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THE "DARK SIDE" OF CREDIT DEFAULT SWAPS INITIATION: A CLOSE LOOK AT SOVEREIGN DEBT CRISES

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We examine the effect of sovereign credit default swaps (CDS) trading initiation on the occurrence of sovereign debt crises (SDC). Estimations on a large sample of 141 countries for 1980–2013 reveal that, by affecting the fiscal stance, CDS initiation increases by around 1.5 percentage points on average the probability of SDC in countries with CDS compared to the other countries. This result holds for different robustness tests and is found to be stronger for developing countries, for countries with initial lower creditworthiness, and when the degrees of central bank independence and public sector transparency are low. Consequently, compared to existing work emphasizing favorable effects, CDS trading initiation is found to have adverse effects, by increasing the occurrence of SDC. These opposite effects should fuel the literature on measuring the consequences of CDS trading initiation, and its design and implementation from a policy perspective.

Keywords: Credit Default Swaps, Sovereign Debt Crises, Sovereign Bonds

1. INTRODUCTION

Credit default swaps (CDS) are one of the most important and controversial financial innovations of the past decades, extolled by some and disparaged by others. Recently, it was highlighted the prominent role of CDS in the emergence of the

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Greek debt crisis and its spread toward other peripheral Eurozone countries. This concern led German regulators to prohibit naked CDS trading on the bond market in May 2010, and in July 2011 the European Union Parliament voted for their exclusion from the Eurozone debt market.

However, at odds with the passionate public debate and financial regulators' initiatives, and also with the research on corporate CDS,[1] the literature on the effects of *sovereign* CDS trading is surprisingly sparse. In a seminal contribution, Blanco et al. (2005) stress that the presence of CDS may foster the aggregation of information and beliefs, more complete markets, and greater bond market liquidity, making it easier for distressed borrowers to issue bonds. In addition, Stulz (2010) argues that CDS trading should not affect bond markets, due to their relative small proportion compared to debt outstanding. As such, focusing on the access to bond markets and on their depth, Ammer and Cai (2011) and Ismailescu and Phillips (2015) notably found that CDS trading improves price discovery and efficiency and reduces bond yield spreads.

The goal of this paper is to extend the nascent literature on the consequences of *sovereign* CDS trading by looking at their effect on the stability of bond markets. Using primary data from Markit Group Limited (a leading CDS data vendor) to identify CDS trading countries, we examine the impact of CDS initiation on the occurrence of sovereign debt crises (SDC), in a large sample of 141 countries over 1980–2013. Since we focus on sovereign CDS, our analysis complements the recent work of Subrahmanyam et al. (2014) on corporate CDS; indeed, as stressed by Ismailescu and Phillips (2015), the two markets differ in various ways. First, contrary to corporate issuers, countries in financial difficulties do not go bankrupt, and their assets are not liquidated; in the event of sovereign default, debt is generally rescheduled or restructured, making the risk on sovereign bonds different. Second, CDS trading is particularly active on sovereign debt markets, making them more liquid compared to corporate bond markets [Ammer and Cai (2011)]; thus, the effect of CDS trading, if any, may be different in government bond markets. Finally, while corporate debt is mostly owned by insurance companies [Massa and Zhang (2012)], sovereign debt is held by a large set of investors, including central banks, commercial and investment banks, pension, insurance and hedge funds, and other governments [Acharya et al. (2014)]. Since these investors may react differently to the presence of CDS markets, the potential effect of CDS trading on debt crises may equally differ between corporate and sovereign issuers.

From an empirical perspective, a challenging task is to identify a causal relationship running from CDS trading to SDC, due to the endogeneity of CDS trading initiation. Indeed, potential differences between CDS and non-CDS countries regarding their (un)observable characteristics may exacerbate a selection bias. Besides, CDS trading initiation may occur more likely when market participants are relatively pessimistic about borrowing governments' ability to repay the debt and its burden on time. To address these concerns, we combine the bias-corrected matching estimator of Abadie and Imbens (2006) with the entropy

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balancing approach of Hainmueller (2012), and we alternatively rely on instrumental variables (IVs), Heckman two-stage estimations, and a falsification test.

Our benchmark finding is that CDS trading initiation significantly increases the probability of SDC in CDS countries compared to non-CDS countries. The magnitude of the estimated effect is meaningful, namely around 1.6 percentage points (hereafter pp). This result holds for alternative specifications (such as altering the sample, or adding covariates), is robust to the use of alternative methods (namely, entropy balancing, IVs, or Heckman two-stage estimations), and is supported by the conclusions of a falsification test.

In addition, we unveil that the impact of CDS trading initiation on SDC occurrence is sensitive to countries' characteristics, and to the considered time span. Regarding the former, the effect is stronger (i) under a bad fiscal stance (high debt-to-GDP, low rating grades, and high sovereign bond yield spreads), (ii) for developing, compared to developed, countries, (iii) for countries with a "low" degree of public sector transparency, and (iv) for countries with "low" central bank independence. Regarding the latter, the adverse cumulative effect of CDS trading on SDC occurrence becomes significant only starting 2005 and converges toward its benchmark magnitude over time.

The value of our analysis is twosome. First, in the context of a scarce literature on debt financing for sovereign entities, our results are a complement of existing studies that examine, particularly in the Eurozone, the pattern of information transmission and prices relationships between sovereign CDS and the bond market [see, e.g., Ammer and Cai (2011), Delatte et al. (2012), Arce et al. (2013), Calice et al. (2013), and Hassan et al. (2015)], or the contagion among sovereign CDS spreads [Broto and Pérez-Quirós (2015)].[2]

Second, compared to the study of Ismailescu and Phillips (2015), emphasizing a favorable effect of CDS trading initiation on bond yield spreads, we unveil that CDS trading can also have adverse effects, by increasing SDC occurrence. Taken together, these opposite effects should fuel the literature on measuring the consequences of CDS trading initiation and its design and implementation from a policy perspective.

The rest of the paper is organized as follows. Section 2 discusses theoretical arguments motivating a potential effect of CDS trading on SDC occurrence, Section 3 presents the data and the methodology, Section 4 reports the main results, Section 5 explores their robustness, Section 6 deals with heterogeneities, and Section 7 concludes.

2. THEORETICAL CONSIDERATIONS

The main channel through which CDS trading may affect the occurrence of SDC transits through the fiscal stance. We can link the fiscal stance to our context in three ways.

First, looking at corporate bond markets, firm leverage increases after CDS initiation [Saretto and Tookes (2013)]. This is because CDS help lenders hedge their

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underlying exposure to borrowers and enhance price discovery through increasing available information on traded entities. Analogously, CDS initiation may foster public debt. However, if the sovereign debt stock increases following CDS trading initiation, default risk may correspondingly increase.

Second, CDS trading can negatively affect bond markets through the presence of naked CDS. Besides, if protection against sovereign default can be purchased by investors that do not hold the underlying sovereign bonds (naked CDS), investors who are pessimistic about a borrowing government's fiscal sustainability can exploit the implicit leverage that derivatives provide. The presence of naked CDS can turn the fears about borrower's ability to repay its debt into self-fulfilling, making default more likely to occur.

Third, and related to the previous point, studies on the corporate debt market highlight the potential indirect adverse effect of CDS contracts on credit crises, through the reduction of *ex post* monitoring [Ashcraft and Santos (2009)]. Indeed, by providing bondholders a new mechanism to lay off their credit exposures, CDS initiation allows a new way to sever their credit links to borrowers. In other words, bondholders without direct exposure to borrowers' default can reduce their incentives to monitor them. For instance, bondholders with CDS protection can lower their political pressure on a borrowing government, even if its fiscal policy follows an unsustainable trend; this can reduce government's incentives to engage in positive net-present-value projects, and, consequently, lower its likelihood to repay the debt and its burden on time.

These arguments suggest testing the following hypothesis:

(**H**): CDS trading initiation increases the occurrence of SDC.[3]

Since there is, to the best of our knowledge, no previous work on this issue, we will draw upon several alternative econometric techniques and specifications to test this hypothesis.

3. DATA AND METHODOLOGY

3.1. Data

Our panel consists of 141 developing and developed countries over the period 1980–2013. Our main explanatory variable is sovereign CDS, which are issued by the market, and mainly by investment banks. We identify the CDS trading initiation date as the first appearance of sovereign CDS spreads in the primary data of Markit Group Limited, a leading global provider of financial information services.[4] The Markit initiation dates are also used by Ismailescu and Phillips (2015) to identify sovereign CDS introduction [and by, e.g., Massa and Zhang (2012) and Das et al. (2014), to identify CDS trading for corporate entities]. CDS contracts in Markit are available in different currencies and maturities, and begin at different dates; however, comparing CDS trading beginning dates by issuing currencies reveals that USD-denominated contracts generally appeared prior to

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all other currencies. Consequently, we focus on USD-denominated contracts with a maturity of 5 years (the benchmark in derivative markets), to identify the first sovereign CDS trading event. The final CDS sample consists of 74 countries,[5] of which 46 developed and 28 developing, called the treatment group (see Appendix 1 in the Supplementary Material for the list of CDS countries and their starting dates).

