Echoes of Discord: The Effects of Global Conflicts and Disputes on Entrepreneurship

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Appendix
(for online publication)

A - Sample Construction and Generalizability

Sample Construction

The estimation sample is built from the population of multi-founder firms incorporated in Great Britain in which at least one founder is a non-UK national. I discard any firm that is dormant (i.e., not active) or that belongs to the public administration or extraterritorial organizations industries. For simplicity, firms with five or more founders (less than 6% of the sample) are also dropped. I assign each firm to a nationality dyad defined by the pair of nationalities represented on the founding team, then aggregate to a dyad $\times$ year panel.[22] I retain all nationality dyads that cofounded at least one business in Great Britain at any point during the panel window, as dyads with no entry contribute no identifying variation to the regression. This procedure yields 4,076 unique nationality dyads drawn from 192 distinct countries.

The panel is fully balanced: every dyad is observed for all 13 years from 2002 to 2014, with no missing year-observations. The outcome variable is the count of new cofounded firms in year $t+1$ (2003–2015); the one-year lead is constructed prior to panel assembly and does not create gaps.

Two exclusions are applied. First, I remove the (UK, UK) dyad capturing firms founded exclusively by British nationals. Second, I exclude dyads in which one country was ever in conflict with the United Kingdom during the period of analysis: specifically, the pairs (Argentina, UK), (Iran, UK), (Iraq, UK), (Libya, UK), (Russia, UK), (Spain, UK), and (Syria, UK). This exclusion is motivated by identification concerns: the UK's involvement in a conflict could affect the host-country entrepreneurial environment through domestic channels. However, including these dyads does not alter the main estimates.

Regarding the conflict variation underlying identification, 127 of the 4,076 dyads (3%) are ever exposed to conflict during the panel, accounting for 386 treated dyad-years (0.7% of all observations). Of these, 126 are *switcher dyads* that exhibit within-dyad variation in conflict status across years; only one dyad remains in conflict throughout the entire 13-year panel. Under pair fixed effects, identification of the conflict coefficient comes from these 126 switcher dyads, which contribute 1,638 dyad-years to the estimation (373 treated, 1,265 untreated). Among ever-conflict dyads, the median number of conflict years is 2 (mean: 3), and approximately 35% experience two or more distinct conflict spells.

[22] For firms with more than two founders spanning multiple nationality pairs, the firm is assigned to a pair in conflict at incorporation when one exists, and to one of its pairs otherwise. These cases represent less than 5% of the sample. For individuals with multiple nationalities, I retain the foreign nationality (if British dual citizen) or the first nationality specified if both nationalities are non-British.

Generalizability

With 192 unique countries in the data, there are 18,528 possible dyads. Of these, 4,076 (22.0%) are observed in the sample, having cofounded at least one business in Great Britain over the study period. The remaining 78% of potential pairs, predominantly involving smaller diasporas or more geographically and institutionally distant country combinations, never cofound a business during the panel window and are thus not included.

Table A-19 shows the distribution of unique countries in the sample across continents. The composition broadly mirrors the distribution of the world's sovereign states across continents, of which Africa hosts the largest share (28%), followed by Asia (25%), Europe (23%), North America (12%), Oceania (7%), and South America (6%). This suggests that the sample provides geographically comprehensive coverage of the world's countries.

The picture changes when considering diaspora size rather than country count. Using migrant stocks in 2013 as a proxy for the entrepreneurially relevant population, the majority of the diaspora in the sample originates from Europe and Asia, which together account for over 70% of the migrant population in Great Britain. Africa and North America are represented to a lesser extent, while South America and Oceania account for relatively small shares. This distribution reflects the well-documented structure of migration into Great Britain, and contrasts with the composition of immigrant inflows in other major host economies. In the United States, for example, approximately 40% of new lawful permanent residents in 2013 originated from Asia and 32% from North America (chiefly Mexico), while Europe accounted for less than 10% of inflows.[23] Results should therefore be interpreted in light of the specific migration patterns characterizing Great Britain, and caution is warranted when generalizing to host countries with substantially different diaspora compositions.

Table A-20 reports coverage of the dyad sample relative to the universe of possible country pairs, broken down by continent pair. European dyads exhibit the highest cofounding rate: 66.5% of all possible Europe–Europe pairs are observed in the sample. South America–South America pairs follow at 37.4%, and Europe–Asia pairs at 37.2%. Coverage falls sharply for pairings involving smaller or more distant diasporas: Africa–South America (3.6%), Africa–Oceania (5.7%), and Africa–North America (7.2%) pairs are rarely observed. These patterns are consistent with the geographic and institutional proximity of European and Asian countries to Great Britain, as well as the larger and more entrepreneurially active diasporas they supply.

[23] Source: U.S. Department of Homeland Security, Yearbook of Immigration Statistics 2013.

B - Creation of Social Media Embeddings

To create an alternative measure of mistrust that can also capture the bilateral nature of this concept, I leverage social media posts, and specifically, the text of posts from X hosted on the Internet Archive, from 2011 to 2015 (Bruns & Weller, 2016). Posts are aggregated by month and year, representing approximately a 1% sample of the total number of posts. In total, this sample includes more than 5.5 billion posts. These were created by users from all over the world and are thus multilingual. To focus on posts that might provide insights into international relations and sentiments, a comprehensive list of all country names (206 states) and their variations in 35 different languages was compiled. Using this list, I filtered the posts mentioning at least one country or its citizens, which resulted in roughly 16 million posts.

The next step was to determine the geographic location where the posts were sent from. The posts' origin was determined using user profile location, timezone information, and available latitude and longitude coordinates. Using these variables, approximately 11 million posts can be geolocated. For each post, information is available on which country the post originated from, as well as which country is mentioned. A basic text-cleaning process was performed on the posts to remove noise and ensure that the text was in a suitable format for further analysis. This process included removing special characters, URLs, and other non-informative elements from the post text.

