the past history of credit risk as instruments, that is, the variables in H_t. As a result, our estimate of the variance of market price innovations is given by $\hat{\sigma}_u^2/\hat{\beta}^2$.

To measure the excess variance produced by market prices (σ_u^2) compared to the fundamentals (σ_v^2), we compute the following variance spread for each firm:

$$W := \sigma_v^2 \hat{\phi}^{-2} - \hat{\sigma}_u^2 \hat{\beta}^{-2}. \tag{E5}$$

The null hypothesis of market efficiency is $\mathbf{H}_0 : \hat{W} > 0$. To estimate the standard error of $\hat{W}$, we estimate Equations (E2) and (E4) jointly by the multi-equation GMM method (e.g., Hayashi, 2000). We thus obtain a variance-covariance matrix $\mathbf{V}$ for the vector of estimates $\boldsymbol{\theta} := [\hat{\phi}_1, \cdots, \hat{\phi}_q, \hat{\beta}, \hat{\sigma}_u^2, \hat{\sigma}_v^2]$ that is robust to heteroskedasticity and autocorrelation in the credit risk innovations (Hansen, 1982; Newey and West, 1987). Since W is a nonlinear function $f(\boldsymbol{\theta})$, its variance can be obtained in standard fashion by the delta method as $\text{Var}(W) = [\partial f/\partial \boldsymbol{\theta}]' \, \mathbf{V} \, [\partial f/\partial \boldsymbol{\theta}]$.

Similarly to West (1988), it will be more convenient to compute and report the relative variance spread comprised between -100 and 100:

$$w := 100 \times \frac{\sigma_v^2 \hat{\phi}^{-2} - \hat{\sigma}_u^2 \hat{\beta}^{-2}}{\max\left(\sigma_v^2 \hat{\phi}^{-2}; \hat{\sigma}_u^2 \hat{\beta}^{-2}\right)}. \tag{E6}$$

We interpret a negative value as indicating excess volatility in the stock market, and a value of w close to 100 as pointing out a nearly-efficient stock market. In other words, the spread w can be interpreted as a market efficiency score.

E.2 Calculation of $\check{p}_t$

We follow Hansen and Sargent's (1980) approach. The goal is to express the credit risk forecast $\check{p}_t$ in terms of current and past values of variables in H_t. we can insert the perfect-foresight log-price (B9) into the identity $\check{p}_t = \mathbb{E}[p_t^* \mid H_t]$ to obtain:

$$\check{p}_t = \sum_{i=1}^{\infty} \mathbb{E}\left[\varepsilon_{t+i} \Delta \ln(\lambda_{t+i}) \mid H_t\right]. \tag{E7}$$

We first assume that the series $\varepsilon_t \Delta \ln(\lambda_t)$ is covariance stationary and has a q-th order vector autoregressive representation ARIMA$(q,0,0)$. Let $\Phi(L) \equiv I - \phi_1 L - \cdots - \phi_q L^q$ the characteristic polynomial of the process $\varepsilon_t \Delta \ln(\lambda_t)$ so that $\Phi(L)[\varepsilon_t \Delta \ln(\lambda_t)] = v_t$, and let $\Phi^{-1}(L) \equiv \sum_{j=0}^{\infty} \phi'_j L^j$ denote its MA(∞) representation. To transform the conditional expectations in (E7) as functions of variables in the information subset H_t, we use for all $i > 0$:

$$\mathbb{E}\left[\varepsilon_{t+i} \Delta \ln(\lambda_{t+i}) \mid H_t\right] = \mathbb{E}\left[L^{-i}(\varepsilon_t \Delta \ln(\lambda_t)) \mid H_t\right] = \mathbb{E}\left[L^{-i}(\Phi^{-1}(L) v_t) \mid H_t\right] = \frac{\Phi^{-1}(L)}{L^i} v_t. \tag{E8}$$