Regarding the outcome variable, we identify SDC using the database of Laeven and Valencia (2013). The authors define a debt crisis as the period when a borrowing government fails to meet principal or interest payments on the due date, or when debt repayment is rescheduled. Given the aim of our analysis, we also consider episodes of debt restructuring as debt crises because markets relate them to credit worthiness.[6] Using this definition, our SDC dummy variable equals one if a country experiences a debt crisis or debt restructuring *à la* Laeven and Valencia (2013) in a year, and zero otherwise. Based on the 105 SDC experienced by the 141 countries in our sample during 1980–2013, Figure 1 in the Supplementary Material suggests that, contrary to the period prior to CDS trading initiation, SDC occur more frequently in CDS countries after CDS introduction.

3.2. Methodology

To test our hypothesis (**H**), we study the effect of CDS trading initiation on SDC occurrence, by comparing CDS and non-CDS countries, matched based on their characteristics. Following the treatment effect literature, the introduction of CDS contracts is the treatment, and SDC occurrence is the outcome variable. The units of analysis are country–year observations, and observations with (without) CDS trading in place represent the treatment (control) group.

The matching is performed in two steps. First, we estimate the likelihood of CDS trading, conditional on observable covariates correlated with both SDC and CDS trading. Second, the likelihood of CDS trading is used to pair CDS trading observations with no-CDS observations. In this second step, we compute the impact of CDS trading on SDC occurrence, namely the so-called average treatment effect on the treated (ATT), as the mean difference between the matched groups of treated and untreated.

Previous studies drawing upon matching methods generally use simple covariate matching [e.g. Lin and Ye (2007), Minea and Tapsoba (2014), and Balima et al. (2016, 2017)]. With continuous matching variables, Abadie and Imbens (2006) suggest a bias-corrected matching estimator that relies on estimating a regression function only on the control group to predict the missing potential outcomes. This approach combines matching, which compares each treated observation with control observations with comparable covariates, and regression, which reduces potential remaining biases from covariates imbalances [for more details, see Abadie and Imbens (2006, 2011)]. In line with their recommendation, we examine the link between CDS trading and SDC using bias-corrected matching.

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Moreover, following Imbens (2004), we use pretreatment characteristics as matching variables to circumvent potential reverse causality problems. We select variables that may affect the CDS initiation, namely the first lag of the following variables chosen to capture: the fiscal stance (government debt-to-GDP, fiscal balance-to-GDP), the monetary and financial stance (inflation rate, reserves-to-GDP, private credit-to-GDP, financial openness index Kaopen), and external and domestic conditions (current account balance-to-GDP, GDP growth rate, executive constraints).[7] Finally, we also include year and regional fixed effects, to control for time- and region-specific characteristics that may affect SDC occurrence.[8]

4. MAIN RESULTS

We present the results of the effect of CDS trading on SDC occurrence. We first report benchmark results, and then account for alternative specifications.

4.1. Benchmark Results

We compute the average treatment effect of CDS trading on SDC occurrence using the bias-corrected matching estimator. We start by estimating a logit model, in which we explain the dummy variable of CDS trading initiation by the matching variables previously emphasized, together with year and regional fixed effects. Focusing on significant variables, column [0] of Appendix 3 (for appendices discussed, see the Supplementary Material) shows that more exposed countries, namely with poorer fiscal and current account balances and higher inflation, are more likely to introduce CDS contracts, which are potentially designed to mitigate risks. In addition, the introduction of CDS contracts seems to be supported by the presence of larger financial sectors (captured by private credit-to-GDP) and stronger executive constraints. Based on the logit regression, we compute propensity scores (i.e. the probability of adopting CDS). Under the usual common support condition, which ensures that treated and control groups are comparable, we use the bias-corrected matching to estimate the ATT of CDS trading initiation on SDC occurrence.

Table 1 reports benchmark results. ATTs on line [0] are statistically significant at the 5% level and positive, irrespective of the number of matched n, considered between 1 and 10. Thus, between two countries with comparable characteristics, the one with CDS trading is more prone to SDC. In addition, the estimated treatment effect is meaningful: the presence of CDS trading increases by around 1.6 pp the probability of SDC compared to countries without CDS contracts.

4.2. Alternative Specifications: Altering the Sample

We alter the sample as follows.[9] First, we take a closer look at CDS trading initiation dates: when CDS initiation occurs during the last three months of a given

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TABLE 1. The impact of CDS trading on SDC using bias-corrected matching

	Bias-corrected matching estimators				
Dependent variable: SDC	$n=1$	$n=2$	$n=3$	$n=4$	$n=5$
[0] ATT	0.0140**	0.0147***	0.0165***	0.0162***	0.0170***
	(0.0069)	(0.0048)	(0.0043)	(0.0039)	(0.0038)
Z-statistic/observations	2.02/2386	3.06/2386	3.83/2386	4.16/2386	4.46/2386
	$n=6$	$n=7$	$n=8$	$n=9$	$n=10$
[0] ATT	0.0165***	0.0157***	0.0155***	0.0160***	0.0159***
	(0.0037)	(0.0039)	(0.0042)	(0.0044)	(0.0044)
Z-statistic/observations	4.47/2386	4.03/2386	3.62/2386	3.58/2386	3.58/2386

Note: Heteroskedasticity-consistent standard errors in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$.

year t, we attribute the initiation date to the following year $t+1$. ATTs based on these initiation dates reported in line [1] of Table 2 are all statistically significant (except for $n=1$), and quantitatively in line with benchmark results.

Next, we extend the sample to include countries for which the identification of CDS trading initiation dates is less clear-cut, namely Brazil, China, Greece, Hungary, and Mexico, using the beginning date in Markit as the date of appearance of CDS trading. ATTs in line [2] are yet again consistent with benchmark findings.

Then, we account for the fact that CDS traders can anticipate the occurrence of SDC, and, accordingly, initiate CDS contracts for potential distressed countries. Thus, we exclude from the treated group countries that experienced at least one SDC episode in the first three years following their CDS initiation, namely Argentina, Dominican Republic, Indonesia, and Uruguay. Despite some magnitude loss compared to the benchmark (the effect is around 1.3 pp), most ATTs in line [3] are positive and significant.

Moreover, since the 74 CDS trading countries are relatively rich, we improve the comparability of treated and control observations by excluding in line [4] of Table 2 control countries with real GDP per capita below that of the poorest CDS trading country. In the same vein, in line [5] we exclude African countries with nascent stages of development of bond markets. Corresponding ATTs remain statistically significant, and the effect is even stronger when excluding African countries (around 1.7 pp) compared to the benchmark.

Furthermore, given that CDS contracts were invented in 1994, we exclude pre-1994 country–year observations. Alternatively, we drop the post-2008 period to abstract of the recent financial crisis and the restriction period imposed by the European Union Parliament in June 2011 in the Eurozone debt market. Results reported in lines [6]–[7] are consistent with benchmark findings. In particular, we unveil a strong effect climbing even up to 2.1 pp, when excluding post-2008 observations.

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TABLE 2. The impact of CDS trading on SDC using bias-corrected matching: alternative specifications

	Bias-corrected matching estimators									
Dependent variable: SDC	$n=1$	$n=2$	$n=3$	$n=4$	$n=5$	$n=6$	$n=7$	$n=8$	$n=9$	$n=10$
[1] Alternative CDS trading dates	0.0088	0.0123**	0.0145***	0.0147***	0.0158***	0.0157***	0.0150***	0.0149***	0.0148***	0.0151***
	(0.0070)	(0.0048)	(0.0043)	(0.0039)	(0.0038)	(0.0036)	(0.0036)	(0.0038)	(0.0043)	(0.0043)
	1.25/2386	2.54/2386	3.33/2386	3.72/2386	4.13/2386	4.28/2386	4.12/2386	3.86/2386	3.43/2386	3.45/2386
[2] Include Brazil, China, Greece, Hungary, and Mexico	0.0117*	0.0134***	0.0153***	0.0159***	0.0167***	0.0161***	0.0155***	0.0153***	0.0156***	0.0156***
	(0.0063)	(0.0043)	(0.0040)	(0.0038)	(0.0037)	(0.0035)	(0.0037)	(0.0041)	(0.0042)	(0.0042)
	1.83/2481	3.10/2481	3.78/2481	4.15/2481	4.48/2481	4.51/2481	4.13/2481	3.69/2481	3.72/2481	3.72/2481
[3] Drop Argentina, Dominican Republic, Uruguay, and Indonesia	0.0075	0.0131***	0.0132***	0.0132***	0.0137***	0.0136***	0.0136***	0.0137***	0.0136***	0.0137***
	(0.0065)	(0.0032)	(0.0032)	(0.0033)	(0.0031)	(0.0029)	(0.0028)	(0.0028)	(0.0029)	(0.0029)
	1.17/2330	4.06/2386	4.05/2386	4.00/2386	4.43/2386	4.68/2386	4.84/2386	4.75/2386	4.64/2386	4.73/2386
[4] Exclude poorest countries	0.0134***	0.0131***	0.0133***	0.0135***	0.0134***	0.0136***	0.0136***	0.0137***	0.0136***	0.0136***
	(0.0034)	(0.0033)	(0.0034)	(0.0031)	(0.0032)	(0.0032)	(0.0031)	(0.0029)	(0.0029)	(0.0029)
	3.91/2028	3.93/2028	3.91/2028	4.25/2028	4.11/2028	4.22/2028	4.40/2028	4.60/2028	4.62/2028	4.62/2028
[5] Exclude African countries	0.0154***	0.0166***	0.0170***	0.0171***	0.0169***	0.0164***	0.0166***	0.0169***	0.0171***	0.0167***
	(0.0051)	(0.0044)	(0.0038)	(0.0039)	(0.0037)	(0.0036)	(0.0034)	(0.0035)	(0.0034)	(0.0033)
	3.01/1680	3.78/1680	4.43/1680	4.32/1680	4.51/1680	4.52/1680	4.77/1680	4.82/1680	4.93/1680	4.94/1680

