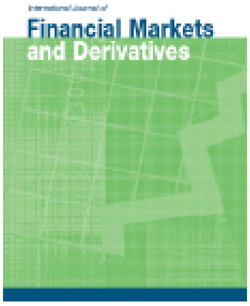

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The relative efficiency of investment grade credit and equity markets

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Abstract: I examine the relative efficiency of investment-grade CDS and equity markets using a set of liquidly tradable indices for both markets. Prior research has focused on manually constructed indices created from matched portfolios for the equity market. While this results in a matching of constituents, it only produces a theoretical trading instrument. Moreover, that research has only examined the 5-year CDS maturity whereas I also examine the 10-year, which better matches the indefinite life of a stock. Finally, I investigate the potential for size bias. I observe that the longer-dated CDS maturity and an equally weighted equity index in which large capitalisation bias is removed are informationally inefficient, with the equity market having a relative advantage. While no such advantage is observed in the other indices, overall results indicate liquidly traded indices are not as efficient as manually constructed matched portfolios and arbitrage profits may be possible using specifically paired indices.

Keywords: credit derivatives; market efficiency; price discovery; lead-lag relationship; credit markets; CDS indices.

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Biographical notes: William J. Procasky is an Assistant Professor of Finance in the Accounting and Finance Department of Texas A&M University-Kingsville. He has 25 years of professional experience in derivatives, energy and corporate banking. His research interests include financial derivatives, market efficiency, credit default swaps and debt capital markets.

1 Introduction

This paper examines the relative market efficiency of the investment-grade CDS and equity markets using a diversified set of liquidly tradable indices differing by maturity (10-year CDS index vs. 5-year) and calculation methodology (market capitalisation weighted equity index vs. equally weighted). The primary purpose and contribution to the literature is to compare the results to prior studies involving CDS indices and matched equity portfolios, of which the latter is not tradable as an index. As a result, there may be differences in the results generated by an actual instrument vs. a theoretical one. Most recently, Procasky (2021) used matched portfolios and observed that neither market has an informational advantage over the other, meaning they are equally efficient. This paper also contributes to the literature by extending the relative efficiency analysis to examine for heterogeneity based on CDS index maturity (prior efforts have only focused on the 5-year index) and size (which I do by testing for size bias in the initial results).

While relative efficiency studies are designed to ascertain whether one capital market has an advantage over the other in incorporating new information into prices, and hence, is more efficient on a relative basis, theoretically, such an advantage should not exist. Why is that? Although the examined asset classes in this study differ in their non-risk/adjusted reward trade-off, per the Merton (1974) model, their values should be driven by the same set of factors. Specifically, as equity is essentially viewed as a long call option on the value of a firm's assets with debt – whether cash or synthetic – being a short put option on the same assets, neither market should possess an informational advantage due to put-call parity. The risk adjusted return on CDS should equal the corresponding long or short cash positions in the equity and/or bond markets, or put another way, they should react in the same way to the same information at the same point in time, otherwise risk-free arbitrage profits are possible on the basis of the implied credit spread embedded in the equity price (Duffie, 1999). However, practically speaking, informational inefficiencies may occur due to frictions and when so, the market quicker to price in information is deemed more efficient, with this information then 'flowing' to the less efficient one and being captured in prices.

Interestingly, almost all relative efficiency studies investigating CDS and equity markets have focused on the non-systematic, or firm-specific relationship, although indices continue to increase their market share and now comprise over 50% of the overall \$9 trillion CDS market.[1] These studies pool individual CDS and stocks prices for firms and then draw conclusions based on the observed relationship for the majority. However, due to the fact that these indices are traded at much narrower bid-offer spreads than firm-specific CDS, investors can buy default protection much more efficiently than if they had to purchase each single name CDS (Fung et al., 2008).

The main exceptions in the research stream and most related to this study are Fung et al. (2008) and Procasky (2021). However, Fung et al. (2008) had to rely on manually constructed CDS index proxies comprised of aggregated single name quotes for half of their 2001-2007 data since the indices were first created in April 2004, potentially skewing the results and precluding generalisation of the findings. In addition, as stated, Procasky's (2021) examination only utilised matched equity portfolios, which are theoretical indices and therefore, not liquidly tradable. Moreover, both studies only used one point along the CDS curve, the 5-year maturity, leaving the potential for heterogeneity in the 10-year unexplored, and neither investigated the potential for size bias. Finally, the studies observed different relationships between the subject markets, with Fung et al (2008) documenting that the equity market leads the CDS while Procasky (2021) observes no lead-lag relationship in either direction, leaving some questions still unanswered with respect to relative market efficiency in systematic markets.

So why has existing research focused on firm specific studies? This is primarily due to how the CDS market evolved, coupled with the advent of the subprime mortgage crisis in 2008. While the product was still rather new, data was only available on non-systematic, single-name CDS and once there was critical mass to construct liquidly tradable aggregate indices, early research focused on asset-backed indices like the ABX deriving their value from the subprime mortgages at the centre of the crisis (Augustin et al., 2014). However, given the growing importance of these indices and greater liquidity [they are up to 5× more liquid than liquid single-name CDS according to Chen et al. (2011)], research into how investors utilise these instruments is very critical in understanding today's market.

