The Costs of Sovereign Default: Evidence from Argentina, Online Appendix

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A Data Construction Details

In this section, we provide additional details about our data construction.

A.1 Data Sources

In the table below, we list the data sources used in the paper. The data source for the credit default swap prices is Markit, a financial information services company. We use Markit's composite end-of-day spread, which we refer to as the "close." The composite end-of-day spread is gathered over a period of several hours from various market makers, and is the spread used by those market makers to value their own trading books. The composite end-of-day spread uses a survey of dealers to estimate the recovery rate. Markit uses a data cleaning process to ensure that the composite end-of-day quotes are reasonable approximations of market prices. Markit provides extensive documentation on their data, including documentation on the "CDS Data Cleaning Process," a "Markit CDS Liquidity User Guide," and other detailed information on the data construction. This very thorough documentation and extensive conversations with Markit give us confidence that this is the most reliable source of CDS pricing available.

We have experimented with alternative providers of CDS data, such as Bloomberg, but found discrepancies between these data sources and Markit. Although the aggregate time series of Markit, Bloomberg, and Datastream appear similar, at a higher frequency it is clear that there are significant issues with the Bloomberg and Datastream data. The primary issue with the Bloomberg data is that the CDS spreads at tenors other than five years appear to be unreliable. In particular, Bloomberg's two-, three-, and four-year CDS spreads have very large daily fluctuations that are completely absent from the five-year spread and from the Markit data. However, the Bloomberg data for the five-year spread appears to be reasonable. This explains why the Bloomberg and Markit results that use a five-year credit triangle approximation, with a 39.5 percent recovery rate, are very similar (see appendix table A7). However, while the credit triangle approximation method is a useful first step, it essentially assumes a constant hazard rate over the life of the five-year CDS. Given that the court case would likely lead to default over the shorter term, as we see in the estimated hazard rates, this assumption is not appropriate. Given the problems with the shorter tenor Bloomberg CDS, we do not attempt to bootstrap a risk-neutral default probability curve using the ISDA Standard Model.

The Datastream data look very similar to Markit on most days, but there are many dates, including several of our events, for which the Datastream data is missing. For instance, the data in Datastream on the day of the major Supreme Court ruling (June 16, 2014) is missing. We conferred extensively with Datastream support, and they confirmed that their source data is from EIKON, and that on that day, as well as several other of the rulings, EIKON did not receive any CDS quotes.

They were unable to explain why there were no prices on these days. Both Bloomberg and Markit have data for these days, and DTCC trading volume data indicates that Argentine CDS were traded during the weeks for Datastream has missing data. When we use the previously mentioned credit triangle approximation with the Datastream data, and discard the days with missing data, we find results that are similar to the full-sample Markit and Bloomberg credit triangle approximation results (see appendix table A7).

Table A1: Data Sources

Data	Data Source
Prices and returns for ADRs	CRSP & Bloomberg
Prices and returns for local equities	Bloomberg
VIX	CBOE
S&P	Global Financial Data
MSCI Emerging Markets Asia ETF	Datastream
High Yield and IG Bond Index	Datastream
Oil Prices	Global Financial Data
Industry Exports	OECD-STAN IO Tables
Firm Imports	Gopinath and Neiman (2014)
Firm Revenue	Compustat Global
Firm Earnings (ADR firms only)	CRSP
Market Capitalization	Bloomberg
Foreign Ownership	Bloomberg
Industry Classification	Fama-French, formatted by Dexin Zhou
Bond Prices for BCS construction	Bloomberg
Dolar Blue Rate	dolarblue.net
Official nominal exchange rate	Datastream
CDS spreads/Recovery Rate/Default Probability	Markit
Alternative CDS Spreads	Bloomberg, Datastream
Argentine Sovereign Bond Prices	Bloomberg

A.2 Firm Classifications

To ensure sufficient data quality, we limit our study of local Argentine equities to firms with a 2011 market capitalization at least 200 million pesos,[1] have returns during at least ten of our event windows, and for which the equity price changes on at least half of all trading days in our sample. We exclude several firms that have neither headquarters or a large fraction of their revenues in Argentina, but are listed on the Argentine exchange for legacy reasons.[2]

[1] About \$50mm USD at market exchange rates in 2011.

[2] See appendix section G.2, for a discussion of these firms.

We classify firms according to their Fama-French industry classifications.[3] We sort firms into their corresponding Fama-French industries according the SIC code of their primary industry, available from Datastream. After this initial sort, we only have one firm, Boldt, classified as Business Equipment, and so we combine it with the telecommunications firms. The "Finance" Fama-French 12 industry classification is also too broad for our purposes, as it combines banks, holding companies, and real estate firms. We therefore split the nine firms initially classified as "Finance" according to their Fama-French 49 industry classification. This gives us six banks, two real estate firms, and one "Trading" firm, Sociedad Comercial del Plata. Because Sociedad Comercial del Plata is a diversified holding company, and is the only company in the Fama-French 49 industry classification of "Trading," we rename its industry "Diversified," and do not merge it with any other industry classification. After these modifications, our sample includes six banks, two chemical firms, one diversified firm, three energy firms, four manufacturing firms, six non-durables firms, two real estate firms, three telecoms, and eight utilities. These industries are listed in table A2.

We also sort firms by their exporter status. Unfortunately, this task is complicated by the fact that publicly available data sources do not comprehensively report firm-level exports. We instead rely on industry-level measures. We use the OECD STAN Input-Output Tables for Argentina to calculate what share of each industry group's output is exported. The Input-Output Table covers 37 industries, each of which covers at least one two-digit ISIC industry, and some of which, such as "Agriculture, hunting, forestry and fishing," cover up to five two-digit ISICs. After we calculate the share of exports for each of these 37 industries, we classify our 33 firms into one of these industries according to the SIC code of its primary output. The most recent Input-Output Table for Argentina uses data from 1995, so our export analysis assumes that the relative tradability of different products has not changed too much over the past 20 years.[4] When we construct a zero-cost long-short portfolio, going long exporters and short non-exporters, we will classify firms as exporters if exports accounted for at least 10 percent of their primary industries' revenues in our Input-Output table, and non-exporters otherwise. The exporter threshold is set at 10 percent because there are no firms with an export share between 3.6 percent and 10.1 percent.

To calculate each firm's import intensity, we use firm level data from Gopinath and Neiman (2014). The most recent available import data is for 2007 and 2008 (through October), and we compute the ratio of imports to firm revenue using data from Compustat Global. Our measure of import intensity is the average ratio of imports to revenue in 2007 and 2008. The importer threshold is set to the median ratio 0.6 percent.

[3] Classifications available on Kenneth French's website. We use the versions formatted by Dexin Zhou.

[4] For those firms that report data on revenue from exports, there is a strong correlation between reported exports as a share of sales and the imputed share of exports from the 1995 input-output table.

The next cut of the data divides firms between those that are subsidiaries of foreign corporations and those that are not. We classify firms as foreign-owned if the headquarters of their ultimate parent is any country other than Argentina in Bloomberg (Field ULT_PARENT_CNTRY_DOMICILE). We use the most recent (as of our data construction) version of this variable and cannot account for the possibility that an Argentine firm was only recently purchased by a foreign parent.

The final variable we use to classify our local equities is an indicator for whether or not the firms have an ADR that is traded in the U.S. This includes some firms with ADRs that trade over-the-counter, and are therefore not included in our analysis of the ADRs.

Table A2: Firms Included in Analysis

Company	Ticker	Industry	Exports	Imports	Market Cap	Foreign	ADR
Aluar	ALUA	Manufacturing	19.4	9.1	9443.0		
IRSA Propiedades Commerciales	APSA	Real Estate			2960.1		Y
Hipotecario Naci	BHIP	Banks			3540.0		Y*
Banco Macro Bansud	BMA	Banks			9379.2		Y
Boldt	BOLT	Telecoms		1.8	1537.5		
Banco Patagonia	BPAT	Banks			3488.4	Y	Y*
Banco Santander Rio	BRIO	Banks			12786.1	Y	Y*
Carlos Casado	CADO	Real Estate			378.1		Y*
Capex	CAPX	Utilities	0.1	0.9	1087.8		
Celulosa	CELU	Chemicals	11.2	1.3	760.3		
Central Puerto Rights	CEPU2	Utilities	0.1	0.4	1814.4		
Sociedad Comercial Del Plata	COME	Diverse	1.5		212.3		
Cresud	CRES	Non-Durables	14.5	0.0	3495.9		Y
Edenor	EDN	Utilities	0.1	0.1	1894.5		Y
Siderar	ERAR	Manufacturing	19.4	10.6	10893.1	Y	
BBVA Banco Frances	FRAN	Banks			7723.6	Y	Y
Gp Finance Galicia	GGAL	Banks			7125.7		Y
Solvay Indupa	INDU	Chemicals	11.2	0.6	1218.0	Y	
IRSA	IRSA	Real Estate			3350.5		Y
Juan Minetti	JMIN	Manufacturing	3.6	2.1	1633.5	Y	
Ledesma	LEDE	Non-Durables	14.5	1.0	4004.0		
Metrogas	METR	Utilities	0.1	0.0	677.3		Y*
Mirgor	MIRG	Manufacturing	10.1	11.8	512.0		Y*
Molinos Rio De La Plata	MOLI	Non-Durables	19.5	0.4	8014.4		
Pampa Energia	PAMP	Utilities	0.1	0.1	3417.2		Y
Quickfood	PATY	Non-Durables	19.5	0.5	641.9	Y	
Petrobras Argentina	PESA	Energy	25.5	3.8	8228.4	Y	Y
SA San Miguel	SAMI	Non-Durables	19.5	0.6	491.1		
Moli Juan Semino	SEMI	Non-Durables	19.5	0.1	325.5		
Telecom Argentina	TECO2	Telecoms	2.7	0.3	21754.8	Y	Y
Transportadores De Gas Del Norte	TGNO4	Utilities	0.1	3.3	540.4		
Transportadora De Gas Del Sur	TGSU2	Energy	25.5	0.9	2558.3		Y
Transener	TRAN	Utilities	0.1	2.1	640.3		
YPF	YPFD	Energy	14.2	2.2	74532.8		Y

Notes: This table lists the 33 firms used in the analysis of local equities, and one firm (IRSA Propiedades Commerciales) whose ADR is included in our ADR sample, but whose local stock returns do not pass our data quality requirement. Ticker indicates the company's local ticker in Bloomberg. Exports denotes the ratio (in percentage terms) of exports to total output for the firm's primary industry. Exports are calculated by classifying the firm into one of the 37 industries in the OECD STAN Input-Output Table according the SIC code of the firm's primary industry. Imports denotes the ratio (in percentage terms) of imports to firm revenue in 2007 and 2008. The import data is from Gopinath and Neiman (2014). Market Cap. is the firm's average end-of-quarter market capitalization in 2011 from Bloomberg, measured in Argentine pesos. ADR is an indicator for whether the firm currently has an American depository receipt. "Y*" indicates that the firm has an OTC-traded or discontinued ADR and is not included in our sample of ADRs. To be included in our ADR sample, the ADR must be exchange-traded and have existed for our entire sample. Foreign is an indicator for whether the firm is owned by a non-Argentine parent company.

A.3 Exchange Rate Construction

The blue-chip swap rate is constructed by dividing the peso price of the government bond by the dollar price of the same bond. The mechanics of this transaction are outlined in Panel A of Figure A1. In Panel B of Figure A1, we demonstrate how to construct an exchange using local equities and ADRs.

We calculate the blue-chip swap rate using the two most liquid available debt instruments, the Bonar X and the Boden 15.[5] To calculate this blue-chip swap rate, we search for the bonds on Bloomberg, use <ALLQ> to find the list of all available pricing sources for the bonds, and then download the full available history of closing prices for every data provider in ARS and USD.[6] Each day, there are around five closing price quotes per bond in ARS and USD. We calculate the median price for each bond every day, by currency, and then construct the implicit exchange rate by dividing the median peso price by the median dollar price. This gives us a blue-chip swap rate for each of our two bonds, and we construct the Blue-Chip Swap rate by taking the average of the two. Despite these bonds being classified as domestic debt, many of these instruments have ISINs and are accepted on Euroclear or Clearstream. This makes it relatively easy for foreign investors to use this process to get money on- or offshore, circumventing Argentina's capital controls.[7] However, it is important to remember that although we calculate the exchange rate using simultaneous prices, an investor implementing this transaction is required to hold the bond for at least three days at an Argentine custodian bank, and therefore bears some price risk when acquiring dollars.[8] Despite being domestic law debt instruments, both of these bonds became entangled in the legal proceedings we focus on in this paper.[9]

For the ADR blue rate, we follow the methodology outlined on dolarblue.net.[10] We collect daily open and close price data on the ADR and local equity for eight firms from Bloomberg.[11] We then calculate the daily implicit exchange rate for each firm, drop the high and low price among the eight firms, and construct our measure as the mean of the remaining six equities. The average difference between the maximum and minimum firm-level exchange rate is 3.6 percent of the level of the ADR Blue Rate. This difference could reflect differences in the closing times of the

[5]The ISIN for the Bonar X is ARARGE03F441 and the ISIN for the Boden 15 is ARARGE03F144.

[6]We drop pricing sources with less than 300 days of data and sources where more than 5 percent of the daily observations record no price change.

[7]Indeed, the dolarblue.net website (now closed) offered a simple guide for how to buy and sell dollars (Dolarblue.net (2014)).

[8]Chodos and Arsenin (2012).

[9]Excellent coverage of turmoil around the domestic debt was provided by Joseph Coterill of FT Alphaville. See, for instance, Cotterill (2015*b*) or Cotterill (2015*a*).

[10]Dolarblue.net (2016).

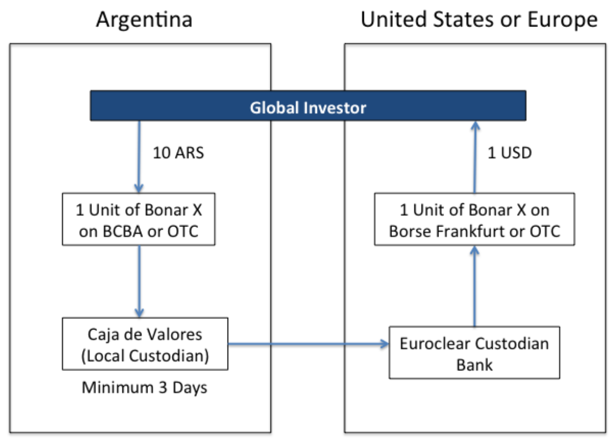
[11]Grupo Financiero Galicia (ADR Ticker: GGAL, Local Ticker: GGAL), Tenaris (TS, TS), BBVA Banco Frances (BFR, FRAN), Banco Macro (BMA, BMA), Pampa Energia (PAM, PAMP), Petrobras Argentina (PZE, PESA), Petroleo Brasileiro (PBR, APBR), and Telecom Argentina (TEO, TECO2).

NYSE/NASDAQ and Buenos Aires stock exchanges, bid-offer spreads, and other forms of illiquidity. Generally speaking, it is very costly for foreign investors to participate in local Argentine markets, which makes the ADR blue rate arbitrage difficult for them to execute. Together, the ADR Blue Rate and the Blue-Chip Swap rate may be known as the dolar contado con liquidación, dolar fuga, or the dolar gris (Infodolar.com (2016*b*)).

