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Three Essays in International Finance

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To: Dean Joanne Li,
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This dissertation, written by Iván M. Rodríguez, Jr., and entitled Three Essays in International Finance, having been approved in respect to style and intellectual content, is referred to you for judgment.

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DEDICATION

To my father, Ivan, and mother, Rina; my sisters Valeska and Karina; and most especially my wife, Qianying. Without their admonishments and sacrificial love, none of my successes would have been possible.

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ABSTRACT OF THE DISSERTATION

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In this dissertation, I focus my research on some of the economically significant and current open problems in international finance, specifically the relationship between Credit Default Swaps (CDS) on sovereign debt, the importance of fundamental dyadic distances on the initiation and completion of cross-border mergers and acquisitions, and the impact of domestic and transnational terrorism on cross-border mergers and acquisitions.

In the first essay, we study the relationship between sovereign debt ratings and the information contained in CDS spreads regarding the credit risk of the reference entity. Using data for 54 countries over a twelve-year period, we find that the variation in average sovereign ratings in a given year can be explained by average CDS spreads over the previous three years. In a horse race between CDS spreads and sovereign ratings, we find that CDS spread changes can predict sovereign events while rating changes cannot.

In the second essay, we study how dyadic distance influences the initiation, completion, and duration of cross-border mergers and acquisitions. Using a sample of 173,616 cross-border deals announced between 1970 and 2016, we find evidence that cross-country cultural, institutional, geographical, religious, and language differences, all play a deciding role in the initiation of mergers and acquisitions. The completion of acquisitions is independent of cultural factors, but largely depends on differences in economy size, language, religion, and

bureaucracy of the acquiring and target countries. Finally, the duration of deals is influenced by idiosyncratic factors only.

In the third essay, we study whether incidents of domestic and transnational terrorism impact the propensity of firms to acquire cross-border firms. We adopt a theoretical model to show that high levels of terrorism in the target countries are associated with lower cross-border acquisition flows. Empirically, we exploit the exogenous variation induced by differences in genetic diversity, ethnic fractionalization, and religious fractionalization between acquirer and target countries. Our results show that an target from a country with lower terrorist incidents than the acquirer country are associated with more cross-border mergers and acquisitions.

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1 Measuring Sovereign Risk

The Eurozone debt crisis that began in late 2009 has brought the stability of sovereign debt back into the focus of academics and investors. The most recent literature on the cost of sovereign defaults has found that debt restructurings are costly to both the issuers and investors. Cruces and Trebesch (2013) study 180 cases over the 1978-2010 period and find that over $8.29 trillion in sovereign debt has been restructured, with an average cost to investors, or haircut, of 37%. Their evidence shows that haircuts have risen substantially, with the average haircut increasing to 50% over the 1998-2010 period.[1]

The high costs associated with debt restructurings and defaults have forced investors to find ways to assess the likelihood of these events. Historically, sovereign debt ratings were relied upon almost exclusively by investors in guiding their investment decisions and by policymakers in financial legislations. This dependence on sovereign ratings means that sovereign rating downgrades negatively affect capital markets and the real economy per se, which in turn affects a firm's ability to raise capital through the debt channel. Almeida, Cunha, Ferreira, and Restrepo (2017) show that sovereign rating downgrades lead to a reduction in investment of about 10% and a 2% reduction in debt for firms in the downgraded country, and the cash holdings of firms decrease substantially in the year of downgrade. These changes are solely due to the sovereign downgrade and not with any changes in the fundamentals of the firm. Our finding that changes in CDS spreads can predict negative sovereign rating events up to seven months before they occur will help firms make timely decisions in alleviating their capital concerns.

Rating agencies are conscious of their impact on the economy and therefore point to rating accuracy and stability as main considerations in their methodologies (see, e.g., Cantor

[1] In addition to the high costs associated with restructurings and defaults, there has been a substantial absolute and relative increase in sovereign debt since the end of the crisis (see Dobbs, Lund, Woetzel, & Mutafchieva, 2015). There is also evidence that large sovereign debt levels can negatively affect future GDP growth (see, e.g., Reinhart, Reinhart, & Rogoff, 2012).

& Mann, 2007). As noted by Altman and Rijken (2006) rating agencies use a through-the-cycle approach, considering only permanent changes in an issuer's financial health. While this approach may seem prudent at first glance, it conflicts with two other main objectives for ratings agencies: rating timeliness and performance in predicting defaults (Altman & Rijken, 2006). Kiff, Kisser, and Schumacher (2013) find that although through-the-cycle ratings are initially stable, they suffer from inferior performance in predicting future defaults due to the smoothed ratings generated by their policy to delay rating changes.[2] They also show that through-the-cycle ratings are prone to large downgrades of several notches when changes do occur; this can lead to market disruptions and dangerous fire-sales. By contrast, indicators that focus on the current condition of the issuer (called point-in-time assessments of risk) may not be as persistent as through-the-cycle ratings; however, they are much better at predicting sovereign defaults and do not lead to these second round liquidity effects caused by large rating changes. We show that CDS spreads are one of the sovereign risk measures available to investors on a timely basis.[3]

Over the last two decades, CDS have become a major instrument used by investors to insure themselves against the risk of credit events, and they have increasingly become an important area of academic study.[4] In an efficient market, the CDS spread should appropriately price and insure against the potential credit risk of the reference entity. Theoretical literature has shown that CDS spreads are a function of both a risk-free rate and a risk-neutral measure

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[2]The stable rating scheme is also supported by the relatively small number of rating categories employed by rating agencies, giving rating agencies more flexibility in timing their changes. Goel and Thakor (2015) show that coarse ratings can endogenously arise from an environment in which increased competition between rating agencies incentivizes them to inflate ratings but still try to maintain unbiasedness. They also show that lowering coarseness can improve social welfare.

[3]We acknowledge that whereas the CDS is directly linked to the probability of sovereign default, the objectives of credit rating agencies are not limited to the prediction of sovereign credit default. Apart from deciding on the entity's creditworthiness, ratings have been embedded in regulations.

[4]See the survey by Augustin, Subrahmanyam, Tang, and Wang (2014) for a discussion on the extant CDS literature.

of default intensity, which can intuitively be thought of as a risk-adjusted loss (Longstaff, Mithal, & Neis, 2005; Pan & Singleton, 2008; Duffie & Singleton, 1997).[5] This theoretical framework led the early literature to assume CDS spreads as pure measures of default. However, more recent empirical literature has acknowledged additional factors that determine CDS spread dynamics. In particular, global factors (Longstaff, Pan, Pedersen, & Singleton, 2011; Pan & Singleton, 2008) and macroeconomic and local factors (Remolona, Scatigna, & Wu, 2008; Caceres, Segoviano Basurto, & Guzzo, 2010; Aizenman, Hutchison, & Jinjarak, 2013; Lee, Naranjo, & Sirmans, 2015) have also been found to be determinants of CDS spreads.

Most attempts to explain the determinants of sovereign debt ratings focus on macroeconomic and political variables. In the first study that systematically investigates the determinants of sovereign debt ratings, Cantor and Packer (1996) examine the power of eight lagged macroeconomic variables in explaining the ratings by Moody's Investor Services (Moody's) and Standard and Poor's (S&P). They find that six factors — per capita income, GDP growth, inflation, external debt, the level of economic development, and default history — play an important role in explaining sovereign debt ratings.

More recently, Maltritz and Molchanov (2013) examine more than 30 factors that the literature has identified as important determinants in assessing sovereign default risk. They conclude that the political and governance factors are not important while recent default and total debt relative to GDP are the significant macroeconomic factors, which is consistent with what prior studies have found. These studies highlight the backward-looking nature of credit ratings. The macroeconomic variables used in rating sovereign debt are released at infrequent

[5] More formally, the CDS spread, s, is

$$s = \frac{\mathbb{E}\left(w \int_0^T \lambda_t e^{-\int_0^t r_s \lambda_s ds} dt\right)}{\mathbb{E}\left(\int_0^T e^{-\int_0^t r_s \lambda_s ds} dt\right)},$$

where w is the recovery rate; λ_t is the default intensity or hazard rate; and r_t if the risk-free rate. This equation was developed by Longstaff et al. (2005) following the Duffie and Singleton (1997) framework, which was extended to sovereign CDS spreads by Pan and Singleton (2008).

intervals and are accounting-type indicators, which contributes to the slow evolution seen in sovereign debt ratings.

The literature on the determinants of CDS spreads and ratings shows that macroeconomic variables are important in explaining the dynamics of both CDS spreads and ratings, albeit on different time-scales. CDS spread changes reflect real-time changes in these macroeconomic variables, while rating agencies may take several months to reflect these changes. Since there are large delays in the measurement and disclosure of the macroeconomic variables, we argue that investors are better off using CDS spreads in lieu of ratings. The lead-lag structure between CDS spreads and ratings and the fact that the same factors price both CDS and ratings indicate that CDS spreads could be an explanatory factor of ratings. Additionally, it is not outside the scope of imagination that rating agencies themselves could be using CDS as a market summary variable in their rating methodologies.

In this essay, we investigate the viability of CDS spreads as a substitute for sovereign debt ratings in predicting sovereign defaults. We find CDS spreads to be significantly associated with average ratings and — after controlling for invariant time and country effects — CDS spreads subsume the macroeconomic controls that have been proposed as determinants of ratings. We find that the explanatory power of the model for the determinants of ratings increases with the addition of CDS spreads, that CDS spread alone can explain 45% of the variability of sovereign debt ratings compared to the 40% explained by macroeconomic variables, and that CDS spreads subsume the explanatory power for every year in our sample.[6] In further robustness tests we regress CDS spreads as dependent variable and lagged changes in ratings as independent variables controlling for agency, country, and time fixed effects. We do not find any influence of rating changes on CDS spreads. Our tests show that CDS spread changes predict rating changes but rating changes do not have any predictive power in explaining CDS changes.

[6] We use the macroeconomic variables in Cantor and Packer (1996) as controls in our study.

The existing studies that explore the connection between CDS markets and debt ratings have either concerned themselves with corporate CDS markets or tests of market efficiency. In particular, they have investigated the question of whether CDS markets anticipate ratings at short horizons, implying that if CDS markets anticipate ratings then they are efficient. Hull, Predescu, and White (2004) analyze the extent to which corporate CDS markets anticipate credit rating events, finding that there is anticipation of negative events by the markets and CDS spreads fully reflect the new information one day after the negative event. However, they find no significant results for positive events. In a similar vein, Ismailescu and Kazemi (2010) conducted an event study on the reaction of CDS spreads to ratings announcements in emerging sovereign markets. In contrast to Hull et al. (2004), they find that CDS markets are unreactive to negative events and have strong reactions to positive events. They additionally find that CDS spread changes in one month can predict negative rating events in the next month.

In contrast to Ismailescu and Kazemi (2010), who study a monthly change in CDS spread, our results suggest that predictability exists at longer lags than solely one month.[7] Therefore, we investigate the possibility of one-month CDS changes to predict sovereign debt rating events m months into the future. We find that one-month CDS changes retain their predictive ability up to seven months solely for negative rating events. Our results are robust to concerns about reverse causation.[8]

[7]They study the ability of the prior month's change in CDS spread to predict rating changes. However, no mention is made of any additional tests or looking at longer horizons.

[8]There may be some apprehension that the results may be contaminated by successive credit rating changes that can occur within seven to 12 months of each other, i.e., a reverse causality concern. We address this concern by restricting our sample to rating events in which there were no other rating events in the previous 24 months. Our results exhibit patterns consistent with our baseline setting. Our results are also not driven by differences in investment grade, differences in the relative stasis of CDS spreads, outliers with many rating changes, or the rarity of rating events. These results are available from the authors upon request.

To ascertain if CDS spreads are a better predictor of negative sovereign events than sovereign debt ratings, we run a horse race between CDS spreads and ratings and directly test their utility to investors as such. Our results show that CDS spread changes can predict negative sovereign events while rating changes contain no ability to predict these events.[9] The predictability of events using CDS spreads is stronger when Moody's and S&P have a one-notch difference or more. This shows that CDS spreads are able to capture additional information than ratings. Our findings are consistent with recent work which shows that sovereign CDS spreads can predict other financial variables (Xiao, Yan, & Zhang, 2017) and with the literature documenting the inability of ratings to predict sovereign crises (Sy, 2004).

Our essay contributes to the literature in several important ways. Firstly, by studying the cross-sectional joint-distribution of sovereign credit ratings and CDS spreads, we document new stylized facts about the relationship between sovereign CDS spreads and ratings. We find evidence that one-month CDS spread changes can predict negative rating changes up to seven months in advance. Secondly, we provide quantitative evidence of the superiority of CDS spreads relative to ratings in predicting sovereign events. Our findings will aide investors and managers in determining whether a change in a country's rating will occur, helping them manage their portfolios or corporate policies. We give a leading indicator of rating downgrades and sovereign events that they can use to hedge against the real economic risks from sovereign downgrades.

The rest of the essay is organized as follows: Section 1.1 formulates the research questions; Section 1.2 describes the data; Section 1.3 presents and explains the results; and Section 1.4 concludes.

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[9] We are grateful to the anonymous referee who suggested this direct test of our hypothesis and studying agency disagreement.

1.1 Research Questions

In this section we show how contemporaneous, or forward-looking, macroeconomic factors are related to CDS spreads. We then concentrate on the backward-looking nature of ratings. Lastly, we examine the link between CDS and ratings, which allows us to formulate our research questions and highlight our contributions to the literature.

1.1.1 The Determinants of CDS Spreads

The CDS determinant literature we discussed in the introduction reinforces the intuitive idea that sovereign CDS spreads, which are the prices investors pay to insure themselves against sovereign default, are based on the probability of default, global factors, and local macroeconomic conditions of the reference entity. In particular, prior literature highlights the forward-looking nature of CDS spreads where the spread in period t can be expressed as

$$s_t = f(\mathbb{E}_t\lambda, \mathbb{E}_t G, \mathbb{E}_t M), \tag{1}$$

where $\mathbb{E}_t$ is the expectation at time t; λ is the hazard rate; G is a vector of global factors; and M is a vector of local macroeconomic factors. When coupled with the high frequency availability of CDS spread data compared to macroeconomic data, CDS spreads make a highly viable candidate measure of sovereign default.

1.1.2 Sovereign Debt Ratings

The literature on determinants of ratings discussed in the introduction highlights one key aspect about sovereign debt ratings, the backward-looking nature of the factors and macroeconomic measures implying that we can denote ratings as

$$r_t = f(\lambda_{t-k}, G_{t-k}, M_{t-k}). \tag{2}$$

In other words, the rating at t is a function of past realizations of the probability of default, global factors, and local macroeconomic factors. These variables are available at low frequencies, which means that ratings evolve slowly. Cantor and Mann (2007) argue that the stability (i.e., slow evolution and low variability) is an important feature of ratings. They also point out that the high variability in market-based measures may increase accuracy, but at the cost of stability.

In this essay we exploit the lag-lead structure between CDS spreads, ratings, and their common determinants to model ratings as a function of lagged CDS spreads. We can substitute Equation (1) into Equation (2) to show that we can model ratings as a function of past spreads,

$$r_t = f(s_{t-k}) \tag{3}$$

This specification equates various fundamental factors that drive the dynamics of ratings and spreads. We argue that CDS spreads are a viable alternative to ratings and can be used by investors in their financial decision making. In addition, since CDS spreads are summary variables of macroeconomic and global factors, using them could help reduce the large uncertainty involved in modeling sovereign debt ratings.

1.1.3 *CDS and Sovereign Debt Ratings*

The literature that studies the relationship between CDS spreads and financial markets primarily links CDS spreads to market efficiency.[10] For example, Lee, Naranjo, and Sirmans (2014) find that CDS momentum profits exist even though corporate CDS markets are relatively efficient. Market efficiency is also tested by studying the effects of rating events on the CDS markets. The first to study this aspect of CDS markets were Hull et al. (2004), who analyzed the extent to which corporate CDS markets anticipate credit rating events. They

[10] There has been at least one attempt to tie CDS spreads and ratings together in a theoretical framework. Li, Li, and Yang (2014) develop a rating based continuous time model of sovereign credit risk, which captures both the cross-sectional and time-series properties of sovereign credit spreads. While unrelated to our work, this paper highlights the tight link that can be discerned between CDS spreads and sovereign debt ratings. There have also been efforts from a regulatory perspective in using corporate CDS as an alternative to ratings (Flannery, Houston, & Partnoy, 2010).

find that there is anticipation of negative events by the markets and that CDS spreads fully reflect the new information one day after the negative event. However, there were no significant results for positive events. Similarly, Ismailescu and Kazemi (2010) conducted an event study on the reaction of CDS spreads to ratings announcements in 22 emerging sovereign markets.[11] In contrast to Hull et al. (2004), they find that markets are unreactive to negative events while markets have strong reactions to positive events. This is due to different reactions between investment grade and non-investment grade reference entities, with investment grade entities having strong reactions to negative rating events and non-investment grade entities having a strong response to positive rating events. They also find that CDS spread changes in one month can predict negative rating events in the next month.

Note that while Ismailescu and Kazemi (2010) also studies the information contained in lagged sovereign CDS spreads, our study differs in several key aspects. Ismailescu and Kazemi (2010) study the efficacy of a one-month change in spread in predicting a negative rating event by the end of the following month solely for S&P. In contrast, we study how far back one-month spreads retain their predictive ability for rating events for both S&P and Moody's. Furthermore, we are the first to study and directly test the ability of sovereign ratings and CDS spreads in predicting sovereign events. Our methodology is therefore broader in scope, allowing us to show the extent of the predictability and contrast the approaches taken by the biggest rating agencies.

1.1.4 Research Questions

In Section 1.1.1, we have discussed that CDS spreads are functions of forward looking default rates, global factors, and local macroeconomic factors. In Section 1.1.2, we highlight the fact that the literature implies sovereign debt ratings are functions of backward looking

[11] Afonso, Furceri, and Gomes (2012) find similar results to Ismailescu and Kazemi (2010) for 24 developed E.U. member reference entities.

macroeconomic measures. The lead-lag structure between the determinants of ratings and the determinants of CDS spreads allows us to model rating as functions of lagged spreads and investigate the viability of CDS spreads to substitute for sovereign debt ratings. This then naturally leads us to our research questions: Can CDS spreads explain the variation in ratings? Could we identify the number of months (m) that one-month CDS changes have the ability to predict sovereign rating events? And between CDS spreads and debt ratings, which is better at predicting sovereign events?

1.2 *Data*

Our analysis takes place at two different levels of aggregation: (i) we use annual data to study the explanatory power of CDS spreads and (ii) monthly data to study the predictability of ratings using CDS spreads. For our annual analysis we merge the ratings data, CDS spread data, and macroeconomic data. We get an unbalanced panel data set from 2005 to 2016 with 54 countries and a total of 543 observations. We continue to work with the 54 countries in our monthly dataset over the same time-period.

We download the data on sovereign debt ratings from Bloomberg. The data includes both Moody's and S&P's letter credit ratings and their respective credit outlooks. We convert the ratings, including the credit outlook, into a numerical scale, or comprehensive credit rating (CCR). Rating agencies announce credit outlooks to indicate potential ratings in the medium term. The credit outlooks take on the values of -0.5 for a negative outlook and +0.5 for a positive outlook. We follow the CCR convention as in Cantor and Packer (1996) for the annual analysis and Ismailescu and Kazemi (2010) for the monthly analysis.

The CCR for the annual data ranges from B3/B- = 1 to Aaa/AAA = 16. We use the end-of-year CCR in the annual analysis. The CCR for the monthly data ranges from -1 to 17, with selective default ("SD") as the lowest and AAA/Aaa as the highest. We used the end-of-month CCR in our monthly analysis. When needed, we measure each country's average rating by taking the mean of the CCR from each rating agency.

The data for the CDS spreads are also from Bloomberg. For our analysis we use 5-year, US dollar denominated contracts.[12] In Table 1 we present the summary statistics of our monthly CDS data for each country used in our analysis. Our final sample has 54 reference entities, with mean log CDS spreads ranging from a high of 6.87 log bps. for Venezuela to a low of 2.43 log bps. for Sweden.

In our annual analysis we test for the relationship between annual rating changes and the average three year CDS spread one year before the rating change, $cds_{1:3}$. Our variable of interest, $cds_{1:3}$, is the natural log of the three-year arithmetic mean of the CDS spread. This variable is constructed following Cantor and Packer (1996) and is designed to mitigate against simultaneity concerns and the effects of business cycles. The data on the macroeconomic variables is from the World Bank's World Development Indicators (WDI) database, which is supplemented when necessary with the International Monetary Fund's World Economic Outlooks data and with the World Bank's Quarterly External Debt Statistics SDDS database.[13] The control variables we employ are constructed following Cantor and Packer (1996). In Table 2 we provide descriptive statistics for the key variable of interest, denoted $cds_{1:3}$ and the vector of macroeconomic controls, denoted $\boldsymbol{X}$.

For our monthly analysis, we construct a database with monthly CDS spread changes and monthly rating changes. The monthly rating changes are computed as the difference in the end-of-month CCRs. We compute the monthly CDS spread change as the one-month dif-

[12]The 5-year CDS contract is the most highly traded and liquid contract. Since we are interested in the implications of the relations between CDS and ratings for investors, we solely use this contract.

[13]We use the most recent default dates (August 2014) compiled by Cruces and Trebesch (2013) to create our default history indicator. The sample covers the full universe of sovereign debt restructurings with foreign commercial creditors (banks and bondholders) from 1970 until 2010. Based on certain selection criteria, they identify 182 sovereign debt restructurings by 68 countries since 1978 (no restructurings occurred between 1970 and 1977). We supplement the database using data for 2015 and 2016 from Beers and Mavalwalla (2017).

ference in the log of CDS spread. Following Ismailescu and Kazemi (2010), if rating changes occur in two consecutive months, we eliminate the month that immediately follows the first rating change.

Since the number of sovereign defaults after 2000 is too small to analyze in any statistically meaningful way, we use the J.P. Morgan Global emerging market bond indices (EMBI) blended sovereign bond spreads to create a proxy for defaults.[14] Following Sy (2004), we define a negative sovereign event to occur if a country's EMBI sovereign bond spread change is greater than 3 standard deviations from its mean. Although we are able to find EMBI bonds spreads for 64 countries, when we combine the sovereign event data with our monthly CDS spread and ratings data, we are left with data on 26 countries for our analysis.

1.3 Results

1.3.1 Ratings and Credit Default Spreads: OLS Estimates

Baseline In Panel A of Figure 1 we plot $cds_{1:3}$ as a function of time. We observe an increase in $cds_{1:3}$ starting around the start of the financial crisis and peaking with the Eurozone debt crisis. In Panel (B) of Figure 1 we plot average rating between Moody's and S&P as functions of time. Panel (B) counterintuitively documents a small but perceptible bump in overall average rating in our sample, even though a large number of downgrades occurred between 2010 and 2012. Panel C of Figure 1 shows the cross-sectional OLS regression of average ratings on $cds_{1:3}$ for each country in our sample and the pooled OLS regression of our overall sample. We find that countries with higher CDS spreads over the prior three years have substantially lower average ratings.

[14] Although Cruces and Trebesch (2013) document 24 countries with sovereign defaults between 2000 and 2013, we only have CDS data for 5 of the countries.

To substantiate the evidence in Figure 1, Table 3 reports the results from the following reduced-form OLS regressions

$$
\begin{aligned}
r_{kt} &= \alpha + \beta \cdot cds_{1:3,kt} + u_{kt}, \\
r_{kt} &= \alpha + \beta \cdot cds_{1:3,kt} + \boldsymbol{\gamma} \boldsymbol{X}'_{kt} + u_{kt}, \\
r_{kt} &= \beta \cdot cds_{1:3,kt} + \boldsymbol{\gamma} \boldsymbol{X}'_{kt} + \alpha_k + \tau_t + u_{kt}.
\end{aligned}
\tag{4}
$$

where r_{kt} is the rating in year t for country k; $cds_{1:3,kt}$ is the log average CDS spread over the previous three years for country k in year t; $\boldsymbol{X}_{kt}$ is the vector of macroeconomic controls for country k in year t; α_k controls for fixed country characteristics; τ_t controls for the time-varying factors common across all countries; and u_{kt} is a random error term. The coefficient of interest is β, the effect of CDS spread on ratings. Since bias in the standard errors is introduced when there is serial correlation within countries and when there is spatial correlation across countries within years, we cluster the standard errors by country and year following Petersen (2008).

Column (1) of Table 3 presents the results of a univariate specification and no controls [line 1 of Equation (4)]. Column (2) presents the results with the macroeconomic controls but without $cds_{1:3}$. Column (3) presents the regression with both $cds_{1:3}$ and controls [line 2 of Equation (4)]. Comparing across these three specifications, we observe a strong negative relationship between r_{kt} and $cds_{1:3,kt}$. However, the results may be contaminated by unobserved heterogeneity. To mitigate against this concern, we include country fixed effects to control for time-invariant country characteristics and year fixed effects to capture unobservable global characteristics (Gormley & Matsa, 2014).

Column (4) of Table 3 presents the results of the fixed-effects specification with no controls. Column (5) presents the results with the macroeconomic controls and without $cds_{1:3}$. Column (6) includes $cds_{1:3}$, all controls, and fixed effects [line 3 of Equation (4)]. Comparing across these three specifications, we find that the strong negative relationship between r_{kt} and $cds_{1:3,kt}$ remains.

The R^2 of the regression in Column (4) indicates that about 45% of the variation in ratings is explained by $cds_{1:3}$ and it subsumes the explanatory power of the regression with all five controls in Column (5). This key fact supports the framework summarized by Equation (3) and motivates the sufficiency of CDS spreads in predicting sovereign rating events. Note that the explanatory power increases when both $cds_{1:3}$ and the macroeconomic control variables are included in the regressions. This means that even though CDS spreads explains more of the variation in ratings than the macroeconomic controls *per ipsum*, there is still an incremental advantage in using both CDS spreads and macroeconomic variables in explaining a countries sovereign debt rating.

We also run cross-sectional regressions for each year in our sample to see how the relationship between $cds_{1:3}$ and average ratings has evolved over time. The results of this exercise is presented in Figure 2. We observe that CDS spreads are significantly negatively associated with average ratings throughout our sample period and the coefficient of interest shifted even further from zero after 2009. The explanatory power of CDS spreads was high at the beginning of our sample period, fell during the Eurozone crisis, and has rebounded in importance. Throughout the sample period, we find the power of $cds_{1:3}$ to explain the cross-country variation in average ratings to be higher relative to the macroeconomic controls the prior literature has found to be important.

