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Price discovery in the CDS market: the informational role of equity short interest

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Abstract This paper documents a negative relation between equity short interest and future returns on credit default swaps (CDS). This relation is most consistent with the theory that equity short interest telegraphs relevant information to secondary market CDS investors about credit spread not transmitted into prices in other ways. The CDS return predictive pattern also strengthens negatively for equity short-interest positions subject to an outward shift in the demand for shortable stocks, which we view as a proxy for the expected benefits of private information (Cohen et al. in J Finance 62(5):2061–2096, 2007). This suggests that features of the shorting market may help explain the lagged response of CDS spreads to equity short interest. Our tests of economic significance, however, do not support the view that the CDS return predictive pattern is strong enough to cover the round-trip cost of trading in the secondary CDS market.

Keywords Equity short interest · Credit default swaps · Credit spreads · Lagged asset price discovery

JEL Classification G12 · G14 · G24 · M41

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1 Introduction

Equity short interest may significantly influence asset prices in financial markets because short sellers have an information advantage. The focus of most prior literature supporting this informational role, however, has been on how shorting relates to price discovery in the equity market (Senchack and Starks 1993; Dechow et al. 2001; Desai et al. 2002; Christophe et al. 2004; Pownall and Simko 2005; Boehmer et al. 2008; Diether et al. 2009; Werner 2010; Boehmer and Wu 2013). Other work on how the supply of and demand for shortable stocks and other shorting market features affect the returns on shorting strategies has also focused on the equity market (Cohen et al. 2007; Blocher et al. 2013). As such, these studies ignore a seemingly important aspect of the investigation, namely, how equity short interest might relate to other financial markets, particularly the credit markets, wherein, for the most part, institutional participants employ sophisticated strategies to exploit potential pricing inefficiencies. Apart from two recent studies—by Kecskés et al. (2013) and Henry et al. (2014)—of shorting behavior and bond instruments, the relation between equity short interest and non-equity instrument prices remains under-researched.

Our study aims to fill this gap by investigating the relation between equity short interest and price discovery in the credit default swap (CDS) market. Our primary hypothesis is that future returns on CDS instruments, which reflect expected downside risk, relate negatively to equity short selling. We operationalize this hypothesis by testing the potential of equity short interest to predict negative 1-month-ahead CDS returns. The Duffie and Lando (2001) model partially motivates this hypothesis, wherein the pricing of a CDS instrument depends on the likelihood and severity of firm default and the quality of the information available to CDS counterparties about firm value. We ask in this study whether the information in equity short interest might be informative for CDS pricing. This research question matters because CDS counterparties and market dealers represent sophisticated and well-resourced participants whom we expect to understand the role of equity short interest.[1]

Several other factors favor the use of a CDS market setting to study the role of short interest. The first is the appropriateness of the information to the setting, in that equity short-interest positions mostly reflect expectations about downside risk, critically important for assessing credit spread. Whether it relates to default risk (Callen et al. 2009; Correia et al. 2012) or information risk (Duffie and Lando 2001; Yu 2005), CDS spread provides a relatively clean measure of that spread, especially compared to bond spread.[2] For example, CDS spreads do not reflect interest rate

[1] For example, banks, securities firms, and hedge funds comprise most investors in CDSs, and the top five CDS dealers (who set the CDS trade prices) are JP Morgan, Goldman Sachs, Morgan Stanley, Deutsche Bank, and Barclays Group (European Central Bank 2009). For evidence of CDS market efficiency, see Norden and Weber (2004), Zhang and Zhang (2013), and Berndt and Ostrovnaya (2014).

[2] We use the term information risk to recognize the fact that credit investors can only observe imperfect measures of firms' asset values (e.g., from the accounting system), which implies that credit spreads increase in information risk, particularly for instruments of shorter maturities (Duffie and Lando 2001, p. 650).

risk, currency risk, and other risk features that may relate to covenants, guarantees, and other credit terms. The second is the relevance of the results, in that the literature does not clarify whether the relation between short interest and credit returns might be predictable, given the equity market evidence and the equity-like behavior of certain credit instruments, such as when firms are closer to default (Merton 1974). For example, Callen et al. (2009) find a stronger response to negative earnings surprises than positive earnings surprises in the CDS market. Erturk and Nejadmaleyeri (2012) find that the relation between equity short interest and bond yields is only significant for firms with lower credit ratings and greater equity volatility. And Kecskés et al. (2013) and Henry et al. (2014) predict and find stronger results for lower rated bonds and financially constrained firms. On the other hand, Duffee (1998) and Bao et al. (2011) find that economic events and market factors can also significantly affect investment-grade credit instruments. By examining CDS return predictive patterns from short interest under high and low credit-cost conditions, we hope to deepen understanding of this issue. Third, we use a unique dataset on loanable stocks and loan fees to help identify the channel through which CDS prices incorporate features of the equity shorting market. In particular, we distinguish between shorting demand and shorting supply as factors that affect how CDS prices incorporate activity in the equity shorting market. We do this by predicting situations when lagged price discovery in the CDS market may occur, such as when investors bet more on the possibility that the firm's situation will worsen (e.g., equity shorting demand increases) or when more shortable shares become available (e.g., equity shorting supply increases).

We address our primary research question with data from the Markit CDS Composites Pricing database, which provides detailed information about CDS spreads and reference entity credit ratings; the Markit Securities Finance database,[3] which provides data on loanable stocks and loan fees; and the NYSE and NASDAQ exchanges, which provide observations of monthly equity short interest. Of the many available sources of CDS data, the Markit CDS data set has been shown to be a price discovery leader in incorporating information about spreads (Mayordomo et al. 2014).

Our study produces four key results. First, we document a significantly negative relation between monthly short interest and CDS returns in the month following the short interest reporting month. This negative relation dissipates over the next several CDS return months following the short interest reporting month, suggesting that arbitrage opportunities for short sellers in the CDS market are limited. Second, the negative relation is stronger for investment versus speculative grade CDS instruments. This is a potentially interesting result in that investment grade CDS instruments may have less correlation with equity returns and reflect greater distance to default. Moreover, if a significant relation between equity short interest and credit returns persists for higher grade instruments, then such relation does not simply confirm findings on the relation between equity short interest and equity returns. Third, we find that the next month CDS return predictive pattern strengthens

[3] The Markit Security Finance database was previously owned by Data Explorers and recently acquired by Markit.

for equity short interest positions subject to an outward demand or supply shift for shortable stocks. We proxy these shifts by an increase in shortable shares in the prior month at a higher cost (an outward demand shift) and by an increase in shortable shares in the prior month at a lower cost (an outward supply shift). The results are stronger and more significant, however, for outward demand shifts. Hence we find that the demand and supply features of the equity shorting market shown to relate to future equity returns (Cohen et al. 2007) also relate to future CDS returns. Fourth, we interpret our results economically by analyzing the credit returns on hypothetical zero risk hedge portfolios, whereby, as an alternative or complement to shorting equities, investors take long and short positions in CDS instruments conditional on the level of equity short interest. These tests show a statistically significant but economically limited payoff of this hedging strategy. We further document that the hedge portfolio CDS returns conditional on increased equity-shorting demand or supply are only slightly higher. Overall, we can conclude that CDS spreads incorporate the information in equity short interest with a 1-month lag. However, our tests of economic significance do not support the view that the CDS return predictive pattern we document is strong enough to cover the round-trip trading costs in the secondary credit markets.

Section 2 develops our hypotheses. Section 3 provides details about the sample, data sets, and variable definitions. Section 4 presents the multivariate results. Section 5 discusses the economic significance and sensitivity tests. Section 6 concludes.

2 Hypothesis development

Our study builds upon an extensive literature on equity short selling and equity returns.[4] This literature highlights that short selling reflects an information-based activity telegraphed to investors through trading whose implications are reflected in market prices, though not necessarily instantaneously. Stock market prices have been used extensively to test and support information-based hypotheses about short

[4] The literature has three strands. First, several studies document relations between short selling and equity returns in calendar time and around specific events (Senchack and Starks 1993; Desai et al. 2002; Christophe et al. 2004; Pownall and Simko 2005; Boehmer et al. 2008; Diether et al. 2009; Boehmer and Wu 2013). These studies support the view that short sellers trade mostly to exploit an information advantage in stocks rather than to hedge or speculate. Others find exceptions to this view (Woolridge and Dickinson 1994; Drake et al. 2011), suggesting that the Diamond and Verrecchia (1987) hypothesis is far from a settled issue. Diamond and Verrecchia (1987) state that higher levels of short interest convey unpublicized adverse information, thereby contributing to price discovery in securities markets. A second strand covers the information advantage short sellers might telegraph through trading with other investors. Some studies contend that short sellers derive an information advantage through better analysis of accounting information such as accruals (Desai et al. 2006; Bhojraj and Swaminathan 2009; Hirshleifer et al. 2011), financial ratios (Dechow et al. 2001), earnings surprises (Christophe et al. 2004; Lasser et al. 2010), and news items in general (Engelberg et al. 2012). A third strand examines the effects of regulations on short selling. These include the uptick rule (Aitken et al. 1998; Ali and Trombley 2005), the costs and difficulties of short selling as trade-limiting factors (Jones and Lamont 2002; Chen et al. 2002), and other constraints on short selling. These studies conclude that such constraints and costs can lead to overpricing in the equity markets.

selling (with mixed results), whereas CDS market prices have not.[5] Indeed, compared to forty-plus years of studies of stock price reactions to news items, the literature on credit market response is remarkably limited. Data considerations aside, we find this surprising, as valid reasons support why CDS prices might respond differently to stock prices for the same news event. For example, CDS investors have a fixed claim on the firm. This means that they have an asymmetrical interest in the downside risk of their securities compared to the upside potential. Our study addresses this research imbalance by investigating the informational role of equity short interest in the CDS market.