What makes CDS indices so popular? To answer, the most visible, the Markit CDX investment-grade Index ('CDX.NA.IG') and focus of this study, is an aggregation of the risk premiums of 125 large investment-grade firms in North America on which CDS are most liquidly traded, each weighted by 0.8% in calculating the overall index premium.[2] By collecting such a broadly diversified pool of constituent firms into an aggregate index, firm-specific risk is diversified away, leaving only non-diversifiable risk, to systematic factors driving probabilities of default in an economy such as growth in GDP, inflation, interest rate level, etc. Given the benefits of this diversification, investors can efficiently hedge country, region and industry sector risk exposures in their portfolios, in addition to expanding their investment opportunity set in constructing efficient portfolios. Additionally, due to the fact that properly devised measures effectively gauge overall default risk in an economy, such indices are valued by many different types of stakeholders for their informational content.

Against that backdrop, this paper contributes to the literature in the following ways:

1. examines the trade-off between perfectly matched equity portfolios (which an investor can construct on their own) vs. liquidly tradable indices (which do not match but contain less frictions in executing)
2. uses liquidly tradable indices for the entire data set in both markets
3. offering an additional perspective on the relative efficiency of investment grade markets, given mixed prior results
4. analyses multiple maturities along the CDS curve, enabling an understanding of the potential differences in CDS investor preferences based on the duration of the underlying instrument
5. investigates the potential issue of large capitalisation stock bias in cross-market flow, intersecting with and adding a new dimension to the literature stream on the size effect observed by Banz (1981).

Interestingly, I observe that the longer-dated CDS maturity and an equally weighted equity index in which large capitalisation bias is removed are informationally inefficient, with the equity market having a relative advantage. Also, while the other indices examined do not detect any relative advantage in either market, overall the results indicate that liquidly traded indices are not as efficient as manually constructed matched portfolios in the investment grade sector, where Procasky (2021) observed that information is quickly impounded in prices in both markets As a result, this leaves open the possibility that arbitrage profits may be made by taking positions in the 10-year CDX.NA.IG based on prior movements related to smaller capitalisation firms in the S&P 500, captured by an equally weighted S&P 500 ETF. When the ETF return is positive (negative), arbitragers could sell (buy) the CDS index. Of course, any resultant profit would need to more than offset transaction costs related to crossing the bid-ask spread.

The remainder of this paper is structured as follows: the next subsection discusses the origins and evolution of the CDS market while Section 2 examines the related literature. Sections 3 and 4 review the data and methodology/econometric model while Section 5 discusses the empirical results. Section 6 concludes.

1.1 CDS market overview

The first CDS was transacted in 1994 and while the market is now $9 trillion in gross notional volume, growth has not been linear. CDS were developed by banks to give them the ability to transfer credit risk in their corporate loan portfolios, typically syndicated loans to large firms with the critical mass required to issue bonds that could be utilised as reference obligations. These banks wanted an efficient way to avoid being locked into a buy and hold position for the entire tenor of these loans.[3] Previously, they only had the mechanically less efficient option of the secondary loan market to transfer credit-related exposure (Duffee and Zhou, 2001).

Initial growth was slow, only gaining critical mass and liquidity as the 1990s drew to a close. Specifically, in the 1994–1997 time period, volume increased to only $180 bn. However, as outlined by Augustin et al. (2014), the standardised CDS contract/annex in 1999, credit definitions in 2003 and exemption in the commodity futures modernisation Act from CFTC oversight in 2000 established the contractual, legal and regulatory foundation needed for an increase in trading and liquidity. With this framework in place, the market exploded in size to $6 trillion at the end of 2004.

Innovation also started to occur, resulting in the development of credit derivatives beyond the standard single-name CDS, of which one was the CDS index. This multi-name credit derivative enabled a purchaser, usually a large fund manager, to buy protection or invest in a large portfolio of pooled CDS in a specific economy, region, industry, credit quality, etc., more efficiently than purchasing each name individually. Because these instruments aggregate and communicate relevant economic and market-related information, they were also valued as leading indicators.

The most complex multi-name credit derivative was the synthetic collateralised debt obligation (CDO). As the US housing market heated up, banks created CDOs with residential mortgage backed securities backed by pools of residential home mortgages as underlying bonds. This replacement of a corporate bond with a non-traditional asset was a major shift in the market and eventually set the stage for synthetic CDOs and indices backed by such assets to contribute to and exacerbate the housing crisis, although they did not precipitate the crisis (Stulz, 2010).