TABLE 2. Continued

Dependent variable: SDC	Bias-corrected matching estimators									
	$n=1$	$n=2$	$n=3$	$n=4$	$n=5$	$n=6$	$n=7$	$n=8$	$n=9$	$n=10$
[6] Drop pre-1994 sample	0.0143**	0.0146***	0.0166***	0.0164***	0.0169***	0.0164***	0.0158***	0.0155***	0.0158***	0.0159***
	(0.0069)	(0.0047)	(0.0044)	(0.0039)	(0.0038)	(0.0037)	(0.0040)	(0.0043)	(0.0044)	(0.0044)
	2.06/2157	3.08/2157	3.76/2157	4.19/2157	4.45/2157	4.40/2157	3.95/2157	3.60/2157	3.57/2157	3.63/2157
[7] Drop post-2008 sample	0.0129	0.0170*	0.0195**	0.0207***	0.0203***	0.0214***	0.0209***	0.0206***	0.0207***	0.0207***
	(0.0138)	(0.0094)	(0.0084)	(0.0073)	(0.0068)	(0.0067)	(0.0068)	(0.0078)	(0.0077)	(0.0076)
	0.94/1607	1.81/1607	2.33/1607	2.81/1607	2.96/1607	3.16/1607	3.06/1607	2.62/1607	2.69/1607	2.71/1607
[8] Drop Eurozone	0.0227***	0.0227***	0.0227***	0.0228***	0.0227***	0.0231***	0.0230***	0.0230***	0.0230***	0.0231***
	(0.0051)	(0.0050)	(0.0052)	(0.0054)	(0.0051)	(0.0049)	(0.0048)	(0.0048)	(0.0049)	(0.0048)
	4.49/1871	4.46/1871	4.33/1871	4.16/1871	4.42/1871	4.68/1871	4.82/1871	4.77/1871	4.69/1871	4.73/1871
[9] Drop post-2005 sample	0.0072	0.0185	0.0252**	0.0277**	0.0273***	0.0286***	0.0285***	0.0284**	0.0280**	0.0279**
	(0.0228)	(0.0140)	(0.0127)	(0.0111)	(0.0104)	(0.0102)	(0.0106)	(0.0119)	(0.0117)	(0.0117)
	0.32/1334	1.32/1334	1.98/1334	2.49/1334	2.62/1334	2.80/1334	2.69/1334	2.39/1334	2.40/1334	2.38/1334
[10] Drop post-2005 CDS adoption countries	0.0108	0.0191	0.0244*	0.0268**	0.0270***	0.0282***	0.0278***	0.0276**	0.0269**	0.0263**
	(0.0207)	(0.0146)	(0.0127)	(0.0117)	(0.0104)	(0.0102)	(0.0103)	(0.0113)	(0.0112)	(0.0112)
	0.52/1866	1.31/1866	1.93/1866	2.28/1866	2.60/1866	2.74/1866	2.68/1866	2.43/1866	2.41/1866	2.34/1866

Note: Heteroskedasticity-consistent standard errors in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

In addition, we check if our results are robust to the exclusion of Eurozone countries, particularly because such countries experienced major imbalances since the recent crisis. As emphasized by line [8], the estimated effect is negative and statistically significant. In addition, the magnitude of the effect is stronger compared to the benchmark, namely around 2.3, and corroborates our findings when excluding post-2008 observations.

Finally, given that most countries initiated CDS prior to 2005, we exclude post-2005 observations and countries that initiated CDS after 2005. Despite some significance loss (for $n = 1$ and $n = 2$), results reported in lines [9]–[10] of Table 2 reveal stronger effects, roughly by 1 pp, compared to benchmark findings.

4.3. Alternative Specifications: Additional Covariates

We account for different groups of additional covariates, selected since they may affect the likelihood of CDS trading and SDC occurrence. These additional variables capture the level of economic development (GDP per capita); stock market conditions (stock market crisis dummy, stock market capitalization-to-GDP, stock price volatility, stock market return); bond market conditions (sovereign bond yield spreads, sovereign debt ratings, debt crisis contagion dummy); banking sector conditions (banking crisis dummy, financial system deposits-to-GDP); monetary conditions (currency crisis, official exchange rate); institutional and structural features (UK legal origin dummy, IMF program dummy, CDS country dummy); and external conditions (capital account balance, financial account balance). Except for UK legal origin, all these variables are 1-year lagged, to perform the matching on pretreatment observations.[10]

Estimated ATTs are presented on lines [11]–[16] of Table 3. From a general perspective, results are consistent with benchmark findings, since the presence of CDS contracts significantly raises the likelihood of SDC. In addition, the magnitude of this effect is broadly around its benchmark range, with lower (higher) values arising when accounting for stock market conditions (banking crisis and CDS country dummy).

5. ROBUSTNESS

Estimations presented so far seem not to reject our hypothesis (**H**). Next, we follow the recommendations of Li and Prabhala (2007) and Roberts and Whited (2012) in corporate finance literature and draw upon several econometric methods to overcome a potential selection bias and an endogeneity issue.

5.1. Entropy Balancing

Generalizing conventional matching methods, entropy balancing was proposed by Hainmueller (2012). By combining matching and regression approach, it may present some advantages over other treatment effect estimators [Neuenkirch

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TABLE 3. The impact of CDS trading on SDC using bias-corrected matching: additional covariates

	Bias-corrected matching estimators									
Dependent variable: SDC	$n=1$	$n=2$	$n=3$	$n=4$	$n=5$	$n=6$	$n=7$	$n=8$	$n=9$	$n=10$
[11] Adding GDP per capita $(t-1)$	0.0306***	0.0244***	0.0239***	0.0234***	0.0234***	0.0220***	0.0189***	0.0178***	0.0178***	0.0178***
	(0.0054)	(0.0047)	(0.0042)	(0.0039)	(0.0039)	(0.0037)	(0.0038)	(0.0041)	(0.0041)	(0.0043)
	5.63/2794	5.14/2794	5.67/2794	5.90/2794	5.90/2794	5.85/2794	4.90/2794	4.24/2794	4.14/2794	4.13/2794
[12A] Adding stock market crisis $(t-1)$	0.0134**	0.0134**	0.0176***	0.0163***	0.0157***	0.0159***	0.0159***	0.0160***	0.0156***	0.0152***
	(0.0056)	(0.0055)	(0.0053)	(0.0050)	(0.0046)	(0.0046)	(0.0044)	(0.0044)	(0.0042)	(0.0041)
	2.36/830	2.40/830	3.27/830	3.21/830	3.37/830	3.45/830	3.60/830	3.63/830	3.70/830	3.66/830
[12B] Adding stock market capitalization $(t-1)$	0.0082**	0.0082***	0.0082***	0.0082***	0.0096***	0.0106***	0.0103***	0.0100***	0.0098***	0.0096***
	(0.0032)	(0.0027)	(0.0027)	(0.0027)	(0.0025)	(0.0028)	(0.0029)	(0.0030)	(0.0030)	(0.0029)
	2.56/1477	3.00/1477	2.98/1477	3.05/1477	3.72/1477	3.71/1477	3.53/1477	3.33/1477	3.26/1477	3.27/1477
[12C] Adding stock market price volatility $(t-1)$	0.0091***	0.0091***	0.0091***	0.0091***	0.0091***	0.0091***	0.0107***	0.0095***	0.0090***	0.0088***
	(0.0032)	(0.0032)	(0.0028)	(0.0034)	(0.0033)	(0.0033)	(0.0032)	(0.0032)	(0.0033)	(0.0032)
	2.83/1071	2.78/1071	3.21/1071	2.68/1071	2.73/1071	2.76/1071	3.27/1071	2.89/1071	2.75/1071	2.73/1071
[12D] Adding stock market return $(t-1)$	0.0090***	0.0090***	0.0105***	0.0101***	0.0094***	0.0096***	0.0094***	0.0089***	0.0087***	0.0086***
	(0.0033)	(0.0033)	(0.0032)	(0.0034)	(0.0035)	(0.0033)	(0.0032)	(0.0032)	(0.0032)	(0.0032)
	2.68/1135	2.68/1135	3.28/1135	2.92/1135	2.66/1135	2.86/1135	2.95/1135	2.75/1135	2.66/1135	2.67/1135