As noted earlier, the hybrid model of Duffie and Lando (2001), at least partially, motivates our hypothesis. In that model, the pricing of a CDS instrument depends on the likelihood and severity of a credit event such as default. The inputs to this model are (1) factors such as default probability that explain CDS pricing in standard structural models and (2) the imperfect information available to CDS counterparties from reports about the firm's asset dynamics. Although the information in the Duffie–Lando model is completely generic, how and whether equity short interest might be informative for CDS pricing provides a specific focus for our study. If high or increased short selling conveys unpublicized bad news about firm value to equity holders, CDS investors with an asymmetric interest in the downside risk of their securities would also be expected to respond to higher or increasing short selling in assessing returns.

However, CDS investors represent institutional investors such as banks, asset managers, and financial institutions. They employ sophisticated strategies to exploit potential pricing inefficiencies and may have privileged information on the likelihood of firms' default through private communications with firms' managers. For example, using information incorporated into equity prices as a benchmark for public information, Acharya and Johnson (2007) document that CDS prices may reveal significant additional information, supporting the view that banks exploit their lending relation with clients and use clients' nonpublic information in the CDS market. Hence it is ultimately an empirical question whether equity short selling activity transfers fresh bad news to the CDS market. Our primary research hypothesis is that, despite the sophistication of the CDS market, future returns on CDS instruments, which reflect expected downside risk, relate negatively to equity short selling. Formally, we state our first hypothesis in the alternative form as:

H1 The level of equity short interest varies negatively with 1-month-ahead CDS returns.

We next examine whether the effect of equity shorting on the CDS returns differs between investment grade (IG) instruments and speculative grade (SG) instruments.

[5] CDS instruments are insurance contracts against the risk of a credit event (e.g., default) of the underlying firm. The seller of protection pays off to the buyer for the loss if the credit event happens. In return, the buyer of protection provides regular payments based on the swap premium or spread. Unlike corporate bonds and secondary loans markets, CDSs are relatively free of special features such as guarantees, covenants, imbedded options, and coupons. The absence of these features implies that CDS prices or spreads represent a more pure proxy for credit risk compared to others, for example, based on bonds and bank loans.

As demonstrated theoretically by Merton (1974) and empirically by others, when credit instruments are closer to physical default, that is, the fair value of the assets approaches the fair value of the credit instruments, the positive correlation between credit returns and equity returns increases, which means that credit returns become more equity-like. This raises the possibility that an observed empirical relation between equity-market activity and credit returns reflects the same drivers of equity returns (Lok and Richardson 2011). Several studies reflect this possibility (Callen et al. 2009; Easton et al. 2009; DeFond and Zhang 2011; Shivakumar et al. 2011; Erturk and Nejadmalayeri 2012). For example, Callen et al. (2009) and Erturk and Nejadmaleyeri (2012) find that their results hold mainly for lower rated bonds, that is, those with higher default risk. Additionally, Easton et al. (2009) report a higher sensitivity of SG bond prices to earnings news than IG bond prices to earnings news. On the other hand, if equity short interest relates to factors other than firm default risk, these factors could be more important for IG versus SG credit instruments. As such, IG credit returns might relate more strongly to equity short interest. We contend that one potential CDS pricing factor relates to information risk (Duffie and Lando 2001; Yu 2005), although it may not be the only non-equity or default risk factor that drives the lagged relation. Still, most empirical studies on the lagged effects of equity short interest on stock prices attach an informational role to equity short interest, for example, based on its ability to telegraph information about features of the equity shorting market (e.g., constraint relaxation, increased demand) versus unknown firm risk factors.[6] This leads to our second hypothesis, which we state in the alternative form as follows:

H2 The relation between equity short interest and 1-month ahead CDS returns is stronger negatively for IG instruments versus SG instruments.

Cohen et al. (2007) argue that the distinction between shorting demand and supply is critical, as the underlying forces of shorting supply and demand can relate differently to future equity returns. Shifts in the demand curves indicate shifts in the marginal benefits for investors. Shorting demand may also proxy for informed trading or investor sentiment (Lamont and Thaler 2003). In contrast, shifts in supply are caused by changes in marginal costs. For instance, an increase in shorting supply could relate to a decrease in short sale constraints. Since a large body of literature (e.g., Miller 1977; Pontiff 1996; Shleifer and Vishny 1997) shows that investor sentiment, information revelation, limited arbitrage, and short sale constraints relate to future stock price dynamics, understanding the role of shorting demand and supply is important.

We adopt the Cohen et al. (2007) empirical strategy to isolate supply and demand shifts in the equity lending market. Using a unique data set that includes actual loan prices and quantities from Markit Security Finance, we deduce a shift in shorting demand or supply of a stock. We do this by relying on the Cohen et al. methodology based on price/quantity pairs. Specifically, an increase in the loan fee (i.e., price) in conjunction with an increase in shares lent out (i.e., the quantity supplied) represents

[6] Another way to interpret our reasoning is that the proportion of jump-to-default risk in overall credit risk due to *lack of transparency* is greater for IG credit instruments than SG instruments or, equivalently, that the proportion of jump-to-default risk in overall credit risk due to *default probability* is greater for SG credit instruments than for IG instruments. We thank the reviewer for this alternative interpretation.

an increase in shorting demand, as would be the case with any increase in price in conjunction with an increase in quantity. A decrease in the loan fee (i.e., price), in conjunction with an increase in the quantity of shares lent out, represents an increase in shorting supply. By categorizing such shifts, we isolate increases and decreases in shorting demand and supply and then study how these shifts associate with future CDS returns. This leads to our third hypothesis, which we state in the alternative form as follows:

H3 The relation between equity short interest and 1-month-ahead CDS returns is stronger negatively for outward demand or supply shifts of shortable shares.

3 Data sets and samples

We select our sample by merging data from three sources. The first comprises monthly equity short interest, as defined by SEC Rule 200(a), on the last trading day of the month adjusted for stock splits and available from NYSE Market Data and NASDAQ OMX Global Data Products for all NYSE market and NASDAQ market reporting companies. For each firm, we define equity short interest as the number of uncovered short positions scaled by the total number of common shares outstanding from CRSP (hereafter, shares outstanding) as of the end of each calendar month. The second comprises Markit. Specifically, we access the Markit CDS Composites Pricing database and collect 5-year CDS spreads and Markit's Implied credit rating for the same spreads for our sample period, limiting the collection to senior-tier, dollar-denominated CDS contracts with modified restructuring clauses. A merge of the CDS file and the NYSE/NASDAQ short interest file using Markit's RED code[7] produces a CDS-short interest sample of 56,727 firm-month short interest observations for 5798 firm-years over 2001–2011 with at least one monthly CDS return observation. We also access the Markit Security Finance database to obtain equity loan fee data, similar to the data used by Cohen et al. (2007).[8] According to Markit, the stock lending data come from surveys of the largest custodians in the securities lending industry. Merging this file with the CDS sample results in a reduced sample of 44,001 firm-month short interest observations with CDS return and equity lending supply and fee data.

These data enable us to calculate monthly CDS return as follows:

$$RET_t = \frac{1}{12}(CS_t) - Duration_t * \Delta CS_t, \tag{1}$$

where RET_t is the CDS return from the start to the end of month t, CS_t is the 5-year credit spread at the start of month t, $Duration_t$ is the spread's duration (the modified Macaulay calculation based on weighted average time until receipt of interest and

[7] Markit assigns a unique alphanumeric reference entity database (RED) code to each reference entity in North America, which is then linked to CUSIP identifier to identify each debt instrument. We use these CUSIP identifiers to match each CDS reference entity to the short interest data (and data from CRSP and Compustat).

[8] Cohen et al. (2007) indicate that their data on equity lending supply (the same term as lending quantity) and loan fees come from a "large institutional investor" (p. 2062).

principal cash flows, in years) for the CDS contract at the start of month t, and ΔCS_t is the change in the 5-year CDS spread from the start to the end of month t. For both samples, we exclude CDS contracts with spreads greater than 2000 basis points (hereafter, bps) from the monthly cross-sections of RET_t as a way to minimize data error in the Eq. (1) return calculation.

Table 1 summarizes the full sample of NYSE/NASDAQ firms with at least one monthly CDS return from Markit during the sample period. Panel A, which reports sample statistics by year, shows a right skew in the distribution of short interest. Mean and median short interest over all years are 3.95 and 2.40 % of common shares outstanding, respectively. Predictably, the sample has the highest mean (5.46 %), median (3.17 %), and standard deviation (5.62 %) during the financial crisis year of 2008. Panel A also shows reasonably stable numbers of firms and CDS observations per year, with an average of 9.78 (56,727 ÷ 5798) CDS monthly observations per firm/year. Panel B reports the distribution of firms based on industry classifications as defined by Campbell (1996). More than 40 % of the firms in NASDAQ/NYSE sample comprise three industries, for example, the combination of utilities (12.96 %), basic industry (14.64 %), and finance and real estate (15.84 %). We check for industry effects in Sect. 5.

Table 2 reports descriptive summary statistics for the overall sample (All observations) and subsamples of CDS returns partitioned on investment grade (IG) or speculative grade (SG) rating and then on five levels of equity short interest. Quintile 1 contains firm-month observations with the lowest level of short interest. Quintile 5 contains firm-month observations with the highest level of short interest. The IG (63 % of all observations) and SG (37 % of all observations) categories are based on the market implied credit rating assigned by Markit to each CDS instrument. We first note that mean monthly CDS returns (measured as percentage per month) increase for SG versus IG observations, presumably reflecting higher default risk. For example, for quintile one, the mean monthly IG return is 0.0908 % or 9.08 bps versus 0.2352 % or 23.52 bps for SG observations. We then examine whether the mean CDS returns in the month following the short interest position differ by equity short interest quintile. We find that they do. The mean and median CDS return differences of quintile 5 less quintile 1 (Q5 − Q1) are negative and significant based on two-sample t and Mann–Whitney U test statistics, respectively. For example, for the All observations sample, we observe a mean Q1 − Q5 return difference in month $t + 1$ of -22.88 bps, with similar return differences for the IG and SG subsamples. Thus, on a univariate basis, we observe a negative relation between short interest and CDS returns in the following month. This is consistent with equity short interest at month t reflecting new information in CDS returns in the following month.

These are univariate results, however, and thus do not control for other factors that might explain a predictive relation between short interest and future CDS returns. Nor do they test for a relation between short interest and future CDS returns beyond the first month following the short interest month. We examine these and other issues in the next sections.