With these multi-name instruments, the market again experienced explosive growth, morphing from $6 trillion in 2004 of mostly single-name CDS (80%), to approximately $60 trillion in 2007, split between single-name and multi-name credit derivatives (55% vs. 45%). Nonetheless, as per Chen et al. (2011), volume was concentrated in the interdealer market, with 85% of all deals being done by a relatively small number of banks (14), exposing the market to a significant level of systemic risk.[4] With this, as the housing crisis hit in 2008, volume started to decrease, a trend then accelerated by the bankruptcy of Lehman Brothers, a major player in the CDS market, after which regulators starting implementing safeguards to manage systemic risk. By the end of 2009, volume had fallen to $33 trillion and steadily declined thereafter to today's level of $9 trillion.

Despite this shrinkage, though, the market remains relevant, as the original need for which CDS were developed, namely the efficient transferring of corporate credit risk between parties, still exists (Alloway, 2015). In addition, some of the observed is the result of beneficial reforms to improve the safety of the market (Augustin et al., 2014). Two of these are the compression of gross interdealer exposure with a given counterparty into one consolidated net exposure and the elimination of counterparty risk through the movement of OTC trading to centralised clearinghouses (59% of all CDS trades were on CCPs as of June 2020, up from 29% in December 2014). Moreover, the type of trading activity that contributed to the financial crisis, CDS protection written on pools of subprime MBS, is immaterial (BIS, 2021). Accordingly, CDS are still positioned to play a continuing role facilitating economic growth via risk management (Milken Institute, 2014).

2 Literature review

As stated, the majority of historical literature has centred on the firm-specific relationship, leaving systematic flow underexamined. In addition, there has not been a consensus with respect to the relative efficiency of these financial markets. To illustrate, some examinations observe CDS to lead the equity market (Norden and Weber, 2004; Byström, 2006; Acharya and Johnson, 2007; Ni and Pan, 2011; Han and Zhou, 2011; Rodríguez-Moreno and Peña, 2013; Xiang et al., 2017; Zhou et al., 2022), while others document the opposite, i.e., the equity market leads the CDS (Forte and Pena, 2009; Norden and Weber, 2009; Marsh and Wagner, 2012; Narayan et al., 2014; Hilscher et al., 2015; Shahzad et al., 2017; Procasky and Petrus, 2021). Moreover, Fung et al. (2008) and Procasky (2021) observe a two-way relationship in the high-yield systematic market in which each market captures certain information more efficiently while Longstaff et al. (2003) find no relationship at all. Finally, Procasky and Yin (2022) observe a two-way interactive effect on an out-of-sample basis, with informational flow from the CDS to the equity market being stronger overall.

However, much of this disparity in results is due to material differences in the size of the samples, markets investigated, time periods examined, choice of econometric methodology, geography studied, credit quality of the sample and data frequency. Additionally, regarding studies utilising multivariate daily time series data over longer periods of time such as the current one, the equity market generally has led the CDS market in the investment grade sector (Fung et al., 2008; Norden and Weber, 2009; Marsh and Wagner, 2012; Hilscher et al., 2015; Procasky and Petrus, 2021), with Procasky (2021) being the only to observe no such relationship. However, none of the studies have investigated the longer-dated CDS index maturity or the potential for size bias. Also, only the Fung et al. (2008) and Procasky (2021) studies examine systematic markets, as Norden and Weber (2009), Marsh and Wagner (2012) and Hilscher et al. (2015) use single-name CDS data, Procasky and Petrus (2021) investigate investment grade-rated industry subsectors of the CDX.NA.IG and Fung et al. (2008) use aggregated single name data for half of their data set. As a result, Procasky (2021) is the study most comparable to the current one and the primary examination against which to benchmark its findings.

3 Dataset

The sample begins on 29 November 2004 and ends 18 September 2015. CDX.NA.IG data is from Markit and comprised of series three through 24 for the 5-year and 10-year maturities. Markit owns and operates these indices, including their licensing, marketing, administration and calculation on a daily basis (which it publishes on its website). In calculating the value of the index, Markit collects mid, or bid/offer spreads (and applicable prices) from licensed CDX index market makers and calculates the arithmetic average of the mid-points of these spreads after dropping the highest and lowest quartile. Different series are produced given that indices are rebalanced every six months. During this process, constituents may be removed and replaced based on various rules governing the construction process, including but not limited to the level of trading liquidity of individual CDS, change in credit rating or occurrence of a credit event. Once a new series is issued (sequentially one number higher), it replaces the prior one as the on-the-run, or most recent index.

Stock data is sourced from CRSP while the equally weighted S&P 500 index data is downloaded from S&P/Dow Jones' website. Data on the equally weighted S&P 500 index begins on 31 March 2006, resulting in a time period of shorter duration than for the market cap weighted index, however this does not impact the overall findings since this index only is utilised to detect any size bias in the initial result.

Table 1 reflects descriptive statistics for the subject indices. While the mean risk premium for the 5-year CDX.NA.IG (87 bps) is lower than the 10-year maturity (108 bps), the maximum value (279 bps) is higher (250 bps) as CDS curves have been observed to invert during periods of distress and these values occurred during the financial crisis. Also, while standard deviations are greater for the CDX indices, this is not surprising given their lower volume in trading vis-à-vis the stock indices.