TABLE 3. Continued

Dependent variable: SDC	Bias-corrected matching estimators									
	$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$	$n = 6$	$n = 7$	$n = 8$	$n = 9$	$n = 10$
[13A] Adding government bond yield spreads ($t - 1$)	0.0141***	0.0141***	0.0164***	0.0140***	0.0162***	0.0157***	0.0155***	0.0153***	0.0149***	0.0139***
	(0.0036)	(0.0036)	(0.0037)	(0.0038)	(0.0037)	(0.0036)	(0.0036)	(0.0036)	(0.0036)	(0.0035)
	3.84/1139	3.90/1139	4.33/1139	3.62/1139	4.34/1139	4.27/1139	4.26/1139	4.21/1139	4.14/1139	3.96/1139
[13B] Adding sovereign rating ($t - 1$)	0.0156***	0.0172***	0.0158***	0.0155***	0.0150***	0.0151***	0.0151***	0.0148***	0.0148***	0.0146***
	(0.0043)	(0.0038)	(0.0037)	(0.0033)	(0.0031)	(0.0030)	(0.0030)	(0.0030)	(0.0031)	(0.0030)
	3.63/1621	4.45/1621	4.19/1621	4.67/1621	4.78/1621	4.88/1621	4.88/1621	4.85/1621	4.74/1621	4.78/1621
[13C] Adding debt crisis contagion ($t - 1$)	0.0134***	0.0132***	0.0131***	0.0131***	0.0134***	0.0133***	0.0135***	0.0137***	0.0136***	0.0136***
	(0.0034)	(0.0032)	(0.0031)	(0.0032)	(0.0029)	(0.0028)	(0.0027)	(0.0028)	(0.0027)	(0.0026)
	3.92/2386	4.12/2386	4.15/2386	4.11/2386	4.55/2386	4.75/2386	4.90/2386	4.84/2386	4.88/2386	5.06/2386
[14A] Adding banking crisis ($t - 1$)	0.0200***	0.0200***	0.0200***	0.0200***	0.0215***	0.0212***	0.0207***	0.0206***	0.0205***	0.0205***
	(0.0052)	(0.0057)	(0.0053)	(0.0053)	(0.0052)	(0.0052)	(0.0050)	(0.0049)	(0.0047)	(0.0047)
	3.84/1080	3.46/1080	3.74/1080	3.72/1080	4.14/1080	4.07/1080	4.06/1080	4.16/1080	4.32/1080	4.36/1080
[14B] Adding financial system deposits ($t - 1$)	0.0101*	0.0118**	0.0139***	0.0148***	0.0149***	0.0156***	0.0151***	0.0151***	0.0150***	0.0148***
	(0.0059)	(0.0049)	(0.0043)	(0.0043)	(0.0043)	(0.0042)	(0.0045)	(0.0043)	(0.0043)	(0.0044)
	1.69/2249	2.38/2249	3.20/2249	3.43/2249	3.45/2249	3.66/2249	3.35/2249	3.45/2249	3.44/2249	3.33/2249
[15A] Adding UK legal origin	0.0131***	0.0132***	0.0138***	0.0139***	0.0141***	0.0140***	0.0142***	0.0143***	0.0141***	0.0141***
	(0.0044)	(0.0035)	(0.0038)	(0.0039)	(0.0036)	(0.0034)	(0.0033)	(0.0033)	(0.0033)	(0.0033)
	2.92/2386	3.77/2386	3.60/2386	3.53/2386	3.88/2386	4.05/2386	4.24/2386	4.31/2386	4.24/2386	4.17/2386

TABLE 3. Continued

	Bias-corrected matching estimators									
Dependent variable: SDC	$n=1$	$n=2$	$n=3$	$n=4$	$n=5$	$n=6$	$n=7$	$n=8$	$n=9$	$n=10$
[15B] Adding IMF program dummy ($t-1$)	0.0129***	0.0130***	0.0133***	0.0136***	0.0135***	0.0134***	0.0134***	0.0133***	0.0133***	0.0132***
	(0.0047)	(0.0042)	(0.0039)	(0.0037)	(0.0035)	(0.0034)	(0.0034)	(0.0034)	(0.0033)	(0.0032)
	2.72/2341	3.03/2341	3.37/2341	3.66/2341	3.80/2341	3.95/2341	3.93/2341	3.89/2341	4.00/2341	4.09/2341
[15C] Adding CDS country dummy ($t-1$)	0.0129***	0.0181***	0.0163***	0.0169***	0.0171***	0.0169***	0.0166***	0.0166***	0.0181***	0.0173***
	(0.0037)	(0.0038)	(0.0043)	(0.0037)	(0.0033)	(0.0031)	(0.0030)	(0.0029)	(0.0030)	(0.0029)
	3.43/2386	4.68/2386	3.76/2386	4.48/2386	5.14/2386	5.35/2386	5.51/2386	5.66/2386	6.01/2386	5.80/2386
[16A] Adding capital account balance ($t-1$)	0.0132***	0.0129***	0.0134***	0.0134***	0.0134***	0.0134***	0.0134***	0.0133***	0.0133***	0.0133***
	(0.0040)	(0.0033)	(0.0036)	(0.0035)	(0.0032)	(0.0030)	(0.0029)	(0.0029)	(0.0029)	(0.0030)
	3.31/2323	3.86/2323	3.65/2323	3.82/2323	4.10/2323	4.45/2323	4.52/2323	4.54/2323	4.45/2323	4.42/2323
[16B] Adding financial account balance ($t-1$)	0.0137***	0.0135***	0.0136***	0.0140***	0.0143***	0.0141***	0.0139***	0.0139***	0.0140***	0.0139***
	(0.0037)	(0.0032)	(0.0033)	(0.0034)	(0.0031)	(0.0029)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
	3.68/2336	4.09/2336	4.05/2336	4.12/2336	4.52/2336	4.75/2336	4.66/2336	4.59/2336	4.54/2336	4.57/2336

Note: Heteroskedasticity-consistent standard errors in parentheses; $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

and Neumeier (2016)]. Compared to regression approach (e.g. difference-in-difference) or propensity scores matching, since its implementation does not require the use of a model for the selection to treatment, it may avoid potential misspecification or multicollinearity. Compared to matching methods, it may improve covariate balancing between treated and control groups. Finally, entropy balancing allows accounting for unobservable factors related to the panel dimension of the data, through including year and regional fixed effects.

Entropy balancing consists of generating a synthetic control group as close as possible to CDS countries in terms of observable characteristics. To this end, we compute weights for untreated units that may satisfy prespecified balance constraints, involving sample moments of pretreatment characteristics, by remaining as close as possible to uniform base weights. Following Neuenkirch and Neumeier (2016), we impose equal covariate means between the treatment and the control groups; thus, the synthetic control group contains, on average, untreated units that are as close as possible to treated units. We compute weights using the pretreatment covariates from the benchmark specification.

Let us discuss some descriptive statistics before and after weighting. Appendix 5 presents pre-weighting sample means of all matching covariates for the treatment group (CDS trading, column [1]) and the control group (No CDS trading, column [2]), as well as differences in covariates' means (column [3]). Interestingly, aside from reserves-to-GDP, tests in column [3] reveal significantly different covariates' means between the treatment and the control groups,[11] suggesting modifying the control group to make it comparable to the treated group. This modified (synthetic) control group is reported in column [4], together with covariates' means differences with respect to the treated group (column [5]). Column [5] reveals the effectiveness of entropy balancing, as no significant differences remain after weighting—that is, the synthetic and the treatment groups present statistically equal covariates' means.

Using these weights, we perform in Table 4 weighted least squares regressions, in which SDC is the dependent variable and CDS trading is the explanatory variable. Estimations in column [17A] show that CDS trading significantly increases SDC occurrence, consistent with benchmark findings. This result is confirmed when we subsequently add the matching covariates employed to compute weights (column [17B][12]), unobservable time-specific factors (column [17C]), and regional dummies (column [17D]). In particular, in the latter two specifications, the magnitude of the effect is stronger compared to benchmark estimations, namely around 1.8 pp. Consequently, using entropy balancing supports previous findings based on bias-corrected matching.

5.2. Endogeneity: IV Estimation

So far, we employed matching approaches to identify the treatment effect of CDS trading initiation. In the following, we take a closer look at endogeneity. Indeed,

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Table 4. The impact of CDS trading on SDC using entropy balancing

	[17A]	[17B]	[17C]	[17D]
Dependent variable: SDC	Baseline	Adding controls	Adding controls and year fixed effects	Adding controls, year and regional fixed effects
CDS dummy	0.0112**	0.0112**	0.0181***	0.0175***
	(0.0043)	(0.0043)	(0.0060)	(0.0063)
t-Statistic	2.55	2.58	2.99	2.77
Observations	2390	2390	2390	2390

Note: Robust standard errors in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$.

CDS traders and bondholders may anticipate a deterioration of credit quality for a borrowing government, and thus initiate CDS contracts for future distressed borrowers.