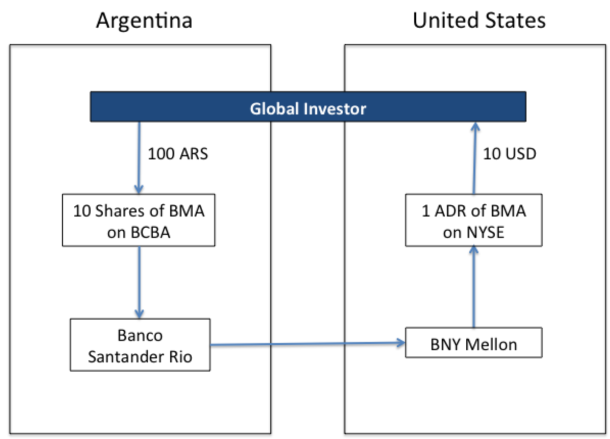
While the CDS-IV results in Table 2 report similar point estimates of the effect of default on the Dolar Blue, ADR Blue, and Blue-Chip Swap Rate, the standard errors and confidence interval for the Dolar Blue are significantly tighter. The reason for this is that the behavior of the ADR Blue rate and Blue-Chip swap rate on the day with the largest increase in the probability of default, the Supreme Court ruling day on June 16, 2014, is a significant outlier. On that day, these measures of the exchange rate significantly appreciated. This is in stark contrast to the Dolar Blue rate, which has a significant depreciation. Mechanically, the reason for the appreciation of the ADR Blue and Blue-Chip Swap rates is that the value of domestically traded securities priced in ARS fell significantly more than those traded by foreign investors in dollars. Based on conversations with market participants, we believe that the ruling caused a major disruption in local trading. If we expand the window size around this ruling, it ceases to be an outlier, consistent with the trading disruption hypothesis. However, a major speech was made by the President of Argentina in the evening following the ruling, so we cannot be certain that this pattern is due to a disruption in trading. We also find that, if that event is excluded, the effect on the exchange rate approximately doubles and is relatively precisely estimated. The importance of this outlier (Event 13) can be clearly seen in Figure A3.

Figure A1: Blue Rate Construction

(a) Blue-Chip Swap



(b) ADR Blue Rate



Panel (a) demonstrates how an investor would convert Argentine pesos into U.S. dollars at an exchange rate of 10 pesos to the dollar, by buying a domestic sovereign bond in ARS and selling the bond offshore in USD. This transaction defines an unofficial exchange rate known as the Blue-Chip Swap rate. Panel (b) demonstrates how an investor would convert Argentine pesos into U.S. dollars at the same exchange rate, by buying shares of Banco Macro onshore and selling an ADR in New York. The transaction defines an unofficial exchange rate known as the ADR Blue Rate.

A.4 Construction of Risk-Neutral Default Probabilities

We convert CDS spreads into risk-neutral default probabilities to provide a clearer sense of the magnitude of the estimated coefficients. We emphasize that we work with risk-neutral probabilities and do not attempt to convert them to physical probabilities. Pan and Singleton (2008) and Longstaff et al. (2011) impose additional structure to estimate the physical default probabilities.

In our baseline results, we will use the five-year cumulative risk-neutral default probability estimated by Markit using the ISDA standard model. This calculation begins with data from Markit on CDS par spreads and the dealer reported recovery rates, as well as a zero-coupon discounting curve.[12] The par spread is the coupon payment that a buyer of CDS protections pays to the seller of the contract such that the CDS contract has zero cost at initiation. Because the seller of a CDS insures the buyer of a CDS against credit losses throughout the duration of the contract, pricing the contract involves calculating the term structure of credit risk on the bond. The recovery rate we use is the average of the recovery rates reported by dealers contributing prices to Markit. In robustness checks, we also consider a case with a constant recovery rate equal to the realized recovery of 39.5 percent.[13]

The market standard for pricing CDS is a reduced form model that models time-varying credit risk as a time-varying hazard rate of default.[14] Because we use the risk-neutral default probabilities calculated by Markit, our exposition will exactly follow Markit (2012). The par spread is the spread that equates the present value of payments from buyer of protection to the seller of protection (Fee Leg) equals the value of the from the seller to the buyer upon default (Contingent Leg). We can write the equation equating the present value of fee leg to the present value of the contingent leg as

$$S_n \sum_{i=1}^{n} \Delta_t P_{S(t)} Df_t + AD = (1-R) \cdot \sum_{i=1}^{N} \left(P_{S(t-1)} - P_{S(t)} \right) Df_t \tag{A1}$$

where

[12] Details on the discounting curve can be found at http://www.cdsmodel.com/cdsmodel/documentation.html. In the robustness checks where we estimate the risk-neutral default probability rather than using the data provided by Markit, we will use the U.S. zero-coupon Treasury curve calculated in Gürkaynak, Sack and Wright (2007) as our discount curve. As Longstaff et al. (2011) point out, changing from the Treasury curve to a zero-coupon curve extracted from Libor and swap rates would have very little effect on the results. Our estimation is performed using the Matlab function *cdsbootstrap*.

[13] See http://www.creditfixings.com/CreditEventAuctions/holdings.jsp?auctionId=9073 for details on the auction to calculate the recovery rate.

[14] White (2013) provides a very thorough discussion of the ISDA standard model.

$$\begin{aligned}
S_n &= \text{Spread for protection to period } n \\
\Delta_t &= \text{Length of Period} \\
P_{Si} &= \text{Probability of survival to time } i \\
Df_i &= \text{Discount factor to time } i \\
R &= \text{Recovery Rate} \\
AD &= \text{Accrual on Default}
\end{aligned}$$

White (2013) provides a detailed explanation of the calculation of accrual on default and we will omit the details here for brevity. If we assume that the default hazard rate is constant between CDS nodes (tenors for which CDS contracts are traded), the survival probabilities map exactly to the hazard rates. For example, if the shortest tenor CDS traded is 6 months, and the hazard rate of default is λ_{6m} from time 0 to 6 months, then the survival probability is equal to $\exp\left(-\lambda_{6M}\cdot\left(\frac{1}{2}\right)\right)$. Given a 6 month par spread, a discounting curve to 6 months, and an assumption on the recovery rate, λ_{6m} can be calculated directly from equation (A1). Once this hazard rate, and therefore the survival probability, has been calculated for the 6 month tenor, the hazard rate between the next node of the CDS curve, 6 months and 1 year, can be calculated in the same way. In this way, the hazard rate curve is bootstrapped until we have calculated the hazard rates between every CDS node. We can then use our estimate hazard rates to calculate the risk-neutral default probabilities for various horizons:

$$\begin{aligned}
Pr(D \leq 6M) &= 1-\exp\left(-\lambda_{6M}\cdot\left(\frac{1}{2}\right)\right) \\
Pr(D \leq 1Y) &= 1-\exp\left(-\lambda_{6M}\cdot\left(\frac{1}{2}\right)-\lambda_{1Y}\cdot\left(\frac{1}{2}\right)\right) \\
&\vdots \\
Pr(D \leq 5Y) &= 1-\exp\left(-\lambda_{6M}\cdot\left(\frac{1}{2}\right)-\lambda_{1Y}\cdot\left(\frac{1}{2}\right)-\lambda_{2Y}-\lambda_{3Y}-\lambda_{4Y}-\lambda_{5Y}\right)
\end{aligned}$$

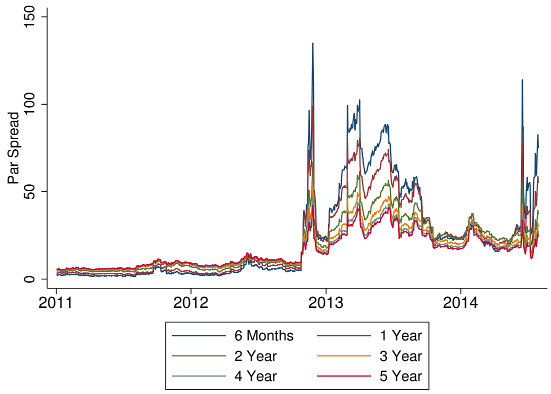
The final equation, the probability that the government defaults in the next five years, is the measure we use for the default probability in our baseline analysis. For the calculation of the default probabilities of the other sovereigns in Section G.1, we approximate the default probability by using the credit triangle relationship. As shown in White (2013), if we assume the premium leg were paid instantly and the hazard rate were equal to a constant λ, then we would have

$$\begin{aligned} S &= (1-R)\lambda \\ \lambda &= \frac{S}{1-R} \\ Pr(D<5Y) &= 1-\exp(-5\lambda). \end{aligned}$$

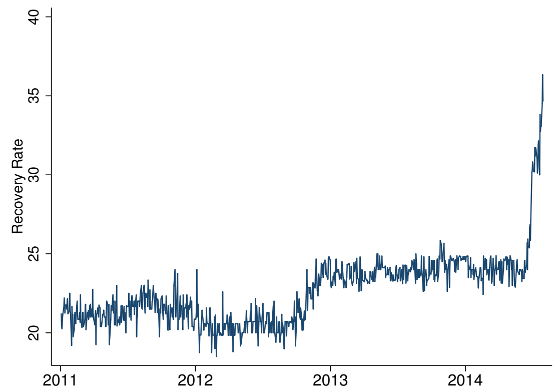
In the figure below, we chart the CDS spreads and recovery assumptions that we use to infer hazard rates of default and cumulative default probabilities. In all regressions in the body of the paper, we use Markit's risk-neutral default probability calculations rather than our own calculations.

Figure A2: From CDS Spreads to Default Probabilities

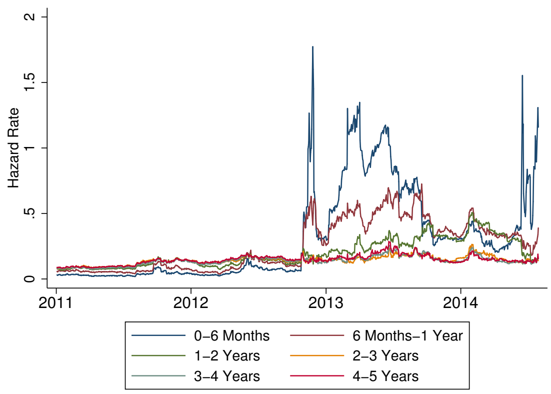
(a) Daily Composite CDS Spreads



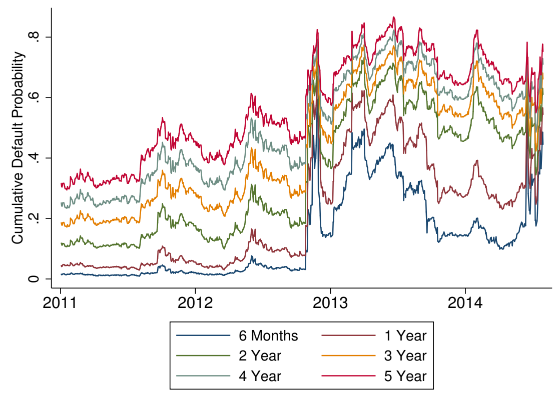
(b) Dealer-Reported Recovery Rate



(c) Estimated Hazard Rate



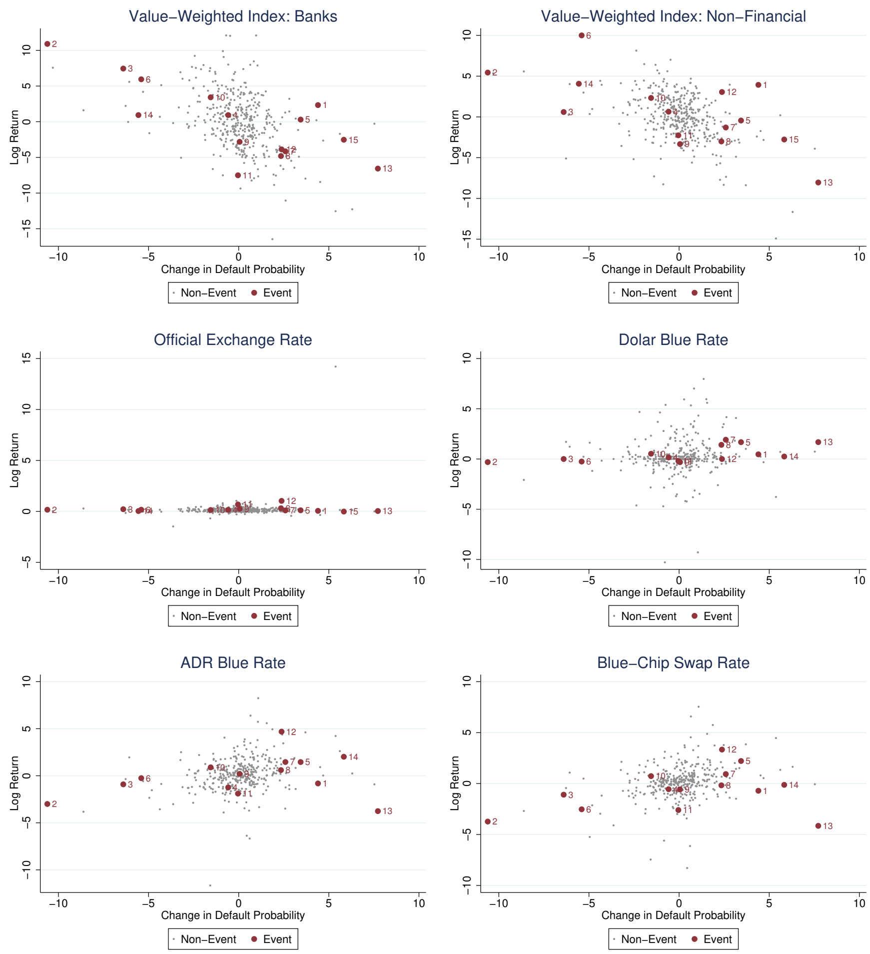
(d) Risk-Neutral Cumulative Default Probability



Notes: Panel (a) plots the daily Composite CDS spreads from Markit. Panel (b) plots the average of all recovery rates of Markit contributors whose CDS curves are used to calculate the Markit CDS End of Day composite curve. Panel (c) plots the default hazard rates estimated using the ISDA Standard model. 0–6 Months indicates the estimated constant hazard rate from initiation to 6 months, 6 Months–1 Year indicates the implied estimated constant hazard rate from 6 months after initiation to 1 year after initiation, and so on. Panel (d) converts the estimated hazard rates in Panel (c) into cumulative risk-neutral default probabilities. 6 Months indicates the probability the government defaults in the next 6 months, 1 Year indicates the probability of default in the next year, and so on. The data and ISDA Standard model are discussed in Sections II and A.4.