Table 1 Descriptive statistics for dataset

Time series	*Obs.*	*Mean*	*Std. dev.*	*Min*	*Max*	*Returns*	
						Mean	*Std. dev.*
CDS							
CDX.NA.IG 5Y	2,680	87.0	42.6	28.8	279.7	0.000505	0.02949
CDX.NA.IG 10Y	2,671	108.8	31.45	53.6	250.5	0.003110	0.02974
EQUITY							
S&P 500	2,684	1,399.0	322.9	676.5	2,130.8	0.000189	0.01240
S&P 500 Equal	2,353	1,424.9	337.1	676.5	2,130.8	0.000157	0.01303

4 Methodology

4.1 Research questions/procedure

I perform four studies on cross-market informational flow by pairing each of the liquidly tradable CDX and equity indices in Table 1 to ascertain the existence of any lead-lag relationship. In addition to the bellwether 5-year maturity of the CDX.NA.IG, I also examine the less liquid 10-year maturity (per DTCC Warehouse Data) for the first time given that its longer duration is a better theoretical approximation of the indefinite average life of a stock, and knowledge of how investors use this point on the CDS curve is useful.

With this being the first investigation of the 10-year index, the first two pairings are the CDX.NA.IG 10-year maturity and the and two S&P 500 indices. After the analysis of the 10-year, I then examine the 5-year CDX index and both equity indices. While the traditional S&P 500 contains more companies than the CDS indices and is calculated on a market capitalisation basis, the analysis has practical relevance for two reasons. First, the S&P 500 consists primarily of higher quality investment-grade constituents and as such, if both indices are effectively capturing systematic risk, the nature of this relationship is essential to understand. Second, the S&P 500 is a much-watched bellwether indicator of the general health of the economy (and therefore, typically a component of financial market 'dashboards' constructed by investors). Investors seeking to monetise perceived arbitrage opportunities, or express views on their future directionality can efficiently use them.

Also, and for the first time in the literature, I examine the CDX.NA.IG maturities and an equally weighted S&P 500 to detect the presence of any size related effect (Banz, 1981), or bias in the first test, since the traditional S&P 500 calculation methodology gives greater weight to large firms. Because large companies tend to have more information flow and greater market efficiencies (Hong et al., 2000), the broader underlying trend in causality could be masked. The rare instances in the literature examining this are mixed in conclusion. While Narayan et al. (2014) observe a size effect, Marsh and Wagner (2012) do not, however both authors examined non-systematic flow.

In each examination, I also investigate for the potential for asymmetries during the financial crisis, as heterogeneity may be present due to shifts in investor behaviour. This period is defined as beginning on June 7th, 2007 and ending on July 8th, 2009, during which time the average level of the VIX was 30.85 compared to 17.02 otherwise.

Finally, I undertake robustness tests to check for the possibility of un-modelled factors to have impacted both markets (thus skewing results through omitted variable bias), confirm the choice of econometric model is correct based on the statistical properties of the sets of time series data, and see whether the 'mood of the market' impacts results (following Fung et al., 2008; Procasky, 2021).

4.2 Econometric model

I use a vector autoregression model (VAR) model often employed in investigating relative market efficiency.[5] This model was devised by Sims (1980) to detect lead-lag relationships between sets of stationary time series variables, in this case daily CDS and equity index returns.[6] Variation in each variable is a function of lagged values of itself and the other time series variable, with both equations solved simultaneously as follows:

$$\begin{aligned} \Delta CDS_t &= a_1 + \sum_{j=1}^{k} b_{1j}\Delta Equity_{t-j} + \sum_{j=1}^{k} c_{1j}\Delta CDS_{t-j} + \varepsilon_1 \\ \Delta Equity_t &= a_2 + \sum_{j=1}^{k} b_{2j}\Delta Equity_{t-j} + \sum_{j=1}^{k} c_{2j}\Delta CDS_{t-j} + \varepsilon_2 \end{aligned} \tag{1}$$

where ΔCDS_t: current percentage change in CDS index, $\Delta Equity_t$: current percentage change in stock index, ΔCDS_{t-j}: lagged percentage change in CDS index with lag order j, $\Delta Equity_{t-j}$: lagged percentage change in stock index return with lag order j, ε_t: error term.