Posts mentioning country names are often about topics that could introduce noise into the analysis. For instance, posts on travel or sporting events such as the World Cup or the Olympics frequently include country names. To filter out irrelevant posts, I use a RoBERTa-based model trained on 124 million posts to assign a prevailing topic to each post. RoBERTa is an enhanced version of BERT that improves performance through a more effective training strategy, including larger batch sizes, more training data and steps, dynamic masking, and the removal of the next sentence prediction task. I exclude posts labeled as pertaining to sports, travel, and celebrities.

Another challenge of the analysis is the multilingual nature of social media, which rendered most of the commonly used embedding models (e.g., Word2Vec, BERT, GloVe) unsuitable for the task. To tackle this obstacle, I leverage LASER (Language-Agnostic SEntence Representations) embedding models (Artetxe & Schwenk, 2019).[24] Unlike the other embedding models, LASER can create coherent, comparable embeddings for text in more than 90 languages, so that similar sentences in different languages will have similar embeddings.

[24] https://github.com/facebookresearch/LASER.

Once every social media post has been transformed into a comparable vector embedding using the procedure above, the next step is to compare each vector with another vector or dimension that captures trust. Following Kozlowski et al. (2019) and Giorcelli et al. (2022), I create a dimension specifically designed to capture the concept of trust. To construct this dimension, I specify a list of words that represent or "span" the trust dimension. This involves selecting pairs of antonyms that are closely related to trust, such as "trustworthy" and "untrustworthy" or "honest" and "dishonest."[25]

To create this dimension, I average the differences between the vectors for each antonym pair using the following formula: $\frac{\sum_{p \in P}(\bar{p}_2 - \bar{p}_1)}{|P|}$, where $\bar{p}_1$ and $\bar{p}_2$ are the vectors corresponding to each word in the antonym pair within the relevant set. Each antonym pair defines a unique dimension, and by averaging across all these pairs, an "average" dimension is formed that more accurately reflects the general concept of trust vs. mistrust.

With this constructed trust dimension, the next step is to compute the projection of the embedding vectors of social media posts involving two countries onto the dimension. In this way, one can assess the position of each post within the constructed trust dimension and also track how these positions evolve over time. Figure A-8 in the Appendix provides an oversimplified image of the dimension and an example vector. The projection scores were then aggregated to calculate average levels of trust for each country pair (originating and mentioned country) over time.[26] This measure captures the sentiment of individuals in all country combinations and how it evolved over the specified period. The variation of this measure over time reflects shifts in trust in the social discourse between each country, potentially influencing the behavior of migrants located in host countries, since they are likely to still be embedded in the social networks of their origin country. Because the primary interest lies in capturing mistrust, the resulting dummy variable captures an increase in the average projection score between each country from year $t-1$ to year t. In other words, the dummy takes the value one when the social media posts between two countries experience an increase in mistrust between years.

To assess whether the resulting measure captures something recognizably "trust-like," I correlate it with the bilateral trust measure from the 1995 Eurobarometer, the most recent year for which

[25] I employ the following list of pairs of antonyms related to trust: ("trust", "mistrust"), ("honesty", "dishonesty"), ("reliability", "unreliability"), ("dependability", "undependability"), ("integrity", "corruption"), ("credibility", "deceit"), ("loyalty", "betrayal"), ("authenticity", "fraudulence"), ("sincerity", "insincerity"), ("faith", "faithlessness"), ("accountability", "irresponsibility"), ("cooperation", "obstruction"), ("transparency", "opacity"), ("truthfulness", "falsehood"), and ("respect", "disrespect").

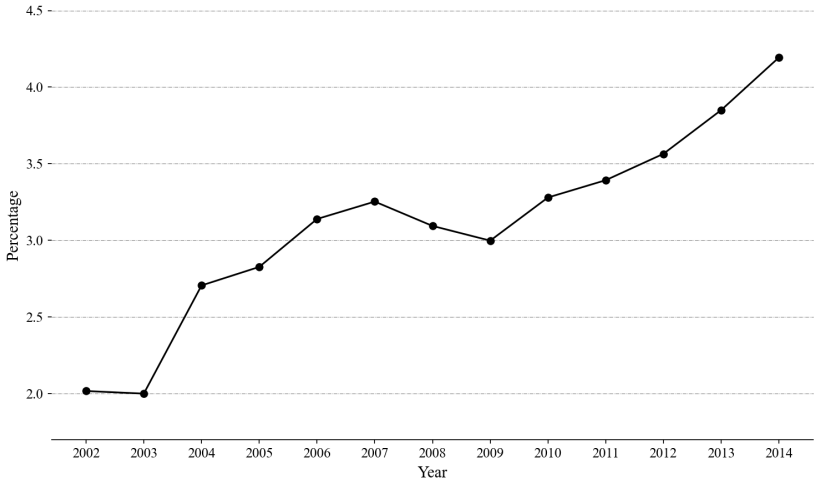
[26] To limit noise from sparsely covered pairs, I retain only country pairs with more than 10 posts in a given year.

dyadic trust data are available. The Eurobarometer measure is limited to 15 European countries, but, despite this and the temporal misalignment, the average mistrust score is negatively and significantly correlated with the Eurobarometer trust measure ($r = -0.24$, $p < 0.001$), consistent with the two measures capturing related underlying constructs. I additionally validate the measure by correlating it with established determinants of bilateral trust documented in Guiso et al. (2009), including religious proximity, log bilateral trade, and UN diplomatic disagreement, using variables from the CEPII Gravity Database. The patterns I recover are broadly consistent with their findings: religious proximity and log bilateral trade are negatively and significantly associated with the mistrust measure, while UN diplomatic disagreement is positively and significantly associated with it. Other variables such as geographic distance, contiguous borders, and common legal origin show no significant correlation, also in line with Guiso et al. (2009), where these variables tended to have limited explanatory power. Finally, I test for the well-documented "home bias" in trust, whereby individuals tend to trust their fellow citizens more than citizens of other countries. Consistent with this pattern, the mean mistrust score for same-country dyads is significantly lower than for cross-country dyads, indicating that countries exhibit less mistrust-like language when discussing themselves than when discussing other countries.[27]

[27] The full set of results from these additional validation exercises is available upon request.