Table 1 Summary sample statistics by calendar year and industry

Year	No. of firm-years	No. of CDSs	Sum of short size, in millions	Mean	Median	Std. Dev.
Panel A—distribution of short interest by calendar year						
2001	232	1399	14,038	0.0234	0.0166	0.0225
2002	352	3055	34,681	0.0269	0.0193	0.0252
2003	468	4077	43,636	0.0302	0.0214	0.0292
2004	564	5369	53,118	0.0311	0.0199	0.0338
2005	637	6380	61,622	0.0344	0.0224	0.0362
2006	632	6505	62,712	0.0367	0.0228	0.0385
2007	648	6667	147,794	0.0442	0.0262	0.0470
2008	622	6410	192,195	0.0546	0.0317	0.0562
2009	566	6005	179,813	0.0460	0.0287	0.0450
2010	553	5817	159,903	0.0426	0.0258	0.0421
2011	524	5043	131,420	0.0412	0.0240	0.0443
Total	5798	56,727	1080,938	0.0395	0.0240	0.0422

	No. of firms	No. of CDSs	Percent CDSs
Panel B—distribution of firms by industry (*Campbell 1966*)			
1 Construction	22	1719	3.03
2 Transportation	23	1522	2.68
3 Food & tobacco	38	2974	5.24
4 Leisure	36	2195	3.87
5 Textiles and trade	46	3312	5.84
6 Services	71	4105	7.24
7 Petroleum	49	3479	6.13
8 Capital goods	64	4701	8.29
9 Utilities	115	7352	12.96
10 Consumer durables	87	6300	11.11
11 Basic industry	122	8302	14.64
12 Finance & real estate	138	8988	15.84
13 Others	39	1778	3.13
Total	850	56,727	100.00

This table reports the distribution of firms covered by NASDAQ and NYSE that have at least 1 monthly buy-and-hold CDS return from Markit CDS Composites and control variables in our main regression model (Eq. (3) in Table 3) during the sample period from 2001 to 2011. Summary statistics are based on the largest possible sample size in the main multivariate analyses in Tables 3 and 4. Short interest equals the ratio of stocks shorted to the total number of shares outstanding at the end of each month

4 Multivariate results

We present our multivariate results in two ways. We first regress 1-month-ahead monthly CDS returns on equity short interest and repeat these 1-month-ahead regressions for subsamples of firms with investment and speculative grade instruments (Table 3) and firms with different shorting market characteristics

Table 2 Summary statistics for short interest and CDS returns by short interest quintile and credit rating

Short interest quintile	Variable	Statistic	All observations	Investment grade (IG)	Speculative grade (SG)
Quintile 1	Short interest	Mean	0.0079	0.0077	0.0082
(Firm-month obs. with the lowest short interest months)	CDS return	Mean	0.1440	0.0908	0.2352
		Median	0.1536	0.0754	0.1856
		Std. Dev.	3.5202	4.1134	2.8093
		No obs.	11,345	7168	4177
Quintile 2	Short interest	Mean	0.0154	0.0149	0.0162
	CDS return	Mean	0.1047	0.0615	0.1789
		Median	0.0867	0.0497	0.1172
		Std. Dev.	3.7098	4.3889	3.3008
		No obs.	11,346	7168	4178
Quintile 3	Short interest	Mean	0.0248	0.0241	0.0261
	CDS return	Mean	0.0387	−0.0218	0.1424
		Median	0.0627	0.0402	0.0785
		Std. Dev.	4.7356	5.2575	4.0915
		No obs.	11,347	7168	4179
Quintile 4	Short interest	Mean	0.0437	0.0439	0.0434
	CDS return	Mean	−0.0179	−0.0913	0.1080
		Median	0.0486	0.0283	0.0637
		Std. Dev.	6.4210	8.3604	4.7361
		No obs.	11,343	7166	4177
Quintile 5	Short interest	Mean	0.1094	0.1196	0.1004
(Firm-month obs. with the highest short interest months)	CDS return	Mean	−0.0343	−0.1018	0.0815
		Median	0.0413	0.0275	0.0514
		Std. Dev.	9.5750	9.9449	9.1684
		No obs.	11,346	7168	4178

Table 2 continued

Short interest quintile	Variable	Statistic	All observations	Investment grade (IG)	Speculative grade (SG)
Difference	Short interest	Mean	0.1015***	0.1119***	0.0922***
(Q5 – Q1)	CDS return	Mean	−0.2288**	−0.1926**	−0.1537*
		Median	−0.1123**	−0.0479*	−0.1342*
		Std. Dev.	6.0548***	5.8315***	6.3591***
		All obs.	56,727	35,838	20,889

This table reports statistics for firm-months categorized by the level of short interest in NASDAQ and NYSE during the sample period from 2001 to 2011. Short interest is defined as a ratio of stocks shorted to the total number of shares outstanding at the end of each month. CDSs are categorized into five equal-sized subgroups based on the size of short interest and two groups by credit rating. CDS data are from Markit CDS Composites database. CDS return (measured in percent per month) is calculated for the calendar month following the month of short interest as defined by Eq. (1). For the mean and median differences, ***, **, and * indicate significance levels of 0.01, 0.05, and 0.10, respectively, based on t and Mann–Whitney U statistics, respectively. Investment grade (IG) firms have Markit Implied Ratings of AAA to BBB, and speculative grade (SG) firms have Markit Implied Ratings of BB and below

(Tables 4, 5). The subsample regressions test empirical hypotheses about factors that might differ across firms and affect the strength and significance of the overall negative relation between short interest and future CDS returns. Second, we estimate excess CDS returns in month $t + 1$ for quintile portfolios formed at each calendar month t based on short interest in that calendar month. We then test whether a strategy of selling the highest short interest quintile and buying the lowest

Table 3 Regression of 1-month-ahead CDS return on short interest conditional on investment or speculative grade credit rating

Variable	Exp. sign	All observations	Investment grade (IG)	Speculative grade (SG)
Intercept		0.9388*	2.0451**	−0.1299
		(1.83)	(2.05)	(−0.22)
Short Interest (β$_1$)	–	−3.1113***	−3.6385***	−1.1138***
		(−5.19)	(−3.62)	(−2.85)
Difference in *Short Interest* coefficient	–			−2.5247**
				(2.07)
MOMS (β$_2$)	+	0.5255***	0.0956	1.5457***
		(8.60)	(1.14)	(15.90)
MOML (β$_3$)	+	0.0229	0.0177	0.0241
		(1.39)	(0.71)	(1.09)
BTM (β$_4$)	+	0.2721***	0.1799***	0.1297
		(13.21)	(10.26)	(0.55)
SIZE (β$_5$)	–	−0.1016***	−0.1213	−0.0526
		(−2.87)	(−1.62)	(−1.38)
E/P (β$_6$)	+	1.0040***	1.4989***	1.3446
		(4.38)	(5.26)	(1.24)
BETA (β$_7$)	+	0.2645***	0.1187***	−0.2551
		(6.58)	(11.11)	(−0.93)
CRV (β$_8$)	+	0.3353**	0.0481	1.5890***
		(2.04)	(0.27)	(4.95)
Adj. R^2		3.01 %	3.00 %	8.80 %
No. of Obs.		56,727	35,838	20,889

This table reports the coefficients from cross-sectional regressions of 1-month-ahead monthly CDS return on short interest and other controls, including the Fama and French equity risk characteristics (Fama and French 1993). The data consist of firm-months that have NASDAQ and NYSE short interest data for the sample period of 2001–2011. The regression is: $RET_{t+1} = \alpha + \beta_1 Short\,Interest_t + \beta_2 MOMS_t + \beta_3 MOML_t + \beta_4 BTM_t + \beta_5 SIZE_t + \beta_6 E/P_t + \beta_7 BETA_t + \beta_8 CRV_t + e_{t+1}$, where t is an event-month index. Appendix 1 defines the variables. The numbers in parentheses are the asymptotic t-statistics based on the Newey and West (1987) correction for heteroskedasticity and serial correlation, and ***, **, and * indicate significance levels of 0.01, 0.05, and 0.10, respectively. Investment grade (IG) firms have Markit Implied Ratings of AAA to BBB, and speculative grade (SG) firms have Markit Implied Ratings of BB and below short interest quintile generates significant excess CDS returns in month $t + 1$ (Tables 6, 7).

4.1 One-month-ahead regressions

Table 3 reports the coefficients from the cross-sectional regressions of 1-month-ahead CDS returns on short interest and control variables for equity risk factors and a measure of relative default probability. In the absence of short interest, these risk

Table 4 Summary statistics for the indicator variables representing demand and supply shifts in the equity shorting market

Variable	N	Mean	Median	Std. Dev.	N	Mean	Median	Std. Dev.
Indicator variable	*DIN = 1*				*DOUT = 1*			
RET_{t+1}	11,527	0.2741	0.0702	5.4894	11,518	−0.2124	0.0482	6.5439
MOMS	11,527	0.0607	0.0309	0.2911	11,518	−0.0356	−0.0050	0.2424
MOML	11,527	0.2627	0.1106	1.4388	11,518	0.2598	0.1143	1.3708
BTM	11,524	0.5697	0.4836	0.5099	11,508	0.5339	0.4621	0.4620
SIZE	11,524	8.8968	8.8855	1.3538	11,508	8.9468	8.9178	1.3360
E/P	11,527	0.0043	0.0133	0.1461	11,518	0.0101	0.0142	0.1158
BETA	11,527	1.3178	1.3602	0.1134	11,518	1.3250	1.3715	0.1151
CRV	11,508	0.0310	0.0125	0.0526	11,500	0.0320	0.0134	0.0525
ΔLoan Fee	11,527	−19.6505	−4.8624	74.7855	11,518	18.7095	5.3562	51.3528
ΔShort Interest	11,527	−1.7715	−0.2251	8.7329	11,518	1.7884	0.2236	8.7591
Indicator variable	*SIN = 1*				*SOUT = 1*			
RET_{t+1}	9515	0.3211	0.0865	4.7957	8722	−0.0327	0.0554	5.2649
MOMS	9515	0.0882	0.0389	0.3416	8722	−0.0548	−0.0099	0.3005
MOML	9515	0.3081	0.1193	1.6159	8722	0.2363	0.0872	1.4719
BTM	9512	0.5938	0.5048	0.5298	8719	0.5710	0.4791	0.5340
SIZE	9512	8.7256	8.6452	1.2974	8719	8.7239	8.6409	1.3041
E/P	9515	0.0045	0.0133	0.1299	8722	−0.0003	0.0141	0.3295
BETA	9515	1.3127	1.3384	0.1161	8722	1.3149	1.3443	0.1162
CRV	9507	0.0270	0.0104	0.0476	8716	0.0256	0.0095	0.0450
ΔLoan Fee	9515	12.7717	3.1834	53.0173	8722	−13.1638	−3.7144	38.3423
ΔShort Interest	9515	−1.8195	−0.2267	9.0138	8722	2.0198	0.2436	10.8509