The number of lags to incorporate in the VAR is determined through utilisation of information criterion developed to identify the best fit from a group of competing models differing in lag order. Specifically, I use the Schwarz Bayesian and Hannon Quinn selection statistics due to, advantages they have over others in obviating overparameterisation.[7]

A Granger causality Wald test (Granger, 1969) is then performed to ascertain whether one time-series variable 'Granger-causes' the other, which in this examination, would mean that new information that comes to market is first captured in the pricing of that market and then 'flows' into the pricing of the other. The null hypothesis is that all lagged coefficients of one market featuring the other as the dependent variable are equal to zero, thus, if rejected, that market is observed to be useful in anticipating future values of the other, meaning it captures news first as it is released. If not rejected, the market is deemed to not possess an informational advantage over the other.[8]

To address the potential for omitted variable bias in a specification with two variables, I also add additional systematic economic variables to (1) and run the tests anew. If different, I conclude that the first was biased due to non-inclusion of these explanatory variables. Following prior literature (Norden and Weber, 2009; Fung et al., 2008; Collin-Dufresne et al., 2001), I include the change in the 3-month T-bill rate for interest rates, slope of the Treasury curve for point along the economic cycle, lagged 5-year swap spreads for the level of default risk and lagged implied volatility of the stock market for level of investor fear.[9] I further investigate the potential for asymmetry associated with market conditions since Granger causality generates an 'average' result across the time period studied. This is done by dividing the data into up and down days based on if the return is negative or positive, and then running the aforementioned tests on each 'bucket' separately. If the results differ, I conclude that market conditions impacted efficiency and information flow. If not, the relationship is unaffected by 'market mood'. The separation into positive and negative return days is accomplished through an interaction term multiplying *CDS* and *Equity* by a dummy variable, *Sign*.

Finally, to confirm the choice of model is appropriate, I add a moving-average (MA) process to the VAR system in (1) to determine if the true form based on the statistical properties of the data should also include lagged unobserved economic shocks (lagged error terms). Known as a VARMA, this model has theoretical advantages vis-à-vis the more widely employed VAR in certain circumstances (Lütkepohl, 2006; Dias and Kapetanios, 2014). One final time, I compare the results to the original and if they do not differ in substance, conclude the VAR is the correct form of model. If they do, the relationship may be better specified with a VARMA model, which would necessitate rerunning the aforementioned tests. Procedurally, a lagged error term of the order of the model is added to (1).

5 Results

Table 2 reflects results for the 10-year CDX.NA.IG and S&P 500. All autoregressive panels are specified as VAR (1) models per the information criterion, meaning that past prices only affect the next day's price across the data set.

Interestingly, an initially significant level of cross-market flow is observable from the S&P 500 to the CDX.NA.IG based on the bordered and bolded p-value of 0.04 (coupled with the Wald test p-value of .00) for the total sample (panels A and F), suggesting the S&P 500 may be more efficient in pricing in new news. However, informational flow from this market is neither evident during the financial crisis (panel B), nor when investor sentiment is negative (panel C and D), a surprising result given the initial finding and the fact that the financial crisis was a time when negative feedback loops from the equity to the less liquid 10-year CDS market might have been expected.[10]

Table 2 CDX.NA.IG 10-Year Index and S&P 500

Dependent variable	*Lagged CDS index*		*Lagged equity index*		*Lagged VAR system*	
	CDX.NA.IG$_{t-1}$	*p-value*[a]	*S&P 500$_{t-1}$*	*p-value*[a]	*chi2*	*p-value*
Panel A: 2004–2015						
S&P 500$_t$	0.001	(0.42)	–0.091	**(0.00)	23.32	**(0.00)
CDX.NA.IG$_t$	–0.097	**(0.00)	–0.588	*(0.04)	27.97	**(0.00)
Panel B: Crisis						
S&P 500$_t$	0.034	(0.19)	–0.101	(0.07)	23.32	**(0.00)
CDX.NA.IGt	0.074	(0.18)	–0.156	(0.17)	9.09	**(0.01)
Panel C: Down market[b]						
S&P 500$_t$	0.008	(0.83)	–0.186	**(0.01)	15.36	**(0.00)
CDX.NA.IG$_t$	–0.176	(0.24)	0.074	(0.35)	9.25	*(0.05)
Panel D: Down Mkt/crisis						
S&P 500$_t$	–0.005	(0.74)	–0.141	**(0.00)	29.71	**(0.00)
CDX.NA.IG$_t$	0.003	(0.98)	–0.655	(0.18)	3.31	(0.51)
Panel E: Exogenous vars						
S&P 500$_t$	0.001	(0.41)	–0.091	**(0.00)	31.25	**(0.00)
CDX.NA.IG$_t$	–0.097	**(0.00)	–0.147	(0.73)	30.86	**(0.00)
Panel F: VARMA						
S&P 500$_t$	0.001	(0.41)	–0.090	**(0.00)	50.91	**(0.00)
CDX.NA.IG$_t$	–0.097	**(0.00)	–0.583	*(0.04)	50.91	**(0.00)

Notes: ** and * denote significance levels of 1%, 5%, respectively.
[a]Relevant intermarket causalities are bordered; significant ones are bolded.
[b]Only down markets results are included in chart since results for the up-market test do not differ.