Inserting Equation (E8) into Equation (E7) and interchanging orders of summation yields:

$$\begin{aligned} \check{p}_t = \sum_{i=1}^{\infty} \sum_{j=i}^{\infty} \phi'_j L^{j-i} v_t = \sum_{j=0}^{\infty} \phi'_j L^j \sum_{i=0}^{j} L^{-i} v_t &= \sum_{j=0}^{\infty} \phi'_j L^j \frac{1 - L^{-j-1}}{1 - L^{-1}} v_t \\ &= \frac{\Phi^{-1}(L) - L^{-1}\Phi^{-1}(1)}{1 - L^{-1}} v_t. \end{aligned} \tag{E9}$$

Inserting $v_t = \Phi(L)[\varepsilon_t \Delta \ln(\lambda_t)]$ into Equation (E9) yields:

$$\check{p}_t = \frac{I - L^{-1}\Phi^{-1}(1)\Phi(L)}{1 - L^{-1}} [\varepsilon_t \Delta \ln(\lambda_t)] \tag{E10}$$

We now notice that the polynomial $\frac{\Phi(L)}{I-L^{-1}}$ may be simplified by polynomial division:

$$
\begin{aligned}
\frac{-\phi_q L^q + \cdots - \phi_1 L + I}{I - L^{-1}} &= -\phi_q L^q + \frac{-(\phi_{q-1}+\phi_q)L^{q-1} + \cdots - \phi_1 L + I}{I - L^{-1}} \\
&= -\phi_q L^q - (\phi_{q-1}+\phi_q)L^{q-1} + \frac{-(\phi_{q-2}+\phi_{q-1}+\phi_q)L^{q-2} + \cdots - \phi_1 L + I}{I - L^{-1}} \\
&= \cdots \\
&= -\phi_q L^q - (\phi_{q-1}+\phi_q)L^{q-1} - \cdots - (\phi_1 + \cdots + \phi_q)L + \frac{I - \phi_1 I - \cdots - \phi_q I}{I - L^{-1}} \\
&= -\sum_{k=1}^{q}\left(\sum_{j=k}^{q}\phi_j\right)L^k + \frac{\Phi(1)I}{I - L^{-1}}. \qquad \text{(E11)}
\end{aligned}
$$

Thus we have:

$$
L^{-1}\Phi^{-1}(1)\frac{\Phi(L)}{1 - L^{-1}} = -\Phi^{-1}(1)\sum_{k=1}^{q}\left(\sum_{j=k}^{q}\phi_j\right)L^{k-1} + \frac{L^{-1}}{I - L^{-1}}. \qquad \text{(E12)}
$$

and then:

$$
\begin{aligned}
\frac{I - L^{-1}\Phi^{-1}(1)\Phi(L)}{1 - L^{-1}} &= \Phi^{-1}(1)\sum_{k=0}^{q-1}\left(\sum_{j=k+1}^{q}\phi_j\right)L^k + I \\
&= \Phi^{-1}(1)\left(\sum_{k=0}^{q-1}\left(\sum_{j=k+1}^{q}\phi_j\right)L^k + \Phi(1)I\right). \qquad \text{(E13)}
\end{aligned}
$$

We obtain the following representation for the credit risk forecast in terms of current and past values of $\varepsilon_t \Delta\ln(\lambda_t)$:

$$
\sum_{i=1}^{\infty}\mathbb{E}\left[\varepsilon_{t+i}\Delta\ln(\lambda_{t+i}) \mid H_t\right] = \frac{1}{\Phi(1)}\left(I + \sum_{k=1}^{q-1}\left(\sum_{j=k+1}^{q}\phi_j\right)L^k\right)[\varepsilon_t \Delta\ln(\lambda_t)]. \qquad \text{(E14)}
$$

E. Additional Robustness Results

E.1 Cross-sectional determinants of market efficiency

In this section, we report additional results to investigate the cross-sectional determinants of our three different metrics of stock market efficiency, namely, the variance ratio v, the MRS variance spread $|q|$, and the efficiency score w. Table 6 reports results for the variance ratio v. Table 7 reports results for the MRS variance spread.