This table summarizes summary statistics for the four equity shorting market quadrants: $DIN = 1$ if the shorted stock has seen its loan fee and lending supply fall in month t, i.e., an inward demand shift, otherwise 0; $DOUT = 1$ if the shorted stock has seen its loan fee and lending supply rise in month t, i.e., an outward demand shift, otherwise 0; $SIN = 1$ if the shorted stock has seen its loan fee rise but lending supply fall in month t, i.e., an inward supply shift, otherwise 0; and $SOUT = 1$ if the shorted stock has seen its loan fee fall but its lending supply rise in month t, i.e., an outward supply shift occurs, otherwise 0. RET_{t+1} is measured in percent per month

Table 5 Regression of 1-month-ahead CDS return conditional on features of the shorting market

Variable	Exp. sign	(1)	(2)	(3)	(4)	(5)
Intercept		−0.0847	−0.0847	−0.0661	−0.0870	−0.0644
		(−0.25)	(−0.25)	(−0.18)	(−0.26)	(−0.19)
DIN	+	0.0413	0.0399	0.0768	0.0387	0.0397
		(0.52)	(0.48)	(0.97)	(0.49)	(0.46)
DOUT	–	−0.3462***	−0.3452***	−0.3246***	−0.3490***	−0.2797***
		(−4.03)	(−3.83)	(−3.63)	(−4.01)	(−3.60)
SIN	+	0.0479	0.0488	0.1621	0.0457	0.0294
		(0.60)	(0.62)	(1.33)	(0.58)	(0.37)
SOUT	–	−0.1949***	−0.1961**	−0.1110	−0.1976***	−0.1997**
		(−2.60)	(−2.45)	(−1.04)	(−2.64)	(−2.51)
ΔLoan Fee	–		0.0001			
			(0.04)			
ΔShort Interest	–				−0.0039**	
					(−2.23)	
DIN x *ΔLoan Fee*	+			0.0019		
				(1.16)		
DOUT x *ΔLoan Fee*	–			−0.0046		
				(−0.94)		
SIN x *ΔLoan Fee*	+			0.0092		
				(1.03)		
SOUT x *ΔLoan Fee*	–			−0.0019		
				(−0.85)		
DIN x *ΔShort Interest*	+					0.0010
						(0.05)
DOUT x *ΔShort Interest*	–					−0.1149*
						(−1.76)

Table 5 continued

Variable	Exp. sign	(1)	(2)	(3)	(4)	(5)
SIN x *ΔShort Interest*	+					0.0111
						(0.66)
SOUT x *ΔShort Interest*	–					−0.0013
						(−0.06)
MOMS	+	1.6009***	1.6012***	1.5509***	1.6165***	1.6407***
		(5.63)	(5.62)	(5.76)	(5.49)	(5.45)
MOML	+	0.0060	0.0061	0.0060	0.0061	0.0055
		(0.38)	(0.38)	(0.38)	(0.39)	(0.34)
BTM	+	0.1304	0.1305	0.1240	0.1309	0.1319
		(1.15)	(1.15)	(1.11)	(1.16)	(1.15)
SIZE	–	−0.0450***	−0.0450***	−0.0465***	−0.0449***	−0.0478**
		(−3.54)	(−3.54)	(−3.51)	(−3.51)	(−2.23)
E/P	±	1.0382	1.0379	1.0430	1.0357	1.0158
		(1.31)	(1.31)	(1.31)	(1.30)	(1.25)
BETA	+	0.4832**	0.4831**	0.4819**	0.4836**	0.4840**
		(2.49)	(2.48)	(2.26)	(2.50)	(2.54)
CRV	+	0.4695*	0.4691*	0.4522*	0.4674*	0.4566*
		(1.87)	(1.87)	(1.78)	(1.86)	(1.78)
Adj. R^2		2.04 %	2.04 %	2.29 %	2.04 %	2.05 %
No. of Obs.		44,001	44,001	44,001	44,001	44,001

This table reports the estimated coefficients from the following cross-sectional regression: $RET_{t+1} = \alpha + \beta_1 DIN_t + \beta_2 DOUT_t + \beta_3 SIN_t + \beta_4 SOUT_t + \beta_5 \Delta Loan\,Fee_t + \beta_6 \Delta Short\,Interest_t + \beta_7 MOMS_t + \beta_8 MOML_t + \beta_9 BTM_t + \beta_{10} SIZE_t + \beta_{11} E/P_t + \beta_{12} BETA_t + \beta_{13} CRV_t + e_{t+1}$, where t is an event month index, *DIN* is an indicator variable for an inward shorting market demand shift in month t, *DOUT* is an indicator for an outward shorting market demand shift in month t, *SIN* is an indicator for an inward shorting market supply shift in month t, *SOUT* is an indicator for an outward shorting market supply shift in month t, and where Appendix 1 defines the other variables. We also interact *DIN*, *DOUT*, *SIN*, and *SOUT* with *ΔLoan Fee* and *ΔShort Interest* to check whether shorting demand and supply increases when loan fees or short interest increase. The numbers in parentheses are the asymptotic t-statistics based on the Newey and West (1987) correction for heteroskedasticity and serial correlation; and ***, **, and * indicate significance levels of 0.01, 0.05, and 0.10, respectively factors have been shown to explain credit returns and thus provide a reasonable basis for CDS investors' expectations of monthly return (Correia et al. 2012, Eq. (14)). Specifically, we estimate the following model:

$$RET_{t+1} = \alpha + \beta\, Short\ Interest_t + \beta_2 MOMS_t + \beta_3 MOML_t + \beta_4 BTM_t + \beta_5 SIZE_t + \beta_6 E/P_t + \beta_7 BETA_t + \beta_8 CRV_t + e_{t+1}, \tag{2}$$

where t is a month from 2001 to 2011; RET_{t+1} is the CDS return (measured in percent per month) for a sample firm in month $t + 1$; *Short Interest*$_t$ is the number of shorted stocks scaled by the number of shares outstanding at end of month t; $MOMS_t$ is the stock return for month t; $MOML_t$ is an exponentially weighted (3-month half-life) average of stock return for the 11 months ending at the start of month t; BTM_t is the book-to-market ratio at the most recent fiscal quarter-end measured as CEQQ/PRCCQ*CSHOQ from Compustat; $SIZE_t$ is the natural logarithm of market capitalization, calculated at the end of the month t as price times number of shares outstanding from CRSP; E/P_t is net income (NIQ from Compustat) from the most recent four quarters divided by the market capitalization at the fiscal period end date; $BETA_t$ is the equity market beta estimated from a rolling regression of 60 months of data requiring at least 36 months of nonmissing return data; CRV_t (credit relative value) is a measure of the relative default risk associated with the firm's debt; and e_{t+1} is residual error.[9] Specifically, CRV_t is the natural logarithm of CDS spread divided by the default probability implied by the KMV-Merton (1974) distance-to-default model, $D2D_t$, which is based on Merton's (1974) bond pricing model (Bharath and Shumway 2008; Correia et al. 2012). We also run separate regressions for the IG and SG subsamples and test for a difference in the short interest coefficient by estimating Eq. (2) including the interaction of a dummy variable defined as $DUM = 1$ if IG firm and 0 otherwise times each independent variable. For the key variable of interest, *Short Interest*, we estimate and report the coefficient for *DUM* x *Short Interest*, which we label as the difference in the *Short Interest* coefficient in Table 3. For brevity, we do not report the coefficients for the interactions between *DUM* and the other independent variables.

Table 3 shows the results of estimating Eq. (2) for three sets of observations (All, IG, and SG firm-months). We show t values in parentheses, where ***, **, and * indicate significance levels of 0.01, 0.05, and 0.10, respectively, versus a null coefficient of zero. The t values represent asymptotic t-statistics based on the Newey and West (1987) correction for heteroskedasticity and serial correlation. First, the coefficients for the control variables in Eq. (2) coincide with expectations and prior work (e.g., Correia et al. 2012, p. 596). For example, for the All observations sample, the coefficients for *MOMS* (equity return), *MOML* (momentum), *BETA*

[9] Appendix B provides additional details on the theory and measurement of this variable. We follow Correia et al. (2012) and specify *CRV* as a relative default risk measure to reflect default information in the theoretical KMV-Merton (1974) measure (*D2D*) not already in actual CDS spread, where the latter incorporates default risk priced by the market. Consistent with Correia et al. (2012), we expect and find a positive coefficient for this variable in Eq. (2) to the extent that actual CDS spreads in expectation revert to their theoretical values in the future.

(equity risk) are positive (albeit only weakly positive for *MOML*), consistent with a momentum or risk effect. Also, the coefficients for *E/P* (earnings to price ratio) and *CRV* (relative default risk) are positive, consistent with an equity or relative default risk effect. Additionally, while the adjusted R^2s are low, they are significant, based on an *F* test (untabulated) and consistent with similar studies.