Robustness While these results are striking, it can be argued that they are being driven by the fact that we used level CDS spreads, and not spread changes. That is, our results may be driven by the possible non-stationarity of CDS spreads. Some might argue that if CDS spreads are non-stationary then the results employing level CDS spreads may be spurious and differencing the spreads may help alleviate the statistical problems. However, the theoretical underpinnings of CDS spreads are not intrinsically described by processes that display drifts which would imply non-stationarity (Doshi, Jacobs, Ericsson, & Turnbull, 2013). Additionally, the impact of non-stationary series on panel model estimates may not be as central as in pure time-series analysis (Kao, 1999; Phillips & Moon, 1999).[15] Regardless, to alleviate these concerns about the spuriosness of our results we test for stationarity using two related panel unit root tests: the test of Levin, Lin, and James Chu (2002) (LLC) and the test of Im, Pesaran, and Shin (2003) (IPS)

Both LLC and IPS are extensions of the Augmented Dickey Fuller test to a panel setting. The LLC tests the null that all the cross-sections have a unit root by assuming that all cross-sections share the same autoregressive parameter. The IPS is not as restrictive as the LLC, as it allows for heterogeneity of the unit root coefficient across panels. More formally, we consider that log CDS spreads (s_{it}) for a sample of N cross-sections (countries) over T periods (months) is generated by

$$\begin{aligned} s_{it} &= (1-\phi_i)\mu_i + \phi_i y_{it-1} + \varepsilon_{it} \\ \Delta s_{it} &= \alpha_i + \beta_i y_{it-1} + \varepsilon_{it}, \end{aligned} \tag{5}$$

where $\alpha_i = (1-\phi_i)\mu_i$ and $\beta_i = -(1-\phi_i)$. We test the null hypothesis of unit roots $\phi_i = 1$ for all i, which is equivalent to testing $\beta_i = 0$ for all i against the alternative $\beta_i < 0,\ i = 1,\ldots,N_1;\ \beta_j = 0,\ j = N_1,\ldots,N$. This general formulation of the hypothesis by IPS allows for β_i to differ across groups and subsumes the homogenous alternative hypothesis ($\beta_i = \beta < 0$ for all i) of LLC.

Since Levin et al. (2002) recommend using their procedure for moderate-sized panels and requires a strongly balanced panel where the asymptotics assume $N/T \to 0$, for the unit root tests we keep only those countries with available CDS spread data for our entire sample period of interest. Out of 54 countries we are left with a balanced sample of $N = 12$ (countries) and $T = 144$ (months). To control for bias due to autocorrelation Equation (5) can be rewritten

[15]See page 273ff of Baltagi (2008) for a survey on panel unit root tests. He notes, *"Unlike the single time series spurious regression literature, the panel data spurious regression estimates give a consistent estimate of the true value of the parameter as both N and T tend to infinity. This is because, the panel estimator averages across individuals and the information in the independent cross-section data in the panel leads to a stronger overall signal than the pure time series case."*

as

$$\Delta s_{it} = \alpha_i + \beta_i y_{it-1} + \sum_{L=1}^{p} \theta_{iL} \Delta s_{it-L} + \varepsilon_{it}. \tag{6}$$

The tests derived when controlling for autocorrelation are denoted as t^*_δ (LLC) and $w_{\bar{t}}$ (IPS).

Table 4 presents the results of the LLC and IPS unit root tests. Column (1) and (3) present the results for the LLC and IPS unit root test respectively without removing the cross-sectional means. The results reject the null of a unit root. Additionally, O'Connell (1998) highlights the importance of controlling for cross-sectional dependence, showing that tests for panel unit roots suffer from significant size distortion in the presence of correlation among contemporaneous cross-sectional error terms. To control for cross-sectional dependence, we remove the cross-sectional means and report our results in Columns (2) and (4). Again, the results reject the null of a unit root. We find that the tests are suggestive of the stationarity of monthly log CDS spreads and imply that the results presented in Table 3 are not spurious. As a robustness test of the reduced-form results in Table 3, we re-run the regression for the subsample of countries that are included in the unit root tests in Table 4 when we limit the sample until the end of 2014, which yields us 21 countries with complete CDS data for each month. These results in Table 5 show that the relationship between ratings and CDS spreads is even stronger for this subsample, as evidenced by the increase in the explanatory power.

Subsamples In order to see which subsamples are driving our results, we run the specifications in Equation (4) on subsamples partitioned by continent: Europe, the Americas, and Asia & Oceania.[16] The results in Table (6) show that the relationship is strongest in the European subsample. The coefficient of interest is negative and significant, and the R^2 of the regression in Column (4) indicates that about 40% of the variation in ratings is explained

[16] We have 8 observations from Oceania and 14 from Africa. We group Asia and Oceania together due to their similarities. We do not study the African subsample in depth due to the small sample size.

by $cds_{1:3}$ and subsumes the explanatory power of the regression with all five controls in Column (5). The America subsample still retains the negative and significant coefficient of interest, but the macroeconomic controls alone have greater explanatory power than $cds_{1:3}$. The Asian & Oceania subsample still retains the negative and but is insignificant and the explanatory power is the weakest.

One interesting aspect is that there is a large variation in CDS spreads for countries that are AAA rated, as can be seen in Panel C of Figure 1. In other words, there are a large number of countries that rating agencies certify as the most credit-worthy with a high-price to insure against sovereign default. In order to study this disagreement between CDS spreads and rating agencies, in Figure 3 we plot the CDS spreads and average ratings for countries that were rated AAA at some point and who's ratings are larger than predicted by our model in column (1) of Table 3 for negative rating events. From this figure, we can graphical check what will happen when ratings and CDS disagree with each other. This figure seems to indicate that if a country has high credit rating but the CDS spreads are abnormally high, suggesting high sovereign risk, then ratings adjust and move towards CDS spreads. This tantalizing graphical evidence will be studied statistically in the next section.

We conclude that the average CDS spread over the previous three years is strongly correlated to average ratings at the end of the following year. Our results are statistically significant, economically significant, and robust. Our evidence shows that CDS spreads are a major determinant of sovereign debt ratings and motivate the use of CDS spreads in predicting rating changes.

1.3.2 *Predicting Rating Events*

Baseline Results. The results in the Section 1.3.1 confirm the correlational structure between ratings and lagged CDS spreads and additionally highlight the importance of CDS spreads by itself in explaining the variation of ratings. In this section we estimate the number of months (m) that one-month CDS changes retain the ability to predict sovereign rating events. We test the predictability of rating events using lagged changes in CDS spreads using the following logistic regression models:

$$\begin{aligned} p\left(\mathbb{1}^{-}_{\Delta r_{i,t}}\right) &= G\left(\alpha + \beta \Delta s_{i,t-m}\right) \\ p\left(\mathbb{1}^{+}_{\Delta r_{i,t}}\right) &= G\left(\alpha + \beta \Delta s_{i,t-m}\right), \end{aligned} \tag{7}$$

where $\mathbb{1}^{-/+}_{\Delta r_{i,t}}$ is an indicator variable that is equal to unity when the difference in the CCR at the end of month t and $t-1$ is negative/positive and zero if there is no change. In other words, the control group comprises of observations where there were no rating changes while the treatment group is comprised of observation with negative/positive rating events. Our independent variable of interest, Δs_{t-m}, is the one-month difference of the log CDS spread lagged back m months; p is the probability of success; and $G(\cdot)$ is the logistic link function.

Tables 7 and 8 presents the results of these pooled logistic regressions. In Table 7 we model rating changes as the dependent variable and the results show that rating changes are positively related to CDS spread changes and significant for up to seven months. To explore the results in more depth, in Table 8 we differentiate between positive changes and negative changes in ratings. We find that one-month log CDS differences are able to predict negative rating changes up to seven months in advance. The coefficients are positive and statistically significant at the one percent level. The coefficients for positive rating changes have the predicted negative sign and are statistically significant up to three months.[17]

Next we quantify the cumulative change that seems to trigger a rating event. Using the estimated period of predictability for negative events, we measure the probability of a rating change given various "buckets" of log CDS spread changes over the seven-month period. The probability is estimated as follows:

$$p\left(\mathbb{1}^{-}_{\Delta r_{i,t}}\right) = G\left(\alpha + \sum I_{it,L:U}\right) \tag{8}$$

[17] The results hold when we partition between Moody's and S&P.

where $\mathbb{1}^{-/+}_{\Delta r_{i,t}}$ is an indicator variable that is equal to unity when the difference in the CCR at the end of month t and $t-1$ is negative and zero if there is no change; and $I_{L:U}$ is an indicator that is equal to unity if the rolling seven-month cumulative change in log CDS spread is within the lower bound L and upper bound U. The results of this estimation are reported in Table 9. We find a substantial increase in the probability of a negative rating change if there is a change of more than 40% in the past seven months, which increases almost monotonically as the cumulative log CDS spread increases. More specifically, a change in the cumulative log CDS spread of 40% is associated with a 74% chance of a negative rating event, which increases almost monotonically to a 93% chance of a negative rating event for cumulative spreads of 200%.

Robustness Tests. We run the following robustness tests to ascertain the validity of our results.

In the previous section we studied the predictability of CDS spreads using a logit specification. However as Shumway (2001) points out, there may be some issues with this specification. Logit models do not account for time explicitly and cannot account for censoring (when an observation is no longer being observed). For this reason, we re-estimate our regression using a Cox proportional hazard model. One additional advantage in this method is that it includes each country year pair as a separate observation, thereby allowing us to exploit more of the data and produce more precise and robust estimates. The results in Table 10 are similar to our baseline results: negative events are predictable up to to 8 months in advance and there is no consistent pattern for positive rating changes.

We also study the ability of CDS spreads to predict the size of rating change using OLS with fixed effects for country, year, and rating agency. We report these results in Table 11. These results again confirm the initial pattern of interest: negative rating changes can be predicted up to seven months in advance and there is no pattern for positive rating changes.

Additionally, the issue of reverse causality may arise in this context. It can be argued that rating events could influence CDS spreads, and that our methodology is capturing the effect of rating events and not CDS spreads per se. In order to alleviate simultaneity concerns, we run the following robustness tests. Firstly, we run an OLS regression with CDS spread changes as the dependent variable and lagged negative and positive rating change indicators as the independent variables controlling for agency, country, and year fixed effects. We present the results of this exercise in Table 12. These results show no discernible pattern of predictability. Secondly, we take a more direct approach to study whether there is any influence from rating changes to CDS spread changes. We accomplish this by isolating rating events where there were no other rating events in the previous 24 months which allows us to mitigate the effects that rating changes have on CDS spreads. The results in Table 13 are qualitatively similar to our baseline. The coefficient of interest is statistically significant up to 4 months before negative rating events while statistically insignificant for positive rating events. This shows that that predictability appears to exist at least up to 4 months before negative rating events.

Finally, we run another robustness test to see whether our results are being driven by countries with a large number of rating upgrade and rating downgrades.[18] We remove any country which is in the upper quintile of rating upgrades and rating downgrades and rerun our baseline logit regression. The results in Table 14 are again qualitatively similar to our baseline, which indicates that there is no discernible effect coming from outliers.

Graphical Evidence. To tackle the question of whether CDS spread changes truly predict rating changes over and above the evidence in the previous section, we plot the evolution of CDS spreads around long-run windows surrounding rating changes inspired by the recent

[18] For downgrades, these countries are Cyprus (CY), Spain (ES), Greece (GR), Hungary (HU), Ireland (IE), Italy (IT), Latvia (LT), Portugal (PT), Slovenia (SI), and Ukraine (UA). For upgrades, these countries are Bulgaria (BG), Brazil (BR), Indonesia (ID), Peru (PE), Philippines (PH), Romania (RO), Russia, (RU), and Slovakia (SK).

literature that has studied event studies in CDS markets (e.g., Ismailescu & Kazemi, 2010; Chava, Ganduri, & Ornthanalai, 2016).

Figure 4 plots the reaction of monthly CDS spreads before and after rating changes. CDS spreads precipitate both negative and positive rating events. CDS spreads increase about 50% before a negative rating event and stabilize afterwards with a total spread change of about 55% in the 18-month window surrounding the event. CDS spreads also show a tendency to anticipate positive rating events, with about a 20% decrease in spreads before the event month and stabilize afterwards with a total spread change of about -20% in the 18-month window surrounding the event. This evidence, in conjunction with the reverse causality tests in Tables 12 and 13 show that CDS spread changes lead rating changes and not vice-versa.

1.3.3 *Horse Race*

Finally, to ascertain if CDS spreads are better than credit ratings as measures of sovereign risk, we run a horse race between both measures. In the spirit of Sy (2004), we run pooled logistic regressions to compare and contrast between k-month changes in CDS spreads, $\Delta_k s_{t-1}$, and ratings, $\Delta_k r_{t-1}$, the month before the event month t in predicting a sovereign event seven months before the event. That is,

$$\mathbb{P}(\text{Event in the next seven months}) = \beta_0 + \beta_1 \cdot \Delta_k s_{t-1} + \beta_2 \Delta_k r_{t-1} + \varepsilon, \quad (9)$$

where a sovereign event is defined as an EMBI spread change greater than three standard deviations from the mean change for that country.

The results of the horse race in Table 15 indicate that a three-month or more CDS spread change the month before a sovereign event is statistically significant in predicting a sovereign event in the next seven months while there is no predictability with for rating changes at any horizon. These results are consistent with what the prior literature has documented, namely, the poor track-record of ratings in predicting sovereign crises.

We then partition our sample into observations in which Moody's and S&P disagree, i.e., a more than one notch difference in a country's rating, and when they agree, i.e., less than one notch difference. The results in Table 16 show that the predictability is greater when there is disagreement between the agencies than when there is agreement. This indicates that CDS spreads are relatively more useful to investors when there is disagreement between the agencies, even though CDS spreads are generally more useful than ratings.

1.4 Conclusion

Understanding the determinants of sovereign debt ratings is important to both investors and corporate managers of domestic firms or multinational firms. Rating downgrades have large implications for the corporate decisions of the firm since they can put a damper on credit-availability, a rating downgrade can affect the capital requirements for banks and insurance companies when they decide to undertake an investment, trigger covenantal obligations, and cause adverse reputational effects. In particular, downgrades cause the firm to reduce its debt issuance and leverage, constraining the options available to the firm. The increased frictions for a firm associated with a corporate downgrades still hold when the country in which it is domiciled is downgraded, particularly if the firm is rated at or above the home country's rating. Hence, understanding the determinants of sovereign ratings and finding a leading indicator to rating downgrades is beneficial to investors and corporate managers in making timely decisions.

In this essay we examine the relationship between sovereign debt ratings and CDS spreads. Using panel data from 2005 to 2016, we find that the information contained in the average credit default swap spread over the three years prior to a rating event is important in explaining sovereign debt rating variation. This evidence, while correlational in nature, motivates the use of CDS spreads in predicting rating changes at the intra-annual level. Our analysis shows that the ability of one-month changes in CDS spreads to predict negative rating changes are significant up to seven months prior to the change for both S&P and Moody's while there is no consistent predictive ability in one-month changes in CDS spreads to predict positive ratings. Also, in a horse race setting, we show that three-month CDS spread changes are able to predict sovereign crises within the next seven months while ratings have no predictive ability. Overall, we find that a sovereign's CDS spread, which is a forward looking measure, is available more frequently, and is less costly to compile than macroeconomic data is the measure of sovereign default that is most useful *per ipsum* to market participants.

The advantages of market variables over judgmental models has been reinforced by our analysis. Academics can use the patterns and stylized facts we uncover to build more realistic theoretical models of sovereign default, ratings, and CDS contracts. Investors and corporate managers of multinational firms as well as policymakers can use the relationship we have documented between CDS spreads and credit ratings to hedge proactively against real economic risks from sovereign downgrades rather than responding reactively.

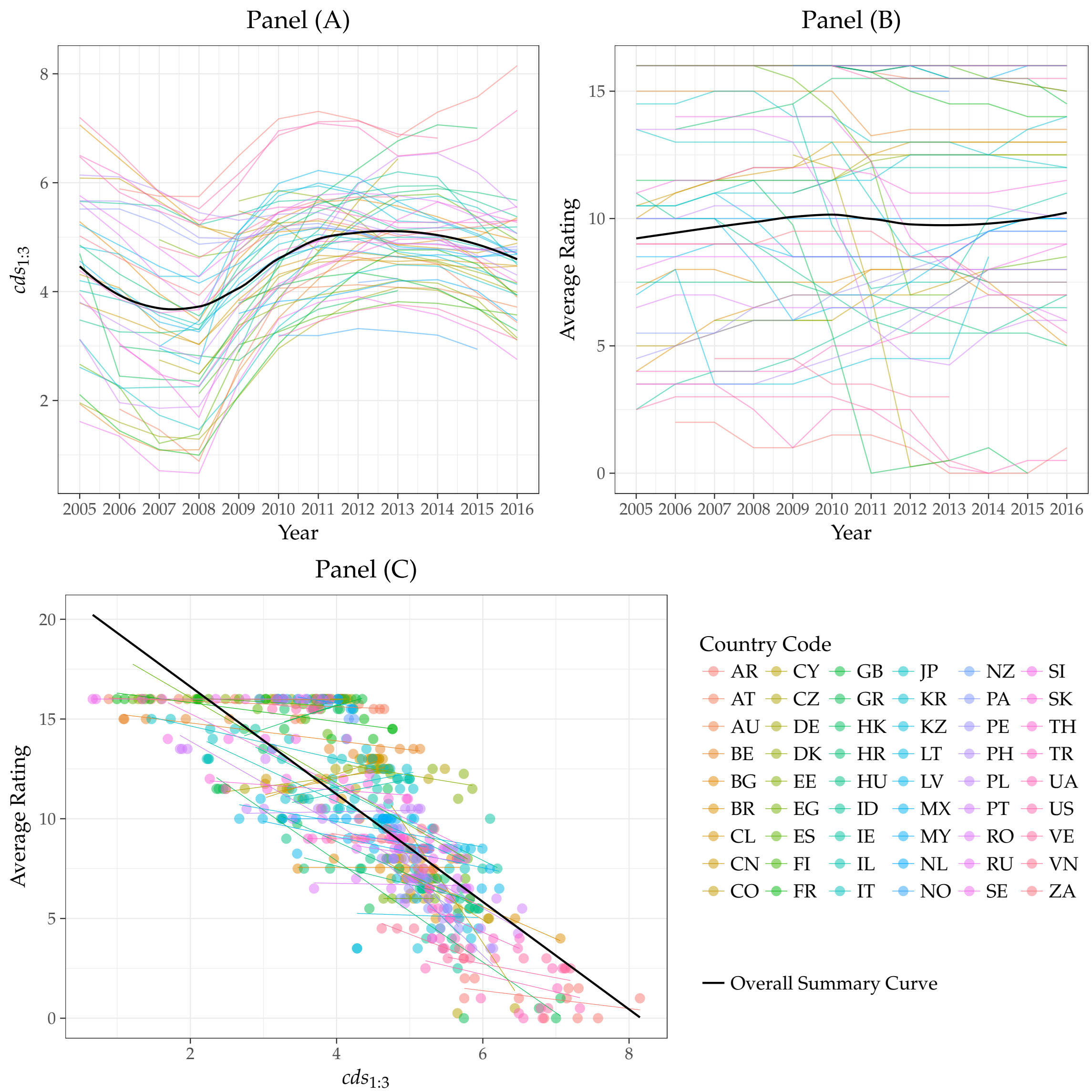

Figure 1: *Summary Plots.* This figure presents summary plots of the 543 observations used in the panel regressions, which covers the twelve-year period from the beginning of 2005 to the end of 2016. Panel (A) plots the natural log of the three-year average CDS spread lagged one year, $cds_{1:3}$, as a function of time for each country in our sample and a local regression (LOESS) curve for the overall sample. Panel (B) plots average rating as a function of time for each country in our sample and a LOESS curve for the overall sample. Panel (C) plots average rating as a function of $cds_{1:3}$ and the regression line for each individual country in our sample and for the overall sample.

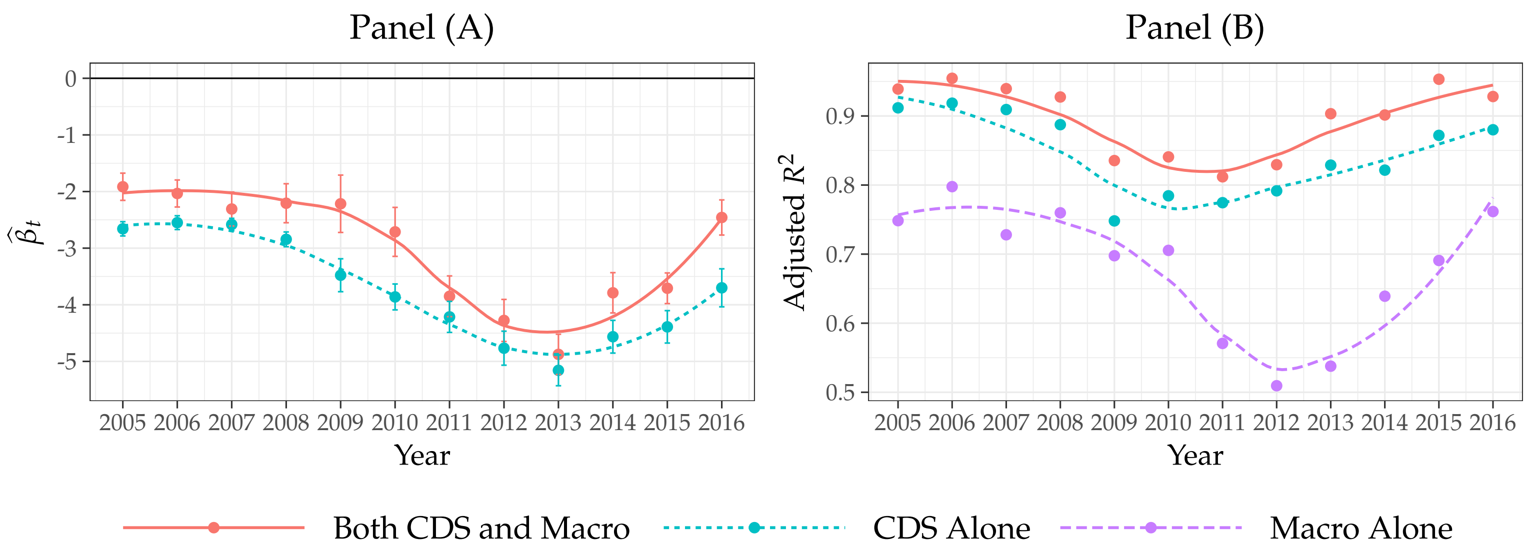

Figure 2: *OLS Estimates by Year.* This figure presents the results of running the following OLS regression for each year in our sample:

$$r_k = \alpha_t + \beta_t cds_{1:3,k} + \boldsymbol{\gamma}_t \boldsymbol{X}'_k + u_k,$$

where r_k is the average rating for country k; $cds_{1:3,k}$ is the log average CDS spread over the previous three years for country k; $\boldsymbol{X}_k$ is the vector of macroeconomic controls for country k; and u_k is a random error term. Panel (A) plots the estimated coefficient of interest in year t ($\hat{\beta}_t$), error bars calculated using robust standard errors, and a local regression (LOESS) curve. Panel (B) plots adjusted R^2 and a LOESS curve. We run the regressions both with and without our macroeconomic control variables.

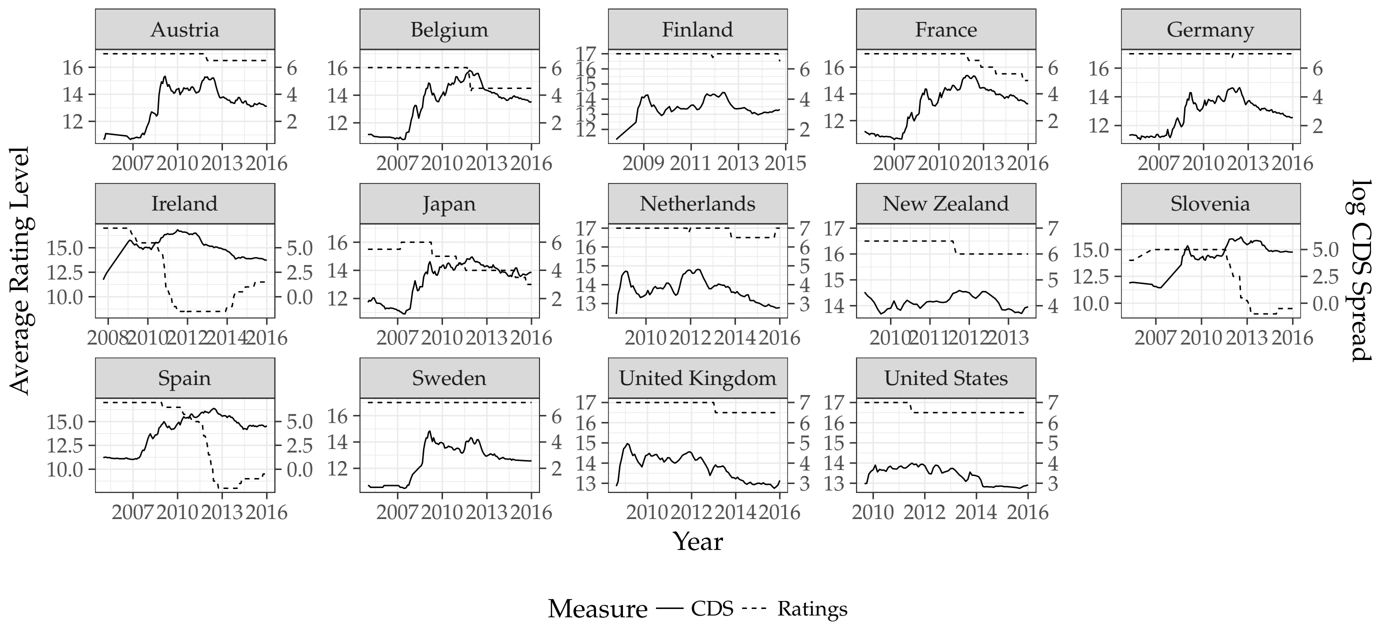

Figure 3: Plotting CDS Spreads and Ratings for Selected AAA Rated Countries. This figure plots the CDS spreads and average ratings for countries that were rated AAA at some point and who's ratings are larger than predicted by the estimated model, $\widehat{r}_{kt} = \widehat{\alpha} + \widehat{\beta} \cdot cds_{1:3}$, for countries with negative rating events.