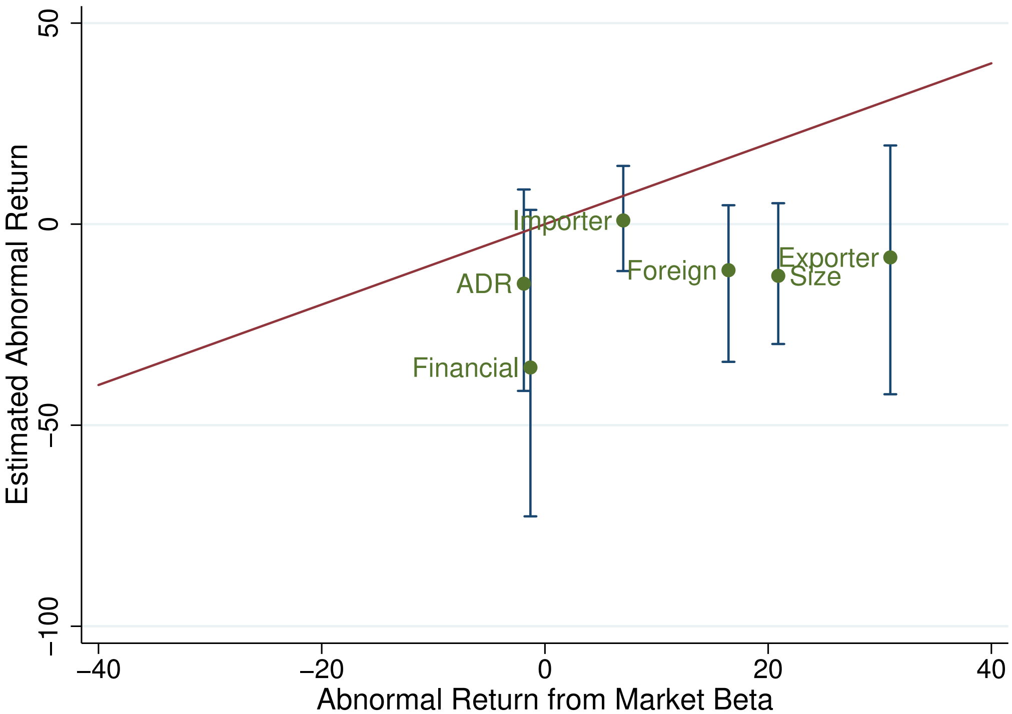
B Additional Figures

Figure A3: Change in Default Probability and other Financial Variables on Event and Non-Event Days



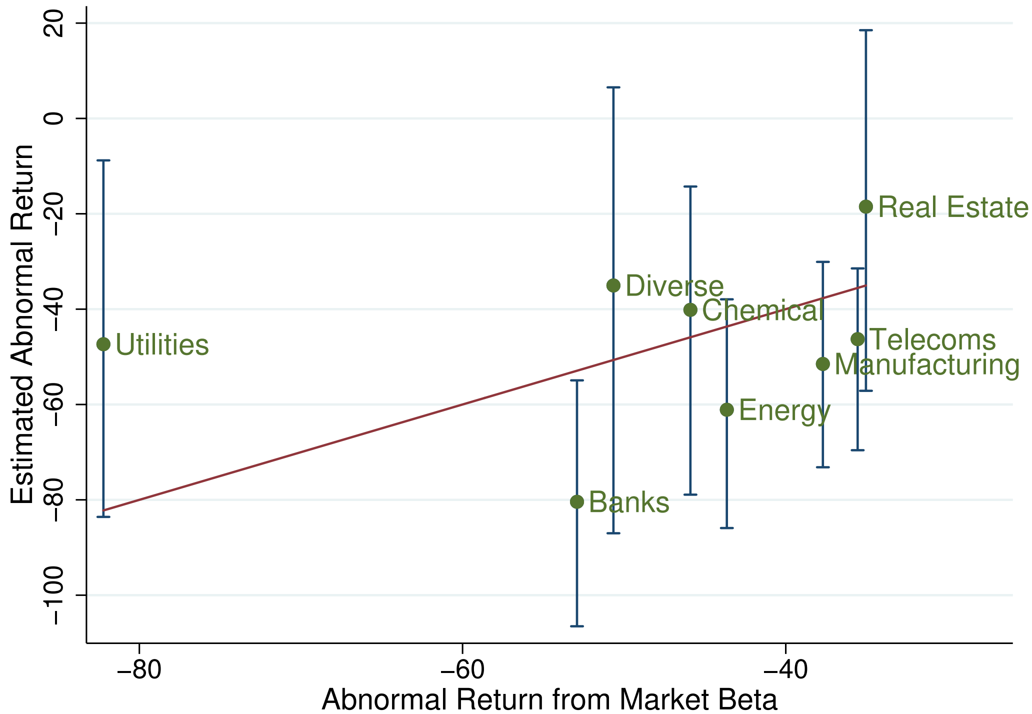
Notes: This figure plots the change in the risk-neutral probability of default and returns on the Value-Weighted Bank and Non-Financial Index and four measures of the exchange rate, on event and non-event days. Official is the government's official exchange rate. Dolar Blue is the onshore unofficial exchange rate from dolarblue.net. ADR Blue is the ADR Blue Rate constructed by comparing the ADR share price in dollars with the underlying local stock price in pesos, as described in Section II. Blue-Chip Swap is constructed by comparing the ARS price of domestic Argentine sovereign debt with the dollar price of the same bond, as described in Section II. Each event and non-event day is a two-day event or non-event as described in the text. The numbers next to each large dark maroon dot references each event-day in the table below Figure 3a. The procedure for classifying events and non-events is described in the text.

Figure A4: Estimated Response to Default Shocks: Long-Short



Notes: Each label denotes a zero-cost long short portfolio. "Exporter" is a portfolio going long export-intensive non-financial firms (NFFs) and short non-export-intensive NFFs. "Importer" is defined equivalently for importers. "Financial" goes long banks and short NFFs. "Foreign" goes long firms with a foreign parent and short domestically owned firms. "Size" goes long firms with above-median market capitalization in 2011, and short firms with below-median market cap. "ADR" goes long firms with an American Depository Receipt and short firms without one. The data sources are described in Section II. On the the x-axis, we plot the expected abnormal return for each portfolio, calculated as the beta of each long-short portfolio on the index times α_M, the effect of an increase in the probability of default in the index. On the y-axis, we plot the sum of the expected abnormal return and $(\alpha_i - \beta_i \alpha_M)$, the additional sensitivity of each portfolio to an increase in the probability of default. Values above (below) the line indicates that the portfolio over-performed (under-performed) following increases in the probability of default, relative to the abnormal return implied by the portfolio's market beta. The ranges indicate bootstrapped 90 percent confidence intervals.

Figure A5: Estimated Response to Default Shocks: Industries



Notes: Industry classifications are based on the Fama-French 12 industry categories with the modifications described in Section II.A. On the the x-axis, we plot the expected abnormal return for each portfolio, calculated as the beta of each long-short portfolio on the index times α_M, the effect of an increase in the probability of default in the abnormal return of the index. On the y-axis, we plot the sum of the expected abnormal return and $(\alpha_i - \beta_i \alpha_M)$, the additional sensitivity of each portfolio to an increase in the probability of default. Values above the line indicates that the portfolio over-performed following increases in the probability of default, relative to what would be implied by the portfolio's market beta. Values below the line indicate underperformance. The ranges indicate bootstrapped 90 percent confidence intervals.

C Standard Errors and Confidence Intervals

To construct confidence intervals for our coefficient estimates, we employ the bootstrap procedure advocated by Horowitz (2001). The advantage of this procedure is that it offers "asymptotic refinements" for the coverage probabilities of tests, meaning that it is more likely to achieve the desired rejection probability under the null hypothesis. Our estimators (except for the OLS) are effectively based on a small number of the data points (the events), and therefore these refinements may provide significant improvements over first-order asymptotic approximations. As a practical matter, our confidence intervals are in almost all cases substantially wider than those based on first-order asymptotic approximations. Nevertheless, these "asymptotic refinements" are still based on asymptotic arguments, and there is no guarantee that they are accurate for our data. We also find (in unreported results) that our confidence intervals for our coefficient of interest, α, are similar to confidence intervals constructed under normal approximations, using a bootstrapped standard error.

We use 1,000 repetitions of a stratified bootstrap, resampling with replacement from our set of events and non-events, separately, so that each bootstrap replication contains 15 events and 386 non-events.[15] In each bootstrap replication, we compute the (asymptotically pivotal) t-statistic $t_k = \frac{\hat{\alpha}_k - \hat{\alpha}}{\hat{\sigma}_k}$, where $\hat{\alpha}$ is the point estimate in our actual data sample, $\hat{\alpha}_k$ is the point estimate in bootstrap replication k, and $\hat{\sigma}_k$ is the heteroskedasticity-robust standard deviation estimate of $\hat{\alpha} - \alpha$ from bootstrap sample k. We then determine the 2.5th percentile and 97.5th percentile of t_k in the bootstrap replications, denoted $\hat{t}_{2.5}$ and $\hat{t}_{97.5}$, respectively. The reported 95 percent confidence interval for $\hat{\alpha}$ is $[\hat{t}_{2.5}\hat{\sigma} + \hat{\alpha}, \hat{t}_{97.5}\hat{\sigma} + \hat{\alpha}]$, where $\hat{\sigma}$ is the heteroskedasticity-robust standard deviation estimate of $\hat{\alpha} - \alpha$ from our original data sample. In the tables, we report the 95 percent confidence interval and the heteroskedasticity-robust standard error from our dataset ($\hat{\sigma}$).

Note that this procedure, like heteroskedasticity-robust standard errors, assumes that the abnormal returns we study are serially uncorrelated.

D Event Studies

D.1 IV-Style Event Study

We present an "IV-style" event study in this section. This study uses the two-day events and non-events described previously. The second-stage equation we wish to estimate is Equation 2 in the text. The instrument we use is $1(t \in E)\Delta D_t$ (and $1(t \in E)$), where E is the set of event days and $\mathbf{1}(\cdot)$ is the indicator function. The first-stage regression is

$$\Delta D_t = \chi 1(t \in E)\Delta D_t + \rho 1(t \in E) + \mu_D + \omega_D^T X_t + \tau_t,$$

where τ_t is a composite of the three unobserved shocks (ε_t, F_t, ν_t) on the non-event days, and X_t are the observable controls. Under the event study assumptions, the unobserved shocks ε_t and F_t (in the second stage) are not correlated with the change in the default probability on event days. The standard errors and confidence intervals for this approach are described in section C.

[15] The number of events and non-events listed apply to the ADRs. The exchange rates have a slightly different number of events and non-events, due to holidays, missing data, and related issues.

Table A3: Equity and Exchange Rate Results, IV-Style Event Study

	(1) MSCI	(2) Value	(3) Bank	(4) Non-Fin.	(5) YPF
ΔD	-75.27	-57.80	-79.05	-56.01	-88.14
SE	(14.36)	(11.77)	(11.97)	(17.81)	(19.67)
95 percent CI	[-107.3,-37.0]	[-86.0,-33.9]	[-109.8,-56.0]	[-105.6,-7.7]	[-136.1,-36.3]
Events	15	15	15	15	15
Obs.	401	401	401	401	401
	(6) Official	(7) Dolar Blue	(8) ADR Blue	(9) BCS	
ΔD	-0.00539	10.17	12.39	13.95	
SE	(1.236)	(2.665)	(13.21)	(12.56)	
95 percent CI	[-3.2,2.1]	[3.3,16.4]	[-23.7,76.1]	[-14.7,66.7]	
Events	15	14	14	14	
Obs.	401	355	353	356	

Notes: This table reports the results for the IV-Style Event Study estimator of the effect of changes in the risk-neutral default probability (ΔD) on several equity indices and exchanges rates. The equity indices are the MSCI Index, the Value-Weighted index, the Value-Weighted Bank Index, the Value-Weighted Non-Financial Index, and YPF. All indices are composed of ADRs. The index weighting is described in the text. For exchange rates, Official is the government's official exchange rate. Dolar Blue is the onshore unofficial exchange rate from dolarblue.net. ADR Blue is the ADR Blue Rate constructed by comparing the ADR share price in dollars with the underlying local stock price in pesos, as described in Section II. BCS is the Blue-Chip Swap is constructed by comparing the ARS price of domestic Argentine sovereign debt with the dollar price of the same bond, as described in Section II. The coefficient on ΔD is the effect on the percentage log returns of an increase in the five-year risk-neutral default probability from 0 percent to 100 percent, implied by the Argentine CDS curve. Standard errors and confidence intervals are computed using the stratified bootstrap procedure described in the text. The underlying data is based on the two-day event windows and non-events described in the appendix. All regressions contain controls for VIX, S&P, EEMA, high-yield and investment-grade bond indices, oil prices.

D.2 Standard Event Studies

We also present the results of two additional event studies that use the methodology described in Campbell, Lo and MacKinlay (1997). The first event study uses two-day windows around events.

Let N denote the set of non-event days, and let $L1 = |N|$. We first estimate the factor model on the non-event days,

$$r_{i,t} = \mu_i + \omega_i^T X_t + \nu_{i,t},$$

and generate a time series of abnormal returns, $\hat{r}_{i,t} = r_{i,t} - \hat{u}_i - \hat{\omega}_i^T X_t$, where X_t is the vector of controls discussed in Section II. We also estimate the variance of the abnormal returns associated with the factor model (assuming homoskedastic errors), $\hat{\sigma}_i^2 = \frac{1}{L1} \sum_{t \in N} \hat{\nu}_{i,t}^2$. We next estimate a similar factor model for the change in the probability of default, ΔD_t, and create a time series of abnormal default probability changes, $\hat{d}_t$. We then classify our event days into three categories, based on the abnormal default probability change during the event window. Let σ_d denote the standard deviation of the abnormal default probability changes. If the probability increases by at least σ_d, we label that day as an “higher default” event. If the probability decreases by at least σ_d, we label that event as a “lower default” event. If the default probability change is less, in absolute value, than σ_d, we label that as a “no news” event.

For each type of event, we report the cumulative abnormal return and cumulative abnormal default probability change over all events of that type (higher default, lower default, no news). We also report two statistics that are described in Campbell, Lo and MacKinlay (1997). In this event study (but not the next one we discuss), which does not aggregate returns across different ADRs, the two statistics are identical, up to a small sample size correction. Define $E_{\{h,l,n\}}$ as the set of event days of each type. The first statistic, $J1$, is computed, for event type j and ADR i, as

$$J1_{ij} = \frac{\sum_{t \in E_j} \hat{r}_{i,t}}{\sqrt{|E_j| \hat{\sigma}_i^2}}.$$

Under the null hypothesis that the events have no effect on the stock returns, $J1_{ij}$ is asymptotically distributed as a standard normal. However, because we have so few events in each category, asymptotic normality will be a poor approximation, if the abnormal returns are themselves far from normal. This is one reason we prefer the variance-based estimators.

The second statistic, $J2$, is nearly identical to $J1$ for this event study (they will be different in the next event study we describe). For each event, we can define a standardized cumulative abnormal return,

$$z_{i,t} = \sqrt{\frac{|E_j| - 4}{|E_j| - 2}} \frac{\hat{r}_{i,t}}{\sqrt{\hat{\sigma}_i^2}},$$

where the first term represents a small-sample correction. The statistic $J2$ is defined as

$$J2_{ij} = \frac{\sum_{t \in E_j} z_{i,t}}{\sqrt{|E_j|}}.$$

This statistic is also asymptotically standard normal under the null hypothesis, subject to the same caveat about return normality. In table A4, we present these two statistics for the value-weighted index.