To deal with such endogeneity issues, we draw upon an external IV strategy. Keeping in mind that an appropriate instrument must satisfy the relevance and the exclusion restrictions—that is it should be correlated with CDS trading and have no direct influence on SDC occurrence—we select the joint votes of nations with the USA at the UN General Assembly (*Joint votes US*) as instrument for CDS trading. This choice is motivated by the fact that CDS contracts were invented in USA in 1994 by JP Morgan, and they are mostly traded by US investment banks and hedge funds. Since the USA is the CDS market leader, we expect CDS sellers to initiate CDS transactions in countries related to the USA because expected losses from the occurrence of credit events may be lower.[13]

Appendix 6 reports first-stage regressions based on a probit model. According to the first column, the variable *Joint votes US* significantly increases CDS trading. Besides, since the *F*-test statistic of the instrument is 12.43, namely above the threshold of 10 recommended by Staiger and Stock (1997), our instrument is relevant, and not weak.[14] However, since we cannot test the exclusion restriction formally with only one instrument, we consider a probit SDC regression in which we include CDS trading, *Joint votes US*, and control variables, and we test the null hypothesis that the effect of *Joint votes US* is statistically zero.[15] Appendix 7 shows that CDS trading is positively correlated with SDC occurrence, and, more importantly, that the coefficient of *Joint votes US* is never statistically significant. Adding to previous findings on its relevance, this last result proves that our instrument is equally valid.

We now turn to the probit estimation of main regressions, reported in Table 5. Following the previous literature on SDC, we include in the benchmark IV regression [18A] the lagged value of: government debt-to-GDP, inflation rate, reserves-to-GDP, financial openness (Kaopen), GDP growth rate, and executive constraints. Confirming matching estimations, results show that instrumented

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TABLE 5. The impact of CDS trading on SDC using IV estimations

Dependent variable: SDC	[18A]	[18B]	[18C]	[18D]	[18E]	[18F]
CDS trading	3.062***	3.070***	2.952***	3.064***	3.075***	3.061***
	(0.157)	(0.109)	(0.350)	(0.121)	(0.111)	(0.173)
CDS trading *marginal effect*	0.0213	0.0214	0.0199	0.0214	0.0218	0.0218
Government debt-to-GDP ($t-1$)	0.000461	0.000480	0.000410	0.000510	−0.000298	0.000477
	(0.00136)	(0.00122)	(0.00133)	(0.00149)	(0.00130)	(0.00151)
Inflation ($t-1$)	−0.00105	−0.00102	−0.00179	−0.00128	−0.00107	−0.000966
	(0.00193)	(0.00165)	(0.00282)	(0.00172)	(0.00174)	(0.00206)
Reserves-to-GDP ($t-1$)	−1.686	−1.296	−2.933	−1.261	−1.354	−1.836
	(1.758)	(1.348)	(2.412)	(1.554)	(1.582)	(1.996)
Kaopen ($t-1$)	−0.137**	−0.123***	−0.174*	−0.128**	−0.121**	−0.126**
	(0.0538)	(0.0446)	(0.0910)	(0.0515)	(0.0512)	(0.0601)
GDP growth ($t-1$)	−0.0125	−0.0104	−0.00782	−0.0113	−0.0104	−0.0110
	(0.0142)	(0.0118)	(0.00735)	(0.0118)	(0.0125)	(0.0140)
Executive constraints ($t-1$)	−0.146***	−0.135***	−0.134***	−0.137***	−0.144***	−0.135***
	(0.0438)	(0.0367)	(0.0476)	(0.0389)	(0.0430)	(0.0456)
UK legal origin		−0.184				
		(0.173)				

TABLE 5. Continued

Dependent variable: SDC	[18A]	[18B]	[18C]	[18D]	[18E]	[18F]
Log US aid ($t-1$)			0.110***			
			(0.0359)			
Current account balance ($t-1$)				2.76e-05		
				(0.00836)		
Capital account balance ($t-1$)					0.0172	
					(0.0140)	
Financial account balance ($t-1$)						−0.00461*
						(0.00271)
Constant	−1.294**	−1.097**	−1.820***	−1.229**	−1.148*	−1.346*
	(0.629)	(0.472)	(0.593)	(0.581)	(0.593)	(0.709)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Wald test of exogeneity (p value)	0.0495	0.0136	0.0625	0.0378	0.0447	0.0721
Wald test (chi^2)	778.96	1066.59	497.25	953.13	1094.37	758.72
Wald test (p value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	1290	1290	1084	1290	1263	1262

Notes: The instrumented variable is CDS trading. Robust standard errors in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

CDS trading increases the probability of SDC. Besides, the magnitude of this effect is stronger compared to our main findings, namely around 2.1 pp.[16] Moreover, we extend specification [18A] by introducing additional control variables, namely UK legal origin, log of US aid, current account balance, capital account balance, and financial account balance. Columns [18B–F] in Table 5 show that, irrespective of the considered specification, instrumented CDS trading significantly increases SDC occurrence, corroborating, yet again, our findings based on bias-corrected matching.

5.3. Selection of CDS Trading

Complementing our IV approach, we use Heckman's (1979) two-stage model to deal with the selection bias of CDS trading. Indeed, the selection of sovereign entities for CDS trading is analogous to an omitted variable problem in the spirit of Heckman, since we do not observe the outcome of CDS countries without CDS trading. To remove this bias, we follow Subrahmanyam et al. (2014) two-step regression approach. In the first step, we estimate the first-stage IV regression using a probit model and then compute the inverse Mills ratio (IMR) representing the omitted variable, using *Joint votes US* as an excluded variable.[17] In the second step, we estimate the likelihood of SDC occurrence using a linear probability model in which we include the IMR as an additional explanatory variable.

Tables 6 reports the estimations of the second-stage Heckman correction, based on IMR computed from Appendix 6. Most control variables are not significant, probably due to potential multicollinearity induced by the inclusion of the IMR. The coefficient of IMR is negative and statistically significant, suggesting that the link between CDS trading and SDC might be driven by a negative selection bias. Finally, and more importantly, CDS trading significantly increases SDC. Although the magnitude of this effect is somewhat lower compared to matching estimates (around 1 pp), its significance is unaltered when considering different specifications (see regressions [19A–F] in Table 6).

5.4. Falsification Test

Finally, we conduct a falsification test to address potential measurement errors in CDS trading. Indeed, given that CDS are not traded on a centralized market, potential measurement errors could arise from the identification of CDS introduction [Subrahmanyam et al. (2014)]. To this end, we generate arbitrary CDS initiation dates for each CDS country, by lagging the CDS introduction by 10 years, that is, the mid-period of the pretreatment period (1980–2001).[18] Results reported in Table 7 based on the bias-corrected matching estimator show that, contrary to our benchmark results, the treatment effect using these placebo CDS introduction dates is not statistically different from zero. Consequently, the falsification test suggests that the effect we unveiled is triggered by CDS trading initiation rather than measurement errors.

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TABLE 6. The impact of CDS trading on SDC when controlling for selection of CDS trading

Dependent variable: SDC	[19A]	[19B]	[19C]	[19D]	[19E]	[19F]
CDS dummy	0.0109***	0.0111**	0.00912**	0.0099***	0.0106***	0.0112***
	(0.0026)	(0.00438)	(0.00461)	(0.0020)	(0.00336)	(0.00289)
Government debt-to-GDP ($t-1$)	0.00005*	5.19e-05	2.16e-05	0.00006	6.10e-05	5.73e-05
	(0.00003)	(4.86e-05)	(6.93e-05)	(0.00011)	(6.27e-05)	(0.000133)
Inflation ($t-1$)	0.0003***	0.000340	−0.000197	0.0003	0.000323***	0.000347**
	(0.00009)	(0.000775)	(0.000155)	(0.00038)	(0.000107)	(0.000154)
Reserves-to-GDP ($t-1$)	−0.0117***	−0.0107***	−0.00980**	−0.0143***	−0.0146***	−0.0143**
	(0.00299)	(0.00282)	(0.00397)	(0.0044)	(0.00173)	(0.00587)
Kaopen ($t-1$)	−0.0011**	−0.000748	−0.00165*	−0.00114	−0.00102	−0.000967**
	(0.00055)	(0.00109)	(0.000963)	(0.00115)	(0.00165)	(0.000408)
GDP growth ($t-1$)	−0.0003	−0.000390	0.000100	−0.00030	−0.000358	−0.000353
	(0.00055)	(0.000467)	(0.000213)	(0.00041)	(0.000389)	(0.000260)
Executive constraints ($t-1$)	−0.0013***	−0.00128	−0.00128	0.0011	−0.00122	−0.00122
	(0.00032)	(0.00176)	(0.00172)	(0.00082)	(0.00157)	(0.000763)
UK legal origin		−0.00413***				
		(0.000903)				