However, this unexpected mixture of inefficiency and efficiency is resolved by the robustness test for systematic factors exerting influence ‘behind the scenes’ (panel E). Specifically, based on the insignificant p-value of .73, which fails to reject the null hypothesis, when these factors are included in the model, informational flow from the equity market disappears, suggesting the initial finding was spuriously driven by another factor. As such, the overall result supports the prior observation from Procasky (2021) that systematic investment-grade markets are efficient and moreover, that this efficiency may be independent of the CDS index maturity. It also underscores the importance of modelling additional systematic economic factors in cross-market studies involving only pairs of variables to ensure they are not influencing results.

Moving onto the next pairing, Table 3 reflects results of the 10-year CDX.NA.IG with the equally weighted S&P 500 index to examine whether size-related inefficiency exists at the longer-dated maturity which may have been masked by the market cap weighting of the S&P 500. Again, all panels are specified as VAR (1), meaning the relationship between systematic investment-grade CDS and equity markets at this maturity point is characterised by relatively little price stickiness, irrespective of the maturity and calculation methodology of the indices.

Table 3 CDX.NA.IG 10-year index and equally weighted S&P 500

Dependent variable	*Lagged CDS index*		*Lagged equity index*		*Lagged VAR system*	
	CDX.NA.IG$_{t-1}$	*p-value*[a]	*S&P 500$_{t-1}$*	*p-value*[a]	*chi2*	*p-value*
Panel A: 2004–2015						
S&P 500$_t$	0.018	(0.22)	–0.037	(0.17)	9.19	**(0.01)
CDX.NA.IG$_t$	0.052	*(0.05)	–0.179	**(0.00)	46.61	**(0.00)
Panel B: Crisis						
S&P 500$_t$	0.043	(0.15)	–0.041	(0.45)	6.02	**(0.05)
CDX.NA.IGt	0.054	(0.33)	–0.201	*(0.05)	10.63	**(0.01)
Panel C: Down market[b]						
S&P 500$_t$	0.019	(0.19)	0.011	(0.75)	21.64	**(0.00)
CDX.NA.IG$_t$	0.051	(0.06)	–0.259	**(0.00)	61.35	**(0.00)
Panel D: Down Mkt/crisis						
S&P 500$_t$	0.052	(0.22)	0.024	(0.752)	8.17	(0.09)
CDX.NA.IG$_t$	0.003	(0.53)	0.141	*(0.02)	12.55	*(0.02)
Panel E: Exogenous vars						
S&P 500$_t$	0.017	(0.26)	–0.023	(0.49)	16.28	**(0.01)
CDX.NA.IG$_t$	0.049	(0.07)	–0.184	**(0.00)	58.24	**(0.00)
Panel F: VARMA						
S&P 500$_t$	0.018	(0.21)	–0.036	(0.18)	55.76	**(0.00)
CDX.NA.IG$_t$	0.054	*(0.04)	–0.176	**(0.00)	55.76	**(0.00)

Notes: ** and * denote significance levels of 1%, 5%, respectively.
[a]Relevant intermarket causalities are bordered; significant ones are bolded.
[b]Only down markets results are included in chart since results for the up-market test do not differ.

Interestingly and in contrast to the prior study, I observe a marked size bias vis-à-vis the market cap weighted results in Table 3 throughout the panels. Specifically, based on the low p-values in the bordered and bolded cells, which result in rejection of the null hypothesis of no causality, coupled with the significant p-values in the accompanying Wald tests, a strong level of one-directional informational flow from the equally weighted S&P 500 to the 10-year CDX.NA.IG is observed in all panels, with no flow in the opposite direction. While the strength of the statistical significance of flow does vary somewhat, it is consistently independent of time period (panel B), marked conditions (panels C and D), other exogenous factors (panel E) and form of the model (panel F). This suggests the equally weighted S&P 500 index is more efficient than the 10-year

CDX.NA.IG in pricing in new information and is the only instance of market inefficiency documented in this paper.

Table 4 CDX.NA.IG 5-year index and S&P 500

Dependent variable	*Lagged CDS index*		*Lagged equity index*		*Lagged VAR system*	
	CDX.NA.IG$_{t-1}$	*p-value*[a]	*S&P 500$_{t-1}$*	*p-value*[a]	*chi2*	*p-value*
Panel A: 2004–2015						
S&P 500$_t$	0.002	$\boxed{(0.18)}$	–0.104	(0.06)	27.01	**(0.00)
CDX.NA.IG$_t$	0.121	*(0.03)	–0.018	$\boxed{(0.81)}$	18.14	**(0.00)
Panel B: Crisis						
S&P 500$_t$	0.034	$\boxed{(0.13)}$	–0.507	(0.67)	13.79	*(0.00)
CDX.NA.IGt	0.056	*(0.03)	–0.002	$\boxed{(0.98)}$	7.62	*(0.03)
Panel C: Down market[b]						
S&P 500$_t$	0.021	$\boxed{(0.16)}$	0.138	(0.71)	21.36	**(0.00)
CDX.NA.IG$_t$	0.152	**(0.00)	0.544	$\boxed{(0.61)}$	22.1	**(0.00)
Panel D: Down Mkt/crisis						
S&P 500$_t$	0.059	$\boxed{(0.06)}$	0.078	(0.66)	20.16	**(0.00)
CDX.NA.IG$_t$	0.101	(0.13)	–0.112	$\boxed{(0.49)}$	7.68	(0.11)
Panel E: Exogenous vars						
S&P 500$_t$	0.004	$\boxed{(0.66)}$	0.104	(0.00)	33.14	**(0.00)
CDX.NA.IG$_t$	0.135	**(0.00)	–0.066	$\boxed{(0.59)}$	37.5	**(0.00)
Panel F: VARMA						
S&P 500$_t$	0.003	$\boxed{(0.82)}$	–0.095	**(0.00)	55.21	**(0.00)
CDX.NA.IG$_t$	0.118	**(0.00)	0.064	$\boxed{(0.30)}$	55.21	**(0.00)