Table A4: Standard Event Study: Index

Shock Type	# Events	CAR (percent)	ΔD (percent)	J_1	J_2
Higher Default	7	-12.95	29.55	-2.21	-2.21
No News	3	-7.62	-0.31	-1.99	-1.99
Lower Default	5	23.07	-29.72	4.67	4.66

Notes: CAR indicates cumulative abnormal return over the event windows, ΔD is the change in the risk-neutral probability of default, and the test statistics J_1 and J_2 are described in the text and in Campbell, Lo and MacKinlay (1997), p. 162. A shock type of higher default indicates that this event raised the default probability by more than one two-day standard deviation, a shock type of lower default indicates that this event lowered the default probability by more than one two-day standard deviation, and a shock type of no news indicates a day with a legal ruling in which the default probability did not move at least one two-day standard deviation in either direction. The underlying data is based on the two-day event windows and non-events described in the text.

The results of this event study are broadly similar to the variance-based estimates. In the seven event days where the default probability significantly increased, the cumulative increase in the default probability was 29.55% and the stock market experienced a cumulative abnormal return of -12.95 percent. Assuming a linear relationship between default probabilities and equity returns, this implies that a 1 percent increase in the probability of default causes a 0.44 percent fall in the stock market. During the five days where the default probability significantly declined, the cumulative fall in the default probability was 29.72 percent with a cumulative abnormal return of 23.07 percent. This implies a 1 percent fall in the probability of default causes an 0.78 percent rise in the stock market. While the large window sizes used in this study raise concerns about the validity of the identification assumptions, we will see that this estimate is very close to the results we find from our heteroskedasticity-based estimates.

The next event study we present uses four different window sizes. To construct these narrower windows, we also use a "sameday" CDS spread from Markit, which is as of 9:30 am EST. We refer to this as the "open," and it is in addition to the "close" defined in the main text. The sameday spread is built under the assumption that the expected recovery rate has not changed from the previous day's close. We convert the open and close CDS spreads into default probabilities ourselves for this analysis, rather than use probabilities provided by Markit, because Markit does not compute "open" default probabilities, only closing ones.

We classify events into several types: close-to-close, open-to-open, close-to-open, and open-to-close. For the Supreme Court ruling on June 16th, 2014, the event occurred in the morning of the 16th, after the U.S. stock market opened. We classify this ruling as "open-to-close" meaning that we will use the CDS spread change from 9:30am EDT on Monday the 16th to roughly 4pm EDT on Monday the 16th, and the ADR returns from 9:30am EDT on Monday the 16th to 4pm EDT on Monday the 16th. If we had instead classified the event as "close-to-close," we would compare the 4pm EDT close on Friday the 13th to the 4pm EDT close on Monday the 16th. The "close-to-open" and "open-to-open" windows are defined in a similar way. We use the narrower window sizes (close-to-open and open-to-close) when possible, and the wider window sizes (close-to-close and open-to-open) when we do not have precise information about the event time.

The heterogenous-window-size event study approach does have one advantage over the heteroskedasticity approach (as we have implemented it). For the heteroskedasticity approach, we use two-day event days, because those are the smallest uniformly-sized windows that all of our events can fit into. If the identification assumptions required for the heterogenous-window-size event study hold, this approach may have more power than the heteroskedasticity-based approach.

Our data set includes one additional event (16 instead of 15), because one of the two-day windows in fact contained two separate legal rulings on consecutive days. Conceptually, the event study is almost identical, except that we must study each type of event (higher default, lower default, no news) for each window size. That is, we separately estimate abnormal returns and abnormal default probability changes for each window size $s \in S$, the set of window sizes. We classify events based on the standard deviation of abnormal default probability changes for the associated window size. Let E_{js} denote an event of type j (higher default, lower default, no news) with window size s (close-to-close, open-to-open, close-to-open, and open-to-close). The abnormal return $\hat{r}_{i,t,s}$ is the abnormal return for ADR i at time t with window size s, and $\hat{\sigma}_{is}^2$ is the variance of the abnormal returns for that window size. The $J1$ statistic is computed as

$$J1_{ij} = \frac{\sum_{s \in S} \sum_{t \in E_{js}} \hat{r}_{i,t,s}}{\sqrt{\sum_{s \in S} |E_{js}| \hat{\sigma}_{is}^2}}.$$

Asymptotically, subject to the same caveats mentioned previously, this statistic is distributed as a standard normal. The second statistic, $J2$, is constructed in a similar fashion. However, the standardized cumulative abnormal returns are now defined with respect to the event window size,

$$z_{i,t,s} = \sqrt{\frac{|E_{js}| - 4}{|E_{js}| - 2}} \frac{\hat{r}_{i,t,s}}{\sqrt{\hat{\sigma}_{is}^2}},$$

and the $J2$ statistic is

$$J2_{ij} = \frac{\sum_{s \in S} \sum_{t \in E_{js}} z_{i,t,s}}{\sqrt{\sum_{s \in S} |E_{js}|}}.$$

This statistic is also, subject to the same caveats, asymptotically standard normal. It is not the same as the $J1$ statistic, because of the heterogeneity in window size. If the cumulative abnormal returns occur mostly in narrower windows (which have smaller variance of abnormal returns), the $J2$ statistic will be larger in absolute value than the $J1$ statistic. If the reverse is true, the $J1$ statistic will be larger. The size of the window may depend in part on the court releasing the opinion, the urgency with which the opinion was required, and other endogenous factors. It is not obvious whether the $J1$ or $J2$ statistic should be preferred. Fortunately, the results presented in table A5 using the two statistics are similar.

Table A5: Heterogenous-Window Event Study: Index

Shock Type	# Events	CAR (percent)	ΔD (percent)	J_1	J_2
Higher Default	6	-13.03	16.09	-3.72	-3.37
No News	5	1.85	2.65	0.52	0.56
Lower Default	5	11.90	-28.40	4.12	3.47

Notes: CAR indicates cumulative abnormal return over the event window, ΔD is the change in the risk-neutral probability of default, and the test statistics J_1 and J_2 are described in the text and in Campbell, Lo and MacKinlay (1997), p. 162. This study pools events across different window sizes (open-open, open-close, close-open, close-close). A shock type of higher default indicates that this event raised the default probability by more than one standard deviation, where the standard deviation is defined for non-events with the same window size. A shock type of lower default indicates that this event lowered the default probability by more than one standard deviation, and a shock type of no news indicates a day with a legal ruling in which the default probability did not move at least one standard deviation in either direction. The underlying data is based on the event windows and non-events described in the text, and uses the narrowest windows possible with our data and uncertainty about event times.

In the six event days where the default probability significantly increased, the cumulative probability of default rose 16.09 percent and the stock market had a cumulative abnormal return of -13.03 percent. This estimate implies that a 1 percent increase in the probability of default causes a 0.81 percent fall in equity returns. During the five days where the default probability significantly declined, the cumulative fall in the default probability was 28.40 percent with a cumulative abnormal equity return of 11.90 percent. This implies a 1 percent fall in the probability of default causes an 0.42 percent rise in the stock market. When we again treat up and down movements symmetrically, we find that a 1 percent increase in the probability of default causes a 0.56 percent fall in the equity market.

Compared with these event studies, the IV-style event study described previously has the advantage of offering an interpretable coefficient, $\hat{\alpha}$, that estimates the change in stock prices given a change in the default probability. It also takes into account the magnitude of the default probability changes on each event day, whereas the event studies discussed above treat each event in a category equally. However, it is not *a priori* clear that the impact of the default probability on stock returns should be linear, and therefore not obvious that this approach is superior to the two-day event study. The similarity of the two results suggests linearity is not a bad assumption. Additionally, because the IV-style event study uses two-day event windows, it requires stronger identification assumptions than the heterogenous-window event study.

E Alternative Specifications

E.1 Alternative Event Windows for the CDS-IV Estimator

In this subsection, we present results for the CDS-IV estimator that use alternative event windows. The "Alternative Two-day Window" results we present refer to events for which there are two possible two-day windows that could encompass the event. For example, if we are certain the event occurred during trading hours on Wednesday, and believe there are no other events, statements by politicians, or the like on any adjacent day, then we can use either the two-day window from Monday close to Wednesday close or the two-day window from Tuesday close to Thursday close. In our main analysis, as discussed in the text, we place the event on the first day; in this example, that would mean that we use the Tuesday-to-Thursday close. In these results, we place the event on the second day; in this example, the Monday-to-Wednesday close. The five two-day windows that move one day earlier in these results are Dec. 5, 2012, Dec. 7, 2012, Aug. 26, 2013, Jan. 13, 2014, and Jun. 27, 2014.

The "One-Day Window" results use a different approach. For these results, each one-day return is a data point; our analysis now has 816 data points, instead of 401. We also gain an additional event (in the two-day analysis, two events fell within the same window). When we are certain that an event occurred during a one-day window, we use only that window as the event. When we are not certain which of the two possible one-day windows contains the event, we call both of those one-day windows a single event.

In effect, we are including some non-event days as events in our one-day window analysis. For the heteroskedasticity-based estimator, this does not bias the results; it is still true that the variance on our "event" days is higher than on our non-event days, even though a few of our events did not actually contain a legal ruling. If we knew which days actually contained the release of our legal rulings, we could improve the power of our analysis by removing the non-events from our event sample; of course, we do not know which days to remove.

For the purposes of bootstrapping the standard errors in this analysis, we bootstrap events, not "event days." That is, we draw (with replacement) 16 events from our event sample, which could contain anywhere from 16 to 32 one-day windows. We have experimented with the alternative approach of drawing 20 event-days; the results seem qualitatively similar, but the latter approach could construct bootstrap replication samples in which there are no actual events.

Table A6: Alternative Window Equity and Exchange Rate Results

	(1) MSCI	(2) Value	(3) Bank	(4) Non-Fin.	(5) YPF	(6) Official	(7) Dolar Blue	(8) ADR Blue	(9) BCS
CDS-IV, Alternative Two-Day Windows									
ΔD	-79.47	-57.48	-78.63	-59.07	-97.61	-0.662	12.58	2.446	8.811
SE	(17.37)	(15.61)	(15.23)	(22.48)	(21.44)	(1.317)	(3.478)	(18.30)	(21.13)
95 percent CI	[-111.0,-33.4]	[-92.7,-29.4]	[-116.3,-51.5]	[-109.9,2.4]	[-146.2,-19.0]	[-2.5,2.2]	[4.6,19.2]	[-61.5,125.0]	[-64.4,137.6]
Events	15	15	15	15	15	15	14	14	14
Obs.	404	404	404	404	404	404	358	356	359
CDS-IV, One-Day Windows									
ΔD	-69.02	-50.50	-71.45	-48.38	-84.07	-0.743	12.74	-0.683	-0.322
SE	(21.76)	(20.11)	(21.69)	(21.32)	(31.36)	(0.957)	(6.453)	(14.18)	(20.61)
95 percent CI	[-177.9,-10.7]	[-185.3,-9.2]	[-169.0,-14.3]	[-146.0,-0.0]	[-212.0,90.5]	[-2.3,2.6]	[-29.9,39.5]	[-87.8,104.7]	[-176.3,313.3]
Event Days	20	20	20	20	20	20	17	17	17
Obs.	815	815	815	815	813	815	737	735	738

Notes: This table reports the results for the CDS-IV estimator of the effect of changes in the risk-neutral default probability (ΔD) on several equity indices and exchanges rates, using alternative event window definitions. The equity indices are the MSCI Index, the Value-Weighted index, the Value-Weighted Bank Index, the Value-Weighted Non-Financial Index, and YPF. All indices are composed of ADRs. The index weighting is described in the text. For exchange rates, Official is the government's official exchange rate. Dolar Blue is the onshore unofficial exchange rate from dolarblue.net. ADR Blue is the ADR Blue Rate constructed by comparing the ADR share price in dollars with the underlying local stock price in pesos, as described in Section II. BCS is the Blue-Chip Swap as constructed by comparing the ARS price of domestic Argentine sovereign debt with the dollar price of the same bond, as described in Section II. The coefficient on ΔD is the effect on the percentage log returns of an increase in the five-year risk-neutral default probability from 0 percent to 100 percent, implied by the Argentine CDS curve. Standard errors and confidence intervals are computed using the stratified bootstrap procedure described in the text. The underlying data is based on the alternative two-day event windows or one-day event windows described in the appendix. All regressions contain controls for VIX, S&P, EEMA, high-yield and investment-grade bond indices, and oil prices.

E.2 Alternate Measures of Default Probability

In this section, we discuss how our results are affected by using different measures for the probability of default. In particular, we change two features of our baseline default probability: the horizon and the assumed recovery rate. In our baseline specification we look at the cumulative default probability over five years, and here we will also consider the one- and three-year horizons. While we have data on CDS spreads out to 30 years, we are reluctant to use them because these longer tenors tend to be traded much less frequently. These are the first set of "Markit" results in Table A7.

The second change we will consider concerns the recovery rate. In our baseline specification, we use the average dealer-reported recovery rate. While this series does vary, and in particular increases towards the eventual actual recovery rate as Argentina approached its eventual default, we cannot be sure how representative the earlier-reported quotes are of market expectations. Therefore, as an alternative to the dealer-reported recovery rates, we set the recovery rate equal to 39.5 percent, the rate at which the CDS auction eventually settled. We estimate the risk-neutral default probability under this assumption using the Matlab command CDS bootstrap and use the U.S. Treasury zero coupon curve as the discounting curve. These results are labeled "Constant Recovery" in Table A7.

We will also consider the raw par spreads and points upfront as alternative measures of the default probability. This approach has the drawback that the coefficients are more difficult to interpret, but does come with the benefit that it uses market prices directly rather than relying on a model. The results are labeled "Par Spread" in Table A7. The final set of results we include looks at the effect of changes in the quoted Points Upfront. The way that CDS generally trade today is not actually with the par spread. Instead, the buyer agrees to pay the seller a fixed coupon (5 percent for Argentine CDS) and "Points Upfront," the percentage of the notional that the buyer pays the seller upon initiation of the CDS. There is a one-to-one mapping between the par spread and points upfront. The results are labeled "Points Upfront" in Table A7.

We also use measures of the risk-neutral probability of default computed using CDS data from Bloomberg and Datastream. For reasons discussed in appendix Section A.1, we have much less confidence in these data sources than Markit and therefore restrict ourselves to only using the five-year spread. Therefore, rather than bootstrapping the risk-neutral probability of default using the ISDA Standard Model, we use the credit triangle approximation as described in appendix Section A.4. We also use the realized recovery rate of 39.5 percent, and so these results should be compared to the results using Markit data and a five-year credit triangle approximation with a constant recovery assumption. These calculations are labeled "Markit CT, Constant Recovery," "Bloomberg CT, Constant Recovery," and "Datastream CT, Constant Recovery," with credit triangle abbreviated CT.

We also consider a specification that does not use any CDS data at all. Instead of CDS spreads or risk-neutral default probability measures imputed from CDS spreads, we instead use the log bond price and yield spread of a restructured bond. In particular, we use the log price and yield spread for a discount USD-denominated bond issued as part of the 2010 restructuring that matures in 2033 (ISIN XS0501194756). We choose this bond because it has the best pricing data of the restructured bonds in Bloomberg. This has the drawback that it is a longer tenor instrument than the CDS spreads and default probability we look at. We define the yield spread as the yield to maturity on the bond over the 20-year U.S. Treasury par yield from Gürkaynak, Sack and Wright (2007). We find very similar qualitative results using these alternative measures, although the magnitudes are difficult to compare given the difference in tenor. We have tried to conduct a similar analysis with bond data from Euro TLX, a European bond exchange. This data appears noisier than the bond data from Bloomberg (which comes, ultimately, from over-the-counter bond dealers), and volumes on this exchange are very low—less than $1mm USD per day during our sample.