TABLE 6. Continued

Dependent variable: SDC	[19A]	[19B]	[19C]	[19D]	[19E]	[19F]
Log US aid ($t-1$)			0.00102***			
			(0.000375)			
Current account balance ($t-1$)				−0.00021		
				(0.00019)		
Capital account balance ($t-1$)					-9.53e-05	
					(0.000203)	
Financial account balance ($t-1$)						$-2.87e-05$***
						(2.50e-07)
IMR ($t-1$)	−0.00059***	−0.000649*	−0.000675***	−0.00053**	−0.000503***	−0.000568*
	(0.00007)	(0.000352)	(0.000222)	(0.00023)	(0.000113)	(0.000311)
Constant	0.0236***	0.0282***	0.00597	0.0222	0.0237***	0.0177
	(0.0008)	(0.00927)	(0.00727)	(0.01954)	(0.000301)	(0.0195)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1.558	1.558	1.477	1.558	1.541	1.519

Notes: Second-stage estimations of the Heckman selection model using a linear regression. The IMR is computed from first-stage probit regressions reported in Appendix 6. Bootstrap standard errors in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE 7. The impact of CDS trading on SDC using a falsification test

	Bias-corrected matching estimators				
Dependent variable: SDC	$n=1$	$n=2$	$n=3$	$n=4$	$n=5$
[20] ATT	0.0219	0.0192	0.0131	0.0230	0.0249
	(0.0175)	(0.0182)	(0.0160)	(0.0157)	(0.0152)
Z-statistic/observations	1.25/1076	1.05/1076	0.82/1076	1.47/1076	1.63/1076
	$n=6$	$n=7$	$n=8$	$n=9$	$n=10$
[20] ATT	0.0225	0.0209	0.0174	0.0143	0.0161
	(0.0152)	(0.0142)	(0.0121)	(0.0118)	(0.0114)
Z-statistic/observations	1.48/1076	1.47/1076	1.44/1076	1.21/1076	1.41/1076

Notes: We shift the true CDS trading initiation date for each CDS country by 10 years, which is the mid-period of the pretreatment period (1980–2001), as a falsification test. Heteroskedasticity-consistent standard errors in parentheses.

6. HETEROGENEITY OF THE CDS TRADING EFFECT

We revealed that CDS trading initiation increases SDC occurrence. Next, we explore potential heterogeneities of this effect related to CDS countries' characteristics, and the time span.

6.1. CDS Countries' Characteristics

We consider several key CDS countries' characteristics, namely (i) the fiscal stance, (ii) the level of economic development, (iii) the degree of public sector transparency, and (iv) the degree of central bank's independence. Bias-corrected matching results based on the benchmark specification are reported in Table 8.

Let us explore the impact of the fiscal stance, which we capture through three variables. First, we look at the level of public debt in ratio of GDP, and split countries into low-debt and high-debt, using the mean debt value from the World Economic Outlook. Lines [21A–B] in Table 8 show that CDS trading initiation increases the SDC occurrence more in countries with "high," compared to countries with "low" public debt-to-GDP ratios. Second, we consider ratings grades at the time CDS trading was introduced. We split CDS countries based on their grades, into investment and speculative. According to initial long-term sovereign debt ratings of the three main rating agencies (Standard and Poor's, Moody's, and Fitch), one third of the 74 CDS countries in our sample had speculative debt rating grades at the time of CDS initiation, while the rest belonged to the investment grade group. Lines [22A–B] show that, in most cases, CDS trading has no statistically significant effect on SDC occurrence in countries with initial investment ratings grades. On the contrary, the adverse effect is significant in speculative grades CDS countries, and its magnitude is larger compared to benchmark results, namely around 3.4 pp. Thus, countries with initial lower

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TABLE 8. Heterogeneity in the impact of CDS trading on SDC using bias-corrected matching: CDS countries' characteristics

	Bias-corrected matching estimators									
Dependent variable: SDC	$n=1$	$n=2$	$n=3$	$n=4$	$n=5$	$n=6$	$n=7$	$n=8$	$n=9$	$n=10$
					Fiscal stance I: public debt					
[21A] Low debt/GDP	0.0138*	0.0157***	0.0177***	0.0174***	0.0173***	0.0165***	0.0159***	0.0156***	0.0163***	0.0167***
	(0.0072)	(0.0047)	(0.0044)	(0.0038)	(0.0038)	(0.0037)	(0.0039)	(0.0043)	(0.0045)	(0.0046)
	1.91/2182	3.29/2182	4.01/2182	4.47/2182	4.56/2182	4.45/2182	4.04/2182	3.60/2182	3.60/2182	3.62/2182
[21B] High debt/GDP	0.0223**	0.0226***	0.0225***	0.0226***	0.0230***	0.0233***	0.0232***	0.0233***	0.0242***	0.0241***
	(0.0105)	(0.0087)	(0.0080)	(0.0075)	(0.0071)	(0.0076)	(0.0080)	(0.0080)	(0.0081)	(0.0084)
	2.12/1737	2.57/1737	2.80/1737	2.99/1737	3.24/1737	3.07/1737	2.89/1737	2.90/1737	2.98/1737	2.87/1737
					Fiscal stance II: rating grades					
[22A] Investment grade	0.0038***	0.0038*	0.0038	0.0038	0.0038	0.0038*	0.0038	0.0038	0.0038	0.0038
	(0.0013)	(0.0022)	(0.0028)	(0.0026)	(0.0024)	(0.0022)	(0.0023)	(0.0026)	(0.0028)	(0.0027)
	2.83/2044	1.73/2044	1.38/2044	1.49/2044	1.59/2044	1.70/2044	1.66/2044	1.47/2044	1.39/2044	1.42/2044
[22B] Speculative grade	0.0307***	0.0333***	0.0345***	0.0335***	0.0342***	0.0345***	0.0351***	0.0344***	0.0348***	0.0346***
	(0.0108)	(0.0096)	(0.0101)	(0.0098)	(0.0096)	(0.0090)	(0.0088)	(0.0087)	(0.0087)	(0.0088)
	2.82/1436	3.44/1436	3.40/1436	3.40/1436	3.56/1436	3.80/1436	3.95/1436	3.95/1436	3.99/1436	3.92/1436
					Fiscal stance III: bond yield spreads					
[23A] Low spreads	0.0138*	0.0157***	0.0177***	0.0174***	0.0173***	0.0165***	0.0159***	0.0156***	0.0163***	0.0167***
	(0.0072)	(0.0047)	(0.0044)	(0.0038)	(0.0038)	(0.0037)	(0.0039)	(0.0043)	(0.0045)	(0.0046)
	1.91/2182	3.29/2182	4.01/2182	4.47/2182	4.56/2182	4.45/2182	4.04/2182	3.60/2182	3.60/2182	3.62/2182
[23B] High spreads	0.0223**	0.0226***	0.0225***	0.0226***	0.0230***	0.0233***	0.0232***	0.0233***	0.0242***	0.0241***
	(0.0105)	(0.0087)	(0.0080)	(0.0075)	(0.0071)	(0.0076)	(0.0080)	(0.0080)	(0.0081)	(0.0084)
	2.12/1737	2.57/1737	2.80/1737	2.99/1737	3.24/1737	3.07/1737	2.89/1737	2.90/1737	2.98/1737	2.87/1737

TABLE 8. Continued

	Bias-corrected matching estimators									
Dependent variable: SDC	$n=1$	$n=2$	$n=3$	$n=4$	$n=5$	$n=6$	$n=7$	$n=8$	$n=9$	$n=10$
					Level of economic development					
[24A] Developed countries	0.0083**	0.0083***	0.0083***	0.0083***	0.0083***	0.0083***	0.0083***	0.0083***	0.0083***	0.0083***
	(0.0032)	(0.0029)	(0.0025)	(0.0022)	(0.0022)	(0.0021)	(0.0020)	(0.0021)	(0.0020)	(0.0021)
	2.53/956	2.83/956	3.27/956	3.65/956	3.70/956	3.82/956	4.05/956	3.83/956	4.04/956	3.89/956
[24B] Developing countries	0.0139*	0.0178**	0.0178**	0.0185***	0.0189***	0.0192***	0.0195***	0.0193***	0.0196***	0.0197***
	(0.0084)	(0.0069)	(0.0071)	(0.0071)	(0.0068)	(0.0067)	(0.0066)	(0.0066)	(0.0065)	(0.0064)
	1.65/1430	2.56/1430	2.49/1430	2.59/1430	2.76/1430	2.88/1430	2.94/1430	2.94/1430	2.99/1430	3.07/1430
					Degree of transparency					
[25A] Low transparency	0.0188**	0.0208***	0.0216***	0.0211***	0.0214***	0.0214***	0.0217***	0.0219***	0.0221***	0.0221***
	(0.0188)	(0.0065)	(0.0069)	(0.0070)	(0.0065)	(0.0063)	(0.0065)	(0.0067)	(0.0067)	(0.0066)
	2.43/1404	3.18/1404	3.13/1404	3.01/1404	3.26/1404	3.38/1404	3.32/1404	3.26/1404	3.28/1404	3.33/1404
[25B] High transparency	0.0068**	0.0068**	0.0068***	0.0068***	0.0068***	0.0068***	0.0068***	0.0068***	0.0068***	0.0068***
	(0.0034)	(0.0027)	(0.0026)	(0.0024)	(0.0022)	(0.0021)	(0.0019)	(0.0022)	(0.0021)	(0.0020)
	2.00/1685	2.45/1685	2.62/1685	2.83/1685	3.04/1685	3.24/1685	3.43/1685	3.10/1685	3.25/1685	3.40/1685
					Central bank independence					
[26A] Low central bank independence	0.0226	0.0232*	0.0232**	0.0245***	0.0228***	0.0227**	0.0224**	0.0222**	0.0220**	0.0218**
	(0.0152)	(0.0130)	(0.0103)	(0.0097)	(0.0087)	(0.0102)	(0.0102)	(0.0102)	(0.0109)	(0.0108)
	1.49/1053	1.78/1053	2.23/1053	2.51/1053	2.61/1053	2.21/1053	2.18/1053	2.18/1053	2.01/1053	2.02/1053
[26B] High central bank independence	0.0120***	0.0120***	0.0120***	0.0120***	0.0125***	0.0124***	0.0123***	0.0126***	0.0125***	0.0127***
	(0.0035)	(0.0032)	(0.0032)	(0.0032)	(0.0033)	(0.0032)	(0.0033)	(0.0033)	(0.0033)	(0.0033)
	3.41/1333	3.70/1333	3.66/1333	3.71/1333	3.78/1333	3.79/1333	3.70/1333	3.81/1333	3.77/1333	3.76/1333