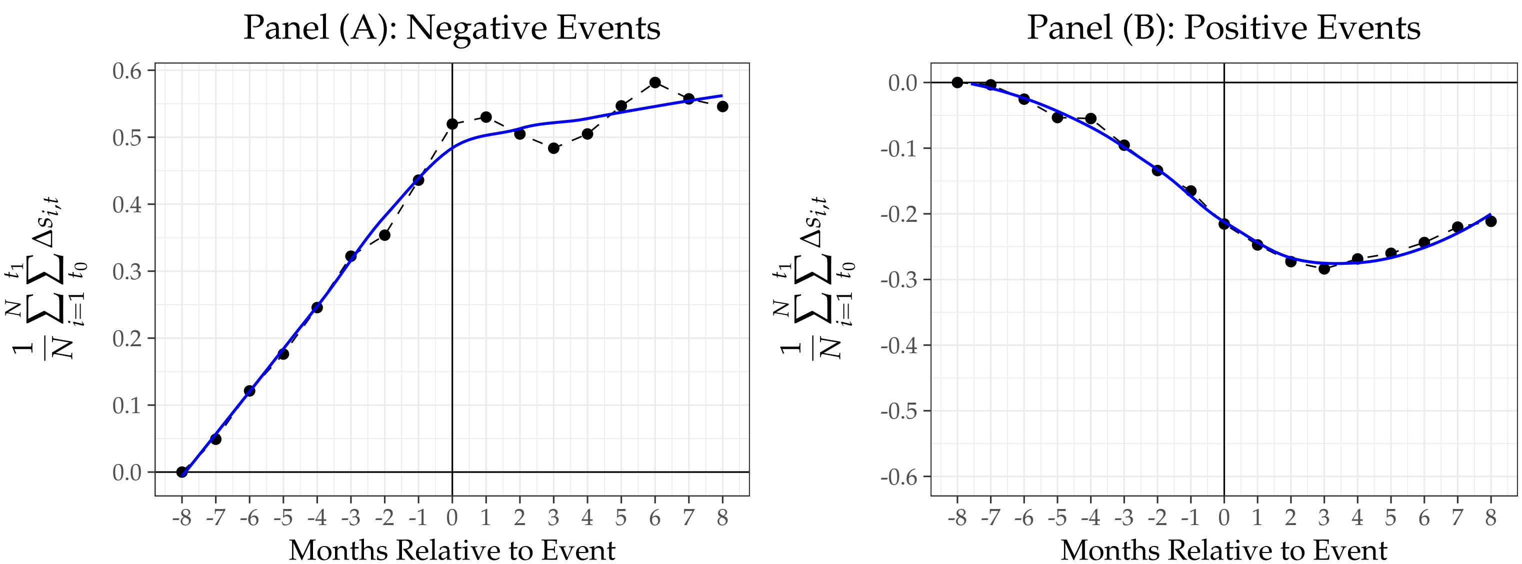

Figure 4: *Monthly CDS Spread Reaction Around Rating Events.* This figure plots the mean cumulative spread change over a 16-month window around (a) negative and (b) positive rating events for our 54 country sample. Rating events refer to downgrades, upgrades, and changes in outlook. Therefore, a negative (positive) rating event can refer to either a downgrade (upgrade) or a downward (upward) revision in outlook. We eliminate an event month that immediately follows another event month. The solid line is a local regression (LOESS) curve while the dashed line connects the mean cumulative spread estimates.

Table 1: *Summary Statistics for CDS Spread Data.* This table presents the summary results of the monthly log spreads and monthly spread changes of our sample.

			log CDS Spread (log bp.)				CDS Change (%)			
	Country	N	Mean	St. Dev.	Skew.	Kurt	Mean	St. Dev.	Skew.	Kurt.
1	Argentina	135	6.68	0.89	0.27	1.98	−0.32	29.55	−4.03	44.13
2	Australia	94	3.82	0.45	0.28	2.94	−0.02	16.85	0.73	5.97
3	Austria	133	3.47	1.17	−0.79	3.28	1.48	21.14	2.34	16.49
4	Belgium	171	3.14	1.54	−0.20	1.74	0.44	17.89	0.18	8.83
5	Brazil	193	5.48	0.83	1.18	4.08	−0.94	14.89	1.15	6.60
6	Bulgaria	188	4.96	0.93	−0.74	2.75	−0.70	15.82	1.31	7.86
7	Chile	178	4.13	0.67	−0.61	2.67	−0.63	14.21	1.75	11.82
8	China	177	4.07	0.71	−0.58	2.43	−0.20	15.59	0.57	6.48
9	Colombia	178	5.16	0.52	0.83	2.72	−1.08	13.68	1.08	5.56
10	Croatia	190	5.06	0.93	−0.86	2.53	−0.24	15.10	1.40	11.03
11	Cyprus	57	5.82	1.04	0.03	1.36	6.20	19.15	0.94	4.74
12	Czech	97	4.01	1.00	−1.18	3.59	1.91	21.05	0.83	7.55
13	Denmark	112	3.50	0.64	0.87	2.84	1.47	27.88	3.43	24.15
14	Egypt	33	5.12	0.74	0.04	1.98	3.22	26.03	1.54	7.43
15	Estonia	94	4.62	0.63	1.56	4.62	−1.30	12.42	1.92	16.83
16	Finland	76	3.51	0.44	0.63	2.60	2.46	22.16	1.90	9.91
17	France	176	3.00	1.44	−0.31	1.76	0.40	17.74	1.28	8.97
18	Germany	174	2.68	1.05	−0.04	1.83	−0.01	17.75	1.17	10.56
19	Greece	110	4.06	1.99	0.55	1.79	4.55	27.70	1.69	17.03
20	Hong Kong	46	3.74	0.58	−1.76	5.01	3.61	31.47	3.94	26.49
21	Hungary	173	4.65	1.15	−0.25	1.59	0.88	15.64	1.28	8.02
22	Indonesia	151	5.22	0.38	1.44	6.30	−0.88	14.60	1.97	14.05
23	Ireland	99	5.01	1.02	0.10	2.02	1.79	35.01	7.38	66.77
24	Israel	138	4.36	0.70	−0.54	2.14	0.25	16.63	0.33	5.85
25	Italy	176	4.11	1.41	−0.41	1.63	1.22	15.52	0.99	5.49
26	Japan	157	3.18	1.22	−0.44	1.71	0.57	17.40	1.22	6.71
27	Kazakhstan	112	5.09	0.75	0.21	3.18	1.18	19.87	1.89	9.82
28	Latvia	86	5.33	0.93	−1.02	5.38	3.03	39.57	1.68	19.29
29	Lithuania	78	5.25	0.88	−1.91	8.68	3.47	40.95	7.32	60.37
30	Malaysia	191	4.37	0.70	−0.66	2.54	−0.53	14.90	0.84	5.32
31	Mexico	193	4.78	0.49	−0.01	3.51	−0.54	14.54	1.54	9.33
32	Netherlands	109	3.63	0.58	0.41	2.33	0.32	18.06	2.02	12.71
33	New Zealand	49	4.12	0.26	0.16	1.95	−1.24	12.86	0.13	2.76
34	Norway	68	3.04	0.36	0.56	2.57	−2.27	13.39	0.84	6.00
35	Panama	168	4.92	0.40	0.74	3.30	−0.83	12.90	1.45	7.41
36	Peru	169	4.97	0.43	0.91	3.60	−0.87	14.44	1.08	6.75
37	Philippines	185	5.20	0.62	0.40	1.92	−0.85	11.55	1.09	7.78
38	Poland	190	4.06	0.87	−0.22	2.33	0.32	15.85	1.09	8.08
39	Portugal	176	4.29	1.83	−0.30	1.61	1.22	16.82	0.77	4.38
40	Romania	164	4.99	0.88	−0.69	2.72	−0.86	15.70	1.06	6.58
41	Russia	204	5.29	0.73	0.01	2.80	−0.96	15.89	2.08	15.11
42	Slovakia	180	3.79	1.02	−0.37	2.20	−0.70	18.24	1.37	9.52
43	Slovenia	105	4.71	1.08	−1.58	5.80	2.68	26.32	5.18	41.71
44	South Africa	204	4.97	0.59	−0.92	3.36	0.01	13.55	1.44	8.67
45	South Korea	187	4.17	0.64	0.24	3.51	0.01	16.64	1.36	9.03
46	Spain	163	3.91	1.70	−0.65	2.01	1.73	14.96	0.75	4.42
47	Sweden	130	2.43	1.40	−0.22	1.50	1.56	17.95	1.79	11.11
48	Thailand	183	4.41	0.58	−0.21	2.03	−0.47	14.43	0.37	4.67
49	Turkey	205	5.63	0.58	1.02	3.03	−0.38	13.72	0.96	5.17
50	Ukraine	129	6.29	0.87	0.20	2.28	0.60	23.75	−1.79	25.88
51	United Kingdom	106	3.73	0.59	0.02	1.75	0.24	15.92	1.34	7.98
52	United States	79	3.38	0.42	−0.26	1.50	0.01	12.65	0.55	5.69
53	Venezuela	178	6.87	1.04	−0.07	2.50	0.95	16.01	1.33	6.90
54	Vietnam	81	5.37	0.61	−0.83	2.58	1.22	14.42	0.34	4.66
	Total	7,578	4.51	1.34	−0.37	3.67	0.30	18.39	2.72	49.87

Table 2: *Annual Data Summary Statistics.* There are a total of 54 countries and 543 observations from 2005 to 2016

Variable	N	Mean	Median	St. Dev.	Min	Max
$cds_{1:3}$	543	4.52	4.70	1.28	0.66	8.15
GNI	543	9.51	9.49	1.04	6.63	11.55
GDP Growth	543	3.15	3.14	2.90	−6.32	12.08
Inflation	543	3.01	2.97	3.04	−7.22	12.07
Fiscal Balance	543	−2.30	−2.23	3.98	−24.37	16.19
External Balance	543	−0.17	−0.33	5.64	−26.21	17.22
External Debt	543	0.52	0.45	1.04	−4.51	4.51
Default	543	0.25	0.00	0.43	0.00	1.00
Development	543	0.56	1.00	0.50	0.00	1.00

Table 3: OLS Estimates. This table presents the reduced form parameter estimates for various specifications of the following equation:

$$r_{kt} = \beta cds_{1:3,kt} + \boldsymbol{\gamma} \boldsymbol{X}'_{kt} + \alpha_k + \tau_t + u_{kt},$$

where r_{kt} is the rating in year t for country k; $cds_{1:3,kt}$ is the log average CDS spread over the previous three years for country k in year t; $\boldsymbol{X}_{kt}$ is the vector of macroeconomic controls for country k in year t; α_k controls for fixed country characteristics; τ_t controls for the time-varying factors common across all countries; and u_{kt} is a random error term. Standard errors clustered by country and time are in parenthesis for the fixed effect regressions while robust standard errors are in parenthesis for the pooled regressions.

	Dependent Variable: Average Rating					
	Pooled			Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)
$cds_{1:3}$	−2.696***	—	−1.952***	−1.704***	—	−1.203***
	(0.088)		(0.114)	(0.231)		(0.212)
GNI	—	3.269***	1.959***	—	4.069***	1.295*
		(0.216)	(0.157)		(0.950)	(0.663)
GDP Growth	—	0.219	0.084	—	0.085	0.102
		(0.156)	(0.109)		(0.160)	(0.118)
Inflation	—	0.074	−0.119	—	0.127	0.030
		(0.136)	(0.095)		(0.106)	(0.078)
Fiscal Balance	—	0.155***	0.045*	—	0.154*	0.125*
		(0.036)	(0.025)		(0.070)	(0.065)
External Balance	—	0.027	0.064***	—	−0.088*	−0.052
		(0.022)	(0.016)		(0.041)	(0.031)
External Debt	—	−0.476***	−0.361***	—	0.017	0.017
		(0.106)	(0.090)		(0.053)	(0.043)
Default	—	0.018	0.185	—	−1.011	−0.375
		(0.267)	(0.189)		(0.569)	(0.467)
Development	—	1.198***	0.043	—	−0.090	−0.004
		(0.451)	(0.298)		(0.261)	(0.296)
Constant	22.014***	−22.230***	0.355	—	—	—
	(0.432)	(2.003)	(1.792)			
FE : Country	—	—	—	•	•	•
FE : Time	—	—	—	•	•	•
Observations	543	543	543	543	543	543
Adj. R^2	0.615	0.592	0.782	0.448	0.396	0.517

Table 4: Panel Unit Root Tests. This table presents the panel unit root tests of Levin, Lin, and James Chu (2002) (LLC) and Im, Pesaran, and Shin (2003) (IPS) for the portion of our sample data of 12 countries that had a balanced sample of monthly CDS spreads from 2005:01-2016:12. The tests derived when controlling for autocorrelation are denoted as t^*_δ (LLC) and $w_{\bar{t}}$ (IPS). The null hypothesis for both tests is that the autoregressive parameter implies a unit root, however, the LLC test assumes homogenous autoregressive parameters across panels while the IPS relaxes this assumption. Columns (1) and (3) presents test statistics that are robust to serial correlation and include panel specific means. Columns (2) and (4) are additionally robust to cross-sectional dependence.

	LLC				IPS			
	(1)		(2)		(3)		(4)	
Lags	t^*_δ	p-value	t^*_δ	p-value	$w_{\bar{t}}$	p-value	$w_{\bar{t}}$	p-value
1	−2.163	0.015	−4.067	0.000	−2.801	0.003	−1.268	0.103
2	−2.078	0.019	−4.534	0.000	−2.624	0.004	−1.633	0.051
3	−2.346	0.010	−5.184	0.000	−3.222	0.001	−2.268	0.012
4	−2.234	0.013	−4.652	0.000	−3.264	0.001	−1.878	0.030
Panel Mean	•	•	•	•	•	•	•	•
XS Demean	—	—	•	•	—	—	•	•

Table 5: *OLS Estimates for Panel Unit Root Subsample.* This table presents the reduced form parameter estimates for various specifications of the following equation:

$$r_{kt} = \beta cds_{1:3,kt} + \boldsymbol{\gamma} \boldsymbol{X}'_{kt} + \alpha_k + \tau_t + u_{kt},$$

where r_{kt} is the rating in year t for country k; $cds_{1:3,kt}$ is the log average CDS spread over the previous three years for country k in year t; $\boldsymbol{X}_{kt}$ is the vector of macroeconomic controls for country k in year t; α_k controls for fixed country characteristics; τ_t controls for the time-varying factors common across all countries; and u_{kt} is a random error term. The sample is restricted to the countries used in the panel unit root tests. Standard errors clustered by country and time are in parenthesis. *Reads: CDS spreads are significantly negatively associated with average ratings, and CDS spreads subsume the macroeconomic controls the literature has proposed as determinants of ratings in explaining the variation of average ratings.*

	Dependent Variable: Average Rating					
	Pooled			Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)
$cds_{1:3}$	-2.334^{***}	—	-1.742^{***}	-1.175^{***}	—	-1.261^{***}
	(0.207)		(0.197)	(0.242)		(0.222)
Controls	—	•	•	—	•	•
FE : Country	—	—	—	•	•	•
FE : Time	—	—	—	•	•	•
Observations	209	209	209	209	209	209
R^2	0.704	0.655	0.828	0.542	0.452	0.656

Table 6: *Continental Subsample Estimates.* This table presents the reduced form parameter estimates for various specifications of the following equation by continental subsample:

$$r_{kt} = \beta cds_{1:3,kt} + \boldsymbol{\gamma}\boldsymbol{X}'_{kt} + \alpha_k + \tau_t + u_{kt},$$

where r_{kt} is the rating in year t for country k; $cds_{1:3,kt}$ is the log average CDS spread over the previous three years for country k in year t; $\boldsymbol{X}_{kt}$ is the vector of macroeconomic controls for country k in year t; α_k controls for fixed country characteristics; τ_t controls for the time-varying factors common across all countries; and u_{kt} is a random error term. Standard errors clustered by country and time are in parenthesis.

	Dependent Variable: Average Rating					
	Pooled			Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. *Europe*					
$cds_{1:3}$	-1.905^{***}	—	-1.334^{***}	-0.963^{***}	—	-1.003^{***}
	(0.293)		(0.222)	(0.244)		(0.256)
Obs.	243	243	243	243	243	243
Adj. R^2	0.489	0.628	0.736	0.398	0.338	0.469
	Panel B. *Americas*					
$cds_{1:3}$	-3.538^{***}	—	-2.865^{***}	-1.047^{**}	—	-0.862^{**}
	(0.321)		(0.381)	(0.463)		(0.355)
Obs.	83	83	83	83	83	83
Adj. R^2	0.786	0.625	0.806	0.230	0.371	0.439
	Panel C. *Asia & Oceania*					
$cds_{1:3}$	-3.082^{***}	—	-1.283^{***}	-0.653	—	-0.652
	(0.448)		(0.386)	(0.462)		(0.398)
Observations	125	125	125	125	125	125
Adj. R^2	0.524	0.703	0.740	0.068	0.213	0.241
Controls	—	•	•	—	•	•
FE : Country	—	—	—	•	•	•
FE : Time	—	—	—	•	•	•

Table 7: Predicting Rating Events: Pooled Logit. This table summarizes the results of estimating $p\left(\mathbb{1}^{-/+}_{\Delta r_{i,t}}\right) = G\left(\alpha + \beta \Delta s_{i,t-m}\right)$, where $\mathbb{1}^{-/+}_{\Delta r_{i,t}}$ is an indicator variable that is equal to one when the difference in the CCR at the end of month t and month $t-1$ is negative/positive and zero if there is no change; α is the intercept; p is the probability of success; and $G(\cdot)$ is the logistic link function. Our independent variable Δs_{t-m} is the one-month difference of the log CDS spread lagged back m months. Since estimating the probability of a rating event may be contaminated by events that occur in two consecutive months, we eliminate the event month that immediately follows another event month. The data is pooled between both agencies. Standard errors are given in the parentheses with stars indicating $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

	Dependent Variable: Δ in Rating								
Lag (in months)	$m = 1$	2	3	4	5	6	7	8	9
Δs_{t-m}	0.583***	0.654***	0.710***	0.616***	0.861***	0.773***	0.670***	−0.157	−0.555**
	(0.193)	(0.190)	(0.186)	(0.193)	(0.177)	(0.182)	(0.189)	(0.253)	(0.261)
Constant	−3.300***	−3.298***	−3.298***	−3.298***	−3.310***	−3.307***	−3.305***	−3.304***	−3.309***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
Total N	15,156	15,048	14,940	14,832	14,724	14,616	14,508	14,400	14,292
Event N	543	541	538	533	527	523	519	510	505

Table 8: *Predicting Positive and Negative Rating Events: Pooled Logit.* This table summarizes the results of estimating $p\left(\mathbb{1}^{-/+}_{\Delta r_{i,t}}\right) = G\left(\alpha + \beta \Delta s_{i,t-m}\right)$, where $\mathbb{1}^{-/+}_{\Delta r_{i,t}}$ is an indicator variable that is equal to one when the difference in the CCR at the end of month t and month $t-1$ is negative/positive and zero if there is no change; α is the intercept; p is the probability of success; and $G(\cdot)$ is the logistic link function. Our independent variable Δs_{t-m} is the one-month difference of the log CDS spread lagged back m months. Since estimating the probability of a rating event may be contaminated by events that occur in two consecutive months, we eliminate the event month that immediately follows another event month. The data is pooled between both agencies. Standard errors are given in the parentheses with stars indicating $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Panel A. Dependent Variable: $-\Delta$ in Rating									
Lag (in months)	$m = 1$	2	3	4	5	6	7	8	9
Δs_{t-m}	1.175***	1.151***	1.358***	1.093***	1.421***	1.247***	1.141***	0.493*	0.136
	(0.219)	(0.210)	(0.201)	(0.213)	(0.202)	(0.219)	(0.212)	(0.296)	(0.347)
Constant	-4.150***	-4.146***	-4.153***	-4.133***	-4.169***	-4.157***	-4.145***	-4.117***	-4.112***
	(0.067)	(0.067)	(0.067)	(0.067)	(0.068)	(0.068)	(0.068)	(0.067)	(0.067)
Total N	14,851	14,744	14,639	14,535	14,428	14,322	14,218	14,118	14,013
Event N	238	237	237	236	231	229	229	228	226
Panel B. Dependent Variable: $+\Delta$ in Rating									
Lag (in months)	$m = 1$	2	3	4	5	6	7	8	9
Δs_{t-m}	-1.033***	-0.683*	-0.825**	-0.383	-0.545	-0.446	-0.469	-1.006***	-1.235***
	(0.329)	(0.359)	(0.350)	(0.361)	(0.363)	(0.364)	(0.365)	(0.347)	(0.341)
Constant	-4.005***	-3.993***	-4.000***	-4.001***	-4.000***	-3.995***	-4.003***	-4.029***	-4.035***
	(0.062)	(0.062)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.065)	(0.065)
Total N	14,883	14,776	14,668	14,561	14,458	14,353	14,245	14,140	14,035
Event N	270	269	266	262	261	260	256	250	248

Table 9: *Predictability Magnitude.* This table presents the probability of a negative rating change for various "buckets" of log CDS spread changes over the seven-month period. The probability is estimated using

$$p\left(\mathbb{1}^{-}_{\Delta r_{i,t}}\right) = G\left(\alpha + \sum I_{i\,t,L:U}\right)$$

where $\mathbb{1}^{-}_{\Delta r_{i,t}}$ is an indicator variable which is equal to one when the difference in the CCR at the end of month t is negative, α is the intercept, p is the probability of success, $G(\cdot)$ is the logistic link function, and $I_{L:U}$ is an indicator that equals unity if the rolling seven-month cumulative change in log CDS spread is within the lower bound L and upper bound U. The upper threshold boundaries are in the first column. The t-statistics are given in parentheses with stars indicating $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

	Coefficients		Probabilities	
U	Moody's	S&P	Moody's	S&P
5%	-0.254	-0.273	-	-
	(-0.277)	(-0.417)		
10%	-0.073	-0.051	-	-
	(-0.079)	(-0.077)		
15%	0.084	-0.113	-	-
	(0.091)	(-0.167)		
20%	-14.339	-0.818	-	-
	(-0.028)	(-0.936)		
30%	0.795	1.422***	-	80.56%
	(1.071)	(2.606)		
40%	1.051**	1.334***	74.10%	79.15%
	(2.113)	(3.084)		
50%	1.870***	1.902***	86.65%	87.01%
	(4.481)	(4.804)		
100%	1.675***	1.881***	84.22%	86.78%
	(5.177)	(6.346)		
150%	2.003***	2.108***	88.12%	89.16%
	(5.371)	(6.041)		
200%	2.172***	1.746***	89.77%	85.15%
	(4.919)	(3.503)		
>200%	2.624***	2.338***	93.24%	91.20%
	(5.126)	(4.208)		

***Table 10:** Predicting Rating Events: Hazard Model.* This table summarizes the results of estimating the instantaneous risk of a downgrade (upgrade) using the Cox proportional hazard model. Our independent variable Δs_{t-m} is the one-month difference of the log CDS spread lagged back m months. This specification allows us to control for each country's period at risk, duration dependence, and the unbalanced nature of our data, i.e., censoring. We are also able to utilize more data since it includes each country-year as a separate observation which helps to produce more efficient and precise estimates. Since estimating the probability of a rating event may be contaminated by events that occur in two consecutive months, we eliminate the event month that immediately follows another event month. Standard errors clustered at the agency, country, and year level are given in the parentheses with stars indicating $^{***}p<0.01$, $^{**}p<0.05$, and $^{*}p<0.10$.