Finally, we have conducted our analysis with Markit's "sameday" quotes, in the place of closing quotes. As discussed in the text, Section II, Markit publishes intraday snapshots of CDS spreads, based on quotes from dealers. There is no guarantee that every dealer will send out a run every hour—in particular, between the Europe and London closes. For this reason, Markit attempts to remove stale runs by comparing older runs to the most recent (within the last 30 minutes) ones it has received. If the most recent ones are very different, it will use only those runs. Otherwise, it averages over old and new runs. The result is that our intraday data (the London close, in particular) contains runs sent out at an indeterminate, somewhat endogenous time—if the market has not moved much, it will average over many dealers and use old data, but if the market has moved, it will include a small number of recent quotes.

Using these sameday quotes, we create default probabilities using the ISDA standard model and the previous night's recovery assumption. We then run our analysis, using opening prices for the ADRs, which are determined at 9:30am EST. Using opening market data prevents us from using the investment-grade and high-yield CDS indices as controls. It also prevents us from generating results for the Dolar Blue and blue-chip swap exchange rates. We employ the same procedure with the EuroTLX bond data, mentioned previously.

Table A7: Alternate Default Probability Measures

		Indices			Exchange Rates		
		Value	Banks	Non-Fin	Blue	ADR	BCS
Markit	1Y	-30.49	-42.45	-30.42	5.716	0.910	1.025
		[-39.9,-21.7]	[-66.4,-25.3]	[-48.4,-11.8]	[3.2,7.6]	[-46.0,80.4]	[-50.0,97.3]
Markit	3Y	-48.95	-67.40	-47.51	8.580	8.245	8.336
		[-71.5,-30.0]	[-88.9,-49.7]	[-83.6,-7.3]	[2.3,14.3]	[-29.6,80.8]	[-34.3,97.0]
Markit	**5Y**	-60.43	-83.16	-58.63	10.37	10.71	11.01
		[-89.4,-36.2]	[-112.2,-61.0]	[-103.4,-9.2]	[3.0,17.0]	[-29.4,86.6]	[-33.3,106.1]
Constant Recovery	1Y	-28.96	-40.63	-28.84	5.701	0.283	0.209
		[-40.3,-20.2]	[-67.1,-24.1]	[-46.2,-12.6]	[3.4,7.5]	[-36.6,79.1]	[-44.5,82.0]
Constant Recovery	3Y	-51.67	-71.16	-50.04	9.044	9.387	8.942
		[-76.3,-30.3]	[-101.2,-46.8]	[-84.1,-10.2]	[1.8,15.5]	[-24.4,86.9]	[-35.2,85.0]
Constant Recovery	5Y	-68.20	-93.80	-66.24	11.67	13.02	12.56
		[-103.5,-37.6]	[-135.8,-61.0]	[-114.2,-13.0]	[2.8,19.6]	[-26.7,92.3]	[-38.7,99.5]
Par Spread	1Y	-0.135	-0.199	-0.134	0.0283	0.00817	0.0151
		[-0.3,-0.0]	[-0.4,-0.1]	[-0.3,0.0]	[0.0,0.0]	[-0.2,0.4]	[-0.2,0.5]
Par Spread	3Y	-0.301	-0.441	-0.295	0.0606	0.0448	0.0631
		[-1.0,-0.1]	[-0.8,-0.2]	[-0.9,0.0]	[0.0,0.1]	[-0.2,0.6]	[-0.3,0.8]
Par Spread	5Y	-0.397	-0.579	-0.391	0.0790	0.0643	0.0911
		[-1.5,-0.1]	[-1.1,-0.3]	[-1.3,0.1]	[0.0,0.2]	[-0.3,0.7]	[-0.3,1.0]
Points Upfront	1Y	-0.350	-0.494	-0.350	0.0668	0.00744	0.0121
		[-0.5,-0.2]	[-0.8,-0.3]	[-0.6,-0.1]	[0.0,0.1]	[-0.6,1.0]	[-0.6,1.2]
Points Upfront	3Y	-0.458	-0.645	-0.448	0.0832	0.0637	0.0697
		[-0.8,-0.2]	[-1.0,-0.4]	[-0.9,-0.1]	[0.0,0.1]	[-0.4,0.9]	[-0.4,1.0]
Points Upfront	5Y	-0.477	-0.671	-0.466	0.0852	0.0688	0.0759
		[-0.9,-0.2]	[-1.1,-0.4]	[-0.9,-0.1]	[0.0,0.1]	[-0.3,0.8]	[-0.4,1.0]

Notes: Table continues on next page.

Table A7: Alternate Default Probability Measures (Continued)

Measure		Indices: Value	Banks	Non-Fin.	Exchange Rates: Blue	ADR	BCS
Markit CT, CR	5Y	-48.83	-66.54	-47.58	8.497	5.799	4.019
		[-66.9,-34.0]	[-91.8,-41.4]	[-77.6,-17.7]	[2.1,14.2]	[-39.9,113.2]	[-49.6,90.4]
Bloomberg CT, CR	5Y	-44.00	-66.30	-40.14	12.04	19.19	17.86
		[-66.9,-22.8]	[-139.0,-4.0]	[-65.7,-14.6]	[2.3,19.0]	[-1.7,56.5]	[-13.1,79.6]
Datastream CT, CR	5Y	-41.36	-58.07	-33.40	4.416	30.09	15.42
		[-55.0,-19.5]	[-93.7,15.8]	[-74.6,14.1]	[-11.8,16.5]	[-8.0,40.1]	[-22.9,39.2]
Log Bond Price	2033	51.11	70.70	47.41	-11.61	-14.37	-12.34
		[24.3,64.9]	[33.9,98.8]	[12.1,67.9]	[-21.5,-0.0]	[-64.5,9.5]	[-82.3,23.4]
Bond Spread	2033	-3.299	-4.761	-2.952	0.755	0.969	0.863
		[-4.4,-1.8]	[-6.2,-3.0]	[-4.6,-0.7]	[-0.1,1.4]	[-0.3,3.4]	[-1.2,4.4]
Log Bond Price (Euro TLX)	2017	35.81	69.23	15.62		-6.818	
		[-39.0,173.1]	[-33.2,187.1]	[-74.0,129.1]		[-93.4,54.1]	
Markit Sameday Europe	5Y	-55.19	-96.14	-34.55		16.40	
		[-98.4,-19.5]	[-154.7,-60.4]	[-81.6,-0.1]		[2.5,45.8]	
Markit Sameday London	5Y	-54.76	-93.31	-34.76		14.34	
		[-102.1,-20.0]	[-154.5,-49.2]	[-85.7,-0.6]		[-7.0,54.1]	

Notes: Measure "Markit" indicates that these are the risk-neutral default probabilities computed by Markit. "Constant Recovery" uses our estimation of the risk-neutral default probability under the assumption that the recovery rate is equal to its realized rate of 39 percent. "Par Spread" directly uses the Composite par spread from Markit and "Points Upfront" uses the points upfront data from Markit. The next three entries use the credit triangle (CT) approximation using Markit, Bloomberg, and Datastream CDS data assuming a constant recovery rate. "Log Bond Price" uses the log of the price of a USD-denominated restructured discount bond issue (ISIN XS0501194756) that matures in 2033. "Bond Spread" uses the yield to maturity of this restructured bond over the 20-year U.S. Treasury par yield from Gürkaynak, Sack and Wright (2007). "Log Bond Price (Euro TLX)" is the log price of the restructured "global 17" bond (ISIN XS0501195480) from the EuroTLX exchange. "Markit Sameday London" and "Markit Sameday Europe" are intraday default probabilities, based on dealer quotes and the previous day's recovery assumption, as described in the text. The Europe sameday, London sameday, and EuroTLX bond prices are determined at 9:30am, 10:30am, and 11:30am EST, respectively. All are run against the opening prices from the stock market (determined at 9:30am EST), exclude the Supreme Court event due to a confounding event later that evening, and use only the VIX, S&P, EEMA, and oil price controls. Dolar Blue is the onshore unofficial exchange rate from dolarblue.net. ADR Blue is the ADR Blue Rate constructed by comparing the ADR share price in dollars with the underlying local stock price in pesos, as described in Section II. Blue-Chip Swap is constructed by comparing the ARS price of domestic Argentine sovereign debt with the dollar price of the same bond, as described in Section II. The Value-Weighted index, the Value-Weighted Bank Index and the Value-Weighted Non-Financial Index are referred to as "Value," "Banks", and "Non-Fin.", respectively, and are included in their standard form and delevered. 95% confidence intervals are computed using the stratified bootstrap procedure described in the text and reported in brackets beneath the coefficients. The underlying data is based on the two-day event windows and non-events described in the text. All regressions contain controls for VIX, S&P, EEMA, high-yield and investment-grade bond indices, and oil prices.

F Issues Regarding Weak/Irrelevant Instruments

In this section, we discuss two issues related to weak instruments problems. First, as noted in the text, the CDS-IV estimator is relevant if there is a difference in the variance of the default probability changes on event and non-event days. If the difference in this variance is small, issues relating to weak instruments can arise (see Nakamura and Steinsson (2013) for a discussion of this issue). We formally test that the difference between the variances on event and non-event days is large.

Second, as noted in the text, there are other possible estimators of α that can be constructed from the difference of the covariance matrix on event and non-event days. These estimators, however, use an "irrelevant instrument" under the null hypothesis that $\alpha = 0$, and therefore are not appropriate for our problem.

F.1 Tests of Differences in Variances

We conduct two tests to verify that the variance of the default probability changes during our event windows is significantly higher than the variance during non-event windows. Following Foley-Fisher and Guimaraes (2013), we conduct a formal test of the hypothesis that $(\Omega_E)_{22} = (\Omega_N)_{22}$ using the method developed by Brown and Forsythe (1974) and Levene (1960). We use the sample associated with our value index (recall that for the exchange rates, the sample is slightly smaller). We strongly reject the hypothesis of equal variances. We also report the first-stage F-statistic of the CDS-IV estimator for the value index, as advocated by Stock and Yogo (2005). For the CDS-IV estimator, this first-stage F-statistic is closely related to the difference in the variance of the default probability during the event and non-event windows.

Table A8: Tests of Differences in Variance

Test	F-statistic	p-value
Levene	53.7	0.0000
Brown-Forsythe trimmed mean	53.0	0.0000
Brown-Forsythe median	52.6	0.0000
First-Stage F-stat	338.3	

Notes: "Test" describes the F-statistic being computed. The Levene test for unequal variances is described in Levene (1960). The Brown-Forsythe tests are described in Brown and Forsythe (1974). These tests all formally test the hypothesis that the variance of the changes in the five-year cumulative default probability is equal on event days and non-event days. The sample associated with these tests is the sample we used to compute the results for our value index, and involves 15 events and 386 non-events. The first-stage F-stat is the first-stage F-statistic from the two-stage least squares IV implementation of the CDS-IV estimator, on the same sample.

An alternative to pre-testing for differences in variance is weak-identification-robust inference.

A procedure for this type of inference in a similar context is described and implemented by Nakamura and Steinsson (2013). The strength of our rejection of the hypothesis of equal variances suggests that this approach is unnecessary for our application.

F.2 Irrelevant Instruments

We use the CDS-IV estimator because the alternative estimators use an "irrelevant instrument" under the null hypothesis that $\alpha = 0$. One alternative is what we refer to as the "Returns-IV" estimator. Using Equation 4 in the text, the coefficient of interest can be identified as the ratio of the first element of the matrix to an off-diagonal:

$$\hat{\alpha}_{RIV} = \frac{\Delta\Omega_{1,1}}{\Delta\Omega_{1,2}} = \frac{\text{var}_E(r_t) - \text{var}_N(r_t)}{\text{cov}_E(\Delta D_t, r_t) - \text{cov}_N(\Delta D_t, r_t)}$$

The estimator $\hat{\alpha}_{RIV}$ is the ratio of the sample estimates of $\Delta\Omega_{1,1}$ and $\Delta\Omega_{1,2}$. The denominator, $\Delta\Omega_{1,2}$, is the covariance between the default probability, which is the variable being instrumented for, and the instrument. Under the null hypothesis, this covariance is zero, meaning that the instrument is irrelevant. As a result, the behavior of the $\hat{\alpha}_{RIV}$ estimator under the null hypothesis is not characterized by the standard IV asymptotics, and our confidence intervals will not have the correct coverage probabilities.[16]

The CDS-IV estimator does not suffer from this issue. The estimator $\hat{\alpha}_{CIV}$ is based on the ratio of the sample estimates of $\Delta\Omega_{1,2}$ and $\Delta\Omega_{2,2}$. Under the null hypothesis that $\alpha = 0$ and $\lambda > 0$, the CDS-IV instrument is still relevant, and the standard asymptotics for $\hat{\alpha}_{CIV}$ apply. The GMM estimator, which uses all three moments, can be thought of as a sort of average of the CDS-IV and Returns-IV estimators. When $\alpha \neq 0$, using all three moments is helpful because it takes advantage of all available information and makes over-identifying tests possible. However, under the null hypothesis that $\alpha = 0$, using the Returns-IV estimator in any way is problematic. More formally, the Jacobian of the moment conditions with respect to the parameters does not have full column rank when $\alpha = 0$, and the identification assumption used to derive the standard GMM asymptotics does not hold. The two-step GMM procedure, implemented using standard asymptotics to estimate the optimal weighting matrix, would generally not correctly estimate the variances, because of the irrelevant instrument. As a result, the weight matrix might effectively place excessive weight on the Returns-IV estimator, relative to the CDS-IV estimator, and end up providing problematic results.

[16] Under a different null hypothesis, that α is near, but not equal, to zero, weak-identification asymptotics may be a better characterization of the sample distribution of $\hat{\alpha}_{RIV}$.

G Additional Results

G.1 Mexico, Brazil, and Other Countries

In this section, we present the results of OLS and CDS-IV regressions for non-Argentine countries' equity indices and default probabilities. With OLS, we find that the Argentine risk-neutral default probability co-moves with other emerging market equity indices and sovereign default probabilities (as measured by those countries' CDS). With the CDS-IV estimator, we find no causal effect for any other country's default probability that is statistically significant at the 5% level. We interpret these results as suggesting that there are common factors in the pricing of emerging market debt and equity, consistent with the findings of Pan and Singleton (2008), but the legal rulings we study did not affect these common factors. Moreover, our results suggest that the legal rulings did not have significant effects on other sovereign debtors. We interpret these results as consistent with the uniqueness of Argentina's circumstances, and the limited applicability of these legal rulings to future cases.