For the full sample (All observations), the third column of Table 3 shows a strong negative relation between short interest in month t and CDS returns in month $t + 1$. This result supports the notion that CDS returns reflect the information in equity short interest with delay, not apparently transmitted to CDS returns through other equity risk factors such as stock returns, equity beta, equity return momentum, and relative default risk, as our model explicitly controls for these factors. These controls increase the likelihood that CDS returns relate to lagged equity short interest incremental to inherent equity risk factors.[10] In addition, because the firm's relative default risk (*CRV*) does not subsume the equity short interest effect, this increases the likelihood that such effect relates to a nondefault risk component of credit spread, for example, credit instrument information risk (Duffie and Lando 2001; Yu 2005). The next subsection further explores the issue of whether our results suggest a distinct role for equity short interest in explaining CDS returns that is additive to a relation that might arise because of the equity-like nature of higher risk credit instruments.

4.2 Effects of investment versus speculative grade credit ratings

While the results for the full sample suggest that equity short interest helps explain 1-month-ahead CDS returns incremental to equity risk factors and default probability, we examine further that finding by partitioning our sample on a second measure of relative default risk. This second measure is whether analysts classify the credit instruments of the shorted stocks as investment grade (IG) or speculative grade (SG). Chiu et al. (2012) provide evidence that the actual average annual default rate is less than 1 % for IG instruments over 1983–2001 versus 4.9 % for SG instruments over the same period. SG instruments should thus respond more to default risk information in short interest than IG instruments. We use Markit's implied rating to classify CDS contracts as those with an implied rating of BBB or above (IG) or below (SG).[11] If our results relate intrinsically to default risk factors, then, similar to the studies mentioned above, we should observe a significantly negative *Short Interest* coefficient for SG instruments. On the other hand, if the *Short Interest* coefficient is stronger negatively for IG instruments, this suggests that equity short interest relates to future CDS returns for reasons that depend less on

[10] While we control equity market momentum as an explanatory variable in our prediction regressions, equity returns also might lead CDS returns in other ways. For example, the significantly negative relations between short interest in month t and CDS returns in months $t + 1$ could reflect an equity market response to short interest in month t but before CDS return month $t + 1$ (Gebhardt et al. 2005).

[11] Markit derives its implied ratings from credit rating agencies' ratings of the five-year public debt of the CDS reference entity.

default risk and the equity-like nature of speculative credit instruments and more on other factors, such as CDS information risk.

The last two columns of Table 3 summarize our test of H2—that the relation between equity short interest and 1-month-ahead CDS returns is stronger negatively for IG instruments versus SG instruments. First, we observe significantly negative *Short Interest* coefficients for IG instruments and SG instruments. Second, the difference between the two coefficients, i.e., $\textit{Short Interest}_{IG}$ less $\textit{Short Interest}_{SG}$, is also negative and significant.[12] These results therefore support H2. Recall that Eq. (2) controls for several equity risk variables and relative default probability (*CRV*), so that the significant explanatory role of equity short interest should relate more to factors affecting CDS returns in ways not affecting equity or SG investors. For example, compared to IG investors, we would expect SG investors to be more affected by relative default risk (*CRV*), which we control for in Eq. (2). Indeed, Table 3 shows a more positive *CRV* coefficient for SG than IG instruments (albeit not significant). In sum, the results for *Short Interest* in Table 3—that strengthen negatively for investment grade CDS instruments—make more credible the contention of a link between equity short interest and credit returns unrelated to the equity-like nature of SG credit returns. The above results suggest that equity short interest could be a signal about the information risk component of credit spread, transmitted to credit investors with apparent delay.

4.3 Effects of features of the shorting market

Cohen et al. (2007) hypothesize that proxies for changes in shorting demand and supply can explain the relation between short interest and future equity returns and, more generally, the role of the shorting market as a mechanism that reveals private information. In their view, when one separates the demand and supply elements of a change in short interest, this enables a better understanding of the mechanisms that might explain how private information in the hands of short sellers affects future returns. Using the percentage of shares outstanding on loan (or short interest) and loan fee as proxies for the quantity and price of shortable shares, respectively, Cohen et al. (2007) identify four quadrants of shifts in equity shorting demand and supply. The four quadrants are as follows. $DIN = 1$ if the shorted stock has seen its loan fee and lending supply fall in month t, i.e., an inward demand shift, and otherwise 0. $DOUT = 1$ if the shorted stock has seen its loan fee and lending supply rise in month t, i.e., an outward demand shift occurs, and otherwise 0. $SIN = 1$ if the shorted stock has seen its loan fee rise but lending supply fall in month t, i.e., an inward supply shift, and otherwise 0. $SOUT = 1$ if the shorted stock has seen its loan fee fall, but its lending supply rise in month t, i.e., an outward supply shift occurs, and otherwise 0. Cohen et al. (2007) hypothesize that negative future equity returns will occur for the *DOUT* and *SOUT* quadrants. In the *DOUT* case, more shares are shorted, even though it is more costly to short, supporting the notion that

[12] We test for a short interest coefficient difference by including dummy variables in Eq. (2) defined as $DUM_t = 1$ if IG firm and 0 otherwise, times each independent variable. For the key variable of our interest, *Short Interest*, we report the coefficient for DUM_t x *Short Interest* under the name of difference in *Short Interest* coefficient (between the IG and SG sub-samples).

Table 6 Regression of 1-month-ahead CDS return on Fama–French risk factors sorted on short interest quintile

Variable	Exp. sign	Quintile 1 (Lowest short interest)	Quintile 2	Quintile 3	Quintile 4 (Highest short interest)	Quintile 5
Panel A—value-weighted portfolio						
Intercept (α)		−0.0344	−0.0628	−0.1046	−0.1245*	−0.2738***
		(−1.25)	(−1.43)	(−1.45)	(−1.76)	(−2.83)
RMRF (β_1)	+	0.1272***	0.1345***	0.1750***	0.2615***	0.4328***
		(3.89)	(3.93)	(4.52)	(4.73)	(5.56)
SMB (β_2)	+	−0.0007	−0.0164	−0.0161	−0.0302	0.0654
		(−0.01)	(−0.25)	(−0.21)	(−0.28)	(0.43)
HML (β_3)	+	0.2358***	0.2875***	0.3058***	0.4640***	0.6780***
		(4.28)	(4.98)	(4.69)	(4.98)	(5.17)
Term (β_4)	±	0.0004	0.0002	0.0005	0.0007	0.0006
		(1.00)	(0.39)	(1.07)	(1.05)	(0.57)
Default (β_5)	+	0.1624***	0.1326***	0.1749***	0.1810***	0.2531***
		(3.16)	(2.58)	(2.83)	(3.28)	(3.20)
α (Q5) − α (Q1)	–	−0.2394*				
		(−1.87)				
Sharpe ratio		0.5638				
Adj. R^2		42.73 %	45.50 %	47.76 %	50.07 %	56.27 %
Panel B—equally-weighted portfolio						
Intercept (α)		−0.0293	−0.0608	−0.1036	−0.1224*	−0.2672***
		(−1.21)	(−1.42)	(−1.44)	(−1.75)	(−2.82)
RMRF (β_1)	+	0.1275***	0.1327***	0.1728***	0.2570***	0.4265***
		(3.90)	(3.89)	(4.48)	(4.68)	(5.55)
SMB (β_2)	+	−0.0016	−0.0162	−0.0148	−0.0311	0.0655
		(−0.03)	(−0.24)	(−0.20)	(−0.29)	(0.44)
HML (β_3)	+	0.2378***	0.2872***	0.3061***	0.4594***	0.6719***
		(4.32)	(5.00)	(4.71)	(4.96)	(5.19)
Term (β_4)	±	0.0004	0.0002	0.0005	0.0007	0.0006
		(1.06)	(0.39)	(1.08)	(0.98)	(0.59)
Default (β_5)	+	0.1609***	0.1326***	0.1746***	0.1812***	0.2473***
		(3.14)	(2.58)	(2.83)	(3.29)	(3.17)
α (Q5) − α (Q1)	–	−0.2379*				
		(−1.89)				
Sharpe ratio		0.5698				
Adj. R^2		43.02 %	45.45 %	47.68 %	49.68 %	56.28 %

Table 6 continued

This table reports the coefficients from time-series regressions of monthly portfolio CDS return on the five credit risk factors suggested by Fama and French (1993) for each of the five short interest quintiles. The following regression is estimated: $RET_t = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 Term_t + \beta_5 Default_t + e_t$, where t is an event-month index over 132 months, RET_t is the portfolio CDS return for the sample in month t, $RMRF_t$ is the excess return of the value-weighted market portfolio, SMB_t and HML_t are returns on zero investment, factor-mimicking portfolios for size and book-to-market equity in stock returns. $Term_t$ is the return on the 30-year Treasury bond minus the return on the 1-month Treasury bill, and $Default_t$ is the value-weighted return of all corporate bonds in FISD Mergent with a maturity greater than 10 years minus the return on the 30-year Treasury bond. The Sharpe ratio is computed as a transformation of the *t*-statistic and is computed as the *t*-statistic multiplied by 12 divided by 132, where 132 reflects the number of months in the regressions (Lewellen 2010). The Fama-McBeth *t*-statistic is reported in parentheses and ***, **, and * indicate significance levels of 0.01, 0.05, and 0.10 respectively

short sellers have nonpublic adverse information on the firm. In the *SOUT* case, more shares are shorted because "lowering the cost makes it possible for more investors to enter the market …," which relaxes the short sale constraint (p. 2073). As the constraint on previously overpriced stocks is reduced, their prices revert to fundamental values. Cohen et al. (2007) also argue that, if this relaxation associates with an instantaneous negative price adjustment, then *SOUT* represents a weaker indicator than *DOUT* for foreshadowing future returns because some mispricing may be resolved instantaneously. Consistent with their hypotheses, they find negative excess returns in the following month for stocks in the *DOUT* quadrant (e.g., −3.144 %, $t = -3.20$, for Regression 1 of their Table 3) and mostly insignificant results for stocks in the *SOUT* quadrant (for eight of the nine regressions in Table 3). They reason that this lagged response occurs because of outside investors' limited awareness of shorting market activity and conclude that "the shorting market is an important mechanism for private information revelation" (p. 2064). Their study has implications for ours because lower stock market efficiency can mean that equity short interest measures have less ability to transmit information quickly to other markets through stock price. Also, higher downside equity risk implies more asymmetric pricing for credit instruments than equities.