Table 6. Robustness analysis: determinants of $\hat{v}$ in the cross-section of firms

This table reports estimates of the panel regression (8):

$$\ln(\hat{v}_{i,t}) = \beta_1 \text{LVG}_{i,t} + \beta_2 \text{CDS}_{i,t} + \beta_3 \text{LVG}_{i,t} \times \text{CDS}_{i,t} + \beta_4 \text{VOL}^{\text{Stock}}_{i,t} + \beta_5 \text{LVG}_{i,t} \times \text{VOL}^{\text{Stock}}_{i,t} + \beta_7 \text{VOL}^{\text{CDS}}_{i,t}$$
$$+ \beta_8 \text{VOL}^{\text{S\&P}}_t + \beta_9 \text{VIX}_t + \beta_{10} \text{RATE}^{(10)}_t + \beta_{11} (\text{RATE}^{(10)}_t - \text{RATE}^{(2)}_t) + \beta_{12} \text{NOTCH DOWN}_{i,t}$$
$$+ \beta_{13} \text{NOTCH UP}_{i,t} + \sum_{j=1}^{8} \gamma_j \text{RATING}^{(j)}_{i,t} + \sum_{j=1}^{11} \delta_j \text{SECTOR}^{(j)}_i + \sum_i \text{Firm FE}_i + \sum_t \text{Year FE}_t + \epsilon_{i,t},$$

where $\hat{v}_{i,t}$ are firm-year variance ratios. t-statistics are calculated via robust standard errors clustered by firm to correct for heteroskedasticity. ***, ** and * denote statistical significance at the 0.1%, 1%, and 5% levels, respectively. The sample period is 2008:01 to 2020:12. Data source: Thomson Reuters.

Variable	(A)		(B)		(C)		(D)	
LVG	−4.792***	(−15.52)	−4.785***	(−15.48)	−4.805***	(−15.21)	−5.718***	(−12.21)
CDS	−0.002***	(−4.92)	−0.002***	(−4.94)	−0.002***	(−4.89)	0.000	(−0.25)
LVG × CDS	0.003***	(6.19)	0.003***	(6.22)	0.003***	(6.12)	0.001	(0.93)
$\text{VOL}^{\text{Stock}}$	2.892***	(7.01)	2.892***	(7.01)	2.919***	(7.07)	3.246***	(5.10)
LVG × $\text{VOL}^{\text{Stock}}$	0.393	(0.78)	0.381	(0.76)	0.338	(0.67)	0.617	(0.80)
LOGSIZE	0.236***	(3.65)	0.236***	(3.64)	0.228***	(3.50)	−0.147**	(−3.06)
DIV	0.011*	(2.02)	0.011*	(2.08)	0.011*	(2.15)	−0.010	(−1.12)
VOL^{CDS}	−2.349***	(−20.11)	−2.354***	(−20.12)	−2.363***	(−20.15)	−3.162***	(−13.89)
$\text{VOL}^{\text{S\&P500}}$	9.165***	(12.91)	9.148***	(12.88)	9.147***	(12.87)	−2.342	(−0.48)
VIX	−0.105***	(−9.37)	−0.104***	(−9.32)	−0.104***	(−9.31)	0.080	(0.92)
$\text{RATE}^{(10)}$	−0.214***	(−6.50)	−0.212***	(−6.43)	−0.214***	(−6.48)	1.293	(1.09)
$\text{RATE}^{(10)}$-$\text{RATE}^{(2)}$	−0.023	(−0.64)	−0.026	(−0.73)	−0.031	(−0.88)	−1.811	(−1.37)
NOTCH DOWN			0.016	(0.31)	0.021	(0.41)	−0.019	(−0.30)
NOTCH UP			0.083	(1.37)	0.088	(1.45)	0.111	(1.65)
RATING AAA					0.169	(0.28)	1.086**	(2.84)
RATING AA					−0.278	(−0.51)	0.391	(1.21)
RATING A					−0.340	(−0.66)	0.127	(0.48)
RATING BBB					−0.427	(−0.84)	−0.232	(−0.92)
RATING BB					−0.443	(−0.89)	−0.257	(−0.95)
RATING B					−0.323	(−0.63)	−0.403	(−1.32)
RATING CCC					−0.459	(−0.83)	−0.479	(−1.42)
FINANCIALS							0.469	(1.87)
UTILITIES							−0.379	(−1.79)
CONS. NON-CYC.							−0.096	(−0.56)
REAL ESTATE							−0.323	(−1.56)
CONS. CYC.							0.162	(1.07)
INDUSTRIALS							0.164	(1.05)
BASIC MAT.							0.066	(0.34)
TECHNOLOGY							0.440*	(2.26)
HEALTHCARE							0.045	(0.25)
ENERGY							−0.030	(−0.17)
Clustered SE	Yes		Yes		Yes		Yes	
Firm fixed effects	Yes		Yes		Yes		No	
Year fixed effects	No		No		No		Yes	
R^2	0.289		0.290		0.291		0.526	
Obs. (firm-years)	3,605		3,605		3,605		3,605	