Table A9: Regressions for Brazil and Mexico

	(2) Brazil MSCI Index	(4) Mexico MSCI Index
OLS ΔD	-11.40	-6.646
Robust SE	(3.464)	(2.857)
95 percent CI	[-17.5,-4.6]	[-12.7,-1.1]
Event IVΔD	1.967	1.932
Robust SE	(5.360)	(3.655)
95 percent CI	[-11.5,13.8]	[-8.1,7.6]
CDS-IVΔD	3.989	3.286
Robust SE	(4.941)	(4.258)
95 percent CI	[-8.4,11.5]	[-10.6,9.3]

Notes: This table reports the results for the OLS, IV-style event study, and CDS-IV estimators of the effect of changes in the risk-neutral default probability (ΔD) on the stock market indices of Brazil and Mexico. The coefficient on ΔD is the effect on the percentage log returns (of stocks) and change in the five-year CDS spread (in bps) of an increase in the five-year risk-neutral default probability from 0 percent to 100 percent, implied by the Argentine CDS curve. Standard errors and confidence intervals are computed using the stratified bootstrap procedure described in the text. The underlying data is based on the two-day event windows and non-events described in the text.

Table A10: Default Probability, Other Countries

(a) OLS

Country	ΔD	Country	ΔD	Country	ΔD
Argentina	1.199	Iceland	-0.00515	Philippines	0.0178
Austria	0.00829	Indonesia	0.0194	Portugal	0.00369
Belgium	0.0154	Ireland	-0.00555	Romania	0.0249
Bahrain	0.00776	Italy	-0.00231	Russia	0.0558
Brazil	0.0427	Japan	0.00616	South Africa	0.0364
Chile	0.0235	Kazakhstan	0.0358	Spain	-0.00267
China	0.00941	South Korea	0.00425	Thailand	0.00681
Colombia	0.0349	Malaysia	0.00123	Turkey	0.0500
Croatia	0.0290	Mexico	0.0367	Ukraine	0.105
Cyprus	0.0729	Morocco	-0.00643	Venezuela	0.172
Egypt	0.0158	Panama	0.0335	Vietnam	-0.00470
France	0.0224	Peru	0.0333		

(b) CDS-IV

Country	ΔD	Country	ΔD	Country	ΔD
Argentina	1.384	Iceland	0.0171	Philippines	-0.0122
Austria	-0.00547	Indonesia	-0.0158	Portugal	0.00355
Belgium	0.0108	Ireland	-0.0238	Romania	-0.00370
Bahrain	-0.00337	Italy	-0.0271	Russia	0.0331
Brazil	0.00191	Japan	-0.00399	South Africa	0.0197
Chile	-0.00376	Kazakhstan	0.0151	Spain	-0.0162
China	-0.00752	South Korea	-0.0170	Thailand	-0.0136
Colombia	0.00157	Malaysia	-0.0220	Turkey	0.0112
Croatia	-0.0239	Mexico	-0.000665	Ukraine	0.128
Cyprus	0.119	Morocco	-0.0156	Venezuela	0.0240
Egypt	-0.0227	Panama	-0.00605	Vietnam	-0.0646
France	-0.00211	Peru	-0.00359		

Notes: This table reports the results for the OLS (a) and CDS-IV (b) estimators of the effect of changes in the five-year risk-neutral Argentine default probability on the five-year risk-neutral default probability for the country listed. The default probability measure used for the outcome variable is derived from the credit triangle approximation described in appendix A.4, which explains why the coefficient on Argentina is not exactly one. The coefficient is the effect on the other country's five-year risk-neutral default probability of an increase in the five-year risk-neutral default probability from 0 percent to 100 percent, implied by the Argentine CDS curve. The underlying data is based on the two-day event windows and non-events described in the text. All regressions contain controls for VIX, S&P, EEMA, high-yield and investment-grade bond indices, soybean and oil prices.

G.2 Multinational Firms

In this section, we discuss several firms that could be considered Argentine, but were excluded from our analysis. Techint is a privately held multinational conglomerate that controls, among other companies, Tenaris and Ternium. Tenaris is a steel pipe company, headquartered in Luxembourg, that conducts most of its business outside of Argentina. Tenaris is listed on the Buenos Aires stock exchange and has an ADR on the NYSE. Ternium is a steel company, also headquartered in Luxembourg, that is listed only on the NYSE, but owns a subsidiary, Siderar, that is listed on the Buenos Aires stock exchange, and that subsidiary conducts a substantial part of its business in Argentina. We include Siderar (ticker ERAR) in our data for local stocks, and do not include Tenaris in either our local stock or ADR datasets. Petróleo Brasileiro (Petrobras) is the state oil company of Brazil. The Argentine subsidiary of Petrobras, Petrobras Argentina (ticker PESA) is included in our dataset, but its parent is not. We also exclude Arcos Dorados ("Golden Arches"), an Argentina-headquartered McDonald's franchisee that has operations across Latin America and is listed only on the NYSE, and not in Argentina. We present results for the ADRs of Tenaris and Petrobras, and the stock of Arcos Dorados, below.

Table A11: Regressions for Tenaris, Petrobras, and Arcos Dorados

	(1)	(2)	(3)
	Tenaris ADR	Petrobras ADR	Arcos Dorados
OLS ΔD	-5.620	-14.44	-11.27
Robust SE	(5.163)	(7.191)	(7.775)
95 percent CI	[-15.3,6.1]	[-30.6,-0.5]	[-24.9,7.0]
Event IVΔD	-0.404	4.271	12.13
Robust SE	(6.775)	(9.612)	(10.20)
95 percent CI	[-18.5,12.9]	[-26.4,27.5]	[-25.4,44.1]
CDS-IVΔD	0.621	7.457	16.68
Robust SE	(7.314)	(10.86)	(13.75)
95 percent CI	[-18.9,12.7]	[-27.3,33.0]	[-26.9,45.8]

Notes: This table reports the results for the OLS, IV-style event study, and CDS-IV estimators of the effect of changes in the risk-neutral default probability (ΔD) on the ADRs of Tenaris and Petrobras, and the stock of Arcos Dorados. These companies are multinationals that conduct a small portion of their business in Argentina, but are listed on the Argentine stock exchange (Tenaris and Petrobras) or headquartered in Argentina but listed on the NYSE (Arcos Dorados). The coefficient on ΔD is the effect on the percentage log returns of an increase in the five-year risk-neutral default probability from 0 percent to 100 percent, implied by the Argentine CDS curve. Standard errors and confidence intervals are computed using the stratified bootstrap procedure described in the text. The underlying data is based on the two-day event windows and non-events described in the text.

G.3 Delevered Portfolios

In table A12 below, we present results with a "crude" deleveraging. We form an index composed of firms' ADRs and U.S. treasury bills. We weight each firm by the previous year's book value of assets, and then assume that the firm has debt equal to the difference between that book value of assets and the previous quarter's market value of common equity. For each firm, we include in the index a mixture of treasury bills and ADRs, in proportion to the firm's mix of debt and equity. We then apply the CDS-IV estimation procedure to these indices.

Table A12: Delevered Indices, CDS-IV

	(1) Value Index	(2) Bank Index	(3) Non-Financial Index
ΔD	-16.00	-10.79	-27.98
SE	(4.253)	(2.259)	(10.18)
95 percent CI	[-31.5,-4.2]	[-16.2,-4.4]	[-57.0,3.5]
Events	15	15	15
Obs.	401	401	401

Notes: All regressions have controls for VIX, S&P, EEMA, oil prices, and CDX indices. Confidence intervals for value index and FX are calculated using a stratified bootstrap following Horowitz (2001). Confidence intervals for the tracking portfolios are calculated using a hybrid bootstrap method, in which the coefficients for the portfolio weights are sampled from their asymptotic distribution, then the high- frequency data is bootstrapped using the stratified bootstrap procedure described in the text.

G.4 Local Stock Results

In this section, we show the response of equal- and value-weighted local stock portfolios to the default shocks. We also show the response of industry portfolios to default shocks, controlling for the response of the Argentine market. We group these firms into equal-weighted industry portfolios, using the industry definitions described in Section II. We also construct an equal-weighted index of all of the firms in our sample, which is restricted to firms passing a data quality test also described in Section II. We use this equal-weighted index as our measure of the Argentine market return. All of the returns we study in this section are dollar returns, converted at the ADR blue rate. In Figure A5 and Table A13 below, we display estimates of the excess sensitivity of the industry portfolios to the default shock, using the CDS-IV estimator and the bootstrapped confidence intervals described in the previous sections.

Table A13: Cross Section: Industry Returns, CDS-IV

	(1) Equal-Weighted Index	(2) Value-Weighted Index	(3) Banks	(4) Chemicals
ΔD	-51.23	-53.74	-27.49	5.756
	(13.61)	(14.31)	(12.45)	(16.78)
95 percent CI	[-92.2,0.4]	[-125.9,-9.2]	[-61.0,4.7]	[-38.3,37.2]
Index β	-	–	1.033	0.896
Events	14	14	14	14
Obs.	353	353	353	351

	(5) Diverse	(6) Energy	(7) Manufacturing	(8) Non-Durables
ΔD	15.63	-17.45	-13.79	-5.701
	(18.69)	(12.96)	(10.02)	(7.501)
95 percent CI	[-45.2,66.5]	[-47.4,15.7]	[-42.1,11.1]	[-23.1,6.0]
Index β	0.989	0.852	0.736	0.750
Events	14	14	14	14
Obs.	353	353	353	353

	(9) Non-Financial	(10) Real Estate	(11) Telecommunications	(12) Utilities
ΔD	6.438	16.54	-10.74	34.87
	(4.336)	(18.03)	(10.27)	(15.79)
95 percent CI	[-10.3,20.3]	[-28.1,71.6]	[-37.9,6.7]	[-13.7,88.8]
Index β	1.015	0.684	0.694	1.605
Events	14	14	14	14
Obs.	353	338	353	353

Notes: This table reports the results for the "CDS-IV" estimator. The column headings denote the outcome variable. The indices are an equal-weighted index of local equities in Table A2 and a value-weighted index of those same stocks, excluding YPF. The returns are expressed as dollar returns, converted from peso returns using the ADR blue rate. The industry classifications are based on Fama-French with modifications described in Section II. The coefficient on ΔD is the effect on the percentage returns of an increase in the five-year risk-neutral default probability from 0 percent to 100 percent, implied by the Argentine CDS curve. Index beta is the coefficient on the equal-weighted index of Argentine local equities, as described in Section IV. Standard errors and confidence intervals are computed using the stratified bootstrap procedure described in the text. The underlying data is based on the two-day event windows and non-events described in the text.

G.5 Individual Bond Prices

As discussed in Section V, one potential complication in interpreting our results is the RUFO clause in the restructured bond contracts. In particular, one might be concerned that as the probability of default increases, the expected payout on the restructured bonds also increases, raising the amount Argentina is expected to repay creditors. In this case, the effect of the legal rulings on bond prices is ambiguous. The effect on CDS-implied probability of default is not ambiguous; if the recovery assumption is updated correctly, then the default probability is correct.

In the table below, we observe that increases in the CDS-implied default probability lead to significant declines in the value of the restructured bonds. If the default probability is measured correctly, this is not consistent with the story that increases in the default probability coincided with increases in the probability of a settlement that offered improved terms to restructured bondholders. That is, either the RUFO clause would be circumvented, or the RUFO clause was binding and a settlement was not likely.

We also investigate the performance of the holdout bonds around the legal rulings. The bonds owned by the holdouts are very illiquid, but we were able to find some prices from Bloomberg. We are uncertain as to the quality of these prices and therefore interpret the results cautiously. Consistent with this, we find large standard errors in our estimation. This could reflect the poor quality of the data, but also has another interpretation. Several rulings coincided with significant increases in the holdout bond prices, while others did not. One possible interpretation of this fact is that some rulings raised the probability of a settlement, while others lowered that probability, but this was largely uncorrelated with whether the rulings raised or lowered the probability of default.

The restructured bond we examine in the table below is a dollar-denominated discount bond issued as part of the 2010 restructuring. The holdout bond we examine is a dollar-denominated bond maturing in 2030 that court documents show NML Capital owned in 2003. For completeness, we also show a domestic-law fixed coupon dollar bond maturing in 2017. Finally, we present results for the "Global 17" restructured bond, using data from the EuroTLX exchange. This exchange ends trading at 5:30pm Frankfurt time, which requires us to use a different default probability measure, different event windows, and different controls, in a manner described in appendix Sections E.2 and G.6.

Table A14: Bond Level Analysis: CDS-IV

	(1) Restructured	(2) Holdout	(3) Domestic	(4) Restructured (EuroTLX)
ΔD	-124.8	1.206	-48.56	-90.14
SE	(11.93)	(40.35)	(10.68)	(16.02)
95 percent CI	[-146.2,-93.5]	[-63.3,103.1]	[-75.0,2.0]	[-132.3,-27.1]
Events	15	15	15	16
Obs.	397	258	401	395

Notes: This table reports the effect of changes in the five-year risk-neutral Argentine default probability (ΔD) on the price (percentage log price return) of Argentine government bonds. The coefficient on ΔD is the effect on the bond price of an increase in the five-year risk-neutral default probability from 0 percent to 100 percent, implied by the Argentine CDS curve. "Holdout" is a USD-denominated bond maturing in 2030. "Restructured" is a dollar-denominated discount bond issued as part of the 2010 restructuring with an ISIN of XS0501194756 that matures in 2033. "Domestic" is domestic-law fixed coupon dollar debt maturing in 2017 with an ISIN ARARGE03F441. "Restructured (EuroTLX)" is the "Global 17" restructured bond, traded on the EuroTLX bond exchange. That exchange ends trading at 5:30pm Frankfurt time, and we run the EuroTLX closes against default probabilities from the Markit sameday London closes, using only the VIX, S&P, EEMA, and oil price controls. All other regressions in the table are run against the Markit end-of-day closes, and use the full set of controls.

G.6 GDP Warrants

As part of the 2005 and 2010 debt restructurings, Argentina issued a number of GDP warrants. These instruments offer the possibility of annual payments, with payment size linked to real GDP growth, using a predefined formula. On each payment date (once a year, in December), the GDP warrants pay the "Available Excess GDP" defined as $(0.05 \times \text{Excess GDP}) \times$ unit of currency coefficient, where "Excess GDP" is expressed in billions of pesos and the unit of currency coefficient for U.S dollars is 1/81.8, Euros is $(1/81.8) \times (1/0.7945)$, and other currencies defined accordingly.[17] "Excess GDP" is defined as "the amount, if any, by which Actual Real GDP (converted to nominal pesos) exceeds the Base Case GDP." Base Case GDP is listed in millions of 1993 pesos and grows at 3.55 percent between 2005 and 2006, with the Base Case growth rate declining gradually to 3 percent in 2015 and staying constant to 2034 thereafter. In order for Argentina to make a payment on the warrants, Actual Real GDP must exceed Base Case GDP *and* the growth rate during that year must exceed the growth rate of Base Case GDP in that year. In addition, the warrant comes with a payment cap, such that only 0.48 may be paid for each unit of notional. An additional complication arises because of the clause that "All calculations for payments on the GDP-linked Securities will be performed by the Ministry of Economy and Production of Argentina."

The best data on the prices of GDP warrants that we can find comes from Borse Frankfurt and covers the 2035 maturity USD- and EUR-denominated warrants. Even from this data source, the most liquid of these warrants have many days where there are no recorded trades and the prices are unchanged. The Euro-denominated security is more frequently traded and has a longer time series, but covers only 13 events, compared to 10 for the USD-denominated warrant. As a result, the CDS-IV estimator has very large confidence intervals and standard errors.