Panel A. $-\Delta$ in Rating									
Lag (in months)	$m=1$	2	3	4	5	6	7	8	9
Δs_{t-m}	0.853***	1.165***	1.467***	0.879***	1.437***	1.488***	1.321***	0.977***	0.639
	(0.188)	(0.256)	(0.237)	(0.229)	(0.242)	(0.232)	(0.284)	(0.294)	(0.493)
Total N	14,920	14,812	14,705	14,597	14,490	14,387	14,281	14,173	14,066
Event N	238	237	237	236	231	229	229	228	226
Panel B. $+\Delta$ in Rating									
Lag (in months)	$m=1$	2	3	4	5	6	7	8	9
Δs_{t-m}	-0.768***	-1.239**	-1.280**	-0.597	-1.765**	-1.043	-0.172	-0.914	-1.764**
	(0.296)	(0.565)	(0.577)	(0.391)	(0.844)	(0.897)	(0.853)	(0.906)	(0.866)
Total N	14,946	14,839	14,734	14,630	14,523	14,416	14,312	14,209	14,103
Event N	270	269	266	262	261	260	256	250	248

Table 11: *Explaining the Size of the Rating Event.* This table summarizes the results of estimating the expected magnitude of a rating change at the end of month t, Δr_t, conditioned on the one-month CDS spread lagged m months, Δs_{t-m} and controlling for country, year, and agency fixed effects. Since the estimation may be contaminated by events that occur in two consecutive months, we eliminate the event month that immediately follows another event month. Standard errors clustered on the country, year, and agency level are given in the parentheses with stars indicating $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Panel A. $-\Delta$ in Rating									
Lag (in months)	$m = 1$	2	3	4	5	6	7	8	9
Δs_{t-m}	-0.0209**	-0.0407***	-0.0399***	-0.0199**	-0.0317***	-0.0258***	-0.0257***	-0.0007	0.0148*
	(0.0086)	(0.0115)	(0.0093)	(0.0081)	(0.0105)	(0.0092)	(0.0085)	(0.0075)	(0.0088)
FE : Country	•	•	•	•	•	•	•	•	•
FE : Time	•	•	•	•	•	•	•	•	•
FE : Agency	•	•	•	•	•	•	•	•	•
Total N	14,851	14,744	14,639	14,535	14,428	14,322	14,218	14,118	14,013
Adj. R^2	0.022	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023
Panel B. $+\Delta$ in Rating									
Lag (in months)	$m = 1$	2	3	4	5	6	7	8	9
Δs_{t-m}	-0.0183**	0.0025	-0.0056	-0.0015	-0.0015	-0.0021	-0.0012	-0.0112**	-0.0111**
	(0.0089)	(0.0091)	(0.0051)	(0.0048)	(0.0058)	(0.0053)	(0.0057)	(0.0051)	(0.0050)
FE : Country	•	•	•	•	•	•	•	•	•
FE : Time	•	•	•	•	•	•	•	•	•
FE : Agency	•	•	•	•	•	•	•	•	•
Total N	14,883	14,776	14,668	14,561	14,458	14,353	14,245	14,140	14,035
Adj. R^2	0.009	0.007	0.007	0.007	0.007	0.007	0.008	0.008	0.008

Table 12: *Do rating changes predict CDS spread changes?* This table summarizes the results of predicting the one-month log change in CDS spread, Δs_{t-1}, using an indicator variable for the one-month change in upgrades and downgrades m months prior, $\pm\Delta r_{t-m}$, and controlling for country, year, and agency fixed effects. Since the estimation may be contaminated by events that occur in two consecutive months, we eliminate the event month that immediately follows another event month. Standard errors clustered on the country, year, and agency level are given in the parentheses with stars indicating $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Panel A: Negative Rating Events									
Lag (in months)	$m = 1$	2	3	4	5	6	7	8	9
$-\Delta r_{t-m}$	0.0110	-0.0036	-0.0155*	0.0222**	0.0202**	-0.0051	-0.0174*	-0.0208	-0.0159
	(0.0263)	(0.0134)	(0.0093)	(0.0107)	(0.0087)	(0.0126)	(0.0098)	(0.0162)	(0.0104)
FE : Country	•	•	•	•	•	•	•	•	•
FE : Time	•	•	•	•	•	•	•	•	•
FE : Agency	•	•	•	•	•	•	•	•	•
Total N	14,852	14,748	14,644	14,538	14,431	14,324	14,217	14,113	14,008
Adj. Within-R^2	0.108	0.104	0.110	0.112	0.111	0.109	0.108	0.110	0.112
Panel A: Positive Rating Events									
Lag (in months)	$m = 1$	2	3	4	5	6	7	8	9
$+\Delta r_{t-m}$	-0.0073	-0.0118	0.0106	0.0120	0.0018	-0.0018	0.0210	0.0091	-0.0109
	(0.0152)	(0.0073)	(0.0089)	(0.0089)	(0.0108)	(0.0112)	(0.0156)	(0.0102)	(0.0091)
FE : Country	•	•	•	•	•	•	•	•	•
FE : Time	•	•	•	•	•	•	•	•	•
FE : Agency	•	•	•	•	•	•	•	•	•
Total N	14,881	14,779	14,673	14,568	14,460	14,353	14,249	14,144	14,040
Adj. Within-R^2	0.110	0.103	0.111	0.111	0.111	0.108	0.109	0.114	0.112

Table 13: *Predicting Rating Events: Reverse Causality Robustness Test.* This table summarizes the results of estimating the probability of a rating change at the end of month t, Δr_t, conditioned on the one-month CDS spread lagged m months, Δs_{t-m}. Observations with less than 24 months between rating changes are excluded to mitigate against reverse causality concerns. Since estimating the probability of a rating event may be contaminated by events that occur in two consecutive months, we eliminate the event month that immediately follows another event month. Standard errors are given in the parentheses with stars indicating $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Panel A. $-\Delta$ in Rating									
Lag (in months)	$m = 1$	2	3	4	5	6	7	8	9
Δs_{t-m}	1.364**	1.215*	2.051***	1.773***	0.881	1.096	0.865	-1.498	-1.046
	(0.687)	(0.717)	(0.569)	(0.609)	(0.780)	(0.740)	(0.779)	(1.028)	(1.003)
Constant	-4.709***	-4.719***	-4.773***	-4.745***	-4.714***	-4.717***	-4.702***	-4.695***	-4.677***
	(0.154)	(0.155)	(0.16)	(0.158)	(0.156)	(0.157)	(0.156)	(0.156)	(0.154)
Total N	4,842	4,820	4,800	4,779	4,751	4,724	4,696	4,668	4,635
Event N	45	44	44	44	43	43	43	43	43
Panel B. $+\Delta$ in Rating									
Lag (in months)	$m = 1$	2	3	4	5	6	7	8	9
Δs_{t-m}	-0.530	-0.139	-1.403	-1.054	-1.401	-1.660*	-0.736	-1.068	-0.405
	(0.914)	(0.877)	(0.980)	(0.960)	(0.967)	(0.977)	(0.922)	(0.971)	(0.910)
Constant	-4.584***	-4.579***	-4.612***	-4.599***	-4.581***	-4.582***	-4.556***	-4.617***	-4.581***
	(0.144)	(0.144)	(0.148)	(0.146)	(0.146)	(0.147)	(0.144)	(0.149)	(0.147)
Total N	4,846	4,825	4,804	4,783	4,757	4,730	4,702	4,671	4,639
Event N	49	49	48	48	49	49	49	46	47

Table 14: *Predicting Rating Events: Dropping Countries With Many Rating Changes.* This table summarizes the results of estimating $p\left(\mathbb{1}^{-/+}_{\Delta r_{i,t}}\right) = G\left(\alpha + \beta \Delta s_{i,t-m}\right)$, where $\mathbb{1}^{-/+}_{\Delta r_{i,t}}$ is an indicator variable that is equal to one when the difference in the CCR at the end of month t and month $t-1$ is negative/positive and zero if there is no change; α is the intercept; p is the probability of success; and $G(\cdot)$ is the logistic link function. Our independent variable Δs_{t-m} is the one-month difference of the log CDS spread lagged back m months. Since estimating the probability of a rating event may be contaminated by events that occur in two consecutive months, we eliminate the event month that immediately follows another event month. The data is pooled between both agencies. We drop observations in the top quintile of rating downgrades (upgrades). For downgrades, these countries are Cyprus (CY), Spain (ES), Greece (GR), Hungary (HU), Ireland (IE), Italy (IT), Latvia (LT), Portugal (PT), Slovenia (SI), and Ukraine (UA). For upgrades, these countries are Bulgaria (BG), Brazil (BR), Indonesia (ID), Peru (PE), Philippines (PH), Romania (RO), Russia, (RU), and Slovakia (SK). Standard errors are given in the parentheses with stars indicating $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Panel A. $-\Delta$ in Rating									
Lag (in months)	$m = 1$	2	3	4	5	6	7	8	9
Δs_{t-m}	1.052***	1.049***	1.165***	1.066***	1.501***	1.184***	1.212***	0.406	0.401
	(0.363)	(0.323)	(0.303)	(0.319)	(0.278)	(0.346)	(0.302)	(0.476)	(0.478)
Constant	-4.724***	-4.728***	-4.727***	-4.724***	-4.785***	-4.761***	-4.759***	-4.723***	-4.725***
	(0.098)	(0.098)	(0.098)	(0.099)	(0.102)	(0.101)	(0.101)	(0.100)	(0.100)
Total N	12,130	12,043	11,955	11,871	11,784	11,698	11,614	11,532	11,446
Event N	109	108	108	107	103	102	102	102	101
Panel B. $+\Delta$ in Rating									
Lag (in months)	$m = 1$	2	3	4	5	6	7	8	9
Δs_{t-m}	-0.860**	-0.572	-0.711	-0.314	-0.303	-0.222	-0.0364	-1.086***	-1.480***
	(0.408)	(0.441)	(0.433)	(0.433)	(0.439)	(0.435)	(0.425)	(0.402)	(0.378)
Constant	-4.267***	-4.254***	-4.266***	-4.245***	-4.243***	-4.241***	-4.257***	-4.287***	-4.303***
	(0.078)	(0.078)	(0.079)	(0.077)	(0.077)	(0.078)	(0.078)	(0.080)	(0.081)
Total N	12,048	11,957	11,865	12,095	12,006	11,915	11,821	11,730	11,638
Event N	168	168	165	171	170	169	165	161	159

Table 15: *Predicting Sovereign Events: Horse Race.* This table summarizes the results of a horse race between CDS spreads and ratings in the spirit of Sy (2004). We estimate the probability of a sovereign event within seven months conditioned on the k-month CDS spread change in the previous month and the k-month rating change in the previous month. More formally, $\mathbb{P}(\text{Event}) = G(\beta_0 + \beta_1 \cdot \Delta_k s_{t-1} + \beta_2 \cdot \Delta_k r_{t-1})$. Since the number of sovereign defaults since 2005 is too small to analyze, we proxy for them using the J.P. Morgan Global EMBI blended sovereign bond spreads. We define a sovereign event if a country's EMBI sovereign bond spread change is greater than 3 standard deviations from its mean. Standard errors are given in the parentheses with stars indicating $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

	$k = 1$	2	3	4	5	6	7
$\Delta_k s_{t-1}$	-0.034	0.331	0.401**	0.553***	0.699***	0.643***	0.767***
	(0.361)	(0.212)	(0.161)	(0.129)	(0.109)	(0.099)	(0.092)
$\Delta_k r_{t-1}$	0.158	0.012	0.023	-0.144	0.086	0.010	-0.093
	(0.261)	(0.276)	(0.276)	(0.295)	(0.271)	(0.280)	(0.294)
Constant	-2.741***	-2.729***	-2.730***	-2.732***	-2.762***	-2.746***	-2.764***
	(0.068)	(0.068)	(0.069)	(0.070)	(0.072)	(0.072)	(0.073)
Total N	4,036	3,982	3,928	3,874	3,820	3,766	3,712
Event N	247	245	243	241	241	241	241

Table 16: Differential Predictability of Sovereign Events. This table summarizes the results of a horse race between CDS spreads and ratings in the spirit of Sy (2004). We estimate the probability of a sovereign event within seven months conditioned on the k-month CDS spread change in the previous month and the k-month rating change in the previous month. More formally, $\mathbb{P}(\text{Event}) = G(\beta_0 + \beta_1 \cdot \Delta_k s_{t-1} + \beta_2 \cdot \Delta_k r_{t-1})$. Since the number of sovereign defaults since 2005 is too small to analyze, we proxy for them using the J.P. Morgan Global EMBI blended sovereign bond spreads. We define a sovereign event if a country's EMBI sovereign bond spread change is greater than 3 standard deviations from its mean. We create subsample based on whether there is agreement or disagreement between both rating agencies. Agreement is defined as a one notch difference or less between the Moody's and S&P and vice versa. Standard errors are given in the parentheses with stars indicating $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Panel A. Disagreement between Moody's and S&P

	$k = 1$	2	3	4	5	6	7
$\Delta_k s_{t-1}$	-0.397	0.222	0.380*	0.592***	0.727***	0.682***	0.816***
	(0.502)	(0.277)	(0.197)	(0.151)	(0.128)	(0.116)	(0.109)
$\Delta_k r_{t-1}$	-0.258	-0.619	-0.404	-0.394	-0.095	-0.455	-0.551
	(0.398)	(0.464)	(0.427)	(0.430)	(0.382)	(0.438)	(0.455)
Constant	-2.745***	-2.735***	-2.757***	-2.787***	-2.822***	-2.792***	-2.815***
	(0.089)	(0.089)	(0.090)	(0.092)	(0.095)	(0.094)	(0.097)
Total N	2,394	2,376	2,353	2,327	2,296	2,262	2,226
Event N	143	141	139	137	137	137	137

Panel B. Agreement between Moody's and S&P

	$k = 1$	2	3	4	5	6	7
$\Delta_k s_{t-1}$	0.478	0.582	0.479	0.477*	0.650***	0.574***	0.682***
	(0.577)	(0.368)	(0.294)	(0.247)	(0.212)	(0.194)	(0.176)
$\Delta_k r_{t-1}$	0.596*	0.604*	0.468	0.128	0.298	0.469	0.365
	(0.351)	(0.352)	(0.367)	(0.407)	(0.387)	(0.369)	(0.389)
Constant	-2.742***	-2.724***	-2.691***	-2.653***	-2.678***	-2.681***	-2.692***
	(0.107)	(0.107)	(0.107)	(0.106)	(0.109)	(0.110)	(0.113)
Total N	1,642	1,606	1,575	1,547	1,524	1,504	1,486
Event N	104	104	104	104	104	104	104

Hymer (1960), in his dissertation which founded the field of international business, noted that there is a "liability of foreignness" when firms expand their operations to other countries. The introduction of the gravity equation to economics by Tinbergen (1962) – which analogizes Newton's law of universal gravitation to cross-border flows – has allowed researchers to explore the empirical structure of the costs and benefits of cross-border mergers and acquisitions, i.e. "liability of foreignness". From these foundations, both the theoretical literature and empirical literature have focused on studying the determinants of foreign direct investment, international trade, and cross border mergers and acquisitions[19] .

Researchers have focused on completed deals to either investigate if the mergers are value creating or to find out the determinants of cross border mergers and acquisitions. These determinants may either be firm level factors like firm size, public status, industry affiliation, mode of payment or country level factors like differences in institutional and cultural characteristics. We study the impact of differences in cultural, institutional, and geographic factors between an acquirer-target country pair, or the dyadic distances, on cross border mergers and acquisitions. We investigate the differences in country level factors that influence the decision to enter the market for cross border acquisitions. For the initiated deals, we examine the country level differences that influence the likelihood of completion/failure of deal. Furthermore, for the completed acquisitions we investigate what country level factors influence the duration from the time of initiation to the date of completion.

[19] Theoretical work has a long history and remains a vibrant area of study, e.g., Anderson (1979), Helpman and Krugman (1985), Bergstrand (1985), Davis (1995), Deardoff (1998), and Anderson and van Wincoop (2003). The empirical economics literature has evaluated trade protection (Harrigan, 1993), regional trade agreements (Frankel, Stein, and Wei, 1998), exchange rate variability (Frankel and Wei, 1993; Eichengreen and Irwin, 1998), border effects (McCallum, 1995; Anderson and van Wincoop, 2003), and cross border mergers & acquitions (Rossi and Volpin, 2004; Erel, Liao, and Weisbach, 2012; Serdar Dinc and Erel, 2013; Aktas, de Bodt, and Roll, 2013; Kim and Lu, 2013, Ahern, Daminelli, and Fracassi, 2015).

Our study is the first, to our knowledge, to study these three facets of acquisitions – initiation, completion, and duration – within a large-scale unified framework.[20] Our dependent variables – initiation, completion, and duration – are a novel addition to the literature. There are no studies looking at factors influencing the initiation, completion, or duration of the cross-border acquisition deal within a unified framework.[21] Our study fills this gap. Additionally, our sample period captures a longer time-period and a larger cross-section of firms undertaking cross-border mergers and acquisitions.

Using a sample of 173,616 cross-border mergers occurring between 1970 and 2016, we estimate the factors that affect the likelihood that a firm will initiate a cross-border deal, that it will complete the cross-border deal, and the duration of the deal, i.e., time between the announcement and effective date of the deal. We find that cultural, institutional, geographical, religious, and language differences, all play a deciding role in the initiation of mergers and acquisitions. The higher these differences the lower the probability of initiation of cross border merges and acquisitions. Next, we find that completion of deal is independent of cultural and institutional factors, but largely depends on differences in economy size, language, and religion of the acquiring and target countries. Lastly, our analysis of duration reveals that there is no impact of cross-country cultural or institutional differences on the time between the initiation and completion of the deal.

Differences in culture (e.g., Weber, 1930; Veliz, 1994; Landes, 1998; Guiso, Sapienza, and Zingales, 2003, 2006), institutions (e.g., Alesina and Rodrik, 1994; La Porta, Lopez de Silanes, Shleifer, and Vishny, 1998; Hirshleifer, 2001), and geography (e.g., Myrdal, 1968; Sachs, 2003)

[20]While we are the first to analyze the initiation, completion, and duration for cross-border mergers and acquisitions, Dikova et al (2010) uses similar definition for completion and duration. However, they study business service industry only. They do not study initiation, and their completion and duration variables are deal level variables instead of country level variables used in our study.

[21]Aktas, de Bodt, and Roll (2013) study the time between successive mergers and acquisitions to infer the impact of learning through repetitive acquisitions. However, there are no studies to our knowledge looking at the factors influencing the duration between the announcement date and the completion, or effective, date.

have been found to be important fundamental causes of cross-country differences in economic outcomes. Cultural differences between countries – such as differences in religion, language, and general shared experiences – play a key role in shaping economic decision making and outcomes. Different cultures generate diverse sets of beliefs about how to behave, which in turn influence equilibrium outcomes and results in countries coordinating on different equilibria. Differences in institutions shape economic outcomes through various channels; for example, a lack of property rights de-incentivize economic agents while functioning markets help allocate resources efficiently. Differences in geographic endowments naturally determine the preferences and opportunity set of economic agents across different countries. For example, geography may determine the development and availability of different technologies.

These three fundamental factors have also become the recent focus in explaining cross-border acquisition flows between countries. Ahern et al. (2015) isolates the impact of culture on cross-border acquisitions. They find that countries that are more distant culturally have lower cross-border acquisition activity. Rossi and Volipin (2004) find that the volume of cross-country acquisitions is larger in countries with stronger accounting standards and stronger shareholder protection. In a similar vein, Erel, Liao, and Weisbach (2013) find that geographic distance and differences in various institutional factors – such as accounting disclosures and economic development – are positively related to cross-border acquisition flows between countries. Additionally, the literature has documented that in countries with far-right parties or in times of weak government there is more intervention in large-scale foreign acquisitions (Serdar Dinc and Erel, 2014).

While the prior literature has studied the importance of culture, institutions, and geography, the emphasis has been on the flows or propensity of cross-border acquisitions, defined either as dollar volume or as the number of acquisitions between the target-acquirer country pair relative to the sum of domestic mergers in the target country and the number of acquisitions between the target-acquirer country pair. Researchers have also restricted their sample to completed deals where the acquirer acquires majority stakes in the target firm and the value of deal is more than $1 million. They exclude all deals that were initiated but could not be completed. By excluding such deals, the sample is biased towards larger firms from more developed countries.[22]

In our study, we alleviate these sample selection issues by considering all the initiated deals irrespective of their completion status, their size, and the proportion of the stake that the acquirer receives. Moreover, instead of dollar volume, we use number of deals, thus alleviating bias towards the bigger companies and companies from the developed world. This allows us to study the holistic view of cultural differences on cross border mergers.

A priori, we expect that cultural, institutional, and geographic factors should be significant in explaining the initiation of cross-border acquisitions; institutional factors should be significant in explaining the completion of cross-border acquisitions; and that none of the fundamental factors should be significant in explaining the duration of the deal. More specifically, firms prefer to acquire firms domiciled in countries in which the overall dyadic distance is small. Once the decision to initiate an acquisition is made, institutional differences will become more important in determining whether the deal is seen through to completion. The duration of the deal would depend more on institutional factors, however, idiosyncratic factors are more important and will dominate. Our results indicate that culture, geographic distance and institutional differences are all important in explaining the initiation of cross-border deals. However, only the bureaucracy distance measure and the religious distance measure are significant in explaining the completion. Finally, our results show that the duration of the deal is not explained by any fundamental factor implying that there are idiosyncratic factors that explain the variation in the average duration.

[22] Size matters because in developing and under developed economies, a company of $1 million value is a bigger firm.

The remainder of the essay is organized as follows: Section 2 discusses the empirical strategy; Section 3 discusses the empirical results; Section 4 concludes.

2.1 Estimation Strategy

In this section, we provide a simple theoretical model, based on Head and Reis (2004), which generates predictions for each country's cross-border acquisition flows based on its economic size and dyadic distance. The model explicitly considers the acquisition decision and also allows for an arbitrary number of different sized countries. We are able to generate predictions regarding the signs of our coefficients of interest. We then turn to the empirical framework and discusses the statistical implementation of our model.

2.1.1 Theoretical Model

In this section, we re-present the model developed by Head and Reis (2004), changing the notation to fit our sitatio, to show how we expected factors that increase the likelihood of initiation will have positive signs and those that decrease the likelihood will have a negative sign.

Suppose each country i has T_i target firms. Each country j has A_j acquiring firms bidding to acquire the target firms. There are a total of $A_w = \sum_j A_j$ acquiring firms worldwide. The acquiring firms bid on each of the of $T_w = \sum_i T_i$ available target firms. The winning bid for a firm in country i is V_i. This implies that the aggregate stock of capital is $K_i = V_i \cdot T_i$. The probability that a given target firm in i is acquired by an acquirer firm in j is denoted by π_{ij}. The expected level of cross-border acquisitions is therefore

$$M_{ij} \equiv \pi_{ij} \cdot K_i \tag{10}$$

If each acquiring firm has a different valuation for particular firms, and their valuations are i.i.d., then each acquirer has an equal probability of winning the bid, which is equal to

$1/A_w$. As such, the probability that any one firm from country j acquires a particular firm in country i is $\pi_{ij} = A_j/A_w$ and the expected level of cross-border acquisitions is

$$M_{ij} = \frac{K_i \cdot A_j}{A_w}. \tag{11}$$

By summing over all target countries i, we can obtain an equation for the total investment outflows of acquiring country j

$$M_{jw} = \sum_{i \neq j} M_{ij} = \frac{A_j}{A_w} \cdot \sum_{i \neq j} K_i = \frac{A_j}{A_w} \cdot (K_w - K_j) = \frac{A_j}{A_w} \cdot K_w \cdot \left(1 - \frac{K_j}{K_w}\right) \tag{12}$$

The investment inflows to the target country i can be obtained in a similar fashion by summing over all acquiring countries j,

$$M_{iw} = \sum_{j \neq i} M_{ij} = \frac{K_i}{A_w} \cdot \sum_{j \neq i} A_j = \frac{K_i}{A_w} \cdot (A_w - A_i) = K_i \cdot \left(1 - \frac{A_i}{A_w}\right) \tag{13}$$

The overall worldwide level of acquisition investment is equal to the sum of either the inflows or outflows,

$$\begin{aligned} M_{ww} &= \sum_i M_{iw} = \sum_j M_{jw} \\ &= K_w \left[1 - \sum_i (A_j/A_w)(K_j/K_w)\right] \end{aligned} \tag{14}$$

The notation can be simplified by allowing lower case letters to denote the shares of worldwide values, i.e., $x_i = X_i/X_w$. We also let $m_j^O = M_{jw}/M_{ww}$ denote outflow shares and $m_i^I = M_{iw}/M_{ww}$ denote inflow shares. Combining this with equations (12) and (13), the share of inflows and outflows can be recast as

$$m_j^O = a_j \left(\frac{1 - k_j}{1 - \sum_i a_i k_i}\right), \tag{15}$$

$$m_i^I = k_i \left(\frac{1 - a_i}{1 - \sum_j a_j k_j}\right). \tag{16}$$

These equations offer simple predictions of the cross-border acquisition flows as functions of the number and value of target firms in the acquirer country and target country.

These two equations require estimates of the number of firms and the overall capital stock. Lacking readily available measures of A_i and K_i, we consider the simplifying assumption that acquirer and target firms are distributed in proportion to the economy overall size of the economy. This symmetry assumption simplifies the algebra, and we can write replace S_i for A_i and K_i to get

$$m_j^O = m_i^I = s_j \left(\frac{1 - s_j}{1 - H} \right), \tag{17}$$

where $H \equiv \sum_i s_i^2$ is the Herfindahl concentration index for the worldwide distribution of economic activity.

While this simple model yields a remarkably compact expression for the shares of cross-border inflows and outflows, we have ignored the role that frictions play. And there are good reasons to believe that acquirers will be more likely to acquire target firms if they have lower costs. In order to take frictions into account, we need to define v^*_{hij}, which is the private valuation of the acquiring bidder h from country j's for the representative target firm in country i, which is a function of observed and unobserved characteristics,

$$v^*_{hij} = \beta \cdot X_{hij} + \varepsilon_{hij}. \tag{18}$$

We assume that the unobserved characteristics have a Gumbel cumulative distribution function,

$$\exp[-\exp(-\varepsilon_{hij})],$$

and that this refers to the base valuation in a frictionless world.

Due to the cost of controlling a target firm from a remote head office, the acquiring firm reduces its bid by an amount equal to $\theta \ln d_{ij}$, where d_{ij} measures the economic distance or transaction costs between source and host country, which we term the *dyadic distance*. As McFadden's (1974) showed, the probability that a target will yield an acquirer the highest profits within its choice set (assuming the unobserved characteristics have a Gumbel cdf) is given by the logit expression:

$$\frac{\exp(-\theta \ln d_{ij})}{\sum_\ell \exp(\theta \ln d_{i\ell})}, \tag{19}$$

where ℓ indexes all the competing acquirers for the representative firm in country i.

Since all bidders from a given country are assumed to be symmetric, we obtain the aggregate probability of any bidder from acquiring country j winning the bid for the target in country i as

$$\pi_{ij} = \frac{s_i / d_{ij}^{\theta}}{\sum_{\ell} s_{\ell} / d_{i\ell}^{\theta}} \tag{20}$$

where ℓ now indexes all the countries where the competing acquirers are headquartered.[23]

We can now express the cross-border acquisitions levels by substituting Equation (20) into (10)

$$M_{ij}/S_w = s_i s_j p_i d_{ij}^{-\theta}, \tag{21}$$

where $p_i \equiv (\sum_{\ell} s_{\ell}/d_{i\ell}^{\theta})^{-1}$ is the "bid potential" for a representative firm in country i, which measures the proximity of the acquiring firms to the representative target firm.

Therefore our model predicts that cross-border acquisitions are: (i) proportional to the size of the target and acquirer countries and (ii) with closer proximity to the target firm, while it is (ii) inversely proportional with dyadic distance.

2.1.2 *Empirical Formulation*

This theoretical model we deduced in the previous section is an example of the gravity equation used to measure trade flows. More generally, the stochastic version of the gravity equation has the form

$$M_{ij} = \alpha_0 Y_i^{\alpha_1} Y_j^{\alpha_2} D_{ij}^{-\theta} \eta_{ij} \tag{22}$$

which states that cross-border flows are proportional to the product of the economic size, denoted by Y_i and Y_j, and inversely proportional to their distance, D_{ij}‘, broadly construed to include all factors that might create frictions.

We can empirically estimate the gravity equation by log-linearizing Equation (22),

$$\ln M_{ij} = \alpha_0 + \alpha_1 \ln Y_i + \alpha_2 \ln Y_j - \theta \ln D_{ij} + \ln \eta_{ij}. \tag{23}$$

[23]Note that firms from country i are included in the set of bidders for country i's target firms.

However, the issue with this estimation strategy is that it introduces bias since country pairs with zero acquisition flows are necessarily excluded. This selection effect induces a positive correlation between the unobserved errors η_{ij} and the dyadic distance measures d_{ij}.

We collect our mergers and acquisitions data from Thomson Reuters' SDC Platinum database. The initial sample is comprised of 1,005,488 acquisitions from 1970 until June 2016. In line with the literature, we remove 61,830 deals in which the acquirer or target nation data is missing or recorded as "unknown". We additionally remove 724,852 domestic acquisitions. Our final mergers and acquisitions sample consists of cross-border acquisition 218, 806 deals.

Using this mergers and acquisitions sample, we create our measures of *Initiation* and *Completion* used as the dependent variables. First is deal *Initiation*, which is defined as the number of cross-border acquisitions from acquirer country to target country relative to the total number of cross-border acquisitions for acquirer country. This allow us to capture the proportion of deal initiated by acquirer country. Second is deal *Completion*, which is defined as proportion of completed cross-border acquisitions from acquirer country to target country relative to the number of cross-border acquisitions initiated from acquirer country to target country. To capture the effects of culture, we use: Hofstede's (1980) six dimensions – the *Power Distance*, *Individualism*, *Masculinity*, *Uncertainty Avoidance*, *Long-term Orientation*, and *Indulgence* indices – to measure cultural distance; the *Language* variable from One World Nations online; and the *Religion* variable from the 2000 CIA Factbook. To capture role of political institutions, we use the *Corruption*, *Law and Order*, and *Bureaucracy* scores from International Country Risk Guide (ICRG) political risk subcomponents. To capture the effects of geography, we include the natural logarithm of the kilometer distance between the acquirer and target country which we denote as *Distance*.