Table 7. Robustness analysis: determinants of $|\hat{q}|$ in the cross-section of firms

This table reports estimates of the panel regression (8):

$$\ln(|\hat{q}_{i,t}|) = \beta_1 \mathrm{LVG}_{i,t} + \beta_2 \mathrm{CDS}_{i,t} + \beta_3 \mathrm{LVG}_{i,t} \times \mathrm{CDS}_{i,t} + \beta_4 \mathrm{VOL}^{\mathrm{Stock}}_{i,t} + \beta_5 \mathrm{LVG}_{i,t} \times \mathrm{VOL}^{\mathrm{Stock}}_{i,t} + \beta_7 \mathrm{VOL}^{\mathrm{CDS}}_{i,t}$$
$$+ \beta_8 \mathrm{VOL}^{\mathrm{S\&P}}_{t} + \beta_9 \mathrm{VIX}_t + \beta_{10} \mathrm{RATE}^{(10)}_t + \beta_{11} (\mathrm{RATE}^{(10)}_t - \mathrm{RATE}^{(2)}_t) + \beta_{12} \mathrm{NOTCH\ DOWN}_{i,t}$$
$$+ \beta_{13} \mathrm{NOTCH\ UP}_{i,t} + \sum_{j=1}^{8} \gamma_j \mathrm{RATING}^{(j)}_{i,t} + \sum_{j=1}^{11} \delta_j \mathrm{SECTOR}^{(j)}_{i} + \sum_i \mathrm{Firm\ FE}_i + \sum_t \mathrm{Year\ FE}_t + \epsilon_{i,t},$$

where $\hat{q}_{i,t}$ are firm-year MRS variance spreads. t-statistics are calculated via robust standard errors clustered by firm to correct for heteroskedasticity. ***, ** and * denote statistical significance at the 0.1%, 1%, and 5% levels, respectively. The sample period is 2008:01 to 2020:12. Data source: Thomson Reuters.

Variable	(A)		(B)		(C)		(D)	
LVG	−0.853**	(−2.90)	−0.842**	(−2.87)	−0.806**	(−2.69)	−0.971**	(−2.73)
CDS	0.000	(0.07)	0.000	(0.00)	0.000	(0.11)	0.000	(0.01)
LVG × CDS	−0.001	(−1.24)	−0.001	(−1.19)	−0.001	(−1.35)	0.000	(−0.16)
$\mathrm{VOL}^{\mathrm{Stock}}$	−0.914*	(−2.42)	−0.914*	(−2.42)	−0.887*	(−2.34)	0.375	(0.55)
LVG × $\mathrm{VOL}^{\mathrm{Stock}}$	0.751	(1.61)	0.740	(1.59)	0.725	(1.55)	0.551	(0.68)
LOGSIZE	−0.888***	(−14.9)	−0.888***	(−14.92)	−0.897***	(−15.03)	−0.080	(−1.49)
DIV	0.015	(1.75)	0.015	(1.80)	0.015	(1.75)	−0.027	(−1.13)
$\mathrm{VOL}^{\mathrm{CDS}}$	0.047	(0.53)	0.041	(0.47)	0.030	(0.33)	−0.373	(−2.68)
$\mathrm{VOL}^{\mathrm{S\&P500}}$	−0.420	(−0.69)	−0.439	(−0.72)	−0.370	(−0.61)	0.744	(0.20)
VIX	0.004	(0.41)	0.004	(0.46)	0.003	(0.33)	−0.003**	(−0.04)
$\mathrm{RATE}^{(10)}$	0.276***	(9.88)	0.278***	(9.96)	0.275***	(9.83)	−0.049	(−0.04)
$\mathrm{RATE}^{(10)}$-$\mathrm{RATE}^{(2)}$	0.431***	(13.96)	0.427***	(13.78)	0.424***	(13.64)	0.045	(0.04)
NOTCH DOWN			0.013	(0.27)	0.012	(0.25)	0.148*	(1.68)
NOTCH UP			0.096	(1.73)	0.098	(1.77)	0.000	(0.00)
RATING AAA					−0.042	(−0.10)	1.172	(1.68)
RATING AA					−0.214	(−0.64)	0.848	(1.70)
RATING A					−0.336	(−1.06)	0.614	(1.33)
RATING BBB					−0.383	(−1.24)	0.320	(0.70)
RATING BB					−0.365	(−1.21)	0.394	(0.85)
RATING B					−0.453	(−1.42)	0.458	(0.88)
RATING CCC					−0.190	(−0.48)	0.423	(0.70)
FINANCIALS							0.518**	(2.86)
UTILITIES							0.244	(1.13)
CONS. NON-CYC.							0.241	(1.44)
REAL ESTATE							−0.002	(−0.01)
CONS. CYC.							0.506***	(3.81)
INDUSTRIALS							0.769***	(5.40)
BASIC MAT.							0.551**	(2.67)
TECHNOLOGY							0.598*	(2.22)
HEALTHCARE							0.767**	(3.29)
ENERGY							0.401*	(2.31)
Clustered SE	Yes		Yes		Yes		Yes	
Firm fixed effects	Yes		Yes		Yes		No	
Year fixed effects	No		No		No		Yes	
R^2	0.338		0.339		0.340		0.080	
Obs. (firm-years)	3,604		3,604		3,604		3,604	