While these GDP warrants offer a theoretically appealing method to estimating the output cost of defaults, in addition to data quality, a number of difficulties remain. First, these warrants are liabilities of the government and are therefore both defaultable and might have had their payments blocked by Judge Griesa's orders. Because real GDP growth was below the threshold from 2012 to 2015, the government of Argentina did not owe any payments on the warrants during the period in which the "pari passu" injunction was being litigated and enforced. We therefore have no way of knowing whether the warrants, had a payment been due, would have been defaulted on due to the injunction. The "pari passu" clause itself refers to "external indebtedness"; these warrants were issued as part of the debt restructuring, but are not debt in the traditional sense, and it is not clear to the authors of this paper whether or not the courts would interpret them as being "external

[17] The prospectus explains "The unit of currency coefficient represents the proportion that one GDP-linked security with a notional amount of one unit of currency bears to the aggregate Eligible Amount of all Eligible Securities outstanding as of the date of this prospectus supplement (approximately U.S.$81.8 billion), calculated using exchange rates in effect on December 31, 2003."

indebtedness.” As a result, changes in the probability of default might directly affect the value of the warrants (because the warrants would also be defaulted upon), or they might not.

Second, because the warrant coupon is a function of official real GDP, there are additional complications. The Argentine government can and did change the way it calculated GDP, changing the payoff of the warrants (Porzecanski (2014)). In addition to GDP calculation changes, the warrants are also dependent on an accurate reporting of real GDP. During the period in question, this cannot be taken for granted; nominal GDP was generally believed to be credible, but Argentina manipulated its inflation rate during this period, overstating real GDP. Changes in the probability of default may have induced changes in the probability of Argentina continuing to overstate real GDP, or changes in the likelihood that Argentina would redenominate its GDP index to avoid making payments, rather than changes in expectations of the actual future real GDP.

Third, ignoring measurement, default, and liquidity issues, the warrants are complex options on the stochastic process of real GDP, requiring both level and growth targets to be hit before making payments. Shocks to the default probability could have affected expected future real GDP and uncertainty about future real GDP, and therefore affected the value of the warrants through multiple channels. Without assumptions about the risk-neutral stochastic process for Argentine real GDP, and how that process is affected by changes in the default probability, it is impossible to translate a change in the option price to changes in the underlying mean, variance, and higher moments of future Argentine real GDP.

Qualitatively, it is possible to make some general statements about the relationship between reported real GDP and the warrants. The warrants were “out-of-the-money” during the period of our study, and have a long (2035) maturity. As a result, transient shocks to reported real GDP would have minimal impact on the value of the warrants, whereas persistent or permanent shocks could have a large impact. Because both the level and growth rates need to be high to trigger repayment, persistent growth rate shocks would have particularly large effects. Increasing volatility and positive skewness of the distribution of future reported real GDP would also increase the value of the warrants.

Lastly, as mentioned above, the source of our warrants data is the Frankfurt Borse, which ends trading at 5:30pm Frankfurt time (usually 11:30am EST). To run our estimator, we use Markit’s London “sameday” data (usually 10:30am EST) and adjust some of our two-day windows to ensure that each event falls within a single window. As a result, the warrants data are run on a slightly different data sample than our main analysis. For comparison, in our robustness section (table A7), we reproduce our results for stocks, using opening prices (9:30am EST) and the London “sameday” marks. This requires us, for the stocks but not the warrants, to exclude the Supreme Court day (June 16, 2014), and also prevents us from using the entire set of controls used in the other regressions. As mentioned in the text, the Supreme Court event occurs between 9:30am and 10:30am EST, and there is a confounding event that night which prevents us from shifting the window one day ahead. Nevertheless, our results for the value index are similar to our main results.

The results in this section should only be interpreted as suggestive, given the concerns mentioned above. The results of the OLS and CDS-IV estimates are reported in Table A15 and reported visually in Figure A6. As can be seen in Figure A6, the GDP warrant data is often stale, and returns are very concentrated around no change. While in response to large increases (decreases) in the default probability we usually see a decrease (increase) in the price of the warrants, given that on many of the days the excess return is very close to zero, it is unsurprising that the results in A15 have enormous point estimates and confidence intervals.

Table A15: Returns on GDP Warrants

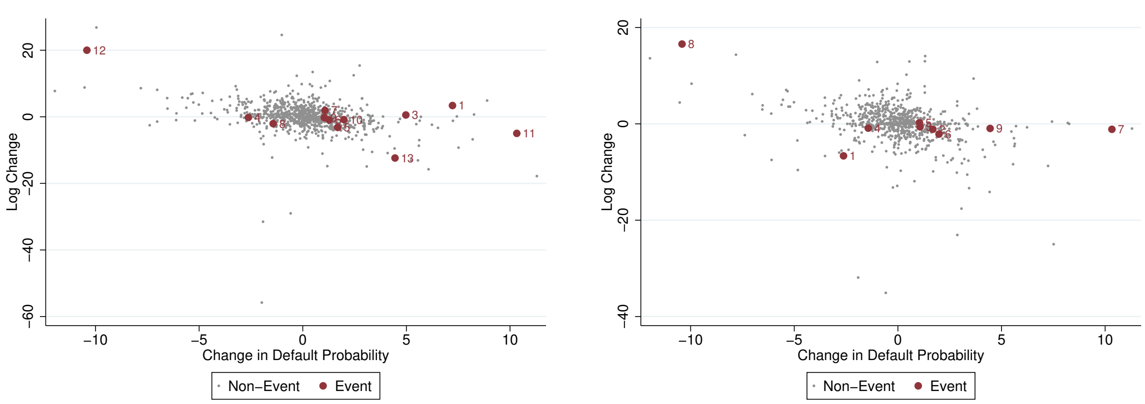
	(1) **OLS** **EUR**	**(2)** **OLS** **USD**	**(3)** **CDS IV** **EUR**	**(4)** **CDS IV** **USD**
ΔD	-63.28	-48.39	-101.3	-33.59
SE	(19.15)	(13.60)	(88.20)	(25.46)
CI	[-99.2,-19.1]	[-75.0,-18.4]	[-588.8,205.2]	[-165.6,66.2]
Events	13	10	13	10
Obs.	392	352	392	352

Notes: EUR is the euro-denominated GDP warrant with ISIN XS0209139244 and USD is the dollar-denominated with ISIN US040114GM64. Both of the warrants use data from Borse Frankfurt. The change in default probability is constructed from the Markit Sameday London close, and the regressions use only the VIX, S&P, EEMA, and oil price controls. Columns 1 and 2 are the OLS estimates and Columns 3 and 4 are the CDS-IV estimates.

Figure A6: Default Probability and GDP Warrant Returns

(a) Euro-Denominated

(b) USD-Denominated



Notes: EUR is the euro-denominated GDP warrant with ISIN XS0209139244 and USD is the dollar-denominated with ISIN US040114GM64. The warrants data is from Borse Frankfurt. The change in the CDS is the two-day change in default probability implied by the Markit sameday London close.

H Holdings and Liquidity Data

In this section, we provide additional background on the likely holders of the ADRs we study. We also provide information about the relative liquidity of the ADRs and local stocks, and information on the liquidity of Argentine sovereign CDS relative to other CDS.

H.1 ADR Holdings Data

In this section, we use 13-F filings to document that the ADRs we study are owned in significant quantities by large, diversified financial institutions headquartered in the U.S. and other developed countries. 13-F filings are quarterly filings mandated by the SEC for financial institutions that control more than $100mm USD of financial assets. These institutions must disclose their ownership of certain assets, including ADRs that trade on the NYSE and NASDAQ. We collect quarterly data from Thompson Reuters, which is available via WRDS, on all 13-F reported holdings of the ADRs we study, by financial institution. There are no Argentine financial institutions that both manage over $100mm USD and own any shares of the ADRs, during any quarter between 2011Q1 to 2014Q2. We list the top ten holders of the ADRs we study, by average market value, for the 2011–2014 period. We note that these institutions are sophisticated, mostly U.S.-based financial institutions that are unlikely to be significantly affected by Argentina's default.

Table A16: Top Institutional Holders of ADRs

Rank	Institution	Country	Avg. Holdings ($MM USD)
1	LAZARD CAPITAL MARKETS LLC	USA	413
2	MASON CAPITAL MANAGEMENT	USA	293
3	ETON PARK CAPITAL MGMT, L.P.	USA	256
4	CAPITAL INTL INC. (SINGAPORE)	Singapore	158
5	BLACKSTONE GROUP	USA	143
6	SOROS FUND MANAGEMENT, L.L.C.	USA	128
7	MSDW & COMPANY	USA	126
8	HIGHFIELDS CAPITAL MGMT, L.P.	USA	112
9	WELLINGTON MANAGEMENT CO, LLP	USA	109
10	THIRD POINT LLC	USA	87

Notes: This table reports the ten institutions that file 13-F reports with the largest dollar value of average holdings of the twelve exchange-traded ADRs we study, over the period of 2011Q1 to 2014Q2. Institutions are required to file 13-F reports if they manage more than $100mm USD of eligible securities (a set that includes exchange-traded stocks and other assets). "Country" is the the country of incorporation, the nationality of the legal vehicle that manages the assets, not its ultimate parent. "Avg. Holdings" is the mean dollar amount of holdings of the twelve ADRs, in millions of U.S. dollars.

H.2 ADR and Equity Liquidity Data

In this section, we compare the average monthly turnover of ADRs with the average monthly turnover of the underlying equities traded on the local stock exchange. Local turnover comes from Bolsar.com, the website of the Bolsa de Comercio de Buenos Aires (BCBA) and ADR Turnover is from CRSP, accessed via WRDS. During the sample period, all of the ADRs we studied had higher turnover in the ADR market than their respective underlying equities on the local exchange, often by an order of magnitude.

Table A17: Average Monthly Turnover of ADRs and Local Equities

Ticker	Turnover - ADR, $M	Turnover - Local, $M	ADR/Local Turnover
BFR	81.1	18.0	4.5
BMA	232.0	33.9	6.8
CRESY	67.8	1.5	44.5
EDN	23.3	15.3	1.5
GGAL	207.6	95.2	2.2
IRCP	2.0	0.2	11.8
IRS	32.1	2.5	12.8
PAM	56.4	29.7	1.9
PZE	71.8	13.8	5.2
TEO	259.7	42.1	6.2
TGS	16.1	1.7	9.2
YPF	1512.8	80.5	18.8

Notes: Ticker is the ticker of ADR. Turnovers for the ADRs and Local equities are reported in millions of U.S. Dollars. The daily dollar value of the turnover of local equities is calculated by dividing the ARS turnover by the ADR Blue Rate. The ratio of ADR/Local Turnover first sums all turnover from January 2011–July 31, 2014 and then computes the ratios.

H.3 CDS Liquidity

In this section, we use data from the Depository Trust and Clearing Corporation (DTCC) to compare the liquidity of Argentine CDS to that of other sovereigns, financial corporations, and non-financial corporations.[18] For each category, we report one entity that trades more than Argentina, one roughly the same amount, and one less. We also report the daily notional traded in millions of USD. Argentine CDS are actively traded, with CDS as liquid as other emerging markets, major financial corporates, and several of the most actively traded non-financial corporates. During our sample period, Argentina was on average the 15th most commonly traded sovereign CDS.

[18] We thank Andreas Stathopoulos for this suggestion.

Table A18: Trading Volume of CDS

	Average Trades/Day	Average Daily Notional ($m)
Argentine Republic	18.2	146.4
Republic Of Korea	26.7	282.1
Republic Of Indonesia	18.3	153.6
Republic Of The Philippines	13.6	130.4
Bank Of America Corporation	23.5	214.3
The Goldman Sachs Group, Inc.	18.2	173.2
Citigroup Inc.	15.5	139.3
Eastman Kodak Company	27.0	81.3
Radioshack Corporation	18.1	76.8
Fiat S.P.A.	13.4	82.1

Notes: This data from the DTCC runs from 2011Q1 to 2014Q2. The sovereign, financial, and non-financial corporate reference entities displayed in this table were chosen to represent entities that experienced somewhat higher, equivalent, and somewhat lower CDS volume, in terms of trades per day.

I Econometric Model

The model we use is

$$\begin{aligned}\Delta D_t &= \mu_d + \omega_D^T X_t + \gamma^T r_t + \beta_D F_t + \varepsilon_t \\ r_t &= \mu + \Omega X_t + \alpha \Delta D_t + \beta F_t + \eta_t,\end{aligned}$$

where r_t is a vector of returns, ΔD_t is the change in the default probability, X_t is a set of global factors (S&P 500, etc...), F_t is an unobserved factor, and ε_t is the idiosyncratic default probability shock, and η_t is a vector of return shocks that do not directly affect the probability of default. Through some algebra, we show that this is equivalent to the systems described in equations 1 and 2, used in most of our analysis, and the equations used in the cross-sectional analysis.

We begin by separating the equation governing the vector of returns r_t into the return of asset i, $r_{i,t}$, which is the asset of interest, and the returns of some other assets, denoted $r_{-i,t}$. We separate the various coefficient vectors and matrices, $\mu, \Omega, \alpha, \beta, \gamma$, and shocks η_t, into versions for asset i, μ_i, ω_i^T, etc..., and versions for the other assets, μ_{-i}, Ω_{-i}, etc... This system can be written as

$$\begin{aligned}\Delta D_t &= \mu_d + \omega_D^T X_t + \gamma_i^T r_{i,t} + \gamma_{-i}^T r_{-i,t} + \beta_D F_t + \varepsilon_t \\ r_{i,t} &= \mu_i + \omega_i^T X_t + \alpha_i \Delta D_t + \beta_i F_t + \eta_{i,t} \\ r_{-i,t} &= \mu_{-i} + \Omega_{-i} X_t + \alpha_{-i} \Delta D_t + \beta_{-i} F_t + \eta_{-i,t}.\end{aligned}$$

Most of our analysis considers only a single asset, $r_{i,t}$, and the default probably change ΔD_t. Substituting the returns $r_{-i,t}$ into the ΔD_t equation,

$$\begin{aligned}\Delta D_t &= \frac{\mu_d + \gamma_{-i}^T \mu_{-i}}{1-\gamma_{-i}^T \alpha_{-i}} + \frac{\omega_D^T + \beta_{-i}^T \Omega_{-i}}{1-\gamma_{-i}^T \alpha_{-i}} X_t + \frac{\gamma_i^T r_{i,t}}{1-\gamma_{-i}^T \alpha_{-i}} + \\ &\quad \frac{\beta_D + \gamma_{-i}^T \beta_{-i}}{1-\gamma_{-i}^T \alpha_{-i}} F_t + \frac{1}{1-\gamma_{-i}^T \alpha_{-i}} (\gamma_{-i}^T \eta_{-i,t} + \varepsilon_t) \\ r_{i,t} &= \mu_i + \omega_i^T X_t + \alpha_i \Delta D_t + \beta_i F_t + \eta_{i,t}.\end{aligned}$$

This system, for the two assets, is equivalent to the one in equations 1 and 2, except that is has two shocks, $\gamma_{-i}^T \eta_{-i,t}$ and ε_t, that directly affect ΔD_t without affecting $r_{i,t}$, and includes constants and observable controls X_t. Neither of these differences substantially alter the identification assumptions or analysis. The event study and Rigobon (2003) approach both identify the coefficient α_i, under their identifying assumptions, which is the coefficient of interest.