Our interest lies in estimating the overall effects of dyadic distance on cross border mergers and acquisitions. We create two indices of dyadic distance using the Mahalnobis measure assuming zero covariance between the different dimensions of culture (Kogut and Singh, 1988). Formally, the dyadic distance index between the acquirer country and target country, denoted I_{j-i}, is measured as a weighted-average of the various index components:

$$I_{j-i} = \frac{1}{N}\sum_{n=1}^{N}\frac{c_{nj}-c_{ni}}{\sigma_c^2}, \tag{24}$$

where $c_{nj}-c_{ni}$ is the difference between acquirer j and target i for the n^{th} component of the index; σ_c^2 is the variance of the component across all countries, and N is the total number of components used to create the index. In particular, we create a variable denoted *Culture* with the six cultural dimension indices as components and a variable denoted *Culture & Institutions* which includes the *Corruption*, *Law and Order*, and *Bureaucracy* scores in addition to the six cultural dimension indices.

After merging our final mergers and acquisition sample with the distance measures, we obtain the sample used in the cross-sectional analysis. This final sample consists of 173,616 cross-border mergers and acquisition deals covering 77 countries. Tables 17 and 18 reports the sample summary statistics of selected cultural and institutional variables; Table 19 reports the summary statistics of our regression variables; and Table 20 reports the correlation matrix for all of our variables.

2.1.3 *Cross-Sectional Analysis*

To examine how the differences in culture, institutions, and geography affect the initiation, completion, and duration of cross-border merger and acquisition deals we run various specifications of the following logit models at the cross-sectional level:

$$Initiation_{ij} = G(\alpha + \beta \cdot Cult_{ij} + \gamma \cdot Inst_{ij} + \vartheta \cdot Geo_{ij} + \varsigma \cdot X'_{ij}) + \varepsilon_{ij}, \tag{25}$$

$$Completion_{ij} = G(\alpha + \beta \cdot Cult_{ij} + \gamma \cdot Inst_{ij} + \vartheta \cdot Geo_{ij} + \varsigma \cdot X'_{ij}) + \varepsilon_{ij}, \tag{26}$$

$$Duration_{ij} = G(\alpha + \beta \cdot Cult_{ij} + \gamma \cdot Inst_{ij} + \vartheta \cdot Geo_{ij} + \varsigma \cdot X'_{ij}) + \varepsilon_{ij}, \tag{27}$$

where $Cult_{ij}$ denotes our measures of cultural distance (Culture & Institutions, Culture, Power Distance, Individualism, Masculinity, Uncertainty Avoidance, Long-term Orientation, Indulgence, Language, Religion); $Inst_{ij}$denotes our measures of institutional distance (Culture & Institutions, Corruption, Law and Order, and Bureaucracy); and Geo_{ij} denotes our measures of geography (Distance).

Since the dependent variables range from zero to one, inclusive, we estimate the parameters of interest (β, γ, and ϑ) using a fractional logistic model (Papke and Wooldridge, 2006; Wooldridge, 2011). Following the literature, we cluster the standard errors by the target country in all of our regressions.

2.2 Results

Table 21 displays results of the cross-sectional regressions from Equation (2) related to the initiation of cross-border mergers and acquisitions. We first run the regressions using the fractional logit model as our dependent variable is the probability of initiation of cross border mergers and acquitions and varies between 0 and 1. Additionally we use Poisson pseudo-maximum likelihood methods (PPML) of Silva and Tenreyro (2006) which has been extensively used in the studies that estimate gravity equation (Tenreyro, 2007; Fally, 2013; Irarrazabal, Moxnes, and Opromolla, 2013; Karolyi and Taboda, 2015). As the data of independent variables that we study is retrieved from different sources, there is difference in the number of observations across these variables. In our regressions, we start with the variables that has maximum number of observations (8,813 in column 1) and then include other variables based on a decreasing trend in data availability (3,844 in column 6). This allow us to maximize the use of independent variable observations thereby improving the power of test. We observe several interesting patterns in the regression results. From the fractional logit results in Column (1), we observe that that the coefficients for language and geographic distance are negative and significant whereas the coefficient for prior experience is significantly positive. Large differences in language is related to lower initiation but differences in religion is not significant. The larger the geographical distance, the less initiation there is between countries; more experience leads to more initiations. In column 4, we report PPML estimates for the equation similar to column 1 and find our results to be qualitatively similar.

Next, we add the differences in economy size (GDP) between the acquirer and target countries to our regressions. This reduces our number of observations to 7,862 in column (2). We find the coefficient on size to be negative and highly significant indicating that larger differences in size is related to lower initiations. We have similar results with PPML in column (5).

Finally, we add the cultural and institutional differences between acquirer and target countries to the regression equation and report the results in column (3). We observe negative and significant coefficient for power distance, masculinity, uncertainty avoidance, long term orientation, and indulgence. This supports our argument that there is lower probability of initiation of cross border mergers and acquisitions if there are larger cultural differences between nations. We also find that the coefficient for differences in institutional measures of corruption, law and order and bureaucracy are all insignificant. Again, in Column (6) we observe that our results are qualitatively similar using the PPML method.

Overall our results indicate that cultural differences between target and acquirer countries are important determinants in the decision to initiate a cross border merger or acquisitions. Surprisingly, we do not find any evidence of the institutional differences between acquirer and target countries to impact the initiation of cross border mergers. We also find that differences in size of economy, in the language spoken, religion followed and geographical distances among acquirer and target also play an important role in initiation. Finally, the significance of experience indicates that past-experience of mergers and acquisitions in the same country increases the probability further acquisitions in that target country.

Table 22 displays results of the cross-sectional regressions from Equation (2) related to the completion of cross-border mergers and acquisitions. We see that differences in individualism, language, religion, and the size of the country affects the completion of the deal. In general, we do not find any effect of cultural factors on the probability of completion of cross border mergers and acquisitions. We find that religion difference does matter in probability of completion of cross border mergers and acquisitions. There is lower probability of completion when the religion of acquirer and target countries are different. We find that larger the difference in size of the acquirer and target countries the lower is the probability of completion. Among institutional factors, we find that difference in bureaucracy between target and acquirer country affect the probability of completion. For the full sample of observations (5302) we do not find language differences to impact the probability of completion but for the reduced sample with all the variables (2007 observations), we find the coefficient of language to be significantly positive. This empirical finding is counter intuitive as it indicates that if the acquirer and target countries have same language then the probability of completion of cross border mergers and acquisition is lower. Overall, our findings suggest that cultural factors do not affect the probability of completion, however completion of the deals is mainly driven by bureaucracy. Similar level of bureaucracy across acquirer and target increases the probability of completion of the deal.

In Table 23, we report the results for OLS and PPML regressions with the duration as dependent variable. We do not find any effect of cultural, institutional, or geographical factors on the duration of deals between acquirer and target nation.

Overall our results indicate that the lower the cultural and bureaucratic distance among the nations, the higher the initiation of cross border merger and acquisitions between them. We also find that the completion of deal does not depend on cultural factors however the higher difference in bureaucracy between the nations the lower is the probability of completion. Finally we find that the duration of the deals from announcement to effective date does not depend on any cultural or institutional factors.

2.3 *Robustness Analysis*

2.3.1 *Effect of Prior Completion and Duration of Completed Deals*

It can be argued that the initiation of deal may depend on whether the firms from the acquiring nation were able to complete mergers and acquisitions with the firms from the target nations in past and how much time did it took for them to complete the deals. If there is a history of successful completion where the deals are completed in a reasonable time, then firms may be motivated to initiate further acquisitions. Similarly, firms may be deterred from initiating mergers and acquisitions if there is history of failed completions or it takes firms unreasonably longer time to complete acquisitions.

It may also be argued that firms from acquiring nations may learn from prior acquisitions in a target nation and hence completing a deal in any year may depend on its history of successful completions in prior years. Also, all acquiring firms who initiate a deal may want to complete the acquisition in shortest possible time. The history of prior completions may provide them useful information on how to complete the deals in reasonable time.

In the context of our dependent variables based on the above arguments, we expect initiation in any year to be dependent on the completions and the duration of completing the deals in prior years. Similarly, the completion and duration of a deal between acquirer and target nations in any year should be influenced by the completion of deals between the same country pairs in the prior years. As these arguments are based on the level of experience between the acquirer and target nation pairs, we use the data on cross border mergers and acquisitions for the latest year in our data when the experience in completing the deals is at a maximum, 2015. We measure the prior year completion experience as the number of completed deals out of the initiated deals between the acquiring and target nation pairs in all the years prior to 2015. Similarly, we measure duration experience between the acquiring and target nation pairs as the average duration between announcement and the deal effective dates prior to 2015. We include the completion experience and duration experience in our prior models for initiation, completion, and duration and report our results in Table 24.

In column (1), we find the initiation of deal between acquirer and target to be unaffected by prior completion and duration experiences. Initiation depends mainly on cultural, geographical, and institutional differences between countries. Next, for completion as dependent variable, in column (2) we find the coefficient of completion experience to be significantly positive indicating that prior experience in completing deals increases the probability of completion for subsequent mergers and acquisitions. In column (3) where we include prior completion experience in explaining the duration, we find the coefficient for completion experience to be statistically insignificant indicating that prior completion experience the deals does not play any role in deciding the time taken to complete a deal.

2.3.2 *Different Measures of Distance*

To test whether our measures of culture, institutions, and geography are adequete proxies, in Table 25 we re-run our regressions using 9 different measures of distance from Berry, Guillen, and Zhou (2010). $\Delta Culture_{j-i}$ measures the log difference in attitudes toward authority, trust, individuality, and the importance of work and family using data from the World Value Survey. $\Delta Geography_{j-i}$ is the log great circle distance between the geographic center of each country. $\Delta Administrative_{j-i}$ measures the log differences in colonial ties, language, religion, and legal systems. $\Delta Demographic_{j-i}$ measures the differences in demographic characteristics. $\Delta Political_{j-i}$ measures the differences in political stability, democracy, and trade-bloc membership. $\Delta Economic_{j-i}$ measures the difference in economic development and macroeconomic characteristics. $\Delta Financial_{j-i}$ measures the difference in financial sector development. $\Delta Integration_{j-i}$ measures the differences in tourism and internet usage. $\Delta Innovation_{j-i}$ measures the differences in patents and scientific production.

Our results using these independently calculated distance measures reconfirm our results. Culture, Geography, Economic, Financial, Integration, and Innovative distance are influence inititations. Culture and Economic distance drop out while Political distance influence completions. Only Innovation differences affect duration, while none of the cultural, geographic, or institutional factors matter.

2.4 Conclusion

All in all, we contribute to this growing area by studying the effects of differences in cultural, institutional, and geographic factors between an acquirer-target country pair, or the dyadic distance, on the initiation, completion, and duration of cross-border acquisition deals. In particular, using a sample of 173,616 cross-border mergers occurring between 1970 and 2016, we estimate the factors that affect the likelihood that a firm will initiate a cross-border deal, complete the cross-border deal, and the time between the announcement and effective date of the deal (see Section 3). Our study is the first, to our knowledge, to study these three facets of acquisitions – initiation, completion, and duration – within a large-scale unified framework. Our results show that culture, institutions, and geography are important determinants in the initiation and completion of cross-border acquisitions. More specifically, culture differences, institutional, and geographical distance are of paramount importance in whether firms decide to initiate cross-border mergers and acquisitions. Cultural and geographic distance do not play a large role in determining whether firms follow through and complete the deal; what matters in the completion of initiated deals are institutional differences. The duration from initiation to completion is unaffected by any institutional, cultural, or geographical factors and solely depends on idiosyncratic factors.

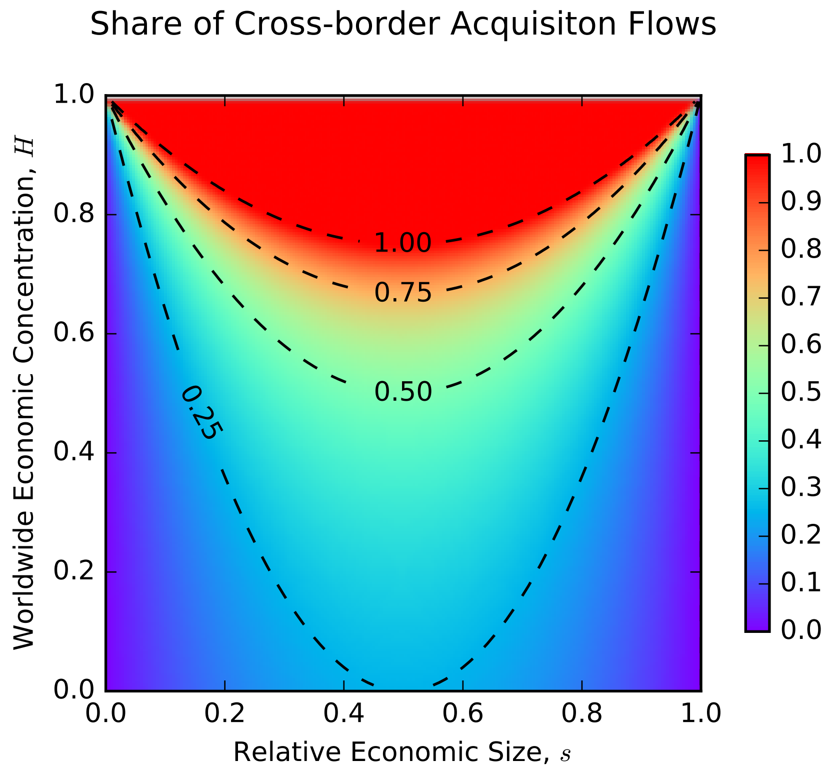

Figure 5: *Share of Acquisition Flow as Function of Economic Size and Concentration.* The figure plots the relationship from equation (8), where we relate acquisition flows to a country's relative economic size and the worldwide economic concentration. *Reads: There is a nonlinear relationship between the acquisition flows and economic size for a given country.*

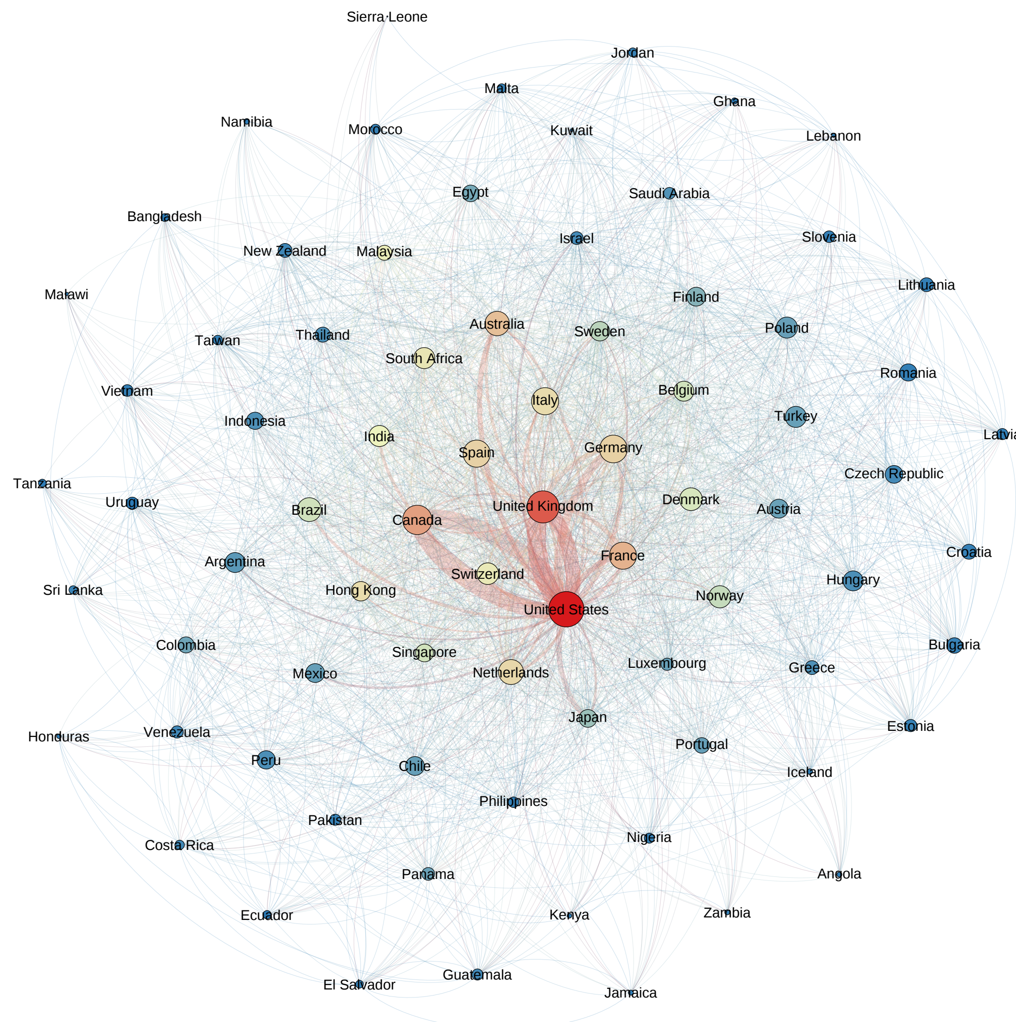

Figure 6: *Network of Completed Deals Between Dyads.* The lines, or edges, between the country pairs are based on the number of completed acquisitions. The larger the width of the edge, the larger the total number of acquisitions between the countries and vice-versa. The size of the node of each country is based on a measure of importance known as *Authority*. The intensity of the color indicates the importance of the country to the overall network measured by the *Betweenness Centrality*. *Reads: The network of countries which complete cross-border acquisitions is dominated by a few ‘countries.*

__Table 17:__ Summary Statistics of Cultural Variables.

This tables presents the country-level measures of culture from Hofstede (1980) that are used to construct the distance measures. These variables are the Power Distance Index (PDI), Individualism Index (IDV), Masculinity Index (MAS), Uncertainty Avoidance Index (UAI), Long-Term Orientation Index (LTO), Indulgence Index (IND), and the Overall Culture Index (OCI).

Country	(1) PDI	(2) IDV	(3) MAS	(4) UAI	(5) LTO	(6) IND	(7) OCI
Afghanistan	41	47	57	75	18	62	1.48
Angola	83	18	20	60	10	83	2.56
Argentina	41	47	57	75	18	62	1.48
Australia	27	99	62	41	22	71	2.40
Austria	0	58	82	60	43	63	2.60
Bangladesh	74	16	56	50	41	20	1.72
Belgium	58	81	54	83	87	57	2.22
Brazil	62	38	49	65	50	59	1.14
Bulgaria	63	28	39	74	72	16	1.83
Canada	30	87	52	38	27	68	1.95
Chile	56	20	26	75	30	68	1.69
China	74	16	68	21	100	24	3.14
Colombia	60	8	66	69	10	83	2.24
Costa Rica	26	11	18	75	—	—	—
Croatia	67	32	39	69	60	33	1.37
Czech Republic	49	61	58	63	73	29	1.54
Denmark	8	80	12	14	34	70	3.37
Dominican Rep	58	28	67	36	10	54	1.10
Ecuador	72	2	64	57	—	—	—
Egypt	63	22	44	69	3	4	2.41
El Salvador	59	15	39	83	18	89	2.23
Estonia	31	64	28	50	87	16	2.35
Fiji	72	9	46	38	—	—	—
Finland	24	67	23	49	38	57	1.73
France	61	76	42	75	66	48	1.59
Germany	26	72	68	55	57	40	1.71
Ghana	74	11	39	55	0	72	2.18
Greece	53	34	58	100	46	50	1.82
Guatemala	90	0	36	89	—	—	—
Honduras	74	16	39	40	—	—	—
Hong Kong	61	22	58	20	74	17	2.30
Hungary	38	87	92	71	60	31	2.66
Iceland	20	64	6	40	27	67	2.48
India	71	49	57	31	52	26	1.60
Indonesia	72	9	46	38	64	38	1.75
Ireland-Rep	18	75	70	26	22	65	2.38
Israel	2	56	47	70	38	—	—
Italy	42	82	72	64	63	30	1.92
Jamaica	37	39	70	5	—	—	—
Japan	46	47	100	81	82	42	2.91

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Table 17 – continued from previous page

Country	(1) PDI	(2) IDV	(3) MAS	(4) UAI	(5) LTO	(6) IND	(7) OCI
Jordan	63	28	44	55	13	43	1.42
Kenya	63	22	61	40	—	—	—
Kuwait	85	22	39	69	—	—	—
Latvia	35	75	4	53	72	13	2.80
Lebanon	69	40	67	40	11	25	1.86
Lithuania	33	64	16	55	87	16	2.56
Luxembourg	31	64	50	60	67	56	1.46
Malawi	63	28	39	40	—	—	—
Malaysia	100	24	50	27	41	57	2.27
Malta	48	62	47	85	48	66	1.49
Mexico	75	28	71	71	22	97	2.46
Morocco	63	22	53	58	11	25	1.67
Namibia	58	28	39	36	29	—	—
Netherlands	29	87	10	43	53	68	2.48
New Zealand	12	86	59	39	28	75	2.44
Nigeria	74	28	61	45	10	84	2.08
Norway	22	74	3	40	34	55	2.53
Pakistan	47	9	50	60	23	0	2.26
Panama	90	6	43	75	—	—	—
Peru	57	12	41	76	23	46	1.55
Philippines	89	31	66	35	20	42	2.03
Poland	61	64	66	82	31	29	1.71
Portugal	56	25	29	92	27	33	1.93
Romania	85	28	41	79	53	20	1.95
Saudi Arabia	90	22	61	69	36	52	1.83
Serbia	81	22	42	81	53	28	1.77
Sierra Leone	63	16	39	40	—	—	—
Singapore	68	16	48	0	58	46	2.51
Slovenia	65	25	16	77	50	48	1.76
South Africa	41	69	64	39	33	63	1.54
South Korea	53	14	38	74	87	29	2.11
Spain	49	53	41	75	49	44	1.22
Sri Lanka	74	34	6	36	38	—	—
Surinam	80	48	36	81	—	—	—
Sweden	22	76	0	20	40	78	3.31
Switzerland	25	73	72	48	78	66	2.20
Taiwan	51	13	44	59	88	49	1.86
Tanzania	63	22	39	40	33	38	1.37
Thailand	57	16	32	54	40	45	1.35
Trinidad	39	12	59	45	10	80	1.44
Turkey	59	36	44	74	47	49	1.19
United Kingdom	26	98	68	26	52	69	2.62
United States	40	91	62	46	29	68	1.90
Uruguay	54	35	37	88	24	53	1.59
Venezuela	75	7	76	65	13	100	2.98
Vietnam	63	16	39	21	59	35	1.86
Zambia	53	34	39	40	29	42	1.23

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Table 17 – continued from previous page

Country	(1) PDI	(2) IDV	(3) MAS	(4) UAI	(5) LTO	(6) IND	(7) OCI
Average	53.82	40.21	46.86	55.20	42.01	49.25	2.01

Table 18: Summary Statistics of Institutional Variables.

This tables presents the country-level measures of institutions from International Country Risk Guide. These variables are the Corruption Index, the Law and Order Index, the Bureaucracy Index, and the overall Institutions Index.