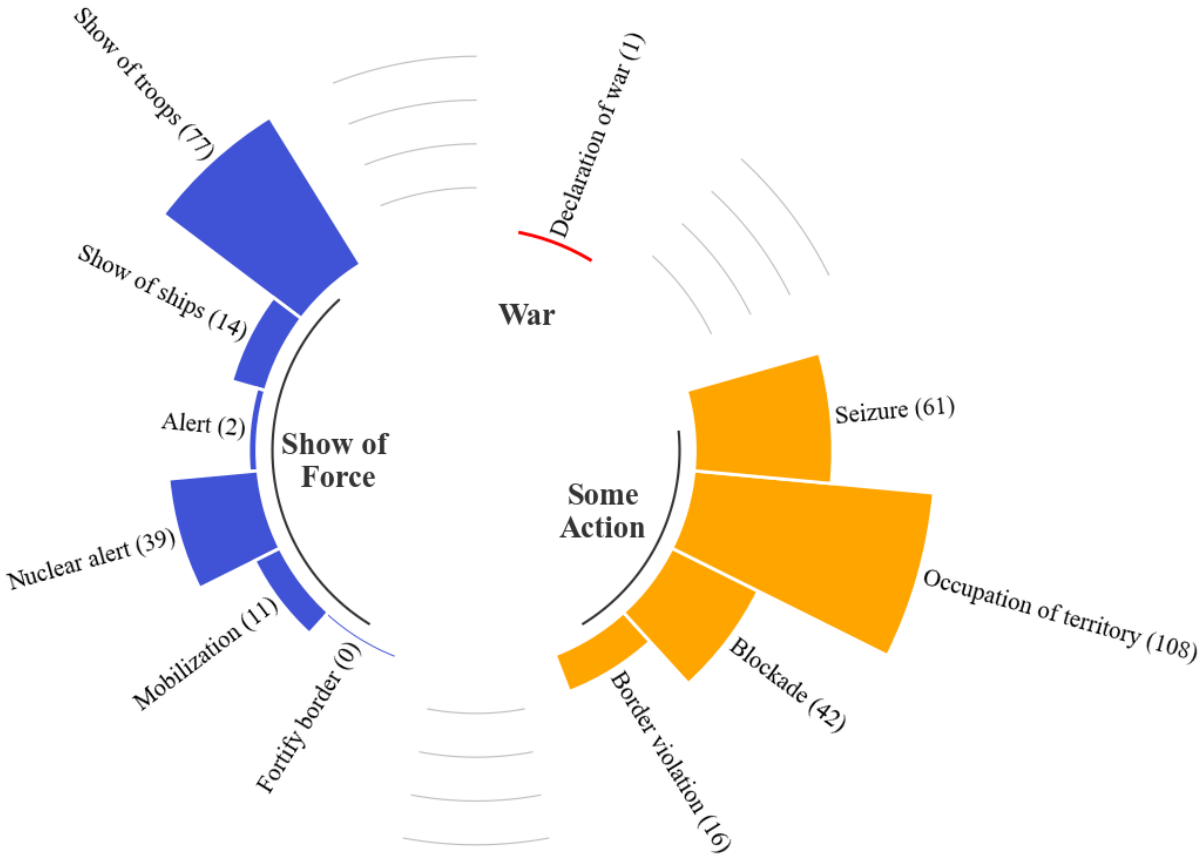
Appendix Figures and Tables

Figure A-1: Mixed-Nationality Teams



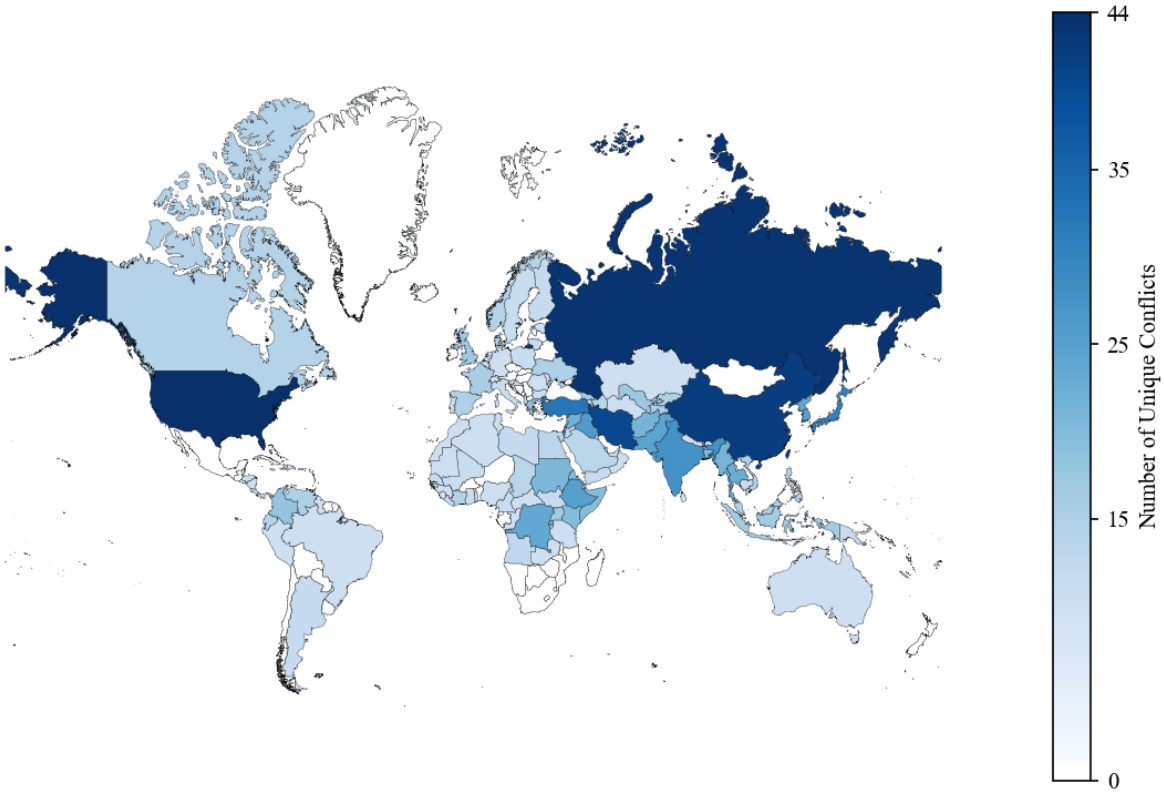
Notes: The figure shows the percentage of total companies in Great Britain founded each year by teams with mixed nationalities.