Notes: ** and * denote significance levels of 1%, 5%, respectively.
[a]Relevant intermarket causalities are bordered; significant ones are bolded.
[b]Only down markets results are included in chart since results for the up-market test do not differ.

From where does this inefficiency come? First, I attribute it to the greater informational flow and related efficiency associated with larger firm size and by extension, analyst coverage, as documented by Hong (2000). Once the disproportionate impact of the more efficient components of the S&P 500 index is removed, the contributions of constituents are normalised. Inefficiencies related to smaller companies with less of a following can then flow through to the return calculation. Second, I believe this bias is exacerbated by the relative illiquidity of the 10-year CDX.NA.IG maturity vs. the 5-year, meaning investors taking a view on investment-grade rated credit generally opt for the 5-year maturity. With the comparatively lower level of information impounded in the 10-year price, it is reactive to events in the equity market involving smaller, less covered firms more efficiently priced there. This leaves open the possibility for arbitrageurs to take positions in the 10-year CDX.NA.IG based on prior movements related to smaller capitalisation firms in the S&P 500, captured by an equally weighted S&P 500 ETF. When the ETF return is positive (negative), arbitragers could sell (buy) the CDS index. However, any perceived gross profit would need to be sufficient to cover transaction costs, in particular the presumed much wider bid-ask spread of the less liquid 10-year index vis-à-vis the 5-year maturity.

Moving onto the analyses with the 5-year CDS index, Table 4 reports the results of the 5-year CDX.NA.IG and S&P 500 examination. All autoregressive panels are specified as VAR (1) models per the information criterion, meaning that past prices only affect the next day's price across the data set for the 5-year point along the curve as well.

As evident by the high p-values in the cells that are bordered, which indicate the lagged independent variables of interest columns (reflecting cross-market flow) and which do not reject the null hypothesis of no causality, for the time period covering 2004–2015 (panel A), there is no observed lead-lag relationship between the markets. This result is interesting given Fung et al. (2008) had observed that the equity market led the CDS while Procasky documented equal efficiency using the 5-year CDS maturity. In fact, the presence of 'stickiness' in the examined autoregressive relationship is due solely to lagged values of the dependent variable, i.e., past CDS (stock) prices affect current CDS (stock) prices only.

This result is also documented during the financial crisis period (panel B), meaning efficiency persisted even during this time of upheaval and in the tests for asymmetry (panels C and D), indicating it is independent of the general mood of the market (although the p-value of 0.06 in panel D related to flow from the credit market just falls short of significance). Finally, the trend is robust to the inclusion of lagged systematic exogenous factors (panel E), meaning it was not biased by omitted variables 'working behind the scenes', as well as exogenous unobserved shocks (panel F), indicating VAR is the appropriate model. From this, I conclude the CDX.NA.IG and liquidly tradable S&P 500 are equally efficient in impounding investor information, a result in accordance with the Merton model of one risk-adjusted return across-markets, and that this efficiency holds for liquidly tradable instruments as well as matched portfolios, as previously documented by Procasky' (2021).

For the final analysis, Table 5 reflects the relationship between the 5-year CDX.NA.IG and equally weighted S&P 500, undertaken to see if size bias affected the initial S&P 500 result as it did with the 10-year CDX.NA.IG. All panels remain VAR (1), meaning price stickiness is independent of the influence of large companies at this maturity point.

In comparing the above table with Table 4, it is clear there is no bias in the initial result. Inefficiencies related to size do not exist in cross-market informational flow. In fact, p-values in the table are almost the exact same, with no cross-market transmission of information observed in either direction with respect to the aggregate sample (panel A), financial crisis (panel B), prevailing market conditions (panels C and D), inclusion of other systematic factors (panel E) and VARMA specification (panel F). Size clearly is not a factor in the initial result using the 5-year CDS index. With that, I conclude that overall, the 5-year maturity behaves differently than the 10-year. More specifically, results using the 5-year index are entirely consistent with the equal efficiency across markets observed by Procasky (2021) whereas some inefficiency is observed with 10-year index [partially in line with Fung et al. (2008)]. I attribute this difference primarily to the previously referenced greater volume and liquidity of the 5-year CDS index vs. the 10-year. Attendant with this greater volume and liquidity is the amount of information impounded in the pricing of the index by investors and by extension, its relative informational efficiency.