Country	(1) Corruption	(2) Law and Order	(3) Bureaucracy	(4) Institutions
Albania	2	2.5	2	2.06
Algeria	2	3	2	1.90
Angola	1.5	2.5	1.5	2.22
Argentina	2	2.5	3	1.61
Armenia	1.5	3	1	1.59
Australia	4.5	5.5	4	3.32
Austria	4.5	6	4	3.43
Azerbaijan	1.5	3.5	1	1.84
Bahamas	4	4.5	3	1.47
Bahrain	3	4.5	2	1.14
Bangladesh	3	2	2	1.72
Belarus	1.5	3.5	1	2.38
Belgium	5	5	4	3.06
Bolivia	1.5	2.5	2	2.55
Botswana	3.5	3.5	2	1.34
Brazil	2.5	2	2	1.73
Brunei	2.5	5	3.5	1.16
Bulgaria	2	2.5	2	1.73
Burkina Faso	2	3	1	—
Cameroon	2	2	1.5	—
Canada	5	5.5	4	4.09
Chile	4.5	4.5	3	1.75
Colombia	2.5	2	2	1.73
Costa Rica	2.5	3	2	1.36
Croatia	2	4.5	3	1.31
Cuba	2.5	3	2	1.97
Cyprus	4	5	4	2.01
Czech Republic	2.5	5	3	1.28
Denmark	5.5	6	4	4.25
Ecuador	2.5	2.5	2	1.49
Egypt	2	3	2	1.45
El Salvador	2	2	2	2.02
Estonia	3.5	4	2.5	1.11
Ethiopia	1.5	4.5	1.5	1.73
Finland	5.5	6	4	4.06
France	4.5	5	3	2.24
Gabon	2	3	1.5	3.12
Gambia	2	3.5	2	1.64
Germany	5	5	4	3.09
Ghana	2.5	2.5	2.5	1.49
Greece	2	4.5	3	1.36
Guatemala	1.5	1.5	2	2.50
Guinea	1.5	2.5	2	4.31

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Table 18 – continued from previous page

Country	(1) Corruption	(2) Law and Order	(3) Bureaucracy	(4) Institutions
Guyana	1.5	1.5	3	5.11
Honduras	1.5	1.5	2	2.50
Hong Kong	4.5	5	3	2.11
Hungary	3	4	3	1.09
Iceland	5	6	4	3.52
India	2.5	4	3	1.12
Indonesia	3	3	2	1.25
Iran	1.5	4	2	2.03
Iraq	1	1.5	1.5	4.93
Israel	3.5	5	4	2.11
Italy	2.5	4	2.5	1.10
Jamaica	2	2	3	1.91
Japan	4.5	5	4	2.72
Jordan	2.5	4	2	1.15
Kazakhstan	1.5	3.5	2	1.82
Kenya	1.5	2	2	2.05
Kuwait	2.5	5	2	1.36
Latvia	2.5	5	2.5	1.29
Lebanon	1.5	4	2	1.42
Liberia	2.5	2.5	0	5.85
Libya	1	4	1	2.51
Lithuania	2.5	4	2.5	1.09
Luxembourg	5	6	4	3.69
Malawi	2	2.5	2.5	1.76
Malaysia	2.5	4	3	1.11
Mali	1.5	3	0	3.79
Malta	3.5	5	3	1.44
Mexico	2	1.5	3	2.28
Moldova	2	4.5	1	0.13
Mongolia	2	4	2	1.59
Morocco	2	4.5	2	1.40
Namibia	3	5	2	1.33
Netherlands	5	6	4	4.24
New Zealand	5.5	5.5	4	3.88
Nicaragua	1.5	3.5	1	2.78
Niger	1.5	2	1.5	1.01
Nigeria	1.5	2	1	2.58
Norway	5.5	6	4	4.26
Oman	2.5	5	2	1.25
Pakistan	2	3.5	2	1.41
Panama	2	3	2	1.46
Paraguay	1.5	2	1	4.99
Peru	2	3	2	1.49
Philippines	2	2.5	3	1.59
Poland	3	4.5	3	1.25
Portugal	3.5	5	3	1.52
Qatar	3	5	2	1.27
Romania	2	4	1	1.88

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Table 18 – continued from previous page

Country	(1) Corruption	(2) Law and Order	(3) Bureaucracy	(4) Institutions
Saudi Arabia	2.5	5	2	1.32
Senegal	2	3	1	5.10
Sierra Leone	1.5	3.5	0	3.32
Singapore	4.5	5	4	2.60
Slovenia	3.5	4.5	3	1.34
South Africa	2.5	2.5	2	1.39
Spain	4	5	3	1.83
Sri Lanka	2.5	2.5	2	1.49
Sudan	0.5	2.5	1	4.55
Sweden	5.5	6	4	4.27
Switzerland	5	5	4	3.18
Syria	1.5	4.5	1.5	2.04
Taiwan	3	5	3	1.32
Tanzania	2	5	1	2.08
Thailand	2	2.5	2	1.69
Togo	1.5	3	0	1.21
Tunisia	2.5	5	2	1.10
Turkey	2.5	3.5	2	1.19
Uganda	1.5	3.5	2	2.04
Ukraine	1.5	4	1	2.59
United Kingdom	4.5	5	4	3.13
United States	4	5	4	2.68
Uruguay	4	2.5	2	1.70
Venezuela	1	1	1	3.87
Vietnam	2.5	4	2	1.19
Zambia	2.5	4	1	1.73
Zimbabwe	1	3	1.5	3.20
Average	2.68	3.77	2.32	2.21

Table 19: *Summary Statistics of Main Regression Variables.*

Panel A: Country-Level Measures						
	N	Mean	Median	Std. Dev.	Min	Max
$Culture_i$	56	1.77	1.71	1.00	0.00	3.85
$Power_i$	79	2.19	0.91	3.21	0.00	19.86
$Individualism_i$	79	1.89	0.77	2.39	0.00	10.00
$Masculinity_i$	79	1.62	0.73	2.12	0.00	10.36
$Uncert.\ Aviod._i$	79	2.05	0.87	2.66	0.00	15.35
$Long\text{-}Term\ Orient._i$	61	1.39	0.62	1.74	0.00	7.44
$Indulgence_i$	56	2.01	0.90	3.17	0.00	19.53
$Institutions_{j-i}$	112	2.09	1.51	1.98	0.05	9.20
$Corruption_i$	112	2.28	0.68	2.81	0.00	10.95
Law_i	112	2.07	1.30	2.47	0.00	11.72
$Bureaucracy_i$	112	1.93	0.82	2.21	0.00	13.15

Panel B: Country-Pair Measures						
	N	Mean	Median	Std. Dev.	Min	Max
$Initiation_{ij}$	3844	0.30	0.01	1.58	0.00	49.13
$Completion_{ij}$	2007	0.79	0.81	0.18	0.14	1.00
$Duration_{ij}$	2007	43.60	0.00	155.34	0.00	3653.00
$\Delta Culture_{j-i}$	3844	1.97	1.84	1.13	0.07	6.89
$\Delta Power_{j-i}$	3844	1.85	0.91	2.46	0.00	20.68
$\Delta Individualism_{j-i}$	3844	2.14	1.06	2.45	0.00	12.02
$\Delta Masculinity_{j-i}$	3844	2.29	1.01	3.20	0.00	25.29
$\Delta Uncert.\ Aviod._{j-i}$	3844	1.93	0.87	2.56	0.00	21.75
$\Delta Long\text{-}Term\ Orient._{j-i}$	3844	1.74	0.90	2.18	0.00	12.92
$\Delta Indulgence_{j-i}$	3844	1.89	0.95	2.43	0.00	18.38
$\Delta Institutions_{j-i}$	3844	1.84	1.22	1.78	0.00	9.20
$Corruption_i$	3844	3.28	2.50	1.27	1.50	5.50
Law_i	3844	4.17	4.50	1.27	1.50	6.00
$Bureaucracy_i$	3844	2.81	3.00	0.92	1.00	4.00
$Corruption_j$	3844	3.30	2.75	1.27	1.50	5.50
Law_j	3844	4.18	4.50	1.28	1.50	6.00
$Bureaucracy_j$	3844	2.84	3.00	0.90	1.00	4.00
$Size_{ij}$	3844	−8.51	0.04	49.38	−1694.95	1.00
$\Delta Language_{j-i}$	3844	0.95	1.00	0.22	0.00	1.00
$\Delta Religion_{j-i}$	3844	0.72	1.00	0.45	0.00	1.00
$\Delta Distance_{j-i}$	3844	8.57	8.89	0.95	4.39	9.89
$Experience_{ij}$	3844	0.19	0.00	0.27	0.00	1.00

This table presents the summary statistics of our dependent and independent variables of interest. We include both the country-level summary in Panel A and the country-pair data that is actually used in our regressions in Panel B.

Table 20: *Correlation Table.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(1)	1																					
(2)	0.99*	1																				
(3)	0.02	0.02	1																			
(4)	−0.12*	−0.19*	0.01	1																		
(5)	−0.06*	−0.10*	0.05*	0.52*	1																	
(6)	−0.07*	−0.12*	0.03	0.53*	0.35*	1																
(7)	−0.02	−0.05*	−0.00	0.51*	0.11*	0.00	1															
(8)	−0.04*	−0.08*	−0.01	0.32*	0.01	0.01	−0.01	1														
(9)	−0.07*	−0.08*	−0.02	0.35*	−0.07*	0.05*	0.01	−0.10*	1													
(10)	−0.07*	−0.09*	−0.04	0.40*	−0.02	0.05*	−0.00	−0.08*	0.20*	1												
(11)	−0.10*	−0.16*	0.02	0.38*	0.42*	0.37*	0.09*	0.01	0.03*	0.09*	1											
(12)	0.12*	0.13*	−0.03	0.13*	0.11*	0.10*	0.19*	0.10*	−0.06*	−0.14*	0.11*	1										
(13)	0.09*	0.10*	−0.03	0.10*	0.12*	0.05*	0.19*	0.09*	−0.08*	−0.17*	0.02	0.74*	1									
(14)	0.14*	0.16*	−0.01	0.17*	0.13*	0.09*	0.21*	0.11*	−0.04*	−0.12*	0.05*	0.82*	0.69*	1								
(15)	0.16*	0.12*	0.01	0.15*	0.14*	0.10*	0.19*	0.11*	−0.07*	−0.14*	0.13*	−0.02	−0.01	−0.01	1							
(16)	0.13*	0.10*	0.01	0.10*	0.13*	0.05*	0.19*	0.09*	−0.08*	−0.17*	0.03	−0.01	−0.02	−0.01	0.74*	1						
(17)	0.19*	0.16*	0.03	0.18*	0.17*	0.10*	0.20*	0.12*	−0.05*	−0.11*	0.08*	−0.01	−0.01	−0.02	0.82*	0.70*	1					
(18)	0.02	0.02	0.01	−0.00	0.05*	−0.03*	−0.05*	0.03	0.00	0.01	0.01	−0.09*	−0.06*	−0.14*	0.04*	−0.01	0.06*	1				
(19)	−0.19*	−0.24*	−0.05	0.09*	−0.01	−0.07*	0.12*	0.10*	0.09*	−0.01	−0.01	0.01	0.03	−0.02	0.01	0.03	−0.01	0.02	1			
(20)	−0.09*	−0.11*	−0.02	0.07*	0.06*	0.07*	−0.05*	0.02	0.08*	0.04*	−0.00	−0.16*	−0.21*	−0.08*	−0.07*	−0.05*	−0.07*	0.08*	0.07*	1		
(21)	−0.15*	−0.15*	0.03	0.17*	0.09*	0.21*	−0.11*	0.11*	0.07*	0.13*	0.18*	−0.09*	−0.23*	−0.12*	−0.09*	−0.22*	−0.12*	−0.02	−0.02	0.16*	1	
(22)	0.08*	−0.03	0.02	0.00	0.01	0.09*	0.04*	0.01	−0.08*	−0.09*	0.03	0.03	0.00	0.04*	0.24*	0.21*	0.28*	0.01	−0.08*	−0.03*	−0.21*	1

(1)	$\mathit{Initiation}_{ij}$	(12)	$\mathit{Corruption}_i$
(2)	$\mathit{Completion}_{ij}$	(13)	$\mathit{Law\ and\ Order}_i$
(3)	$\mathit{Duration}_{ij}$	(14)	$\mathit{Bureaucracy}_i$
(4)	$\Delta \mathit{Culture}_{j-i}$	(15)	$\mathit{Corruption}_j$
(5)	$\Delta \mathit{Power}_{j-i}$	(16)	$\mathit{Law\ and\ Order}_j$
(6)	$\Delta \mathit{Individualism}_{j-i}$	(17)	$\mathit{Bureaucracy}_j$
(7)	$\Delta \mathit{Masculinity}_{j-i}$	(18)	$\Delta \mathit{Size}_{j-i}$
(8)	$\Delta \mathit{Uncert.\ Aviod.}_{j-i}$	(19)	$\Delta \mathit{Language}_{j-i}$
(9)	$\Delta \mathit{Long\text{-}Term\ Orientation}_{j-i}$	(20)	$\Delta \mathit{Religion}_{j-i}$
(10)	$\Delta \mathit{Indulgence}_{j-i}$	(21)	$\mathit{Distance}_{ij}$
(11)	$\Delta \mathit{Institutions}_{j-i}$	(22)	$\mathit{Experience}_{ij}$

This table presents the correlation matrix between our dependent and independent variables of interest. Significance at 10% is denoted by (*).

Table 21: *Cross-section of Deal Initiations.*

	Fractional Logit			PPML		
	(1)	(2)	(3)	(4)	(5)	(6)
Experience_{ij}	0.287***	0.289***	0.985***	0.279***	0.276***	0.981***
	(0.099)	(0.109)	(0.108)	(0.076)	(0.085)	(0.092)
$\Delta\text{Language}_{j-i}$	−0.822***	−0.905***	−0.938***	−0.762***	−0.830***	−0.873***
	(0.125)	(0.130)	(0.111)	(0.087)	(0.090)	(0.093)
$\Delta\text{Religion}_{j-i}$	−0.236*	−0.306**	−0.048	−0.234**	−0.313***	−0.056
	(0.132)	(0.145)	(0.132)	(0.107)	(0.121)	(0.094)
$\Delta\text{Distance}_{j-i}$	−0.853***	−0.909***	−0.996***	−0.784***	−0.839***	−0.930***
	(0.048)	(0.049)	(0.046)	(0.028)	(0.030)	(0.030)
ΔGDP_{j-i}		0.000**	0.002***		0.000***	0.002***
		(0.000)	(0.000)		(0.000)	(0.000)
ΔPower_{j-i}			−0.013			−0.013
			(0.019)			(0.016)
$\Delta\text{Indv.}_{j-i}$			−0.029			−0.026*
			(0.021)			(0.015)
$\Delta\text{Masc.}_{j-i}$			−0.062***			−0.060***
			(0.011)			(0.008)
$\Delta\text{Uncert. Aviod.}_{j-i}$			−0.134***			−0.131***
			(0.020)			(0.013)
$\Delta\text{Long Term Orient.}_{j-i}$			−0.060**			−0.060***
			(0.029)			(0.022)
$\Delta\text{Indulgence}_{j-i}$			−0.054**			−0.052***
			(0.027)			(0.019)
$\Delta\text{Corruption}_{j-i}$			−0.050**			−0.050***
			(0.024)			(0.018)
ΔLaw_{j-i}			0.007			0.002
			(0.024)			(0.019)
$\Delta\text{Bureaucracy}_{j-i}$			0.030			0.036
			(0.037)			(0.032)
Acquirer Fixed Effect	✓	✓	✓	✓	✓	✓
Target Fixed Effect	✓	✓	✓	✓	✓	✓
Obs.	8,813	7,862	3,844	8,736	7,787	3,844
pseudo R^2	0.347	0.346	0.233	0.749	0.760	0.748

The dependent variables is the number of cross-border acquisitions from acquirer country j to target country i relative to the total number of cross-border acquisitions for acquirer country j. We use a logit fractional response and PPML model to estimate the cross sectional regressions. These measures are constructed using the Mahalanobis method restricting the covariance terms to zero following Kogut and Singh (1988). Significance at 10%, 5%, and 1% is denoted by (*, **, ***) with standard errors clustered on the target countries in parentheses.

Table 22: *Cross-section of Deal Completions.*

	Fractional Logit			PPML		
	(1)	(2)	(3)	(4)	(5)	(6)
Experience_{ij}	−0.027	−0.062	−0.072	−0.006	−0.010	−0.014
	(0.071)	(0.076)	(0.107)	(0.010)	(0.011)	(0.021)
$\Delta\text{Language}_{j-i}$	0.128	0.057	0.092	0.020	0.009	0.018
	(0.086)	(0.088)	(0.121)	(0.013)	(0.014)	(0.021)
$\Delta\text{Religion}_{j-i}$	−0.025	−0.004	0.147	0.001	0.003	0.035
	(0.077)	(0.080)	(0.145)	(0.012)	(0.012)	(0.022)
$\Delta\text{Distance}_{j-i}$	0.276***	0.284***	0.234***	0.051***	0.054***	0.051***
	(0.035)	(0.038)	(0.045)	(0.004)	(0.004)	(0.007)
ΔGDP_{j-i}		−0.000	−0.001*		−0.000	−0.000***
		(0.000)	(0.001)		(0.000)	(0.000)
ΔPower_{j-i}			0.013			0.004
			(0.015)			(0.003)
$\Delta\text{Indv.}_{j-i}$			−0.044***			−0.010***
			(0.014)			(0.003)
$\Delta\text{Masc.}_{j-i}$			−0.016**			−0.003*
			(0.008)			(0.001)
$\Delta\text{Uncert. Aviod.}_{j-i}$			−0.002			0.000
			(0.012)			(0.002)
$\Delta\text{Long Term Orient.}_{j-i}$			0.006			0.001
			(0.019)			(0.003)
$\Delta\text{Indulgence}_{j-i}$			0.016			0.003
			(0.017)			(0.003)
$\Delta\text{Corruption}_{j-i}$			−0.002			0.000
			(0.023)			(0.004)
ΔLaw_{j-i}			0.015			0.002
			(0.023)			(0.004)
$\Delta\text{Bureaucracy}_{j-i}$			−0.079**			−0.017***
			(0.034)			(0.006)
Acquirer Fixed Effect	✓	✓	✓	✓	✓	✓
Target Fixed Effect	✓	✓	✓	✓	✓	✓
Obs.	5,281	4,586	2,002	5,281	4,586	2,002
(pseudo) R^2	0.090	0.085	0.044	0.269	0.270	0.212

The dependent variables is the proportion of completed cross-border acquisitions from acquirer country j to target country i relative to the number of cross-border acquisitions from from acquirer country j to target country i. We use a logit fractional response model to estimate the cross sectional regressions. These measures are constructed using the Mahalanobis method restricting the covariance terms to zero following Kogut and Singh (1988). Significance at 10%, 5%, and 1% is denoted by (*, **, ***) with standard errors clustered on the target countries in parentheses.

Table 23: Cross-section of Deal Duration.

	Fractional Logit			PPML		
	(1)	(2)	(3)	(4)	(5)	(6)
Experience_{ij}	−3.466	−4.371	8.354	−0.051	−0.062	0.216
	(4.846)	(5.411)	(8.137)	(0.098)	(0.106)	(0.189)
$\Delta\text{Language}_{j-i}$	10.810	11.970	−0.549	0.191*	0.204*	0.016
	(7.161)	(8.620)	(9.699)	(0.109)	(0.120)	(0.178)
$\Delta\text{Religion}_{j-i}$	−4.007	−3.969	−13.490*	−0.092	−0.099	−0.347*
	(5.657)	(5.897)	(7.515)	(0.105)	(0.108)	(0.183)
$\Delta\text{Distance}_{j-i}$	1.009	0.506	−4.521**	0.027	0.013	−0.092*
	(1.908)	(2.212)	(2.149)	(0.036)	(0.037)	(0.048)
ΔGDP_{j-i}		0.000	0.003		0.000	0.000
		(0.000)	(0.009)		(0.000)	(0.000)
ΔPower_{j-i}			2.028			0.058**
			(1.452)			(0.028)
$\Delta\text{Indv.}_{j-i}$			0.569			0.006
			(1.170)			(0.021)
$\Delta\text{Masc.}_{j-i}$			0.201			0.008
			(0.325)			(0.012)
$\Delta\text{Uncert. Aviod.}_{j-i}$			0.430			0.010
			(0.861)			(0.017)
$\Delta\text{Long Term Orient.}_{j-i}$			−0.239			−0.002
			(0.983)			(0.027)
$\Delta\text{Indulgence}_{j-i}$			−1.800			−0.046
			(1.413)			(0.035)
$\Delta\text{Corruption}_{j-i}$			−0.347			−0.011
			(1.148)			(0.034)
ΔLaw_{j-i}			−1.023			−0.020
			(1.822)			(0.031)
$\Delta\text{Bureaucracy}_{j-i}$			2.617			0.057
			(2.590)			(0.053)
Acquirer Fixed Effect	✓	✓	✓	✓	✓	✓
Target Fixed Effect	✓	✓	✓	✓	✓	✓
Obs.	5,284	4,588	2,001	5,200	4,520	1,991
(pseudo) R^2	0.170	0.187	0.097	0.265	0.306	0.130

The dependent variables is the average difference between the announcement date and effective date for each acquirer-target pair. We use an OLS model to estimate the cross sectional regressions. These measures are constructed using the Mahalanobis method restricting the covariance terms to zero following Kogut and Singh (1988). Significance at 10%, 5%, and 1% is denoted by (*, **, ***) with standard errors clustered on the target countries in parentheses.

Table 24: Robustness to Prior Experience.

	Initiation		Completion	Duration	
	(1)	(2)	(3)	(4)	(5)
	FL	PPML	FL	OLS	PPML
Experience_{ij}	−0.079	−0.077	0.218	9.709	0.322
	(0.119)	(0.091)	(0.200)	(7.858)	(0.237)
$\Delta\text{Language}_{j-i}$	−0.026	−0.025	−0.009	−0.353	−0.012
	(0.018)	(0.016)	(0.034)	(0.882)	(0.036)
$\Delta\text{Religion}_{j-i}$	−0.056**	−0.055***	−0.009	−0.056	−0.003
	(0.026)	(0.017)	(0.027)	(0.916)	(0.030)
$\Delta\text{Distance}_{j-i}$	−0.049***	−0.047***	0.045**	−0.117	−0.005
	(0.013)	(0.011)	(0.018)	(0.430)	(0.017)
ΔGDP_{j-i}	−0.042*	−0.041***	−0.034	0.136	0.006
	(0.022)	(0.015)	(0.024)	(0.935)	(0.022)
ΔPower_{j-i}	−0.094***	−0.092***	0.072*	−0.064	−0.003
	(0.036)	(0.033)	(0.042)	(1.209)	(0.039)
$\Delta\text{Indv.}_{j-i}$	−0.041	−0.040	−0.012	−0.294	−0.009
	(0.032)	(0.030)	(0.038)	(1.347)	(0.039)
$\Delta\text{Masc.}_{j-i}$	−0.093***	−0.091***	0.130***	0.235	0.008
	(0.027)	(0.024)	(0.021)	(1.256)	(0.046)
$\Delta\text{Uncert. Aviod.}_{j-i}$	0.022	0.021	−0.013	0.599	0.018
	(0.038)	(0.028)	(0.034)	(1.342)	(0.036)
$\Delta\text{Long Term Orient.}_{j-i}$	−0.057	−0.054	−0.070	1.536	0.050
	(0.047)	(0.039)	(0.048)	(1.382)	(0.053)
$\Delta\text{Indulgence}_{j-i}$	−0.813***	−0.771***	0.168	1.519	0.060
	(0.142)	(0.143)	(0.171)	(3.574)	(0.171)
$\Delta\text{Corruption}_{j-i}$	−0.285***	−0.273***	−0.064	5.292	0.196
	(0.082)	(0.085)	(0.114)	(3.614)	(0.149)
ΔLaw_{j-i}	−0.205***	−0.196***	−0.013	0.639	0.027
	(0.057)	(0.041)	(0.057)	(1.640)	(0.065)
$\Delta\text{Bureaucracy}_{j-i}$	−0.002**	−0.002***	−0.002	0.039	0.003
	(0.001)	(0.001)	(0.002)	(0.024)	(0.003)
$\Delta\text{Completion Exp.}_{j-i}$	0.256	0.244	2.177***	−17.510	−0.606
	(0.281)	(0.255)	(0.554)	(22.390)	(0.601)
$\Delta\text{Duration Exp.}_{ij}$	−0.001	−0.001			
	(0.001)	(0.001)			
Constant	−0.647	−0.805*	−0.314	26.890	3.238***
	(0.578)	(0.476)	(0.746)	(19.570)	(0.692)
Obs.	899	899	781	781	781
(pseudo) R^2	0.049	0.268	0.029	—	—

The dependent variables is the average difference between the announcement date and effective date for each acquirer-target pair. We use an OLS model to estimate the cross sectional regressions. These measures are constructed using the Mahalanobis method restricting the covariance terms to zero following Kogut and Singh (1988). Significance at 10%, 5%, and 1% is denoted by (*, **, ***) with standard errors clustered on the target countries in parentheses.

Table 25: *Robustness using Different Measures of Distance.*

	(1) $Initiation_{ij}$	(2) $Completion_{ij}$	(3) $Duration_{ij}$
$\Delta Culture_{j-i}$	−0.131*	−0.117	−3.449
	(0.075)	(0.074)	(5.269)
$\Delta Geography_{j-i}$	−0.354***	−0.332***	0.999
	(0.040)	(0.062)	(3.746)
$\Delta Administrative_{j-i}$	−0.207***	−0.233***	−3.069
	(0.025)	(0.047)	(2.323)
$\Delta Demographic_{j-i}$	−0.398***	−0.355***	4.214
	(0.044)	(0.077)	(5.514)
$\Delta Political_{j-i}$	−0.040	−0.238***	−6.959
	(0.037)	(0.091)	(4.915)
$\Delta Economic_{j-i}$	−0.194***	−0.061	3.165
	(0.054)	(0.065)	(2.779)
$\Delta Financial_{j-i}$	0.090***	0.187***	−4.515
	(0.035)	(0.054)	(3.835)
$\Delta Integration_{j-i}$	0.064*	−0.128**	8.009
	(0.038)	(0.057)	(5.120)
$\Delta Innovation_{j-i}$	0.071***	0.253***	−5.271***
	(0.015)	(0.026)	(1.839)
Constant	0.058	4.859***	160.900***
	(0.328)	(0.555)	(32.740)
N	5,938	5,938	2,032
(Pseudo) R^2	0.051	0.118	0.012

The dependent variables are: (1) $Initiation_{ij}$: the number of cross-border acquisitions from acquirer country j to target country i relative to the total number of cross-border acquisitions for acquirer country j; (2) $Completion_{ij}$: the proportion of completed cross-border acquisitions from acquirer country j to target country i relative to the number of cross-border acquisitions from from acquirer country j to target country i; and (3) $Duration_{ij}$: the average difference between the announcement date and effective date for each acquirer-target pair, removing acquisitions with the same announcement and effective date. We use a logit fractional response model for models (1) and (2) and an OLS model for model (3). The cross-national distance measures are from Berry, Guillen, and Zhou (2010). $\Delta Culture_{j-i}$ measures the log difference in attitudes toward authority, trust, individuality, and the importance of work and family. $\Delta Geography_{j-i}$ is the log great circle distance between the geographic center of each country. $\Delta Administrative_{j-i}$ measures the log differences in colonial ties, language, religion, and legal systems. $\Delta Demographic_{j-i}$ measures the differences in demographic characteristics. $\Delta Political_{j-i}$ measures the differences in political stability, democracy, and trade-bloc membership. $\Delta Economic_{j-i}$ measures the difference in economic development and macroeconomic characteristics. $\Delta Financial_{j-i}$ measures the difference in financial sector development. $\Delta Integration_{j-i}$ measures the differences in tourism and internet usage. $\Delta Innovation_{j-i}$ measures the differences in patents and scientific production. These measures are constructed using the Mahalanobis method. Time-varying distance measures use the time-varying covariance matrix in computing the distance and are averaged across each acquirer-target pair. Significance at 10%, 5%, and 1% is denoted by (*, **, ***) with t-statistics based on standard errors clustered on 84 target countries in parentheses.

3 The Impact of Terrorism on Cross-Border Acquisition Flows

The terrorist attack of 9/11, the instability of the Middle East and Northern Africa, and the subsequent mass migration of a large portion of its populace to Europe has brought terrorism to the forefront of the West's conscience after a period of relative peace in the 1990s. Figure 7 shows terrorism, at the worldwide level, has had two periods of severe growth since the 1970s. The first is the period starting in the early 1970s and ending in the early 1990s and the second is the period starting in the early 2000s to the present day. Over the period starting from 1970 to 1990, there was an annual growth rate of 9.34% over the period starting from 1990 to 2000, there was an annual growth of 7.34%; and over the most recent period there has been a growth rate of 15.03% per annum.[24] How might this increasing trend of terrorism impact economic activity between countries?

Classical economic theory predicts that terrorism will not have a substantial effect on economic activity since it affects a small proportion of a country's total capital stock (Becker & Murphy, 2001). However, more recent empirical work has overturned this view, showing that terrorism has large impacts on economic outcomes (e.g., Abadie & Gardeazabal, 2003). Researchers who study the effect of terrorism on international trade, however, have not come to a general agreement that it impacts trade by reducing the volume of trade between importing and exporting countries. On the one hand, early work found empirical evidence that terrorism reduces the volume of trade between importing and exporting countries (Nitsch & Schumacher, 2004). On the other hand, theoretical work has shown that terrorism may either increase or decrease trade depending on the impact that terrorism has on the terms of trade between exporters and importers (Bandyopadhyay & Sandler, 2014).