Figure A-2: Number of Conflicts by Type



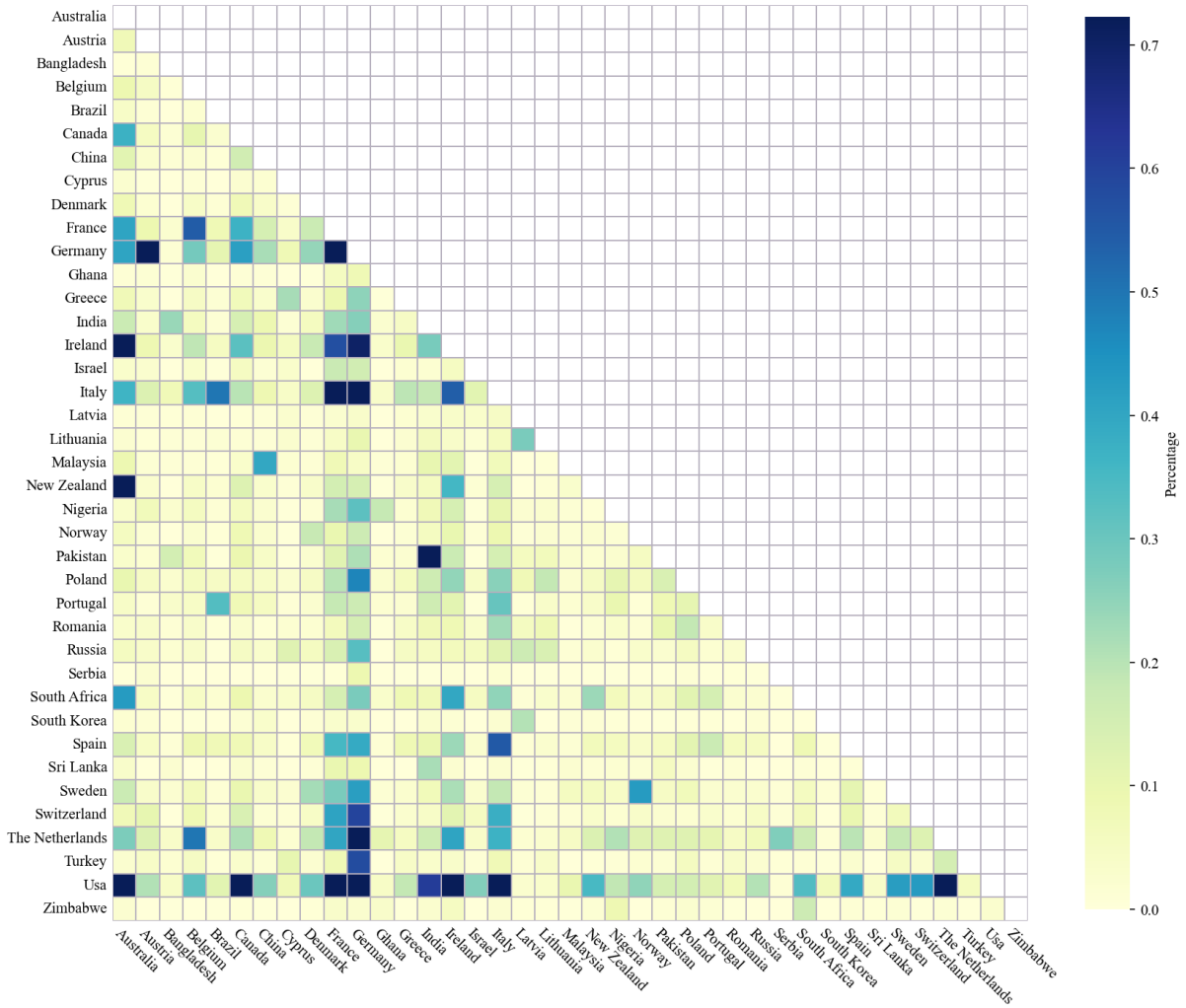
Notes: This figure shows the number of conflicts by type observed worldwide from 2002 to 2014.