Table 5 CDX.NA.IG 5-year index and equally weighted S&P 500

Dependent variable	*Lagged CDS index*		*Lagged equity index*		*Lagged VAR system*	
	CDX.NA.IG$_{t-1}$	*p-value*[a]	*S&P 500$_{t-1}$*	*p-value*[a]	*chi2*	*p-value*
Panel A: 2004–2015						
S&P 500$_t$	0.002	(0.89)	–0.097	**(0.00)	23.27	**(0.00)
CDX.NA.IG$_t$	0.115	**(0.00)	–0.053	(0.42)	23.84	**(0.00)
Panel B: Crisis						
S&P 500$_t$	0.034	(0.18)	–0.104	(0.06)	13.79	**(0.00)
CDX.NA.IGt	0.121	**(0.03)	–0.002	(0.98)	7.62	*(0.03)
Panel C: Down market[b]						
S&P 500$_t$	0.006	(0.59)	–0.027	(0.76)	56.61	**(0.00)
CDX.NA.IG$_t$	0.116	**(0.00)	–0.008	(0.99)	43.66	**(0.00)
Panel D: Down Mkt/crisis						
S&P 500$_t$	0.052	(0.11)	0.022	(0.78)	20.69	**(0.00)
CDX.NA.IG$_t$	0.146	(0.04)	–0.024	(0.88)	10.35	*(0.04)
Panel E: Exogenous vars						
S&P 500$_t$	0.004	(0.75)	–0.102	**(0.00)	28.92	**(0.00)
CDX.NA.IG$_t$	0.136	**(0.00)	–0.054	(0.49)	33.71	**(0.00)
Panel F: VARMA						
S&P 500$_t$	0.002	(0.89)	–0.096	**(0.00)	47.33	**(0.00)
CDX.NA.IG$_t$	0.116	**(0.00)	–0.056	(0.40)	47.33	**(0.00)

Notes: ** and * denote significance levels of 1%, 5%, respectively.
[a]Relevant intermarket causalities are bordered; significant ones are bolded.
[b]Only down markets results are included in chart since results for the up-market test do not differ.

6 Conclusions

I examine the relative efficiency of the investment-grade CDS and equity markets using a set of liquidly tradable CDS and stock indices which differ by maturity and calculation methodology. Prior research has focused on matched equity portfolios which only produced a theoretical instrument rather than a liquidly tradable one (and/or the firm-specific relationship). In addition, this research has not investigated the potential for heterogeneity in the longer-dated 10-year CDS index maturity, which theoretically matches the indefinite life of a stock, as well as size bias in the S&P 500 index, which can be influenced by large capitalisation stocks.

Interestingly, I observe that the longer-dated CDS maturity and an equally weighted S&P 500 index in which large capitalisation bias is removed are informationally inefficient, with the equity market having a relative advantage over the CDS market. Also, while the other indices examined do not detect any relative advantage in either market, overall the results suggest that liquidly traded indices are not as efficient as manually constructed matched portfolios, where Procasky (2021) observed results consistent with the Merton (1974) model of one risk-adjusted return across markets.

The results have implications for practitioners and academicians alike, as they suggest that arbitrage profits based on prior market movements in the CDX.NA.IG and S&P 500 may be feasible, but only if arbitrageurs take positions in the 10-year CDX.NA.IG based on prior movements in an equally weighted S&P 500 ETF. However, any gains would need to more than cover higher transaction costs driven by the comparatively wider bid-ask spread of this less liquid, longer-dated CDS index. Accordingly, an examination of whether arbitrage profits can be generated using these two instruments would be an opportune avenue for future research. In addition, the analysis of the potential for heterogeneity between matched portfolios and liquidly tradable indices as well as the 10-year vs. 5-year CDS index could be extended to the non-investment grade sector.

Declarations of interest

The author alone is responsible for the content and writing of the paper.

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Notes

1 BIS Bank for International Settlements Statistical Release: OTC Derivatives at June 30, 2020, March 1, 2021

2 125 × 0.08% = 100%.

3 The J.P. Morgan Guide to Credit Derivatives, 1999.

4 See Getmansky et al. (2016) for additional context.

5 Including but not limited to Longstaff et al. (2003), Rodríguez-Moreno and Peña (2013), Fung et al. (2008), Norden and Weber (2009), Hilscher et al. (2015) and Procasky (2021).

6 Dickey-Fuller tests were carried out on all data, with unit roots rejected at a 1% significance level in every test.

7 Excerpted from Stata manual referencing pp.148–152 from Lütkepohl (2005).

8 In addition, although not required, both VAR equations are tested for robustness though the addition of lags of the dependent variable utilising a Wald test.

9 Sourced from https://fred.stlouisfed.org/.

10 For brevity, I only report results of down-market tests in this and subsequent analyses when they are substantially the same as the up-market (results available upon request).