Note: Heteroskedasticity-consistent standard errors in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

creditworthiness appear more prone to SDC following CDS initiation. Third, we look at sovereign debt yield spreads,[19] by differentiating between countries with low and high spreads, based on the mean value of yield spreads from Bloomberg. Lines [23A–B] show that CDS initiation increases more the probability of SDC in a context of high spreads. Altogether, these results, emphasizing a stronger effect when the fiscal stance is less good (namely, higher debt, lower ratings, and higher spreads), provide support for the importance of the channel that we are considering in our analysis.

Next, lines [24A–B] show that the magnitude of the effect of CDS trading on SDC occurrence dramatically changes with the level of economic development: around 0.8 (1.8) pp for developed (developing) countries. One possible explanation is that credibility in financial markets is better anchored in developed countries, which may help mitigating adverse adjustments between bonds and CDS markets.

Moreover, we condition the effect of CDS trading on countries' degree of transparency. Following Alesina and Weder (2002) and Gande and Parsley (2014), we proxy the degree of transparency by public sector's corruption perception index (CPI) of Transparency International and define "low" ("high") countries with CPI between 0 and 5 (6–10). Lines [25A–B] show that although ATTs are significant in both groups, their magnitude is around three times larger in "low" compared to "high" countries, namely around 2.1 pp. Thus, by helping borrowing governments to build reputation with private agents and improve market efficiency, transparency may mitigate the adverse effect of CDS trading on SDC occurrence.

Finally, we investigate the role of the limits imposed on central bank's lending to the Government, by differentiating between "low" and "high" central bank independence, using the mean level of central bank lending to Government Index from Crowe and Meade (2008). Lines [26A–B] in Table 8 show that the effect of CDS trading on SDC occurrence is more important for countries with relatively "low" central bank independence. Thus, limits imposed on central bank's lending to government may improve fiscal discipline and help avoid potential adverse consequences arising from fiscal dominance.

6.2. The Time Span

To understand how the effect of CDS trading on SDC occurrence evolves over time, we follow Balima et al. (2017) and estimate cumulative ATT_t, $t = \overline{1;13}$, spanning from the year of the first CDS trading initiation (2001), until the last year of the sample (2013). Lines [27A–M] in Table 9 reveal the following. Except for some cases, the impact of CDS trading is not significant over 2001–2004. Moreover, the cumulative effect of CDS trading on SDC occurrence becomes significant starting 2005, corroborating the findings of Peristiani and Savino (2011), who outline higher expected default frequency of CDS markets since 2004 for US firms. Finally, although remaining significant, the cumulative adverse effect

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TABLE 9. Heterogeneity in the impact of CDS trading on SDC using bias-corrected matching: cumulative ATTs and the time span

	Bias-corrected matching estimators									
Dependent variable: SDC	$n=1$	$n=2$	$n=3$	$n=4$	$n=5$	$n=6$	$n=7$	$n=8$	$n=9$	$n=10$
[27A] ATT_1	0.0384	0.0384	0.0384	0.0384	0.0384	0.0511*	0.0463*	0.0395*	0.0388*	0.0389*
	(0.0471)	(0.0384)	(0.0339)	(0.0301)	(0.0275)	(0.0256)	(0.0239)	(0.0227)	(0.0225)	(0.0213)
	0.82/822	1.00/822	1.13/822	1.28/822	1.40/822	1.99/822	1.94/822	1.74/822	1.73/822	1.82/822
[27B] ATT_2	−0.0468	−0.0293	−0.0189	−0.0159	−0.0135	−0.0129	−0.0135	−0.0171	−0.0294	−0.0323
	(0.0803)	(0.0473)	(0.0431)	(0.0359)	(0.0337)	(0.0322)	(0.0315)	(0.0346)	(0.0365)	(0.0354)
	−0.58/947	−0.62/947	−0.44/947	−0.44/947	−0.40/947	−0.40/947	−0.43/947	−0.49/947	−0.81/947	−0.91/947
[27C] ATT_3	−0.0256	0.0011	0.0133	0.0190	0.0222	0.0243	0.0253	0.0259	0.0211	0.0192
	(0.0449)	(0.0276)	(0.0250)	(0.0213)	(0.0201)	(0.0191)	(0.0198)	(0.0223)	(0.0220)	(0.0220)
	−0.57/1076	0.04/1076	0.53/1076	0.90/1076	1.10/1076	1.27/1076	1.27/1076	1.16/1076	0.96/1076	0.87/1076
[27D] ATT_4	−0.0180	0.0050	0.0150	0.0184	0.0198	0.0213*	0.0220*	0.0218	0.0201	0.0194
	(0.0297)	(0.0180)	(0.0161)	(0.0141)	(0.0132)	(0.0126)	(0.0132)	(0.0145)	(0.0149)	(0.0147)
	−0.60/1204	0.28/1204	0.93/1204	1.31/1204	1.50/1204	1.68/1204	1.66/1204	1.50/1204	1.35/1204	1.32/1204
[27E] ATT_5	0.0072	0.0185	0.0252**	0.0277**	0.0273***	0.0286***	0.0285***	0.0284**	0.0280**	0.0279**
	(0.0228)	(0.0140)	(0.0127)	(0.0111)	(0.0104)	(0.0102)	(0.0106)	(0.0119)	(0.0117)	(0.0117)
	0.32/1334	1.32/1334	1.98/1334	2.49/1334	2.62/1334	2.80/1334	2.68/1334	2.39/1334	2.40/1334	2.38/1334
[27F] ATT_6	0.0146	0.0201*	0.0232**	0.0241***	0.0234***	0.0244***	0.0244***	0.0241***	0.0242***	0.0240***
	(0.0167)	(0.0112)	(0.0101)	(0.0089)	(0.0083)	(0.0082)	(0.0083)	(0.0094)	(0.0093)	(0.0092)
	0.88/1470	1.79/1470	2.30/1470	2.71/1470	2.83/1470	2.96/1470	2.94/1470	2.56/1470	2.59/1470	2.60/1470
[27G] ATT_7	0.0129	0.0170*	0.0195**	0.0207***	0.0203***	0.0214***	0.0209***	0.0206***	0.0207***	0.0207***
	(0.0138)	(0.0094)	(0.0084)	(0.0073)	(0.0068)	(0.0067)	(0.0068)	(0.0078)	(0.0077)	(0.0076)
	0.94/1607	1.81/1607	2.33/1607	2.81/1607	2.96/1607	3.16/1607	3.06/1607	2.62/1607	2.69/1607	2.71/1607