Figure A-3: Number of Conflicts by Country



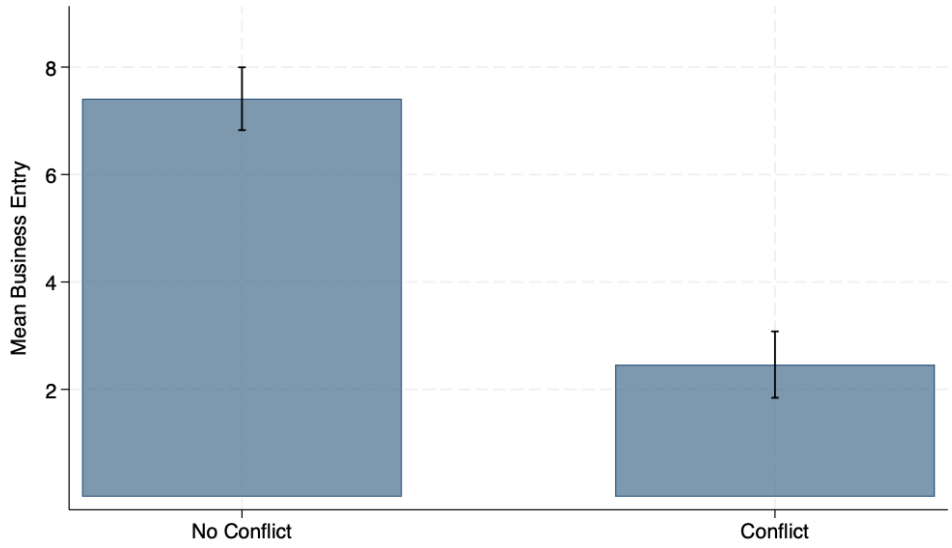
Notes: This figure shows the number of conflicts by country from 2002 to 2014.

Figure A-4: Founding Trends by Nationality Pairs



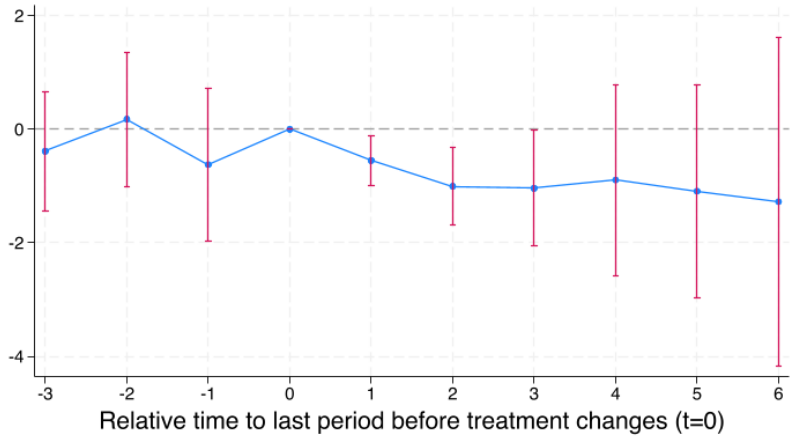
Notes: This figure represents the percentage of companies established by each nationality pair over the total number of companies established by different nationality pairs (of the countries included in the figure) for the 2002–2014 period. Pairs including the United Kingdom and same-nationality pairs have been excluded. For clarity and readability, only the 40 most represented nationalities are included in the figure.

Figure A-5: Average Business Entry in No-Conflict and Conflict Years



Notes: This figure shows the mean number of new mixed-nationality ventures per dyad-year, separately for dyad-years with and without active conflict.

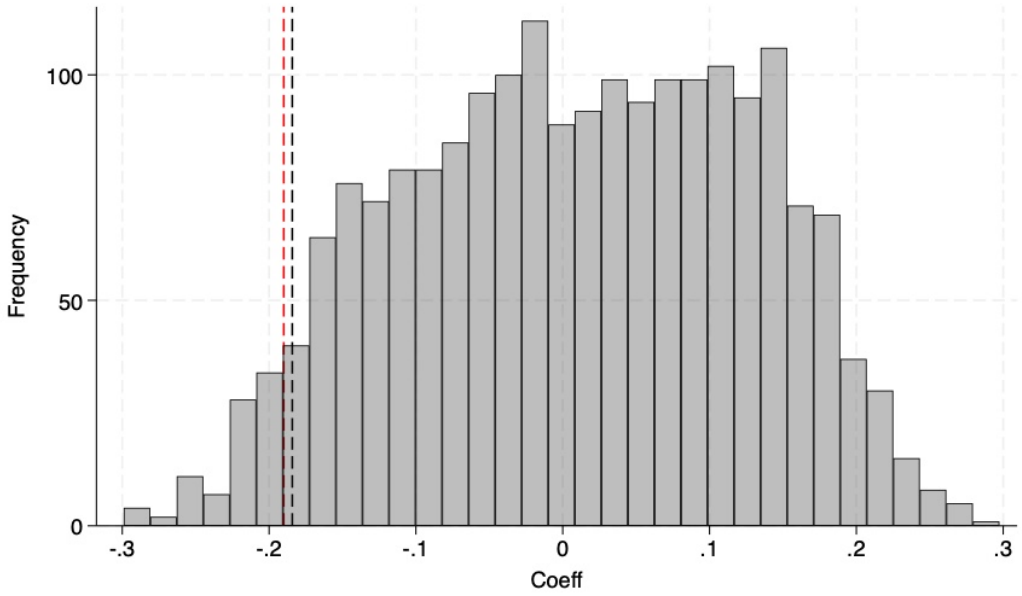
Figure A-6: Alternative Estimation Method for the FE Baseline Model (De Chaisemartin & d'Haultfoeuille, 2024)