Table 4 shows univariate statistics for the four quadrants of the shorting market based on loan fees and the percentage of shares outstanding on loan. Consistent with the predictions in Cohen et al. (2007), we observe negative mean 1-month-ahead CDS returns for the *DOUT* (−21.24 bps) and *SOUT* (−3.27 bps) quadrants. We also observe positive mean 1-month-ahead CDS returns for the *DIN* and *SIN* quadrants. Thus, for outward shifts in short interest demand and supply, CDSs on average generate negative returns 1 month later. This comports with the view that these features of the shorting market—known at *t*—telegraph private information to the CDS investors, which is reflected in CDS prices on a lagged basis. The univariate results in Table 4, however, do not control for other variables that might explain the 1-month-ahead CDS returns.

To align our study with that of Cohen et al. (2007) and to control for other explanatory variables, we estimate the following regression of 1-month-ahead monthly CDS returns on shorting market demand and supply shifts and other controls, including the same equity return risk factors as in Eq. (2).

$$\begin{aligned} RET_{t+1} = {} & \alpha + \beta_1 DIN_t + \beta_2 DOUT_t + \beta_3 SIN_t + \beta_4 SOUT_t + \beta_5 \Delta Loan\,Fee_t \\ & + \beta_6 \Delta Short\,Interest_t + \beta_7 MOMS_t + \beta_8 MOML_t + \beta_9 BTM_t + \beta_{10} SIZE_t \\ & + \beta_{11} E/P_t + \beta_{12} BETA_t + \beta_{13} CRV_t + e_{t+1}, \end{aligned} \tag{3}$$

where t is an event month index, the shorting market variables are defined above, and the others are shown as part of Eq. (2) and defined in Appendix 1. Given this model, H3 states that we should observe negative coefficients for *DOUT* and *SOUT* in Eq. (3), in that these variables reflect investors' increased interest in shorting potentially related to knowledge of adverse private information. We also modify Eq. (3) by adding variables that represent the interaction of *DIN*, *DOUT*, *SIN*, and *SOUT* with *ΔLoan Fee* and the interaction of *DIN*, *DOUT*, *SIN*, and *SOUT* with *ΔShort Interest*. This is a way of testing whether the predicted negative coefficients for *DOUT* and *SOUT* are more informative about future CDS returns for short positions with tighter shorting constraints such as increased loan fees (Saffi and Sigurdsson 2011) or increased levels of short interest (Desai et al. 2002).

To implement these tests, we use the same shorting market definitions and terms as Cohen et al. (2007). First, we define the lending supply for stock i as the percentage of shares outstanding on loan, which earlier we defined as short interest ($Short\ Interest_t$) at time t. Second, we calculate the loan fee by using loan transactions data with information on the loan fee and the borrowed amount. Fees can be categorized into two groups contingent upon the type of collateral used. If borrowers pledge cash, which is pervasive in the United States, then the loan fee is defined as the difference between the risk-free interest rate and the rate paid for the collateral. If instead the transaction is based on other securities as collateral, the fee is directly negotiated between the borrower and the lender. Appendix 1 provides the details of the loan fee calculation.

Table 5 summarizes the results of estimating Eq. (3). Each column includes a different set of short interest variables in the regression. First, despite the slightly smaller sample sizes compared to Table 3 (from the absence of lending supply and loan fee data for all CDS return observations), we note that the coefficients for the control variables (from *MOMS* to *CRV*) resemble those summarized in the earlier table. Second, regarding the short interest variables, all five regressions show significantly negative coefficients for *DOUT*. Additionally, four regressions (Regressions 1, 2, 4, and 5) show significantly negative coefficients for *SOUT*, although the *SOUT* coefficients are notably smaller in absolute magnitude. For example, Regression 1 shows $\beta_2 = -0.3462$, whereas $\beta_4 = -0.1949$. On the other hand, none of the inward shift variables *DIN* or *SIN* significantly explains 1-month ahead CDS returns, either positively or negatively. These results thus support H3, suggesting that outward shifts in equity shorting demand and, to a lesser degree, shorting supply may explain a lagged CDS market response to equity short interest in the prior month. These results also mirror those of Cohen et al. (2007, p. 2077), who show significantly negative coefficients for *DOUT* and weaker results for *SOUT* for 1-month-ahead equity returns.[13]

Table 5 documents several other results. First, Regression 4 shows that an increase in short interest at *t* over the prior month further explains 1-month-ahead CDS returns after controlling for *DOUT*, *SOUT,* and the other variables. The coefficient for *ΔShort Interest* in Regression 4 is significantly negative. Additionally, Regression 5 shows that the *DOUT* coefficient is more negative when interacted with *ΔShort Interest*. In other words, Regression 5 shows that *ΔShort Interest* has further potential explanatory power when combined with an increase in shorting demand, as the interaction of *DOUT* x *ΔShort Interest* in Regression 5 is negative and significant. The intuition is that, when short interest increases over the prior month (*ΔShort Interest*), short sellers who observe an outward demand shift are even more sure that the potential benefits from shorting will exceed the costs, such as when short sellers have significant price-relevant negative information. This, in turn, means that the negative relation between short interest and future CDS returns should be greater for positions whose shorting has increased (*ΔShort Interest*), which we show in Table 5 (Regression 5). Overall, the results in Table 5 support H3 regarding outward shorting demand shifts, in that we observe strongly negative coefficients for *DOUT* and a significant but weaker interaction of *DOUT* and *ΔShort Interest* in Eq. (3). The results also support H3 regarding outward shorting supply shifts, although the magnitude of the relation between supply shifts and future CDS returns declines, possibly because CDS spreads can respond more quickly, since with increased supply more investors can enter the market. Overall, armed with the knowledge of these factors at *t*, this suggests that an investor could achieve positive excess returns in the following month by selling a CDS instrument short at month *t* and repurchasing it 1 month later following the negative CDS return produced by an increase in the spread.

5 Additional tests

5.1 Economic significance

So far we have shown a negative statistical relation between short interest and 1-month ahead CDS returns. We have suggested that this could enable CDS investors to earn excess returns. This subsection considers whether this relation might generate economically meaningful excess CDS returns. To implement this test and control for other variables, we regress monthly portfolio CDS returns on the five risk factors suggested by Fama and French (1993) for each of the five short

[13] Cohen et al. (2007) also suggest that the effects of *DOUT* are stronger for stocks with limited information flow, such as small stocks, which they define as those in the lowest quintile of market capitalization of all stocks in the regressions.

Table 7 Regression of 1-month-ahead CDS return on Fama–French risk factors conditional on short interest quintile and liquidity (value-weighted portfolio)

Variable	Exp. sign	Quintile 1 (Lowest short interest)	Quintile 2	Quintile 3	Quintile 4 (Highest short interest)	Quintile 5
Panel A—low liquidity (Markit composite depth score ≤ 3)						
Intercept (α)		0.0006	−0.0764	−0.0777	−0.0382	−0.2594*
		(0.00)	(−1.54)	(−1.43)	(−1.16)	(−1.94)
RMRF (β1)	+	0.0962***	0.1144***	0.1284***	0.2087***	0.3911***
		(2.74)	(3.42)	(3.03)	(3.82)	(4.76)
SMB (β2)	+	−0.0130	−0.0519	0.0330	−0.0468	0.1116
		(−0.19)	(−0.80)	(0.40)	(−0.44)	(0.70)
HML (β3)	+	0.2790***	0.2531***	0.3058***	0.3990***	0.6729***
		(4.71)	(4.50)	(4.29)	(4.33)	(4.86)
Term (β4)	+	0.0006	0.0002	0.0007	0.0003	0.0007
		(1.25)	(0.52)	(1.20)	(0.37)	(0.69)
Default (β5)	+	0.1363***	0.1285***	0.1647***	0.1359**	0.3101***
		(2.63)	(2.52)	(2.93)	(2.40)	(3.56)
α (Q5) − α (Q1)		−0.2600**				
		(−2.00)				
Sharpe ratio		0.6030				
Adj. R^2		35.86 %	36.03 %	36.17 %	37.89 %	51.59 %
Panel B—high liquidity (Markit composite depth score > 3)						
Intercept (α)		−0.0694	−0.0629	−0.0454	−0.2301*	−0.3518**
		(−1.46)	(−1.46)	(−1.27)	(−1.93)	(−2.00)
RMRF (β1)	+	0.1491***	0.1426***	0.1942***	0.3309***	0.4846***
		(4.16)	(4.45)	(4.89)	(5.70)	(5.85)
SMB (β2)	+	0.0066	−0.0024	−0.0185	−0.0160	0.0072
		(0.09)	(−0.04)	(−0.24)	(−0.14)	(0.04)
HML (β3)	+	0.2460***	0.2672***	0.2669***	0.5371***	0.7035***
		(4.07)	(4.95)	(3.99)	(5.49)	(5.04)
Term (β4)	+	0.0004	0.0002	0.0004	0.0013*	0.0003
		(0.76)	(0.43)	(0.69)	(1.78)	(0.28)
Default (β5)	+	0.1874***	0.1270***	0.1614***	0.2258***	0.2233***
		(3.49)	(2.51)	(2.95)	(3.32)	(2.91)
α (Q5) − α (Q1)		−0.2824*				
		(−1.82)				
Sharpe ratio		0.5488				
Adj. R^2		39.98 %	45.70 %	46.08 %	55.62 %	53.63 %

This table reports the coefficients from time−series regressions of monthly portfolio CDS return on the five credit risk factors suggested by Fama and French (1993) for each of the five short interest quintiles. The following regression is estimated: $RET_t = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 Term_t + \beta_5 Default_t + e_t$, where t is an event month index over 132 months and the variables and tests are the same as in Table 6 interest quintile portfolios. We then stipulate the alpha coefficient as a measure of risk-adjusted excess CDS return.[14] We state this model as Eq. (4) below.

$$RET_t = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 Term_t + \beta_5 Default_t + e_t, \quad (4)$$

where t is a short interest observation-month, RET_t is the portfolio CDS return for the sample in month t, $RMRF_t$ is the excess return of the value-weighted market portfolio, SMB_t and HML_t are returns on zero investment, factor-mimicking portfolios for size and book-to-market value of common equity in stock returns, $Term_t$ is the return on the 30-year Treasury bond minus the return on the 1-month Treasury bill, and $Default_t$ is the value-weighted return of all corporate bonds in FISD Mergent with a maturity greater than 10 years minus the return on the 30-year Treasury bond. As a measure of economic significance, we calculate the difference in the regression alphas in Eq. (4) of the highest (quintile 5) less the lowest (quintile 1) short interest portfolios. We also calculate the Sharpe ratio associated with the difference in the regression alphas.[15] We calculate this ratio as a transformation of the t-statistic for the annualized credit return difference as measured by the regression alpha (Lewellen 2010).