Next, we discuss a version of this system with the market return. Let the market return be a weighted version of the return vector, $r_{m,t} = w^T r_t$. Separating the vectorized version of the system into four equations,

$$\begin{aligned}\Delta D_t &= \mu_d + \omega_D^T X_t + \gamma_i^T r_{i,t} + \gamma_{-i}^T r_{-i,t} + \beta_D F_t + \varepsilon_t \\ r_{i,t} &= \mu_i + \omega_i^T X_t + \alpha_i \Delta D_t + \beta_i F_t + \eta_{i,t} \\ r_{-i,t} &= \mu_{-i} + \Omega_{-i} X_t + \alpha_{-i} \Delta D_t + \beta_{-i} F_t + \eta_{-i,t} \\ r_{m,t} &= \mu_m + \omega_m^T X_t + \alpha_m \Delta D_t + F_t + w^T \eta_t,\end{aligned}$$

where $\mu_m = w^T \mu$, $\omega_m^T = w^T \Omega$, and so on. We have assumed that $w^T \beta = 1$, which is a normalization. Substituting out $r_{-i,t}$,

$$\begin{aligned}\Delta D_t &= \frac{\mu_d + \gamma_{-i}^T \mu_{-i}}{1-\gamma_{-i}^T \alpha_{-i}} + \frac{\omega_D^T + \beta_{-i}^T \Omega_{-i}}{1-\gamma_{-i}^T \alpha_{-i}} X_t + \frac{\gamma_i^T r_{i,t}}{1-\gamma_{-i}^T \alpha_{-i}} + \\ &\quad \frac{\beta_D + \gamma_{-i}^T \beta_{-i}}{1-\gamma_{-i}^T \alpha_{-i}} F_t + \frac{1}{1-\gamma_{-i}^T \alpha_{-i}} (\gamma_{-i}^T \eta_{-i,t} + \varepsilon_t) \\ r_{i,t} &= \mu_i + \omega_i^T X_t + \alpha_i \Delta D_t + \beta_i F_t + \eta_{i,t} \\ r_{m,t} &= \mu_m + \omega_m^T X_t + \alpha_m \Delta D_t + F_t + w^T \eta_t,\end{aligned}$$

as above. Next, we solve for F_t using the market return equation:

$$F_t = r_{m,t} - \mu_m - \omega_m^T X_t - \alpha_m \Delta D_t - w^T \eta_t.$$

Plugging this into our system of equations,

$$
\begin{aligned}
(1+\alpha_m\frac{\beta_D+\gamma_{-i}^T\beta_{-i}}{1-\gamma_{-i}^T\alpha_{-i}})\Delta D_t &= (\frac{\mu_d+\gamma_{-i}^T\mu_{-i}}{1-\gamma_{-i}^T\alpha_{-i}}-\frac{\beta_D+\gamma_{-i}^T\beta_{-i}}{1-\gamma_{-i}^T\alpha_{-i}}\mu_m)+(\frac{\omega_D^T+\beta_{-i}^T\Omega_{-i}}{1-\gamma_{-i}^T\alpha_{-i}}-\frac{\beta_D+\gamma_{-i}^T\beta_{-i}}{1-\gamma_{-i}^T\alpha_{-i}}\omega_m^T)X_t+ \\
&\quad \frac{\gamma_i^T r_{i,t}}{1-\gamma_{-i}^T\alpha_{-i}}+\frac{\beta_D+\gamma_{-i}^T\beta_{-i}}{1-\gamma_{-i}^T\alpha_{-i}}r_{m,t}+(\frac{\gamma_{-i}^T}{1-\gamma_{-i}^T\alpha_{-i}}-\frac{\beta_D+\gamma_{-i}^T\beta_{-i}}{1-\gamma_{-i}^T\alpha_{-i}}w_{-i}^T)\eta_{-i,t}+ \\
&\quad \frac{\beta_D+\gamma_{-i}^T\beta_{-i}}{1-\gamma_{-i}^T\alpha_{-i}}w_i\eta_{i,t}+\frac{1}{1-\gamma_{-i}^T\alpha_{-i}}\varepsilon_t \\
r_{i,t} &= (\mu_i-\beta_i\mu_m)+(\omega_i^T-\beta_i\omega_m^T)X_t+(\alpha_i-\beta_i\alpha_m)\Delta D_t \\
&\quad +\beta_i r_{m,t}+(1-w_i\beta_i)\eta_{i,t}+w_{-i}^T\eta_{-i,t}.
\end{aligned}
$$

From these equations, it follows that the event study approach and Rigobon (2003) approach both identify the coefficient $(\alpha_i-\beta_i\alpha_m)$, under their identifying assumptions, which is the coefficient of interest.

J Event and Excluded Dates

Table A19: Default Probability Changes and Returns during Event Windows

Event Number	Two-Day Window End Date	ΔD (percent)	Equity Return (percent)
1	November 27, 2012	4.40	3.90
2	November 29, 2012	-10.61	6.75
3	December 5, 2012	-6.40	2.84
4	December 7, 2012	-0.58	0.10
5	January 11, 2013	3.44	0.08
6	March 4, 2013	-5.41	7.44
7	March 27, 2013	2.59	-2.07
8	August 26, 2013	2.35	-3.21
9	October 4, 2013	0.05	-2.64
10	October 8, 2013	-1.56	2.60
11	November 19, 2013	-0.04	-3.99
12	January 13, 2014	2.38	-0.95
13	June 16, 2014	7.72	-6.50
14	June 24, 2014	-5.56	2.92
15	June 27, 2014	5.83	-2.73

Notes: ΔD refers to the percent change in the risk-neutral probability of default and Equity Return refers to the log return on the value-weighted index of ADRs.

Two-Day Window End	Event Type	Description	PDF Time (EST)	Decision Link	News Time (EST)	News Link	Comments
07Dec11	Excluded	Original ruling by Judge Griesa with regards to Pari Passu clause.	07Dec11, 12:55pm	Decision	Missing	Missing	There was very little contemporaneous news coverage, and we are unable to determine when the ruling became public. The first story we found about the ruling is based on an article in *La Nación* published on 05Mar12.
23Feb12	Excluded	Order by Judge Griesa requiring "ratable payment."	Missing	Order	Missing	Missing	See above.
05Mar12	Excluded	Stay granted by Judge Griesa, pending appeal.	Missing	Stay	05Mar12, 7:11am	Bloomberg	See above.
26Oct12	Excluded	Appeals court upholds Judge Griesa's ruling that the Pari Passu clause requires equal treatment of restructured bondholders and holdouts.	25Oct12, 12:43pm	Decision	26Oct12, 2:14pm	Bloomberg	The appeals court releases opinions during the middle of the day. Unfortunately, the closing marks on this day are questionable, given the impending impact of "Superstorm Sandy."

Two-Day Window End	Event Type	Description	PDF Time (EST)	Decision Link	News Time (EST)	News Link	Comments
23Nov12	Excluded	Judge Griesa removes the stay on his order that Argentina immediately pay the holdouts, if they also pay the exchange bondholders.	Missing	Order	22Nov12, 5:33am	Business News Americas	Nov 22 was Thanksgiving in the United States, and all CDS marks on that date and the morning of the 23rd appear in our data to be the same as on the 21st. The opinion was filed by Judge Griesa on the night of the 21st, but was embargoed until the 23rd. On the 22nd, the Argentine market fell a lot, but bounced back on the 23rd. We cannot observe this in the ADR data, so we exclude this event.
27Nov12	Open-to-Open, 26Nov12 to 27Nov12	Judge Griesa denies the exchange bondholders request for a stay. The bondholders immediately appealed.	26Nov12, 3:43pm	Denial	27Nov12, 5:00am	New York Post	The denial occurred on the 26th, and both the government of Argentina and the exchange bondholders immediately appealed. We compare the open on the 27th to the open on the 26th. The 26th is an Argentine holiday, so the ADR Blue Rate is missing (for the open-to-open, but not the two-day window).

Two-Day Window End	Event Type	Description	PDF Time (EST)	Decision Link	News Time (EST)	News Link	Comments
29Nov12	Close-to-Open, 28Nov12 to 29Nov12	Appeals court grants emergency stay of Judge Griesa's order.	28Nov12, 5:04pm[19]	Stay	29Nov12, 8:24am	Bloomberg	
05Dec12	Open-to-Close, 04Dec12	Appeals court denies request of holdouts to force Argentina to post security against the payments owed.	04Dec12, 1:15pm[20]	Denial	04Dec12, 1:46pm	Bloomberg	
07Dec12	Close-to-Close, 05Dec12 to 06Dec12	Appeals court allows the Bank of New York (custodian of the exchange bonds) and the Euro bondholders to appear as interested parties.	05Dec12, 10:13pm	Order	06Dec12, 11:47am	Bloomberg	

[19]This order has a 9pm "creation time" and a 5pm "modification time."

[20]The "creation time" of this PDF is actually at 4pm, 3 hours after the "modification time".

Two-Day Window End	Event Type	Description	PDF Time (EST)	Decision Link	News Time (EST)	News Link	Comments
11Jan13	Close-to-Open, 10Jan13 to 11Jan13	Appeals court denies certification for exchange bondholders to appeal to NY state court for interpretation on Pari Passu clause.	10Jan13, 4:10pm	Order	11Jan13, 12:01am	Bloomberg	The ruling was written immediately after the closes on the 10th.
28Feb13	Excluded	Appeals court denies request for en banc hearing of appeal.	28Feb13, 3:27pm	Decision	Missing	Shearman	The denial occurred at the beginning of a hearing, during which lawyers for both sides argued various issues. Lawyers from Argentina may have changed their arguments in response to expectations about the Argentine economy, violating the exclusion restriction.
04Mar13	Open-to-Open, 01Mar13 to 04Mar13	Appeals court asks Argentina to submit a payment formula as an alternative to the full repayment demanded by the holdouts and the lower courts.	01Mar13, 11:49am.	Order	01Mar13, 4:46pm	Financial Times	The FT story is the earliest we could find. Most other coverage is from the following day (a Saturday).

Two-Day Window End	Event Type	Description	PDF Time (EST)	Decision Link	News Time (EST)	News Link	Comments
27Mar13	Open-to-Open, 27Mar13 to 26Mar13	Appeals court denies Argentina's request for en banc rehearing.	26Mar13, 11:58am	Order	26Mar13, 2:35pm	Bloomberg	The Bloomberg story specifically mentions a 374bps increase in the five-year CDS spread, which does not appear in our data until after the NY close at 3:30pm. We use the one-day window to ensure we are capturing the event.
01Apr13	Non-Event (neither event or excluded)	Argentina files payment plan. Offer roughly 1/6 of Judge Griesa ordered.	N/A	N/A	30Mar13, 12:05pm	Bloomberg	Argentina filed just before midnight on 28Mar13. Actions by Argentina are endogenous. This is neither an event nor excluded.
22Apr13	Non-Event (neither event or excluded)	Holdouts reject Argentina's payment plan.	19Apr13, 5:20pm	Reply	20Apr13, 12:01am	Bloomberg	Holdouts reject Argentina's payment plan. Also conceivably endogenous. The rejection was filed after business hours on Friday, 19Apr13. This is also neither an event nor excluded.
26Aug13	Close-to-Close, 22Aug13 to 23Aug13	Appeals court upholds Judge Griesa's decision.	22Aug13, 4:21pm	Decision	23Aug13, 4:02pm	Bloomberg	The appeals court announces decisions during the business day. The modification date of the PDF is 10:17am.

Two-Day Window End	Event Type	Description	PDF Time (EST)	Decision Link	News Time (EST)	News Link	Comments
11Sep13	Non-Event	Supreme Court schedules hearing to consider Argentina's appeal.	Missing	Docket Info.	11Sep13, 2:35pm	Bloomberg	The Supreme Court distributed case materials related to Argentina's petition. We were advised that this is routine and not "news," so we do not count is as a ruling.
26Sep13	Excluded	Holdouts had petitioned Judge Griesa to consider the Argentine central bank liable for the defaulted debt. Argentina moved to dismiss, and Griesa rejected Argentina's motion.	Missing	Missing	25Sep13, 5:40pm	Bloomberg	We were not able to find Judge Griesa's ruling, so we exclude this event.
04Oct13	Open-to-Open, 03Oct12 to 04Oct13	Judge Griesa bars Argentina from swapping the exchange bonds into Argentine-law bonds.	03Oct13, 2:43pm	Order	03Oct13, 6:27pm	Bloomberg	
08Oct13	Open-to-Close, 07Oct13	Supreme Court denies Argentina's first petition.	N/A	Order	07Oct13, 11:45am	SCOTUS Blog	The stock market opens (9:30am EST) before the Supreme Court issues decisions (9:30am or 10:00am EST).

Two-Day Window End	Event Type	Description	PDF Time (EST)	Decision Link	News Time (EST)	News Link	Comments
19Nov13	Open-to-Open, 18Nov13 to 19Nov13	Appeals Court denies Argentina's request for an en banc hearing.	18Nov13, 11:04am	Denial	19Nov13, 12:01am	Bloomberg	The modification time of the orders is 4:53pm.
13Jan14	Open-to-Close, 10Jan14	Supreme Court agrees to hear Argentina case.	10Jan14, 2:42pm	Order	10Jan14, 2:48pm	SCOTUS Blog	The Supreme Court usually announces orders at 10am. The document was likely posted afterwards.
16Jun14	Open-to-Close, 16Jun14	Supreme Court denies Argentina's second petition.	See Text.	Denial	See Text.	SCOTUS Blog	The text discusses this event in detail.
23Jun14	Close-to-Open, 20Jun14 to 23Jun14	Judge Griesa prohibits debt swap of exchange bonds to Argentine-law bonds.	20Jun14, 2:17pm	Order			20Jun14 is an Argentine holiday, so the local stocks are missing. During day of the 20th, the Argentine president made a market-moving speech, which we do not want to include, so we start this event only at the close of the 20th.
24Jun14	Open-to-Open, 23Jun14 to 24Jun14	Judge Griesa appoints special master to oversee negotiations.	23Jun14, 12:36pm	Order	23Jun14, 7:35pm	Bloomberg	The modification date for the order is 1:05pm. With two-day windows, this event is pooled with the previous event.

Two-Day Window End	Event Type	Description	PDF Time (EST)	Decision Link	News Time (EST)	News Link	Comments
27Jun14	Open-to-Close, 26Jun14	Judge Griesa rejects Argentina's application for a stay, pending negotiations.	26Jun14, 11:40am	Order	26Jun14, 2:05pm	Bloomberg	
30Jun14	Non-Event	Argentina misses a coupon payment					
29Jul14	Excluded Event	Judge Griesa allows Citi to pay Repsol bonds for one month.	28Jul14, 3:51pm	Order	28Jul14, 12:01am	Bloomberg	The modification time on the order is 5:07pm. This event almost certainly occurred post-close, but we use the one-day window to be safe. Excluded because the main news during this period was government statements and news about negotiations, not the ruling.
30Jul14		The 30-day grace period for the missed payment expires.				Bloomberg	We end our dataset on 29Jul14.

K Appendix References

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