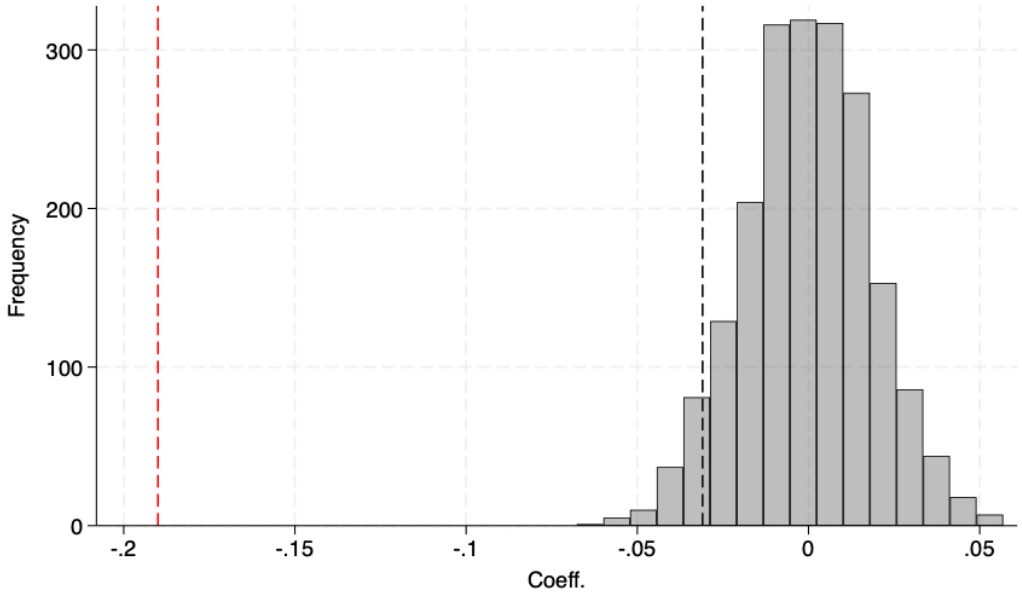
Notes: This figure plots event-time coefficients from the De Chaisemartin and d'Haultfoeuille (2024) estimator, in the balanced "same-switchers" specification, with $t-1$ as the omitted reference period. The x-axis denotes years relative to conflict onset and the y-axis the estimated effect on new mixed-nationality venture entry; bars are 90% confidence intervals.

Figure A-7: Placebo Tests

Panel A

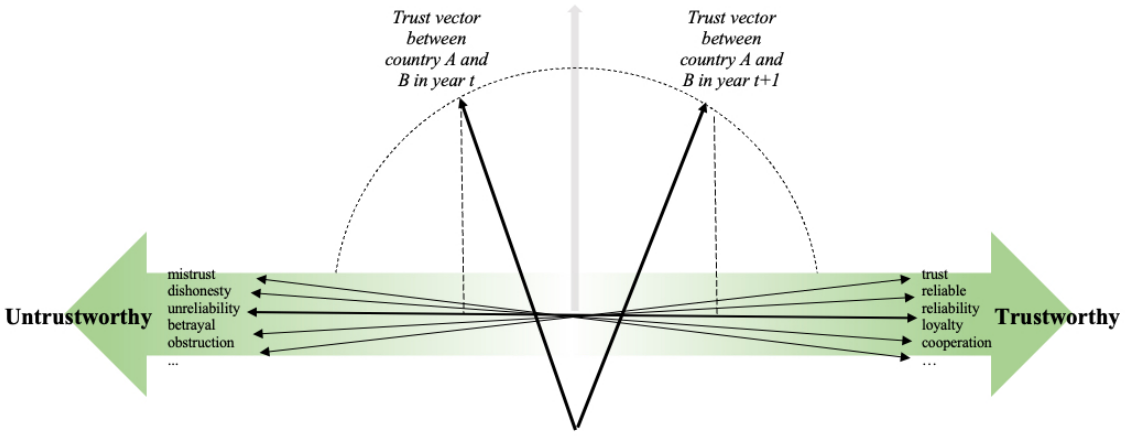


Panel B



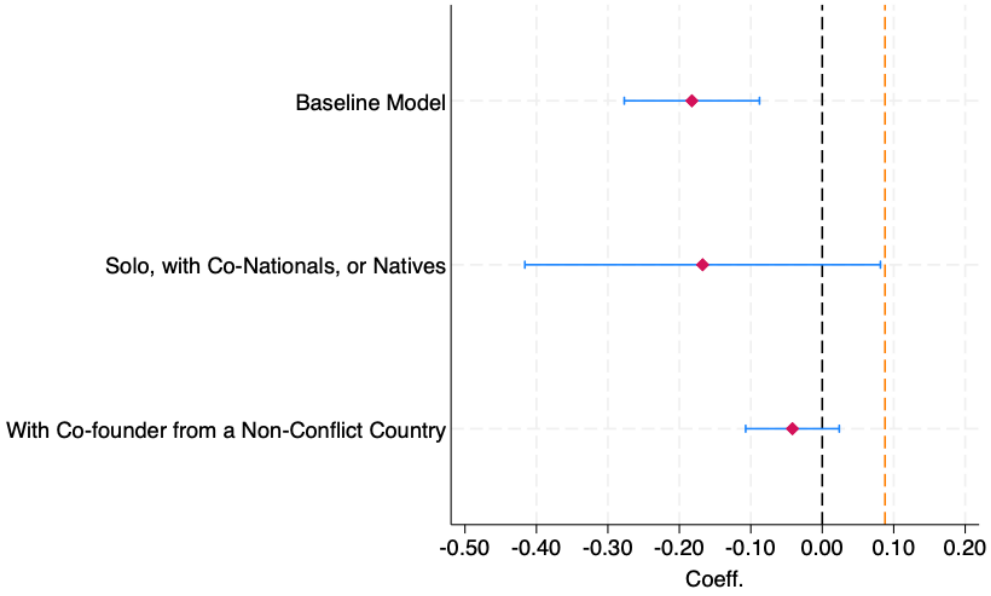
Notes: The placebo test in Panel A reassigns conflict spells of identical length to different years within the same dyads, preserving their incidence but shifting their timing to non-conflict periods; the distribution of coefficients from 2,000 such regressions shows the estimate (red line) lies past the 5th percentile (black line) in the extreme left tail. The placebo test in Panel B assigns an artificial number of conflict years to dyads that never experience conflict, drawing from the empirical distribution of treated dyads; the resulting coefficients are tightly centered on zero, with even the most negative coefficient well above the actual estimate (red line).