Panels A and B of Table 6 summarize the results of estimating the Fama–French model for each short interest quintile with value weights and equal weights, respectively, for the components of each portfolio. First, we find coefficients for the control variables similar to prior work. For example, the coefficient for *Default* is positive, indicating that average credit returns and the credit risk premium (albeit measured with error) co-move in the same way. Second, we find that the alphas vary across the five portfolios. For example, quintile 1 produces insignificantly negative alphas, whereas quintile 5 produces larger significantly negative alphas. Third, Panels A and B show significant CDS return differences for the value-weighted and equally-weighted portfolios of −23.94 and −23.79 bps per month, respectively. This is despite the fact that the control variables already explain a high overall percentage of the variation in CDS returns. However, the Sharpe ratios for these monthly hedge portfolio excess returns of 0.5638 and 0.5698, respectively, are low. Since the Sharpe ratio captures excess return relative to variation in excess return, we interpret these ratios as evidence that the predictive relation between equity short interest in month t and CDS return in month $t + 1$ has only limited economic significance.[16]

The hedge returns and Sharpe ratios also do not consider the transactions costs of trading in and out of long and short positions in CDSs, which we view as broadly equivalent to buying and selling offsetting CDS credit instruments. Prior evidence based on bonds suggests that the round-trip cost of such transactions may well

[14] We form these quintiles based on equity short interest in the month before each CDS return observation.

[15] Strictly speaking, this is a conditional Sharpe ratio, since the alpha coefficient in each regression is conditional on the credit risk factors specified as explanatory variables in each regression.

[16] These 1-month-ahead hedge portfolio returns and Sharpe ratios apply to the full sample and not to the conditional samples based on *DIN*, *DOUT*, *SIN*, and *SOUT* in Table 5. Untabulated analysis shows that we do not obtain significantly more negative 1-month-ahead hedge portfolio returns or higher Sharpe ratios for these subsamples.

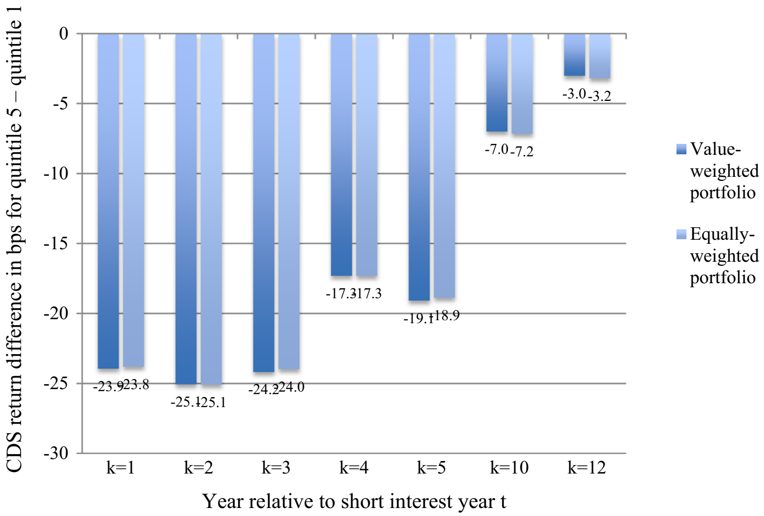

Fig. 1 Monthly excess CDS return differences for hedge portfolios of CDS returns. This figure plots the monthly excess CDS return differences in bps for hedge portfolios of CDS return on quintile 5 (high short interest portfolio) minus CDS return on quintile 1 (low short interest portfolio) for value-weighted and equally-weighted portfolios for CDS return months k = 1 (same as Table 5), 2, 3, 4, 5, 10, and 12. The CDS excess return differences are calculated as α (Q5) − α (Q1), where α (Q) is the intercept term in the regression of $RET_{t+k} = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 Term_t + \beta_5 Default_t + e_t$ for observations in short interest quintile 1 and observations in short interest quintile 5. This regression modifies Eq. (4) by replacing the dependent variable regression RET_t with RET_{t+k}

exceed the 1-month-ahead hedge returns in Table 6. For example, for round-trip costs as a whole, Schultz (2001) and Bessembinder et al. (2006) suggest an average round-trip transaction cost of 27 bps (based on insurance company bond trades from Capital Access International) and 18 bps (for a sample of institutional bond trades from the TRACE system), respectively. Additionally, as part of the overall round-trip cost, Asquith et al. (2013) report an average loan fee during 2004–2007 of 16 bps for shorting bonds (based on a proprietary data set). Also, Correia et al. (2012) report an average loan fee of 13 bps for shorting bonds during 2005–2010. Of course, the cost of hedging positions in CDS instruments subject to an increase in equity shorting demand or supply could differ from these averages. Notwithstanding this caveat, these cost data cast doubt on whether the statistically significant 1-month-ahead hedge portfolio CDS returns in Table 6 would be profitable net of round-trip transaction costs.

5.2 Sensitivity tests

We conduct several tests to check the reliability of our results. First, we replicate the regressions in Table 6 for RET_{t+k}, where k = 2–12 months. We predict attenuation of the monthly excess CDS return differences for hedge portfolios of CDS return on quintile 5 (high short interest portfolio) minus CDS return on quintile 1 (low short interest portfolio) as k increases. We show the untabulated results in Fig. 1. For the value-weighted portfolios, Fig. 1 shows monthly excess CDS return differences, stated in bps per month, of −23.9 (same as Panel A of Table 6), −25.1, −24.2, −17.3, −19.1, −7.0, and −3.0, for months $k = 1, 2, 3, 4, 5, 10$, and 12, respectively. For the equally weighted portfolios, Fig. 1 shows similar excess monthly excess returns. Although not strictly monotonically decreasing (negatively) in k, these panels confirm the prediction that the monthly excess CDS returns on the hedge portfolios diminish as the future month k increases. On the other hand, these results suggest that the hedge portfolio returns in Table 6 would increase if a portfolio formed at t were held for more than 1 month. If held for 3 months, Fig. 1 shows that the cumulative monthly excess CDS return differences would be 73.2 and 72.8 bps for the value-weighted and equally-weighted portfolios, respectively. These 3-month returns would likely exceed round trip transaction costs.

Second, we repeat the regressions in Table 6 for CDSs with low and high liquidity based on Markit's composite depth score (score ≤ 3 = low liquidity, score > 3 = high liquidity) for the CDSs in our sample. We assume that CDSs with a Markit score of greater than three are easier and less expensive to borrow, making more feasible the implementation of a hedge strategy based on extreme short interest positions. Table 7 shows the results for low and high liquidity CDSs, where each time-series regression uses only the observations in each liquidity/short interest partition to compute the hedge portfolio returns, and where the portfolios combine the individual CDS observations on a value-weighted basis. Panel A shows a hedge portfolio excess return of −26.00 bps for low liquidity CDSs. Panel B shows a hedge portfolio excess return of −28.24 bps for high liquidity CDSs. In other words, the high and low liquidity portfolios generate similarly negative hedge portfolio excess returns.[17] Put differently, it does not appear that our results are driven solely by low-liquidity CDSs. However, the Sharpe ratios for both the low and high liquidity hedge portfolio returns are low, similar to Table 6, further suggesting that it may be difficult to capture economically meaningful future returns by exploiting our empirical result that CDS spreads reflect equity short interest information with a 1-month lag.

Third, we consider the possibility of time variation in the strength of our results, which we examine in two ways. As one way, we partition the 2001–2011 study period into four subperiods. These are pre-financial crisis period one (January 2001–December 2003), pre-financial crisis period two (from January 2004 to June 2007), the financial crisis (from July 2007 to June 2009), and post-financial crisis (from July 2009 to December 2011). We then estimate Eq. (4) and calculate the hedge portfolio excess returns using the monthly return observations for each of these subperiods. Untabulated results show negative hedge returns in the first three subperiods but not the fourth. The most significant negative 1-month-ahead excess returns occur in the financial crisis period and are −50.53 and −50.52 bps for the value- and equally weighted portfolios, respectively. Consistent with attenuation, the negative 1-month-ahead excess returns in the pre-financial crisis period two

[17] The high and low liquidity portfolios also generate similarly negative hedge portfolio excess returns when the portfolios combine the individual CDS observations on an equally-weighted basis.

(January 2004–June 2007) are marginally less significant than the excess returns for pre-financial crisis period one (January 2001–December 2003). In addition, the 1-month-ahead excess returns in the post-financial crisis period are not significant. These results therefore suggest that the hedge portfolio excess returns may have weakened over time, although the smaller sample sizes for the CDS return subperiods may have hindered the potential for stronger results.

As another way to consider the possibility of time variation, we add a dummy variable for the financial crisis period to Eq. (2) and interact this variable with *Short Interest*. This approach does not reduce the sample size. We state the dummy variable as *Financial Crisis*, set equal to one for observations during July 2007 to June 2009 and zero otherwise. When we re-run the predictive regression in Eq. (2) including *Financial Crisis*, as predicted, untabulated analysis shows strongly negative coefficients for *Financial Crisis* and the interaction of *Financial Crisis* × *Short Interest*. We continue, however, to observe a significantly negative relation between *Short Interest* and 1-month-ahead CDS return, although the short interest coefficient is less negative ($\beta_1 = -1.4194$) than the otherwise equivalent coefficient reported in Table 3 ($\beta_1 = -3.1113$, for All observations).