E.2 Robustness to MRS specification

This section discusses alternative specifications for the MRS orthogonality test. First, we consider a more robust specification of the naive forecast P_t^o based on the annual moving average over the last five years of dividends, that is, 20 quarterly dividend amounts:

$$P_t^o = \frac{1}{r_t + \mathfrak{p}} \cdot \frac{1}{5} \sum_{i=1}^{20} D_{t-i}. \tag{E15}$$

This smoother specification enables controlling for dividend volatility and produces a less noisy naive forecast. Second, we use a robust version of the variance spread statistic q_T to avoid being overly dependent on a single value of the market price at the time horizon T. More precisely, we first consider the realized distribution of the market price P_t over the last year of our full sample period (2008-2020). Then we extract the n dates corresponding to the n percentiles in this distribution, namely $T_1, \cdots, T_n$. We then calculate the n trajectories of the perfect-foresight price $P^*_{t \to T_i}$ originating from $P_{T_1}, \cdots, P_{T_n}$. The robust MRS variance spread statistic is then given by the following average:

$$q := \frac{1}{n} \sum_{i=1}^{n} q_{T_i} = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{1}{T_i} \sum_{t=1}^{T_i} q_{t,T_i} \right). \tag{E16}$$

To check the robustness of the orthogonality test results reported in Section 4, we investigate the determinants of the robust MRS statistic q in the cross-section of firms. For that purpose, for every firm i and every year t ($2008 \leqslant t \leqslant 2020$), we run the orthogonality test with a robust variance spread $q_{i,t}$ implemented as in Equation (E16) and $n = 10$ trajectories for the perfect-foresight price $P^*_{t \to T_i} (1 \leqslant i \leqslant 10)$. Then we collect the set of statistics $|\hat{q}_{i,t}|$ similarly to the methodology employed in Table **??**. Finally, we estimate the following panel regression with firm- and year-fixed effects:

$$\begin{aligned}\ln(|\hat{q}_{i,t}|) =& \beta_1 \cdot \mathrm{LVG}_{i,t} + \beta_2 \cdot \mathrm{CDS}_{i,t} + \beta_3 \cdot \mathrm{LVG}_{i,t} \times \mathrm{CDS}_{i,t} + \beta_4 \cdot \mathrm{LOGSIZE}_{i,t} \\ &+ \beta_5 \cdot \mathrm{DIV}_{i,t} + \beta_6 \cdot \mathrm{VOL}_{i,t} + \sum_i \gamma_i \cdot \mathrm{FIRM}_i + \sum_t \delta_t \cdot \mathrm{YEAR}_t + \epsilon_{i,t},\end{aligned} \tag{E17}$$