Figure A-8: The Embedding Dimension Capturing Trust



Notes: This figure shows the trust dimension and one hypothetical vector in time t and $t+1$ that averages the projection between the dimension and all the vectors related to country A and B (i.e., social posts in country A mentioning country B and vice versa).

Figure A-9: Change in Team Composition



Notes: This figure plots estimates from Poisson regressions where different types of entry are regressed on the usual dummy variable capturing conflict. The baseline model and the regression for ventures with cofounders from non-conflict countries are run at the country-pair-year level and include single countries × year, country-pair, and year fixed effects, with standard errors clustered at the country-pair level. The regression for ventures started solo, with co-nationals, or with natives is run at the nationality-year level and includes country and year fixed effects, with standard errors clustered at the country level. Bars are 90% confidence intervals. The orange dashed line marks the minimum increase in other types of entry that would be required to offset the baseline decline.

Table A-1: Descriptive Statistics

Country Pair–Year Level					
	Min.	Median	Mean	St.Dev.	Max.
Entry	0	0	7.38	68.16	3,311
Conflict	0	0	0.01	0.09	1
Past Conflicts	0	0	0.52	2.57	56
Stock of Firms	0	1	35.81	358.80	18,512
Observations	52,988				

Notes: This table shows basic descriptive statistics for the sample at the country-pair-year level.

Table A-2: Dynamic Effects and Buffer Window Robustness

	(1)	(2)
DV	Entry	Entry
Model	Distributed Lags	Buffer Window
Conflict (t)	-0.150**	-0.241***
	(0.070)	(0.063)
Conflict ($t-1$)	-0.119**	
	(0.055)	
Conflict ($t-2$)	-0.158*	
	(0.093)	
N	41,355	49,808

Notes: Column (1) reports estimates from a distributed-lag Poisson regression including the contemporaneous conflict indicator and two annual lags (t-1, t-2). Column (2) reports a robustness check that re-estimates the baseline specification after excluding control (untreated) country-pair-years that fall one to two years before conflict onset or one to two years after conflict termination. All regressions are estimated at the country-pair-year level using PPML and include country-pair fixed effects, and single-country $\times$ year fixed effects. All regressions also include controls for the stock of firms and past bilateral conflicts. Standard errors, reported in parentheses, are clustered at the country-pair level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-3: Robustness Checks

DV: Entry	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Exclude Top Litigious Countries	Exclude Iraq War	Exclude Multi-Country Conflicts	Exclude Top Immigrant Groups	Control for Inflow of Immigrants	Control for Stock of Immigrants	Control for Time-Varying Country Origin Features	Exclude London Area	Double-Clust. SE at Country Level
Conflict	-0.209**	-0.188***	-0.176**	-0.245***	-0.190***	-0.199***	-0.217**	-0.200***	-0.190***
	(0.104)	(0.058)	(0.075)	(0.071)	(0.058)	(0.069)	(0.103)	(0.049)	(0.057)
N	46,677	50,361	50,239	46,796	50,370	28,501	47,151	40,650	50,370

Notes: This table shows estimates from a Poisson regression where the number of new businesses is regressed on a dummy variable taking the value one if the country couple is in conflict in a given year or zero otherwise. Column (1) excludes from the analysis the countries involved in the most conflicts over the period (United States, Russia, and Iran). Column (2) excludes a major war present in the period, i.e., the Iraq war; column (3) excludes all multicountry conflicts (i.e., conflicts involving more than two parties). Column (4) excludes some major immigrant groups in Great Britain that have experienced repeated episodes of conflict, i.e., India, Pakistan, and Bangladesh; Columns (5) and (6) include the number of new immigrants (sum) of each nationality in each year, and the stock (sum) of residents of each nationality in each year, respectively. Column (7) includes a battery of time-varying controls at the country level, including population, unemployment rate, and net migration. Column (8) excludes all districts located in the London area. Column (9) double clusters standard errors at the single country level. All regressions are run at the country-pair-year level and include single countries × year, country-pair, and year fixed effects as well as controls for the stock of firms and past bilateral conflicts. Column (7) includes country-pair and year fixed effects only, as the country-level controls would be collinear with the single country × year fixed effects. Standard errors are in parentheses and are clustered at the country-pair level in all columns except column (9): * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-4: Conflicts and Immigration

DV:	(1) Inflow of Immigrants	(2) Stock of Immigrants
Conflict	0.003	0.003
	(0.016)	(0.004)
N	51,428	33,174

Notes: This table reports estimates from a Poisson regression in which the inflow of immigrants (Column 1) and the stock of immigrants (Column 2) are regressed on a dummy variable equal to one if the country pair is in conflict in a given year, and zero otherwise. The regression includes single countries × year, country-pair, and year fixed effects, as well as a control for past bilateral conflicts. Standard errors are in parentheses and are clustered at the country-pair level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-5: Robustness Check: Different Definitions of Conflicts

DV:	(1) Entry	(2) Entry
Conflict Definition	Type of Conflict	Worst Military Act
Var. Type	Continuous	Continuous
Conflict	-0.108***	-0.021**
	(0.039)	(0.009)
N	50,370	50,370

Notes: This table shows estimates from several Poisson regressions where the number of new businesses is regressed on different versions of variables capturing conflicts. The measure of conflict for column (1) is a continuous variable with values ranging from 0 (no conflict) to 2, taking into account the types of conflicts (i.e., no conflict, show of force, some action and wars). Column (2) uses a continuous variable with more detailed sub-types ranging from 0 (no conflict) to 14, capturing the worst military act that happened during the conflict (e.g., blockade, clash, use of chemical weapon). All regressions control for the stock of firms and past bilateral conflicts. All regressions are run at the country-pair-year level and include single countries × year, country-pair, and year fixed effects. Standard errors are in parentheses and are clustered at the country-pair level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-6: Robustness Check: Minimum Number of Businesses per Dyad