Fourth, we analyze CDS subsamples by sequentially removing the three largest industries in the sample (Table 2). Untabulated analysis based on the remaining observations continue to show a negative coefficients for *Short Interest* similar to Table 3, so that industry composition does not appear to affect the results. Fifth, we split the sample by observations in quarterly earnings announcement and nonquarterly earnings announcement months, where, predictably, the first group comprises approximately one-third of the observations. We observe more negative *Short Interest* coefficients for the subsamples of earnings announcement months compared to the non-earnings announcement months. We reason that this occurs because earnings announcement months are the months when equity short sellers might consider news useful for trading purposes, which increases shorting demand.

Sixth, we confirm our results in Table 3 with monthly raw CDS return defined as $RET_t^{CREDIT} = -\Delta CS_t$. To increase the power of the test, we restrict our analysis to heavily shorted stocks, that is, those firm-month CDS return observations for which short interest in the prior month exceeds 2.5 % of the common stock outstanding. Specifically, we subtract from each raw CDS return the CDS return of a matching firm with the same size and book-to-market quintile rank as the sample firm in the month *before* it reaches a 2.5 % threshold level of short interest. Similar to the method used in Desai et al. (2002), we then calculate the average excess CDS return for periods relative to the month that the credit instrument enters the portfolio (i.e., the month after exceeding the threshold level of short interest or month one). Similar to Table 3, these results show significantly negative 1-month-ahead CDS returns, which are negative for the subsequent months as well similar to Fig. 1.[18]

[18] Additionally, we employ risk-adjusted measure of return by deflating our return approximation by duration times spread (e.g., $-\Delta CS_t/(Duration_t * CS_t)$), where Eq. (1) defines the variables. The results are qualitatively the same.

6 Conclusion

This paper presents evidence on the informational role of equity short interest in the CDS market—an under-researched area in accounting and finance. Our tests contribute to the literature in two key ways. We first find that equity short interest varies significantly and negatively with CDS returns in the month following the equity short position. This negative relation strengthens for equities subject to an increase in the demand for shortable shares, consistent with the theory that an increase in shorting demand proxies well for an increase in investors' expected benefits from unpublicized bad news. The negative relation also strengthens for investment grade credit instruments. We view this latter result as potentially interesting, for it implies that the relation between short interest and future CDS returns may not depend solely on credit instruments with equity-like features such as those with higher default risk. Short interest, for example, may inform investors about nondefault factors such as credit instrument information risk, which others have documented as a significant component of credit spread incremental to equity and default risk. Second, we find that a hedging strategy of taking long and short positions in low and high short interest CDS portfolios, respectively, produces statistically significant excess CDS returns in the month following the short interest position. However, our tests of economic significance suggest that this predictive pattern in CDS returns is not strong enough to cover the round-trip costs of trading in the secondary credit markets.

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Appendix 1: Variables used in the regressions

Variable	Description
$BETA_t$	Equity market beta estimated from a rolling regression of 60 months of data requiring at least 36 months of non-missing return data
BTM_t	Book-to-market ratio measured at the most recent fiscal quarter end t, measured as CEQQ/PRCCQ*CSHOQ from Compustat
CRV_t	Credit relative value (a measure of relative default risk) defined as the natural logarithm of the ratio of CDS spread to $D2D$, where $D2D$ = expected default probability implied by the KMV-Merton (1974) distance-to-default ($D2D$) model, as explained in Appendix 2
$Default_t$	Value-weighted return of all corporate bonds in month t in FISD Mergent with a maturity greater than 10 years minus the return on the 30-year Treasury bond

Variable	Description
DIN_t	1 if the shorted stock has seen its loan fee and lending supply fall in month t, i.e., an inward demand shift occurs, otherwise 0
$DOUT_t$	1 if the shorted stock has seen its loan fee and lending supply rise in month t, i.e., an outward demand shift occurs, otherwise 0
E/P_t	Net income (NIQ from Compustat) from the most recent four quarters divided by the market capitalization at the fiscal period end date
HML_t	Fama–French factor-mimicking portfolio for book-to-market value of common in month t stock return
Lending Supply	The same variable as *Short Interest* (Cohen et al. 2007, p. 2068) defined below
Loan Fee	The difference between the risk-free interest rate and the rate paid for the collateral if a borrower pledges cash or the negotiated fee if the transaction is based on other securities as collateral. This can be summarized as: $\text{Loan fee}_{n,i,t} = \begin{cases} \text{Fee}_{n,i,t} & \text{if noncash collateral} \\ \text{Riskfree rate}_{n,i,t} - \text{Rebate rate}_{n,i,t} & \text{if cash collateral} \end{cases}$, where n denotes transaction, i stands for security, and t denotes the date in which the transaction appears in the dataset. We value-weight the loan fee of a given stock on a given date by the loaned amount as: $\text{Loan fee}_{i,t} = \sum_{n=1}^{N_{i,t}} \left[\frac{\text{Loanamount}_{n,i,t}}{\sum_{n=1}^{N_{i,t}} \text{Loanamount}_{n,i,t}} \cdot \text{Loan Fee}_{n,i,t} \right]$, where n denotes the transaction, i stands for security, t represents the week in which the transaction appears in the dataset, and $N_{i,t}$ is the total number of outstanding transactions for the security i in week t
$MOML_t$	Three-month half-life weighted average of stock return for the 11 months ending in the beginning of month t
$MOMS_t$	Stock return for month t
RET_t	CDS return for a sample firm in month t, as defined by Eq. (1)
RET_{t+k}	CDS return for a sample firm in month t + k, as defined by Eq. (1)
$RMRF_t$	Excess return for the value-weighted market portfolio in month t
Short Interest$_t$	The number of uncovered short positions scaled by the total number of common shares outstanding at the end of month t
SIN_t	1 if the shorted stock has seen its loan fee rise but lending supply fall in month t, i.e., an inward supply shift occurs, otherwise 0
$SIZE_t$	Natural logarithm of market capitalization, calculated as price times number of shares outstanding from CRSP at the end of the month t
SMB_t	Fama–French factor-mimicking portfolio for size in month t stock return
$SOUT_t$	1 if the shorted stock has seen its loan fee fall but its lending supply rise in month t, i.e., an outward supply shift occurs, otherwise 0
$Term_t$	Return on the 30-year Treasury bond minus the return on the 1-month Treasury bill

Appendix 2: The KMV-Merton default probability forecasting model

The KMV-Merton default forecasting model yields an expected default probability for each firm in the sample at a given point in time. To compute the probability, the face value of the firm's debt is subtracted from an estimate of the market value of the firm (e.g., the sum of the market values of the firm's debt and the value of its equity) scaled by a measure of the volatility of the firm. The market value of debt is estimated with the Merton (1974) bond-pricing model. The Merton bond-pricing model derives from the assumption that the total value of a firm follows the geometric Brownian motion, stated as:

$$dV = \mu V dt + \sigma_v V dW, \tag{5}$$

where V is the total value of the firm, μ is the expected continuously compounded return on V, σV is the volatility of firm value, and dW is a standard Weiner process. The Merton model also assumes that the firm has issued just one discount bond maturing in T periods. Under these assumptions, the equity of the firm is a call option on the underlying value of the firm with a strike price equal to the face value of the firm's debt and time-to-maturity of T. In addition, the value of equity derives from the Black–Scholes-Merton formula. By put-call parity, the value of the firm's debt equals the value of a risk-free discount bond minus the value of a put option written on the firm, again with a strike price equal to the face value of debt and a time-to-maturity of T. Symbolically, the Merton model stipulates that the equity value of a firm satisfies the following:

$$E = VN(d_1) - e^{-rT} FN(d_2) \tag{6}$$

where E is the market value of the firm's equity, F is the face value of the firm's debt, r is theinstantaneous risk-free rate, $N(\cdot)$ is the cumulative standard normal distribution function, d_1 is:

$$d_1 = \frac{\ln\left(\frac{V}{F}\right) + (r + 0{,}5\sigma_V^2)T}{\sigma_V \sqrt{T}}, \tag{7}$$

and $d_2 = d_1 - \sigma_V \sqrt{T}$. This formula is referred to as the Black–Scholes-Merton option valuation equation. The KMV-Merton model also relates to the volatility of the firm's equity relative to the volatility of firm value. Under Merton's assumptions, the value of equity is a function of the value of the firm and time, so it follows directly from Ito's lemma that:

$$\sigma_E = \left(\frac{V}{E}\right) \frac{\partial E}{\partial V} \sigma_V. \tag{8}$$

In the Black–Scholes–Merton model, it can be shown that $\partial E/\partial V = N(d_1)$, so that under the Merton model's assumptions, the volatilities of the firm and its equity are related by:

$$\sigma_E = \left(\frac{V}{E}\right) N(d_1)\sigma_V. \tag{9}$$

The KMV-Merton model derives from nonlinear Eqs. (6) and (8), which translate the value and volatility of a firm's equity into an implied probability of default. We implement the KMV-Merton default forecasting model in three steps. First, we measure σE from either historical stock return data or from option implied volatility data. Second, we use historical returns data to estimate σE, using a forecasting horizon of 1 year (T = 1) and use the book value of the firm's total liabilities as the face value of the firm's debt. Third, we collect values of the risk-free rate and market equity of the firm. These three steps determine values for each of the variables in Eqs. (6) and (8) except for V and σV, the total value of the firm and the volatility of firm value, respectively. Finally, we simultaneously solve Eqs. (6) and (8) numerically for values of V and σV to calculate the distance to default as where d_1 is defined in Eq. (7). Our measure is:

$$DD = \frac{(\ln(V/F) + (\mu - 0.5\sigma_V^2)T)}{\sigma_{\mathrm{V}}\sqrt{\mathrm{T}}}, \tag{10}$$

where μ is an estimate of the expected annual return of the firm's assets. The corresponding expected default probability ($D2D$), which we use to calculate CRV is:

$$D2D = \mathrm{N}\left(-\left(\frac{\ln\left(\frac{V}{F}\right) + \left(\mu - 0.5\sigma_V^2\right)T}{\sigma_V^2}\right)\right) = \mathrm{N}(-DD). \tag{11}$$

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