Given these large increases in terrorism and the possibility of economic effects, it is also imperative to understand the impact on corporate decision. This essay fills this existing gap

[24]The growth rate g of the log number of terrorist attacks between years s and k is given by $1 + g = \exp(\tau_s - \tau_k)^{1/\Delta t}$ where $\Delta t = k - s$.

in the literature by studying the causal impact of terrorism on cross-border acquisition flows. How might terrorism affect the decision to initiate an acquisition? Let's look at a rough example to see what the effects might be. Turkey has seen a tremendous surge in terrorist attacks, increasing from 421 attacks in 2015 to 540 attacks in 2016 (28% increase). Over this same period, the total number of mergers and acquisitions has decreased from 319 initiated acquisitions to 243 acquisitions (24% decrease) (Ernest and Young, 2015, 2016).

In this essay, we provide a stylized theoretical model of how terrorism influences cross border mergers and then empirically test its predictions. Our model predicts that higher levels of terrorism in the target country are associated with smaller cross border initiations. We empirically test this prediction by exploiting the exogenous variation induced by ethnic and religious fractionalization and genetic diversity. Our empirical results confirm our theoretical prediction, where we show that a 1% increase in terrorism in the target country relative to the acquirer country is related to a 9% decrease in acquistion flows. We further test the differential impact that domestic and transnational terrorism have on acquisition flows. We find that both domestic and transnational terrorism have a negative and significant impact on acquisition flows but the economic significance is larger for transnational terrorist attacks.

3.1 Literature Review

3.1.1 Terrorism

Terrorism is the premeditated use or threat to use violence by individuals or subnational groups to obtain a political or social objective through the intimidation of a large audience beyond that of the immediate noncombatant victims (Enders and Sandler, 2012, p.4). The strategic value in terrorism lies in the the unpredictable nature of the attack, making everyone feel in danger even if the probability of any one person being a victim is as small as drowning in a bathtub (Mueller, 2006). By traumatizing the public through brutal acts, terrorists seek to compel the government to address their demands or diverting funds into protecting potential targets.

For example, 9/11 hijackings were bent on pressuring the USA to remove its troops from Saudi Arabia and intimidated a global audience. The attacks caused temporary losses to the major stock exchanges (Chen and Siems, 2004), and created $80–90 billion in damages (Kunreuther and Heal, 2003). Even though stock exchanges recovered lost values in just over a month, the death of almost 3,000 people caused rich industrial countries to allocate more resources to counterterrorism, shook insurance markets, and made an indelible impression on virtually the entire world.

Research has found some rather interesting stylized facts. Terrorist campaigns are more prevalent in liberal democracies, where the government's legitimacy hinges on its ability to protect the lives and property of its citizens (Eubank and Weinberg, 1994). Terrorist groups were primarily nationalists/separatists or leftists (socialists) during the late 1960s until the late 1980s (Rapoport, 2004). Even the Palestinian terrorists were secular until the end of the 1980s with the rise of Hamas, Palestinian Islamic Jihad, and other groups. After the mid-1990s, the religious fundamentalists came to dominate and increased the carnage (Enders and Sandler, 2000; Gaibulloev and Sandler, 2014).[25]

3.1.2 *Mergers and Acquisition*

In the second essay, we show that culture, institutions, and geography are important determinants in the initiation and completion of cross-border acquisitions using a gravity model. More specifically, culture differences, institutional, and geographical distance are of paramount importance in whether firms decide to initiate cross-border mergers and acquisitions. Cultural and geographic distance do not play a large role in determining whether firms follow

[25]The phenomenon of religious-based transnational terrorism is not novel and can be traced back to the Sicarii or Zealots, a Jewish sect that conducted a terror campaign against the Romans and their Jewish collaborators in Judea from CE 48 to 73 (Bloom, 2005).

through and complete the deal; what matters in the completion of initiated deals are institutional differences. The duration from initiation to completion is unaffected by any institutional, cultural, or geographical factors and solely depends on idiosyncratic factors.

Other work in this area has been founded empirically on the gravity model from trade when studying different factors. Rossi and Volipin (2004) find that the volume of cross-country acquisitions is larger in countries with stronger accounting standards and stronger shareholder protection. In a similar vein, Erel, Liao, and Weisbach (2013) find that geographic distance and differences in various institutional factors – such as accounting disclosures and economic development – are positively related to cross-border acquisition flows between countries. Ahern et al. (2015) isolates the impact of culture on cross-border acquisitions. They find that countries that are more distant culturally have lower cross-border acquisition activity. Additionally, the literature has documented that in countries with far-right parties or in times of weak government there is more intervention in large-scale foreign acquisitions (Serdar Dinc and Erel, 2014).

However, there is no systematic study that tries to measure the causal impact of terrorism on cross-border mergers and acquisitions.

3.2 Theoretical Predictions

In this section, we adapt the model of Helpman et al. (2008) following Bandyopadhyay et al. (2016) to examine the impact that terrorism has on cross-border acquisition to motivate our hypotheses.

Consider a world with J countries, index by $j = 1, \ldots, J$ with $\sum_{j=1}^{J} N_j$ firms in the world. Each country acquires a continuum of firms, indexed by f, with a set of domestic and foreign firms F_j available for acquisition by country j. The standard utility function that characterizes the acquirer country j's acquisition preference is

$$U^j = \left[\int_{f \in F_j} x_j(f)^{\alpha} \, df \right]^{\frac{1}{\alpha}}, \tag{28}$$

where $x_j(f)$ is the acquisition of firm l in country j and α is the parameter that determines the elasticity of substitution across firms, which is given by $\varepsilon = \frac{1}{(1-\alpha)}$, $\varepsilon > 1$. This elasticity is the same across countries.

Using standard utility maximization arguments, country j's optimal demand for acquiring firm f is

$$x_j^*(f) = \frac{p_j(f)^{-\varepsilon} Y_j}{P_j^{1-\varepsilon}}, \tag{29}$$

where Y_j is the income/expenditure of country j and $P_j^{1-\varepsilon}$ is the country's ideal price index, or the aggregation of the acquisition price of each firm f,

$$P_j = \left[\int_{f \in B_j} p_j(f)^{1-\varepsilon} df \right]^{\frac{1}{(1-\varepsilon)}}. \tag{30}$$

This specification implies that every firm f has a constant demand elasticity ε.

The marginal domestic acquisition cost of any firm in country i is a constant c_i, while the productivity of firm f is $a(f)$ such that the firm's marginal cost is $c_i / a(f)$. An acquiring firm also incurs an additional fixed cost φ_{ij} and conversion cost ξ_{ij} for cross-border acquisitions. The conversion cost is defined such that for each acquisition in target country i, the firm needs to acquire ι_{ij} units for one unit to actually become acquired. It is assumed that $\iota_{jj} = 1$ and $\iota_{ij} > 1$.

Terrorism in target country i, τ_i, increases the cross-border acquisition conversion cost such that

$$\xi_{ij} = \xi_{ij}(\tau_i) \ \frac{\partial \xi_{ij}}{\partial \tau_i} > 0. \tag{31}$$

That is, we assume that an increases of terrorism in the target country make it more costly to initiate cross-border acquisitions. As is standard in the literature (e.g., Melitz, 2003; Helpman et al., 2008), we also assume that there is a fixed cost for a firm from nation j to acquire a firm in nation i, denoted φ_{ij}. This cost is likely to be affected by terrorism in the acquiring country i, hence,

$$\xi_{ij} = \xi_{ij}(\tau_i). \tag{32}$$

The profit, π_{ij}, of a firm in country i which is acquired by a firm in country j is

$$\pi_{ij} = x_j(f)\left[p_j(f) - \frac{c_i}{a(f)}\xi_{ij}(\tau_i)\right] - \varphi_{ij}(\tau_i). \tag{33}$$

Equating the marginal revenue and marginal cost gives the acquisition and price levels,

$$\begin{aligned} p_j(f)\left(1-\frac{1}{\varepsilon}\right) &= \frac{c_i}{a(f)}\xi_{ij}(\tau_i) \\ p_j(f) &= \frac{\varepsilon}{1-\varepsilon}\cdot\frac{c_i}{a(f)}\cdot\xi_{ij}(\tau_i) \\ &\equiv p_j(f;\tau_i). \end{aligned} \tag{34}$$

Substituting Equation (34) into Equation (29), we can obtain the value of acquisitions from target country i to acquiring country j,

$$\begin{aligned} V_{ij}\left(a(f);\tau_i,P_j,Y_j\right) &= p_j(f,\tau_i,\tau_j)\cdot x_j(f) \\ &= \left[\frac{p_j(\cdot)}{P_j}\right]^{1-\varepsilon} Y_j. \end{aligned} \tag{35}$$

The profit of firm f from acquisition by country j can be expressed as

$$\pi_{ij}(f,\tau_i,P_j,Y_j) = \left[\frac{c_i\xi_{ij}(\cdot)}{a(f)}\right]^{1-\varepsilon}\frac{\mu Y_j}{P_j^{1-\varepsilon}} - \varphi_{ij}(\cdot) \tag{36}$$

where $\mu = \varepsilon^{-\varepsilon}(\varepsilon-1)^{\varepsilon-1}$. Note that positive acquisition profit can be obtained if and only if

$$a \geq \widetilde{a}_{ij}(\tau_i,P_j,Y_j) = \frac{c_i\cdot\xi_{ij}(\tau_i)}{P_j}\left[\frac{\varphi_{ij}(\tau_i)}{\mu Y_j}\right]^{1/(\varepsilon-1)}, \tag{37}$$

where $\widetilde{a}$ is the threshold synergy (i.e. productivity) level required for profitable acquisitions.

We assume that terrorism, τ_i, affects the productivity distribution of acquisitions in country i, denoted by $g(a;\tau_i)$ with support $(0,\infty)$. An increase in terrorism causes adverse productivity effects (i.e., leftward shifts in the density function). Given a measure N_i of firms in country i, the aggregate volume from target country i to acquiring country j is[26]

[26]A gravity equation can be derived from Equation (38) that involves the terrorism parameters of both nations i and j. See Appendix II of Helpman et al. (2008) for the method of derivation.

$$\widetilde{V}_{ij}(\tau_i, P_j, Y_j) = \int_{\widetilde{a}_{ij}}^{\infty} V_{ij}\left(a; \tau_i, P_j(\tau_i), Y_j\right) \cdot N_i \cdot g\left(a; \tau_i\right)\, da \tag{38}$$

By differentiating this equation with respect to any terrorism related parameter ϑ, we get

$$\begin{aligned} \frac{\partial \widetilde{V}_{ij}(\cdot)}{\partial \vartheta} = N_i & \int_{\widetilde{a}_{ij}}^{\infty} \frac{\partial V_{ij}(a; \tau_i)}{\partial \vartheta} \cdot g(\cdot)\, da \\ & + N_i \int_{\widetilde{a}_{ij}}^{\infty} V_{ij}(\cdot) \cdot \frac{\partial g(a; \tau_i)}{\partial \vartheta}\, da \\ & - N_i \cdot V_{ij}(\widetilde{a}_{ij}) \cdot g(\widetilde{a}_{ij}; \tau_i) \cdot \frac{\partial \widetilde{a}_{ij}}{\partial \vartheta} \end{aligned} \tag{39}$$

Proposition 3.1. *An increase of terrorism in target country i decreases acquisitions from acquirer country j.*

Remark. In the first term of Equation (39), an increase in terrorism τ_i will increase the acquisition price of a firm p_j through an increase of the conversion costs ξ_{ij} (see Equation 34). Since the acquisitions from target country i are likely to be relatively a small subset of all firms in the acquiring country j, we can safely ignore the impact on the aggregate price index P_j. Therefore, the relative price of acquisitions increase (p_j/P_j) produced by the increase in terrorism causes the optimal demand, and hence, the volume of acquisitions to decrease (see Equation 35).

An increase in terrorism τ_i will reduce the productivity distribution of acquisitions. Therefore, the second term will also cause the volume of acquisitions to decrease.

Lastly, the increase in the conversion costs ξ_{ij} will cause the threshold synergy level required for profitable acquisitions to increase (see Equation 37). Therefore the rise of $\widetilde{a}_{ij}$ will imply that the third term also decreases acquisition volume from j.

3.3 Methodology

In this section, we present a simple expositive linear model to understand why we may need an instrument to consistently estimate the causal impact of terrorism on acquisition flows.

We then posit three measures of societal fragmentation that are correlated with terrorism and not correlated with the error term that allow us to exploit exogenous variation. Finally, we discuss in more detail as to how we estimate our model using a multiplicative gravity equation that has been used extensively in other economic work to measure flows between bilateral country pairs.

3.3.1 *Correlation or Causation?*

We model the initiation of cross-border acquisition deals between an acquirer-target pair i as

$$y_i = \kappa + \alpha \cdot \tau_i + u_i, \tag{40}$$

where τ_i is the difference in terrorist attacks between the acquirer and target countries, u_i is an error term, and α is the elasticity parameter of interest. This estimation of α is consistent only if the regressors τ_i is uncorrelated with the error term u_i.

However, it could be argued that an endogenous relationship exists between the error term and our regressor of interest. For example, the error term symbolizes all factors other than terrorism and observable country characteristics that determine cross-border acquisition initiations. Suppose a country has a high level of political or religious fanaticism due to the schooling system. The schooling system of the country also determine the cross-border acquisition initiations by influencing human capital. This association between the error term and the regressor of interest will confound the estimate of the effect of terrorism.[27]

By taking into account observable characteristics we can, at the very least, partially resolve this problem. If we supplement our specification with a vector of observable characteristics

$$y_i = \kappa + \alpha \cdot \tau_i + \gamma \cdot x_i + \varepsilon_i, \tag{41}$$

[27] To see this intuitively, if the error term and terrorism are related, then we can rewrite (1) as $y = \alpha \cdot \tau + u(\tau)$ abstracting away from indices and the constant. Then the total derivative is $\frac{dy}{d\tau} = \alpha + \frac{du}{d\tau}$. The estimation from the data gives us $\frac{dy}{d\tau}$, which means it estimates $\alpha + \frac{du}{d\tau}$ rather than α alone. Therefore the estimates are biased and inconsistent unless there is no relationship between τ and u.

it will allow us to estimate the relationship between terrorism and acquisition deal initiations while controlling for observed country characteristics that are likely to determine both the amount of terrorism and the number of deal initiations. This will lead to unbiased and consistent estimates of α if and only if $\mathbb{E}(\varepsilon \cdot \tau) = 0$. In practice this is not likely to be the case.

3.3.2 *Identification*

To consistently estimate the relationship between terrorism and acquisition initiation, we exploit the exogenous variation in τ_i generated by instruments that are (i) correlated with terrorism and (ii) plausibly uncorrelated with the error term. The instruments that we use are the differences between the acquirer-target pair in ethnic and religious fractionalization and the difference in aggregate genetic distance between the pair. Intuitively, there should be a strong correlation link between the fragmentation of a country's population (ethnically, religiously, and genetically) and intersocietal conflict due to lack of social cohesion. This has been empirically verified both in the prior literature (Abadie, 2006; Arbatli, Ashraf, Galor, and Klemp, 2018) and in our own tests. Therefore, the first condition is satisfied. Since our three instruments overidentify the estimation equations, we are able to statistically test the assumption that the instruments are independent of the error term using the Sargan-Hansen test. The empirical results from this tests is evidence that the instruments plausibly satisfy the second condition. Therefore, we feel that our three instruments meet the two-conditions necessary for valid inferences using instrumental variables.[28]

[28] Of course, the exclusion restriction assumption is the hardest one to defend. As an additional robustness test to verify that our results are not spurious, we conduct a placebo test in which we keep only observations with a low difference (≤ 0.50) in the number of terror attacks between the acquirer-target country and regress the acquisition variable on all of our regressors excluding the terrorism variable. Our results show that our three instruments are not statistically different from zero, giving us further support for the validity of the exclusion restriction.

3.3.3 *Estimation*

We use two alternative approaches to estimate our parameter of interest via a gravity equation. We are motivated by trade studies using the gravity equation model in which exports between countries are proportional to the product of the two countries' GDPs and are inversely proportional to factors that might create frictions. Firstly, we use a traditional two-stage least squares (2SLS). However, 2SLS could lead to inefficient and inconsistent estimation of the gravity model.

To understand why, let's rewrite our simple expositive model in Equation 1 in its exponential form with multiplicative errors following Tenreyo (2007),

$$y_i = \exp(x_i \beta)\varepsilon_i. \tag{42}$$

While one may be tempted to log-linearize the gravity model and estimate β by OLS, it is not advisable. Firstly, the dependent variable may contain a large number of zeroes, which make OLS infeasible. Secondly, the log-linearized error term will, in general, be correlated with the covariates and lead to inconsistent estimates.[29] Non-linear least squares (NLS) would seem to be the most natural estimation technique, and has been shown to be an asymptotically valid estimator for Equation 42. However, since it gives more weight to noisier observations it is considerably inefficient. Therefore, in our second approach we use the (PPML) method proposed by Santos Silva and Tenreyro (2006) to directly estimate the multiplicative model.[30]

The PPML estimator is given by

$$\hat{\beta} = \arg\max \sum_{i}^{n} \left[y_i \times (x_i \beta) - \exp(x_i \beta) \right], \tag{43}$$

[29] The error term will generally be heteroskedastic and it's variance will depend on the regressors. At first glance it may be surprising that the heteroskedasticity of the error term can lead to inconsitency as well as inefficiency, however, the nonlinearity of Equation (42) changes the properties of the error term in a nontrivial way. See §3 of Silva and Tenrayo (2004) for more details.

[30] The PPML estimator gives each observation equal weight and the only requirement for consistency is for the conditional mean to be correctly specified. Due to these desirable properties, it has become standard in the trade literature.

which means that the first order condition solved by the PPML estimator is

$$\sum_{i}^{n} \left[y_i - \exp(x_i \beta) \right] x_i = 0. \tag{44}$$

Consequently, the PPML estimator is a GMM estimator that solves the moment condition in the above equation.

3.4 Data

To construct the cross-border acquisition flow variable, we use data from Thomson's Securities Data Corporation (SDC) Platinum Database. The initial sample is comprised of 1,005,488 acquisitions from 1970 until June 2016. In line with the literature, we remove 61,830 deals in which the acquirer or target nation data is missing or recorded as "unknown". We additionally remove 724,852 domestic acquisitions. Our final sample consists of 218, 806 cross-border deals.

The data on terrorist attacks comes from the Global Terrorism Database (GTD) maintained by the National Consortium for the Study of Terrorism and Responses to Terrorism (START) led by the University of Maryland. The GTD dataset is comprised on publicly available, nonclassified source material, including media articles and electronic news archives, and to a lesser extent, existing data sets, secondary source materials such as books and journals, and legal documents. The START team integrated and synthesized data collected across the entire 1970?2015 time span with the goal of ensuring that the definitions and methodology are as consistent as possible.

The GTD defines a terrorist attack as the threatened or actual use of illegal force and violence by a non-state actor to attain a political, economic, religious, or social goal through fear, coercion, or intimidation. Therefore, for an attack to be included in the dataset it must be: (i) intentional, (ii) level of violence or immediate threat of violence, and (iii) be subnational actors Additionally, at least two of the following three criteria must be met: (a) the act must be aimed at attaining a political, economic, religious, or social goal, (b) There must be evidence of an intention to coerce, intimidate, or convey some other message to a larger audience than the immediate victims, and (c) the action must be outside the context of legitimate warfare activities.

From this database, we use the log average number of terror attacks for each country. Figure 8 plots the spatial distribution of log average terrorist attacks for each country from 1970 to 2015. Although we can see that there seem to clusters within continents, these clusters are pretty evenly distributed globally.

We also differentiate attacks between domestic and transnational (or international) terrorist attacks following the terrorism literature (Enders, Sandler, and Gaibulloev, 2011). Domestic terrorism is defined as an attack in which the venue, target, and perpetrators are all from the same country and should have effects only on the venue country. Since 1970, most terrorist attacks are domestic in nature and are related to mostly leftist guerillas fighting the governemnt (e.g., Shining Path in Peru, Naxalites in India). Through its victims, targets, supporters, or perpetrators, transnational terrorism concerns more than a single country (e.g., 9/11 hijackings). Although the total number of transnational attacks are since 1970 are smaller, they have grown in importance since 1990 are mostly related to jihadist ideology.

Figure 9 plots the spatial distribution of log average relative domestic terrorist attacks for each country from 1970 to 2015. We can see large concentrations of domestic attacks in the developing world (South America, Africa, and Asia). These attacks are related to the mostly communist-affiliated guerillas fighting against the ruling government. England however has experienced mostly transnational terrorist attacks.

Our main variable of interest is defined as the difference in log terrorist attacks between the target and the acquirer country $\Delta\tau = \tau_i - \tau_j$. The sign of $\Delta\tau$ allows for ordered comparison between the acquirer and the target. This variable can be thought of as the amount of terrorism of target country j relative to acquiring country i. For example, if Israel has $\tau = 4.5$ while Mexico has $\tau = 3.5$, then the difference is $\Delta\tau = \pm 1$. The difference will have a positive sign if Israel is the target while the sign will be negative if Mexico is the target. The sign captures if the target has more or less terrorism relative to the acquirer. We choose this variable definition because it succinctly allows us to test our prediction while allowing us to use an instrumental variable approach.[31]

We additionally consider several control variables that have been found to influence cross-border merger and acquisition flows. The economic size of the acquirer and target country are controlled for by using the log GDP; physical distance is controlled for using the log geodesic distance between the main cities of the acquirer and target country; we also included dummies to indicate if the countries share a border, if their official languages are the same, if the majority religion of both countries are the same, if both countries share a colonial link, if both countries share the same legal system; a categorical variable that is equal to zero if both countries have access to the sea, 1 if one country is landlocked, or 2 if both countries are landlocked. We also control for differences in the financial system that both countries have, differences in culture, and differences in the institutional quality of the government.

In Table 26, we present the summary statistics of the variables used in our analysis. After merging our acquisition database with the terrorism database, we are left with a (77×76) matrix of ordered country pairs (5,852). When we merge in our controls and instrumental variables, our sample drops to a (58×57) matrix of ordered country pairs (3,306). Table 27, we present the correlation matrix of our variables. We can see that there are large correlations between overall terrorism and domestic terrorism, showing that domestic terrorism makes up a larger proportion. Domestic terrorism is more correlated with smaller GDP relative to transnational terrorism. As expected, better financial systems are correlated to higher GDP. Finally, our instruments are also significantly correlated to total terrorism.

[31] As noted by Angrist and Pischke, models with multiple endogenous variables are difficult to identify and, even if identifiable with good instruments, difficult to interpret.

3.5 Results

3.5.1 Cross-sectional Results

Table 28 presents the results from naively estimating the projection of acquisition flows between the acquirer and target country on the relative difference in terrorism using OLS. The first column reveals that a one percent increase in terrorism in the acquiring country relative to the target country is associated with a 8.4 percentage decrease in acquisition flows between acquirer and target countries. As we supplement this univariate specification with control variables, we see that this result remains statistically significant and the economics significance becomes larger.

In Table 29, we present results when we use our instrument variables to control for possible endogeneity between acquisition flows and relative difference in terrorism and account for the multiplicative theoretical specification of the gravity equation. Again we show a consistently statistically significant and negative sign for our variable of interest. When we account for the correct model specification, we now see that we fail to reject the null that the instruments are valid.

In order to test the exclusion restriction more directly, we employ the following falsification strategy. The exlcusion restriction assumption states that the instruments do not have a first-order effect on acquisition flows. Therefore, we regress acquisition flows on the instrumental variables for a subsample where the difference in terrorism is relatively low. If the exclusion restriction doesn't hold, we would expect to see the instruments to influence the dependent variable. The results in Tables 30 and 31 provides evidence that there is no correlation between the instrumental variables and the dependent variable without being mediated by terrorism. This further evidence suggests that the plausability of our exclusion restriction when coupled with the J-test.

In sum, all the results in this section are in-line with the predictions from our theoretical model. Cross-border mergers and acquisitions are more likely to involve acquirers from countries with less terrorism relative to the target. The results also show that acquisitions are more likely to involve targets from countries with more terrorism relative to the target. This results are due to the symmetric impact that terrorism has on the acquisition costs: terrorism in the acquiring (target) country increasing (decreasing) acquisition costs.

3.5.2 Subsamples by Terrorism Type

Given evidence provided by the literature, there may be differential effects between domestic terror attacks (attacks perpetrated by domestic groups aimed at domestic targets for a domestic audience) and international terror attacks. Therefore we re-run our regressions on the difference in domestic and international attacks between acquirer and target countries.

Table 32 presents the results from naively estimating the projection of acquisition flows between the acquirer and target country on the relative difference in terrorism using OLS. The first column reveals that a one percent increase in terrorism in the acquiring country relative to the target country is associated with a 4 percentage decrease in acquisition flows between acquirer and target countries. As we supplement this univariate specification with control variables, we see that this result remains statistically significant and the economics significance becomes larger.

In Table 33, we present results when we use our instrument variables to control for possible endogeneity between acquisition flows and relative difference in terrorism and account for the multiplicative theoretical specification of the gravity equation. Again we show a consistently statistically significant and negative sign for our variable of interest. When we account for the correct model specification, we now see that we fail to reject the null that the instruments are valid.

Table 34 presents the results from naively estimating the projection of acquisition flows between the acquirer and target country on the relative difference in terrorism using OLS. The first column reveals that a one percent increase in terrorism in the acquiring country relative to the target country is associated with a 25 percentage decrease in acquisition flows between acquirer and target countries. As we supplement this univariate specification with control variables, we see that this result remains statistically significant and the economics significance becomes larger.

In Table 35, we present results when we use our instrument variables to control for possible endogeneity between acquisition flows and relative difference in terrorism and account for the multiplicative theoretical specification of the gravity equation. Again we show a consistently statistically significant and negative sign for our variable of interest.

Overall our results show that there is a consistently negative and significant sign for both domestic terrorism and international terrorism

3.6 Conclusion

The shocks of recent attacks have raised the specter of negative economic effects. Our essay studies the impact that terrorism has on cross-border merger and acquisition initiation. We develop a simple model to explain the equilibrium acquisition flows and generate predictions of the effect of terrorist attacks. Our model predicts that higher levels of terrorism in the acquirer (target) country are associated with smaller (larger) acquisition flows. To empirically test this prediction, we exploit the plausibly exogenous variation induced by ethnic and religious fractionalization and genetic diversity.

Our empirical results consistently show that a smaller the number of terrorist attacks in the acquirer relative to the target country, there are 9% more acquisition flows between the target and acquirer. Our robustness tests uphold the plausibility of the exclusion restriction. We also test the differential impact that domestic and transnational terrorism have on acquisition flows. Both have a negative and significant impact on acquisition flows. However, the economic significance is larger for transnational attacks relative to domestic terrorist attacks.