TABLE 9. Continued

	Bias-corrected matching estimators									
Dependent variable: SDC	$n=1$	$n=2$	$n=3$	$n=4$	$n=5$	$n=6$	$n=7$	$n=8$	$n=9$	$n=10$
[27H] ATT_8	0.0153	0.0180**	0.0199***	0.0206***	0.0201***	0.0212***	0.0204***	0.0200***	0.0204***	0.0204***
	(0.0118)	(0.0081)	(0.0074)	(0.0065)	(0.0061)	(0.0060)	(0.0061)	(0.0067)	(0.0071)	(0.0070)
	1.30/1742	2.23/1742	2.68/1742	3.14/1742	3.27/1742	3.51/1742	3.36/1742	2.95/1742	2.87/1742	2.89/1742
[27I] ATT_9	0.0166	0.0180**	0.0200***	0.0207***	0.0203***	0.0209***	0.0202***	0.0198***	0.0204***	0.0204***
	(0.0104)	(0.0072)	(0.0066)	(0.0059)	(0.0057)	(0.0055)	(0.0056)	(0.0062)	(0.0066)	(0.0066)
	1.59/1874	2.48/1874	3.03/1874	3.50/1874	3.56/1874	3.77/1874	3.58/1874	3.20/1874	3.06/1874	3.08/1874
[27J] ATT_{10}	0.0181*	0.0185***	0.0203***	0.0205***	0.0206***	0.0210***	0.0202***	0.0198***	0.0205***	0.0204***
	(0.0093)	(0.0062)	(0.0059)	(0.0053)	(0.0051)	(0.0050)	(0.0050)	(0.0056)	(0.0059)	(0.0059)
	1.94/2005	2.96/2005	3.42/2005	3.87/2005	4.03/2005	4.19/2005	4.02/2005	3.50/2005	3.44/2005	3.47/2005
[27K] ATT_{11}	0.0174**	0.0173***	0.0189***	0.0191***	0.0190***	0.0195***	0.0187***	0.0182***	0.0190***	0.0188***
	(0.0083)	(0.0056)	(0.0052)	(0.0047)	(0.0045)	(0.0045)	(0.0046)	(0.0051)	(0.0053)	(0.0052)
	2.08/2135	3.09/2135	3.58/2135	4.00/2135	4.17/2135	4.34/2135	4.01/2135	3.55/2135	3.55/2135	3.56/2135
[27L] ATT_{12}	0.0150**	0.0157***	0.0177***	0.0177***	0.0184***	0.0180***	0.0171***	0.0169***	0.0174***	0.0173***
	(0.0076)	(0.0052)	(0.0048)	(0.0043)	(0.0041)	(0.0040)	(0.0042)	(0.0046)	(0.0048)	(0.0048)
	1.97/2263	3.01/2263	3.70/2263	4.11/2263	4.44/2263	4.47/2263	4.05/2263	3.61/2263	3.57/2263	3.59/2263
[27M] ATT_{13}	0.0140**	0.0147***	0.0165***	0.0162***	0.0170***	0.0165***	0.0157***	0.0155***	0.0160***	0.0159***
	(0.0069)	(0.0048)	(0.0043)	(0.0039)	(0.0038)	(0.0037)	(0.0039)	(0.0042)	(0.0044)	(0.0044)
	2.02/2386	3.06/2386	3.83/2386	4.16/2386	4.46/2386	4.47/2386	4.03/2386	3.62/2386	3.58/2386	3.58/2386

Note: Heteroskedasticity-consistent standard errors in parentheses; $^{***}p < 0.01$, $^{***}p < 0.05$, $^{*}p < 0.1$.

decreases in the following years toward its value in 2013, which corresponds to benchmark values.

7. CONCLUSION

We analyzed the effect of CDS trading initiation on the occurrence of SDC using a large sample of 141 developed and developing countries over 1980–2013. We used different econometric techniques to address the self-selection and endogeneity issues of CDS trading initiation. Results show that SDC increases after the introduction of CDS trading. This effect is meaningful: on average, countries with CDS contracts on their debt present a 1.5–2 pp higher probability of experiencing SDC than countries without CDS contracts. In addition, the impact of CDS trading initiation on SDC occurrence is sensitive to countries' characteristics, and to the considered time span.

Consequently, our paper contributes to the nascent literature on the effect of *sovereign* CDS trading. Complementing previous work emphasizing favorable effects, our analysis suggests that sovereign entities become more vulnerable to debt crisis following CDS trading initiation. Taken together, these effects should, on the one hand, trigger additional research for assessing the impact of CDS trading initiation and, on the other hand, contribute to the policy design of the initiation of CDS trading. On this last point, our study provides some first insights for limiting the effects of CDS trading on SDC, as this detrimental effect is found to be weaker when the fiscal stance is relatively good (low public debt and sovereign debt yield spreads, and even statistically not significant in countries with investment grades at the moment of their CDS initiation), in developed countries, and in countries with high public sector transparency and high central bank independence.

SUPPLEMENTARY MATERIAL

To view supplementary material for this article, please visit http://dx.doi.org/10.1017/S1365100518000627.

NOTES

1. Previous research on the effects of CDS trading focused mainly on the impact of *corporate* CDS trading on the (i) supply and (ii) pricing of debt, and reported mixed results. Bolton and Oehmke (2011) showed that (i) debt supply can increase because of bondholders having more bargaining power in debt renegotiation when they use CDS to protect their exposure, a result confirmed by Saretto and Tookes (2013). However, focusing on the effect of CDS on equilibrium debt contracts, Che and Sethi (2014) argued that CDS may crowd out productive lending, since bondholders might be tempted to trade CDS instead of bonds. Regarding (ii) debt pricing, Ashcraft and Santos (2009) found that credit spreads increase (decrease) for low-(high-)quality firms, following CDS initiation, consistent with Parlour and Winton (2013). At a more aggregated level, Shim and Zhu (2014) established that CDS lowered the cost of issuing bonds and enhanced liquidity in Asian bond markets. On the contrary, Das et al. (2014) concluded that CDS trading reduces the efficiency of corporate bond markets, without

decreasing pricing errors or enhancing liquidity. Finally, beyond these studies on debt supply and cost, Subrahmanyam et al. (2014) revealed an increase in the likelihood of a credit rating downgrade and bankruptcy, following CDS trading initiation in North American corporate issuers.

2. Relatedly, Qian et al. (2017) discuss the link between sovereign CDS spreads and macroeconomic financial indicators in Japan. Moreover, they highlight spillovers from the global stock market to Japan's sovereign credit market.

3. Other arguments could support testing this hypothesis. First, since CDS allow better mitigating risks, more investors are willing to lend [Bolton and Oehmke (2011)]; thus, CDS introduction may trigger a larger number of bondholders, making creditors' coordination more difficult when the borrower faces financial distress, and default more likely [Gilson et al. (1990), Brunner and Krahnen (2008), and Subrahmanyam et al. (2014)]. Second, CDS introduction can trigger the emergence of empty creditors who have greater stake to push a borrowing government into default if their total payoffs (including CDS payments) would be boosted by this event [Bolton and Oehmke (2011)]. Third, as stressed by Stein (1987), the entry of new speculators into a market can deteriorate the informational content of prices and reduce the ability of preexisting investors to properly infer assets' value, which could increase risks. Finally, trading in the CDS market presents some advantages compared to the bond market, notably due to the opacity of over-the-counter (OTC) CDS markets [Acharya and Johnson (2007)]; through diverting investors off the bond market, CDS trading could lower their participation and bond liquidity and therefore increase the likelihood of default.

4. Since CDS transactions occur in an OTC market, and not as centralized exchanges, we compare Markit initiation dates with concurrent data sources, including GFI, Fenics, Reuters, CMA, and JP Morgan. Initiation dates usually appear earlier in the Markit data set.

5. CDS data from Markit begin in January 2001 and include 79 developed and developing CDS countries. We exclude the three countries (China, Greece, and Mexico) present in Markit database at the start of CDS trading in January 2001, as we are not able to infer their initiation dates. Moreover, we follow Ismailescu and Phillips (2015) and compare Markit initiation dates with the International Financing Review (IFR), which reports weekly CDS prices for 1998–2000, namely prior to the Markit data set. Since Brazil and Hungary appear in the IFR database, suggesting that CDS trading began prior to the Markit introduction date, we equally exclude them.

6. Besides, the International Swaps and Derivatives Association considers debt restructuring as a credit event leading to CDS payments.

7. Appendix 2 presents definitions and data sources for all variables.

8. Since some countries did not experience any crisis in the study period, including country fixed effects would lead to loss of information from dropping them.

9. Estimated ATTs presented in the main text are based on propensity scores computed in Appendix 3.

10. Estimations for the computation of propensity scores are presented in Appendix 4.

11. On average, CDS countries present significantly lower debt, fiscal deficit, and inflation, and higher current account balance, and private credit-to-GDP ratio, while no-CDS countries present significantly higher GDP growth, and lower executive constraints.

12. Including covariates employed in the first step of entropy balancing in the regression step is similar to introducing control variables in a randomized experiment [Neuenkirch and Neumeier (2016)].

13. For instance, monitoring in case of credit events may be less complex in countries ideologically close to the USA.

14. These findings are confirmed when successively introducing additional control variables that may affect both joint US votes and SDC, namely a common law legal origin, log of US development aid, current account balance, capital account balance, and financial account balance (see Appendix 6).

15. This should be the case if the joint US votes is not directly correlated with SDC occurrence.

16. Our instrumentation strategy, which consists of using binomial probit models both in the instrumentation (first-stage) and in the main regressions, follows closely the one of Subrahmanyam et al.'s 2014; see their Section 3.3 at pages 2940–2942. Alternatively, we performed the instrumentation using

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OLS both in the first-stage and in the main regressions; and then we used OLS in the first-stage regression and a probit model in the main regression. These two additional estimations, available upon request, reveal that although with a higher magnitude (which may be related to the use of OLS in the first stage), instrumented CDS still significantly increase SDC probability, consistent with the main results.

17. The use of a nonlinear model for computing the IMR makes our analysis comparable to the related literature [see, e.g., Ismailescu and Phillips (2015)].

18. Alternatively, Subrahmanyam et al. (2014) and Ismailescu and Phillips (2015) shift forward the CDS introduction by 1 year in their falsification tests; however, this is not appropriate for our analysis focusing on the average treatment effect.

19. Although related, notation agencies' marks and sovereign bonds yields' spreads may not always capture exactly the same dimensions of risk [see Balima et al. (2017), for such differences related to IT adoption].

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