where $\epsilon_{i,t}$ are i.i.d. disturbances. Here, $\mathrm{LVG}_{i,t}$ (resp. $\mathrm{CDS}_{i,t}$, $\mathrm{LOGSIZE}_{i,t}$, $\mathrm{DIV}_{i,t}$, $\mathrm{VOL}_{i,t}$) is the average financial leverage (resp. CDS par spread, logarithm of market capitalization, dividend yield, 1-year stock volatility) of firm i over year t. Standard errors are clustered by firm to control for timewise heteroskedasticity and serial correlation within firm clusters. We expect the estimate $\hat{\beta}_1$ to be statistically significant and negative to confirm the findings of Section 4.

Table 8 reports estimates of regression (E17) with a robust variance spread statistic q implemented as in Equation (E16). We also report three different assumptions for the equity risk premium ($\mathfrak{p} = 0.03, 0.05$, and 0.07). The reported results show that estimate $\hat{\beta}_1$ is statistically significant and negative, confirming that the robust MRS statistic consistently decreases along with firm leverage.

Table 8. Robust orthogonality tests at the firm level

This table reports estimates of the following panel regression with firm and year fixed effects:

$$\ln(|\hat{q}_{i,t}|) = \beta_1 \text{LVG}_{i,t} + \beta_2 \text{CDS}_{i,t} + \beta_3 \text{LVG}_{i,t}\text{CDS}_{i,t} + \beta_4 \text{LOGSIZE}_{i,t} + \beta_5 \text{DIV}_{i,t} + \beta_6 \text{VOL}_{i,t} + \sum_{i,t} \text{FE}_{i,t} + \epsilon_{i,t},$$

where $\hat{q}_{i,t}$ is the robust MRS statistic given by Equation (E16) and estimated for every firm i and every year t ($2008 \leqslant t \leqslant 2020$) in the sample. $n = 10$ trajectories of the perfect-foresight price $P^*_{t \to T_j}$ ($1 \leqslant j \leqslant 10$) have been used for each firm-year sample. t-statistics in parentheses are calculated via standard errors clustered by firm to correct for timewise heteroskedasticity and serial correlation. ***, ** and * denote statistical significance at the 0.1%, 1%, and 5% levels, respectively. Data source: Thomson Reuters.

	Naive forecast P^o_t					
	$P^o_t = \sum_{i=1}^{4} D_{t-i}/(r_t + \mathfrak{p})$			$P^o_t = \frac{1}{5}\sum_{i=1}^{20} D_{t-i}/(r_t + \mathfrak{p})$		
Variable	$\mathfrak{p} = 0.03$	$\mathfrak{p} = 0.05$	$\mathfrak{p} = 0.07$	$\mathfrak{p} = 0.03$	$\mathfrak{p} = 0.05$	$\mathfrak{p} = 0.07$
LVG	−0.91*	−0.84*	−0.74	−0.98*	−0.85*	−0.73*
	(−2.18)	(−2.05)	(−1.84)	(−2.46)	(−2.22)	(−2.01)
CDS	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00
	(−0.84)	(−1.20)	(−1.36)	(−0.61)	(−0.78)	(−1.26)
LVG × CDS	0.00	0.00	0.00	0.00	0.00	0.00
	(0.88)	(1.18)	(1.20)	(0.47)	(0.13)	(0.57)
LOGSIZE	−0.68***	−0.77***	−0.78***	−0.68***	−0.72***	−0.74***
	(−6.10)	(−7.30)	(−7.51)	(−5.84)	(−6.32)	(−5.81)
DIV	0.03**	0.02	0.02	0.02*	0.02*	0.02*
	(2.70)	(1.64)	(1.26)	(1.93)	(2.40)	(2.18)
VOL	−0.01	−0.02	−0.03*	−0.01	−0.02	−0.03*
	(−0.68)	(−1.17)	(−2.00)	(−0.63)	(−1.48)	(−2.04)
Clustered std. errors	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.047	0.058	0.061	0.036	0.050	0.058
Obs. (firm-years)	2,975	2,977	2,976	2,974	2,976	2,974

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