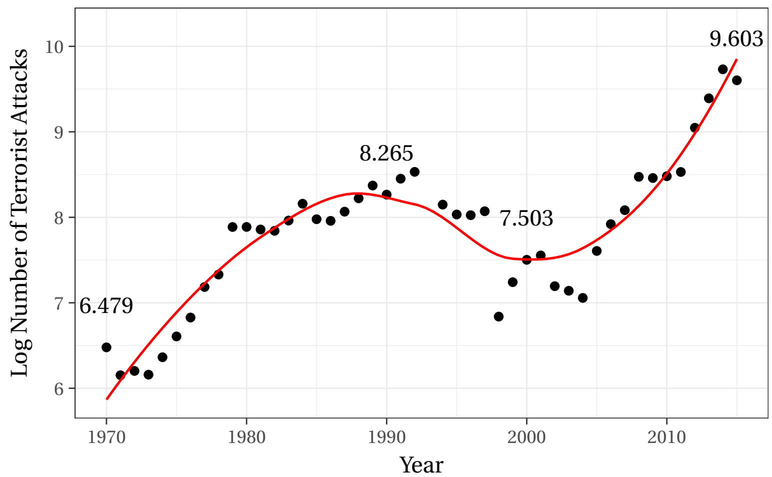

Figure 7: *Temporal Distribution of Total Terrorist Attacks.* This figure plots the natural log of the total number of terrorist attacks starting from 1970 until the end of 2015.

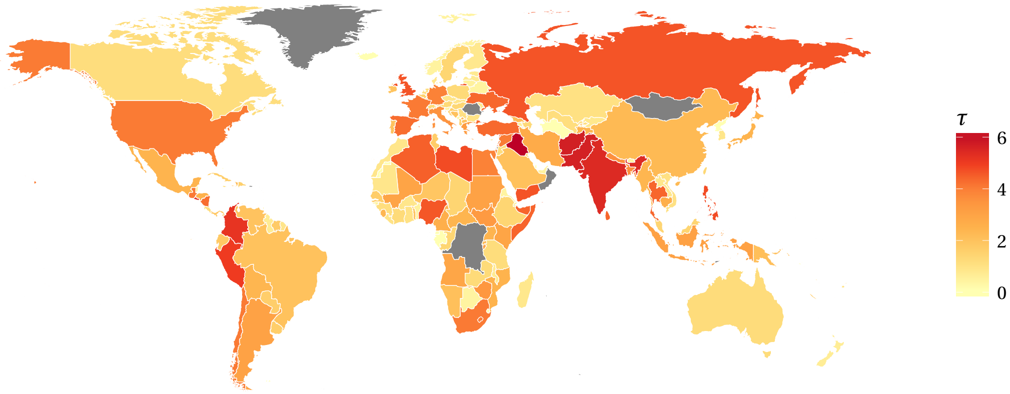

Figure 8: *Spatial Distribution of Terrorist Attacks.* The lines, or edges, between the country pairs are based on the number of completed acquisitions. The larger the width of the edge, the larger the total number of acquisitions between the countries and vice-versa. The size of the node of each country is based on a measure of importance known as *Authority*. The intensity of the color indicates the importance of the country to the overall network measured by the *Betweenness Centrality*. *Reads: The network of countries which complete cross-border acquisitions is dominated by a few 'countries.*

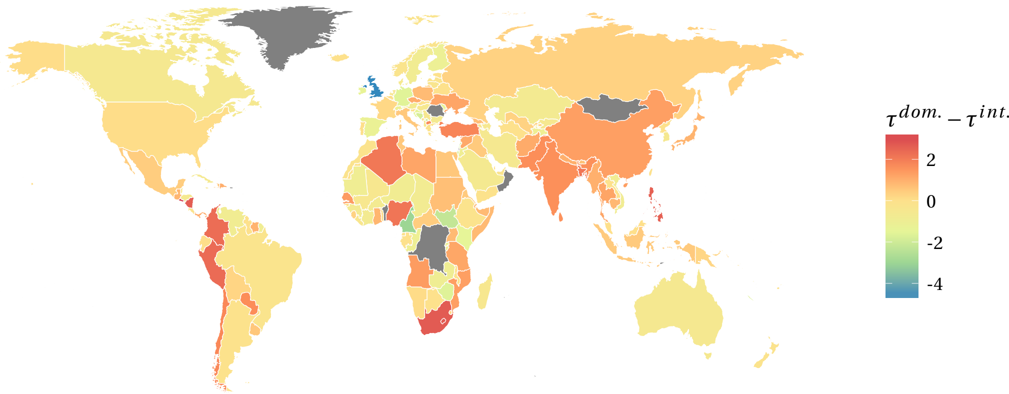

Figure 9: *Spatial Distribution of Differential Terrorist Attacks.* We graph difference between the log number of domestic terror attacks and the log number of transnational/international terror attacks.

Table 26: *Summary Statistics*

	Obs.	Mean	Std. Dev.	Min.	Max.
		Variables of Interest			
Initiation$_{ij}$	5,852	1.316	2.805	0.002	58.602
Terrorism$_{i-j}$	5,852	0.000	2.033	−5.051	5.051
		Instrumental Variables			
Ethnic Fract.$_{j-i}$	5,852	0.000	0.348	−0.847	0.847
Religious Fract.$_{j-i}$	5,852	0.000	0.339	−0.857	0.857
Genetic Dist.$_{j-i}$	5,700	0.000	0.118	−0.291	0.291
		Control Variables			
GDP$_{j-i}$	5,700	0.000	1.619	−4.819	4.819
Distance$_{j-i}$	5,852	8.681	0.888	4.394	9.892
Contiguity$_{j-i}$	5,852	0.026	0.158	0.000	1.000
Language$_{j-i}$	5,852	0.128	0.334	0.000	1.000
Colonial$_{j-i}$	5,852	0.022	0.146	0.000	1.000
Landlocked$_{j-i}$	5,852	0.182	0.404	0.000	2.000
Legal System$_{j-i}$	5,852	0.706	0.456	0.000	1.000
Financial System$_{j-i}$	4,290	0.000	1.823	−5.950	5.950
Religion$_{j-i}$	5,852	0.444	0.497	0.000	1.000
Culture$_{j-i}$	4,032	2.003	1.146	0.071	7.362
Institutions$_{j-i}$	5,852	1.960	1.976	0.000	11.910

NOTES — This table presents the summary statistics of the data used in our regression analysis. Our data set is composed of matrices of $(77 \times 76 = 5,852)$ ordered country pairs. Our sample drops to a low of $(58 \times 57 = 3,306)$ in some regressions because of limited data for the control variables and instrumental variables.

Table 27: Correlation Table

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1)	1.000																	
(2)	−0.035*	1.000																
(3)	−0.046*	0.946*	1.000															
(4)	0.023	0.791*	0.683*	1.000														
(5)	−0.061*	0.148*	0.212*	−0.008	1.000													
(6)	0.066*	−0.123*	−0.128*	−0.066*	0.232*	1.000												
(7)	0.036*	−0.246*	−0.268*	−0.109*	−0.100*	−0.008	1.000											
(8)	0.155*	−0.350*	−0.407*	−0.112*	−0.510*	−0.031	−0.080*	1.000										
(9)	−0.280*	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000									
(10)	0.315*	0.000	0.000	0.000	0.000	0.000	0.000	0.000	−0.404*	1.000								
(11)	0.213*	0.000	0.000	0.000	0.000	0.000	0.000	0.000	−0.057*	0.163*	1.000							
(12)	0.156*	0.000	0.000	0.000	0.000	0.000	0.000	0.000	−0.073*	0.116*	0.146*	1.000						
(13)	0.010	0.000	0.000	0.000	0.000	0.000	0.000	0.000	−0.216*	0.075*	−0.006	−0.004	1.000					
(14)	−0.108*	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.084*	−0.143*	−0.352*	−0.095*	0.108*	1.000				
(15)	0.183*	−0.230*	−0.309*	−0.047*	−0.260*	0.102*	0.063*	0.646*	0.000	0.000	0.000	0.000	0.000	0.000	1.000			
(16)	−0.139*	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.224*	−0.112*	−0.020	−0.069*	−0.157*	0.004	0.000	1.000		
(17)	−0.152*	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.205*	−0.154*	−0.148*	−0.050*	−0.027	0.237*	0.000	0.083*	1.000	
(18)	−0.119*	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.189*	−0.115*	−0.017	−0.007	0.007	0.068*	0.000	−0.041*	0.379*	1.000

(1)	Initiation_{ij}	(10)	Contiguity_{j-i}
(2)	Terrorism_{i-j}	(11)	Language_{j-i}
(3)	$\text{Domestic Terrorism}_{i-j}$	(12)	Colonial_{j-i}
(4)	$\text{International Terrorism}_{i-j}$	(13)	Landlocked_{j-i}
(5)	$\text{Ethnic Fract.}_{j-i}$	(14)	$\text{Legal System}_{j-i}$
(6)	$\text{Religious Fract.}_{j-i}$	(15)	$\text{Financial System}_{j-i}$
(7)	$\text{Genetic Dist.}_{j-i}$	(16)	Religion_{j-i}
(8)	GDP_{j-i}	(17)	Culture_{j-i}
(9)	Distance_{j-i}	(18)	$\text{Institutions}_{j-i}$

This table presents the correlation matrix between our dependent and independent variables of interest. Significance at 5% is denoted by (*).

Table 28: *Cross-sectional Relationship between Initiations and Terrorism: OLS*

	(1)	(2)	(3)	(4)
Terrorism_{i-j}	−0.084***	−0.125***	−0.125***	−0.140***
	(0.013)	(0.013)	(0.015)	(0.018)
GDP_i		−0.970***	−0.460***	−0.438***
		(0.092)	(0.070)	(0.075)
GDP_j		−0.141***	−0.076*	−0.032
		(0.026)	(0.042)	(0.050)
Distance_{j-i}		0.367***	0.421***	0.514***
		(0.034)	(0.046)	(0.056)
Contiguity_{j-i}			6.169***	6.643***
			(0.895)	(0.989)
Language_{j-i}			1.099***	1.462***
			(0.263)	(0.344)
Colonial_{j-i}			0.646	0.647
			(0.708)	(0.776)
Landlocked_{j-i}			−0.564***	−0.694***
			(0.107)	(0.127)
$\text{Legal System}_{j-i}$			−0.477***	−0.409***
			(0.106)	(0.124)
$\text{Financial System}_{j-i}$			−0.032	−0.026
			(0.022)	(0.025)
Religion_{j-i}			−0.194**	−0.086
			(0.081)	(0.091)
Culture_{j-i}				−0.319***
				(0.052)
$\text{Institutions}_{j-i}$				−0.002
				(0.022)
Constant	1.316***	7.704***	2.362**	1.495
	(0.044)	(0.919)	(1.029)	(1.136)
Obs.	5,852	5,700	4,290	3,306
adj. R^2	0.004	0.131	0.275	0.317

Notes — This table presents the results from OLS estimations of the relationship between initiation flows and the difference between acquiror and target countries in terrorism. Heteroskedasticity-robust t-statistics clustered on the acquirer-target pair are reported in parentheses. The symbols *, **, and *** are used to indicate significance at the 10%, 5%, and 1% level, respectively.

Cross-sectional Relationship between Initiations and Terrorism: PPML
Table 29:]

	(1)	(2)	(3)	(4)
Terrorism_{i-j}	−0.390***	−0.245***	−0.111***	−0.092***
	(0.074)	(0.038)	(0.016)	(0.013)
GDP_i		−0.203***	−0.124***	−0.080***
		(0.013)	(0.015)	(0.015)
GDP_j		0.250***	0.251***	0.291***
		(0.013)	(0.012)	(0.012)
Distance_{j-i}		0.200***	0.262***	0.287***
		(0.013)	(0.012)	(0.012)
Contiguity_{j-i}			0.480***	0.466***
			(0.066)	(0.065)
Language_{j-i}			0.425***	0.475***
			(0.043)	(0.047)
Colonial_{j-i}			0.331***	0.294***
			(0.090)	(0.080)
Landlocked_{j-i}			−0.130***	−0.154***
			(0.028)	(0.029)
$\text{Legal System}_{j-i}$			−0.067**	−0.030
			(0.031)	(0.034)
$\text{Financial System}_{j-i}$			0.061***	0.064***
			(0.006)	(0.006)
Religion_{j-i}			0.048*	0.111***
			(0.026)	(0.029)
Culture_{j-i}				−0.110***
				(0.013)
$\text{Institutions}_{j-i}$				−0.005
				(0.007)
Constant	0.664***	−1.907***	−3.317***	−4.070***
	(0.115)	(0.214)	(0.218)	(0.223)
Obs.	5,700	5,700	4,290	3,306
Pseudo-R^2	0.000	0.161	0.327	0.373
J-stat p-value	0.265	0.671	0.405	0.128

NOTES — This table presents the results from Poisson pseudo-maximum liklihood (PPML) regressions of the multiplicative relationship between initiation flows and the difference between acquiror and target countries in terrorism. To address endogeneity concerns, we instrument the difference in terrorism using the difference in the index of ethnic fractionalization, religious fractionalization, and genetic distence. The Sargen-Hansen J-test of overidentifying restrictions assesses the joint null hypothesis that the instruments are valid, or uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation. Under the null, the test statistic is distributed as chi-squared (χ^2) in the number of overidentifying restrictions. A rejection casts doubt on the validity of the instruments. Heteroskedasticity-robust t-statistics clustered on the target country are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 30: *Falsification Test of the Exclusion Restriction: OLS Regressions*

	(1)	(2)	(3)	(4)
Ethnic Fract.$_{j-i}$	0.685***	0.093	0.058	0.074
	(0.246)	(0.275)	(0.318)	(0.359)
Religious Fract.$_{j-i}$	−0.654***	−0.664***	−0.584**	−0.552*
	(0.241)	(0.229)	(0.259)	(0.288)
Genetic Dist.$_{j-i}$	1.231*	0.975	1.874**	2.056*
	(0.725)	(0.689)	(0.893)	(1.224)
Distance$_{j-i}$		−0.866***	−0.505***	−0.519***
		(0.075)	(0.096)	(0.104)
GDP$_i$		−0.150**	−0.058	−0.033
		(0.073)	(0.104)	(0.118)
GDP$_j$		0.296***	0.392***	0.386***
		(0.073)	(0.104)	(0.118)
Contiguity$_{j-i}$			4.409***	4.896***
			(0.551)	(0.589)
Language$_{j-i}$			0.901***	0.696**
			(0.285)	(0.315)
Colonial$_{j-i}$			2.468***	2.249***
			(0.697)	(0.696)
Landlocked$_{j-i}$			−0.588***	−0.713***
			(0.180)	(0.194)
Legal System$_{j-i}$			−1.075***	−1.009***
			(0.220)	(0.249)
Financial System$_{j-i}$			0.017	0.032
			(0.058)	(0.062)
Religion$_{j-i}$			−0.358*	−0.291
			(0.188)	(0.222)
Culture$_{j-i}$				−0.394***
				(0.105)
Institutions$_{j-i}$				−0.049
				(0.065)
Constant	1.367***	7.394***	3.397**	4.192**
	(0.079)	(1.220)	(1.504)	(1.636)
Obs.	1,468	1,468	1,128	888
adj. R^2	0.008	0.110	0.218	0.274

Notes — This table presents the results from OLS estimations of the relationship between initiation flows and our instruments for a subsample that has low differences in terrorism between the acquirer and target countries. If the instruments have a first-order effect on our dependent variable and hence violate the exclusion restriction, then the coefficients should significant. The instruments are the difference in terrorism using the difference in the index of ethnic fractionalization, religious fractionalization, and genetic distance. Heteroskedasticity-robust t-statistics clustered on the acquirer-target pair are reported in parentheses. The symbols *, **, and *** are used to indicate significance at the 10%, 5%, and 1% level, respectively.

Table 31: *Falsification Test of the Exclusion Restriction: PPML Regressions*

	(1)	(2)	(3)	(4)
Ethnic Fract.$_{j-i}$	−0.141*	0.056	0.042	0.033
	(0.075)	(0.063)	(0.067)	(0.070)
Religious Fract.$_{j-i}$	0.096	0.132***	0.084*	0.088
	(0.071)	(0.049)	(0.051)	(0.055)
Genetic Dist.$_{j-i}$	0.035	0.241	0.170	0.370
	(0.232)	(0.152)	(0.170)	(0.232)
Distance$_{j-i}$		−0.163***	−0.080***	−0.046**
		(0.015)	(0.019)	(0.019)
GDP$_i$		0.334***	0.317***	0.339***
		(0.014)	(0.018)	(0.019)
GDP$_j$		0.152***	0.217***	0.222***
		(0.015)	(0.018)	(0.020)
Contiguity$_{j-i}$			0.428***	0.439***
			(0.081)	(0.071)
Language$_{j-i}$			0.288***	0.260***
			(0.054)	(0.057)
Colonial$_{j-i}$			0.575***	0.477***
			(0.121)	(0.108)
Landlocked$_{j-i}$			−0.077**	−0.078**
			(0.031)	(0.033)
Legal System$_{j-i}$			−0.175***	−0.161***
			(0.048)	(0.054)
Financial System$_{j-i}$			0.059***	0.064***
			(0.011)	(0.012)
Religion$_{j-i}$			−0.090**	−0.060
			(0.038)	(0.044)
Culture$_{j-i}$				−0.075***
				(0.019)
Institutions$_{j-i}$				−0.024**
				(0.012)
Constant	0.391***	−2.796***	−3.836***	−4.147***
	(0.024)	(0.241)	(0.273)	(0.278)
Obs.	1,468	1,468	1,128	888
Pseudo-R^2	0.003	0.394	0.447	0.473

Notes — This table presents the results from Poisson pseudo-maximum liklihood (PPML) regressions of the multiplicative relationship between initiation flows and our instruments for a subsample that has low differences in terrorism between the acquirer and target countries. If the instruments have a first-order effect on our dependent variable and hence violate the exclusion restriction, then the coefficients should significant. The instruments are the difference in terrorism using the difference in the index of ethnic fractionalization, religious fractionalization, and genetic distance. Heteroskedasticity-robust t-statistics clustered on the target country are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 32: *Domestic Terrorism Subsample: OLS*

	(1)	(2)	(3)	(4)
Domestic Terr.$_{i-j}$	0.008	−0.018***	−0.035***	−0.038***
	(0.005)	(0.005)	(0.006)	(0.007)
GDP$_i$		−0.970***	−0.460***	−0.438***
		(0.092)	(0.070)	(0.075)
GDP$_j$		−0.128***	−0.062	−0.012
		(0.027)	(0.045)	(0.053)
Distance$_{j-i}$		0.354***	0.408***	0.494***
		(0.033)	(0.045)	(0.053)
Contiguity$_{j-i}$			6.169***	6.643***
			(0.895)	(0.989)
Language$_{j-i}$			1.099***	1.462***
			(0.263)	(0.344)
Colonial$_{j-i}$			0.646	0.647
			(0.708)	(0.776)
Landlocked$_{j-i}$			−0.564***	−0.694***
			(0.107)	(0.127)
Legal System$_{j-i}$			−0.477***	−0.409***
			(0.106)	(0.124)
Financial System$_{j-i}$			−0.042*	−0.034
			(0.022)	(0.025)
Religion$_{j-i}$			−0.194**	−0.086
			(0.081)	(0.091)
Culture$_{j-i}$				−0.319***
				(0.052)
Institutions$_{j-i}$				−0.002
				(0.022)
Constant	1.316***	7.704***	2.362**	1.495
	(0.044)	(0.919)	(1.029)	(1.136)
Obs.	5,852	5,700	4,290	3,306
adj. R^2	0.000	0.125	0.271	0.314

NOTES — This table presents the results from OLS estimations of the relationship between initiation flows and the difference between acquiror and target countries in domestic terrorism. Heteroskedasticity-robust t-statistics clustered on the acquirer-target pair are reported in parentheses. The symbols *, **, and *** are used to indicate significance at the 10%, 5%, and 1% level, respectively.

Table 33: *Domestic Terrorism Subsample: PPML Regressions*

	(1)	(2)	(3)	(4)
Domestic Terr.$_{i-j}$	−0.038***	−0.031***	−0.029***	−0.033***
	(0.003)	(0.003)	(0.005)	(0.005)
GDP$_i$		−0.204***	−0.128***	−0.086***
		(0.012)	(0.015)	(0.015)
GDP$_j$		0.271***	0.263***	0.293***
		(0.008)	(0.010)	(0.011)
Distance$_{j-i}$		0.193***	0.257***	0.290***
		(0.009)	(0.011)	(0.013)
Contiguity$_{j-i}$			0.458***	0.449***
			(0.066)	(0.066)
Language$_{j-i}$			0.427***	0.474***
			(0.042)	(0.046)
Colonial$_{j-i}$			0.341***	0.305***
			(0.090)	(0.080)
Landlocked$_{j-i}$			−0.123***	−0.147***
			(0.027)	(0.028)
Legal System$_{j-i}$			−0.072**	−0.028
			(0.030)	(0.034)
Financial System$_{j-i}$			0.061***	0.064***
			(0.006)	(0.007)
Religion$_{j-i}$			0.061**	0.121***
			(0.026)	(0.029)
Culture$_{j-i}$				−0.108***
				(0.013)
Institutions$_{j-i}$				−0.006
				(0.007)
Constant	0.382***	−2.146***	−3.357***	−4.080***
	(0.017)	(0.182)	(0.214)	(0.221)
Obs.	5,700	5,700	4,290	3,306
Pseudo-R^2	0.001	0.307	0.343	0.365
J-stat p-value	0.000	0.000	0.000	0.000

Notes — This table presents the results from Poisson pseudo-maximum liklihood (PPML) regressions of the multiplicative relationship between initiation flows and the difference between acquiror and target countries in domestic terrorism. To address endogeneity concerns, we instrument the difference in terrorism using the difference in the index of ethnic fractionalization, religious fractionalization, and genetic distence. The Sargen-Hansen J-test of overidentifying restrictions assesses the joint null hypothesis that the instruments are valid, or uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation. Under the null, the test statistic is distributed as chi-squared (χ^2) in the number of overidentifying restrictions. A rejection casts doubt on the validity of the instruments. Heteroskedasticity-robust t-statistics clustered on the target country are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 34: *International Terrorism Subsample: OLS*

	(1)	(2)	(3)	(4)
Int. Terrorism$_{i-j}$	-0.138^{***}	-0.117^{***}	-0.197^{***}	-0.249^{***}
	(0.014)	(0.014)	(0.024)	(0.030)
GDP$_i$		-0.970^{***}	-0.460^{***}	-0.438^{***}
		(0.092)	(0.070)	(0.075)
GDP$_j$		-0.090^{***}	-0.051	0.004
		(0.028)	(0.044)	(0.052)
Distance$_{j-i}$		0.316^{***}	0.396^{***}	0.478^{***}
		(0.031)	(0.045)	(0.054)
Contiguity$_{j-i}$			6.169^{***}	6.643^{***}
			(0.895)	(0.989)
Language$_{j-i}$			1.099^{***}	1.462^{***}
			(0.263)	(0.344)
Colonial$_{j-i}$			0.646	0.647
			(0.708)	(0.776)
Landlocked$_{j-i}$			-0.564^{***}	-0.694^{***}
			(0.107)	(0.127)
Legal System$_{j-i}$			-0.477^{***}	-0.409^{***}
			(0.106)	(0.124)
Financial System$_{j-i}$			-0.025	-0.021
			(0.021)	(0.024)
Religion$_{j-i}$			-0.194^{**}	-0.086
			(0.081)	(0.091)
Culture$_{j-i}$				-0.319^{***}
				(0.052)
Institutions$_{j-i}$				-0.002
				(0.022)
Constant	1.316^{***}	7.704^{***}	2.362^{**}	1.495
	(0.044)	(0.919)	(1.029)	(1.136)
Obs.	5,852	5,700	4,290	3,306
adj. R^2	0.010	0.131	0.278	0.323

Notes — This table presents the results from OLS estimations of the relationship between initiation flows and the difference between acquiror and target countries in international terrorism. Heteroskedasticity-robust t-statistics clustered on the acquirer-target pair are reported in parentheses. The symbols *, **, and *** are used to indicate significance at the 10%, 5%, and 1% level, respectively.

Table 35: *International Terrorism Subsample: PPML*

	(1)	(2)	(3)	(4)
Int. Terrorism$_{i-j}$	−0.038***	−0.031***	−0.029***	−0.033***
	(0.003)	(0.003)	(0.005)	(0.005)
GDP$_i$		−0.204***	−0.128***	−0.086***
		(0.012)	(0.015)	(0.015)
GDP$_j$		0.271***	0.263***	0.293***
		(0.008)	(0.010)	(0.011)
Distance$_{j-i}$		0.193***	0.257***	0.290***
		(0.009)	(0.011)	(0.013)
Contiguity$_{j-i}$			0.458***	0.449***
			(0.066)	(0.066)
Language$_{j-i}$			0.427***	0.474***
			(0.042)	(0.046)
Colonial$_{j-i}$			0.341***	0.305***
			(0.090)	(0.080)
Landlocked$_{j-i}$			−0.123***	−0.147***
			(0.027)	(0.028)
Legal System$_{j-i}$			−0.072**	−0.028
			(0.030)	(0.034)
Financial System$_{j-i}$			0.061***	0.064***
			(0.006)	(0.007)
Religion$_{j-i}$			0.061**	0.121***
			(0.026)	(0.029)
Culture$_{j-i}$				−0.108***
				(0.013)
Institutions$_{j-i}$				−0.006
				(0.007)
Constant	0.382***	−2.146***	−3.357***	−4.080***
	(0.017)	(0.182)	(0.214)	(0.221)
Obs.	5,700	5,700	4,290	3,306
Pseudo-R^2	0.001	0.307	0.343	0.365
J-stat p-value	0.000	0.000	0.000	0.000

Notes — This table presents the results from Poisson pseudo-maximum liklihood (ppml) regressions of the multiplicative relationship between initiation flows and the difference between acquiror and target countries in international terrorism. To address endogeneity concerns, we instrument the difference in terrorism using the difference in the index of ethnic fractionalization, religious fractionalization, and genetic distance. The Sargen-Hansen J-test of overidentifying restrictions assesses the joint null hypothesis that the instruments are valid, or uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation. Under the null, the test statistic is distributed as chi-squared (χ^2) in the number of overidentifying restrictions. A rejection casts doubt on the validity of the instruments. Heteroskedasticity-robust t-statistics clustered on the target country are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

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