DV:	(1) Entry	(2) Entry	(3) Entry	(4) Entry	(5) Entry
Min. Businesses	Baseline	≥ 5	≥ 10	≥ 15	≥ 20
Conflict	-0.190***	-0.177***	-0.151***	-0.174***	-0.152***
	(0.058)	(0.057)	(0.054)	(0.061)	(0.057)
N	50,370	18,833	11,951	9,106	7,490

Notes: This table shows estimates from Poisson regressions where the number of new businesses is regressed on a dummy variable taking the value one if the country couple is in conflict in a given year or zero otherwise. Each column restricts the sample to dyads with at least the indicated minimum number of businesses created over the full sample period. Column (1) shows the baseline specification with no restriction. All regressions control for the stock of firms and past bilateral conflicts. All regressions include single countries × year, country-pair, and year fixed effects. Standard errors are in parentheses and are clustered at the country-pair level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-7: Conflicts and Percentage of Individuals Looking for Employment

DV:	(1) Share of individuals seeking paid employment vs. Entrepreneurship
Conflict	0.011*
	(0.006)
N	32,656

Notes: This table presents estimates from an OLS regression where the dependent variable is the percentage of individuals from the two nationalities in each pair who report actively seeking employment (rather than self-employment) in a given year. The main independent variable is a binary indicator equal to one if the two countries in the pair are in conflict in that year. All regressions control for past bilateral conflicts. The specification is run at the country-pair level and includes single countries × year, country-pair, and year fixed effects. Standard errors are clustered at the country-pair level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-8: Validation of the Document-Length Quality Proxy

Model:	(1) Logit	(2) Logit	(3) Survival (Cox)
DV:	Patent	Financial Growth	Hazard of Dissolution
Inc. Doc. Length	0.0047***	0.0031***	-0.0008***
	(0.0007)	(0.0005)	(0.0002)
N	390,762	206,946	363,910

Notes: This table regresses several measures related to firm quality on the length of the incorporation document. Column (1) reports estimates from a logit regression where the outcome is an indicator for patenting. Column (2) reports estimates from a logit regression where the outcome is a dummy measure of financial growth (calculated based on whether the firm's financial reporting category increased within six years). Column (3) reports estimates from a survival analysis where the outcome captures the hazard of dissolution. All regressions include controls for sector and company legal form. Robust standard errors are reported in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-9: Heterogeneity Results: Conflicts and Entrepreneurship by Venture Growth Orientation

DV:	(1) Entry	(2) Entry
	Non-Growth Oriented	Growth Oriented
Conflict	-0.184***	-0.171**
	(0.065)	(0.082)
N	41,518	33,572

Notes: This table shows estimates from a Poisson regression where the number of new businesses is regressed on a dummy variable taking the value one if the country couple is in conflict in a given year or zero otherwise, for growth-oriented firms versus not, which is proxied by the length of the incorporation document of companies. Column (1) considers startups with short incorporation documents, while column (2) considers those with long ones. The median value of the sample is used as the cut-off. All regressions control for the relevant firm stock and past bilateral conflicts. All regressions are run at the country-pair-year level and include single countries $\times$ year, country-pair, and year fixed effects. Standard errors are in parentheses and are clustered at the country-pair level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-10: Heterogeneity Results: Conflicts and Entrepreneurship by Sector

DV: Entry	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Manufacturing	Construction	Wholesale and Retail Trade	Hotel and Restaurant	Transport and Storage	Finance	Real Estate and Business	Education, Health, and Social Work
Conflict	0.414	-0.117	-0.078	-0.200*	-0.160	-0.523*	-0.350***	0.184
	(0.310)	(0.296)	(0.182)	(0.119)	(0.383)	(0.312)	(0.083)	(0.160)
N	11,037	8,014	21,243	12,812	9,967	8,909	34,208	21,946

Notes: This table shows estimates from a Poisson regression where the number of new businesses by industry is regressed on a dummy variable taking the value one if the country couple is in conflict in a given year or zero otherwise. All regressions control for the relevant firm stock and past bilateral conflicts. All specifications are run at the country-pair level and include single countries × year, country-pair, and year fixed effects. Standard errors are in parentheses and are clustered at the country-couple level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-11: Heterogeneity Results: Conflicts and Entrepreneurship by High- and Low-Tech Sectors

DV	(1) Entry	(2) Entry
	High-Tech	Low-Tech
Conflict	-0.298*	-0.181***
	(0.154)	(0.059)
N	16,146	48,435

Notes: This table shows estimates from a Poisson regression where the number of new businesses is regressed on a dummy variable taking the value one if the country couple is in conflict in a given year or zero otherwise, split by high- and low-tech sectors. High-tech sectors are classified according to the U.S. Bureau of Labor Statistics' high-tech classification, which is based on the concentration of STEM-related occupations in industries. All regressions control for the relevant firm stock and past bilateral conflicts. All specifications are run at the country-pair level and include single countries $\times$ year, country-pair, and year fixed effects. Standard errors are in parentheses and are clustered at the country-couple level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-12: Heterogeneity Results: Conflicts and Entrepreneurship by Centrality of Physical Goods Flows

DV	(1) Entry	(2) Entry
	Physical Goods	Non-Physical Goods
Conflict	0.002	-0.238***
	(0.209)	(0.055)
N	27,522	45,106

Notes: This table shows estimates from a Poisson regression where the number of new businesses is regressed on a dummy variable taking the value one if the country couple is in conflict in a given year or zero otherwise, split by whether physical goods flows are central to the industry's business activity. Column (1) includes industries involved in the production or physical distribution of shippable goods (manufacturing, wholesale and retail trade, transportation, mining, and agriculture); Column (2) includes the remaining industries. All regressions control for the relevant firm stock and past bilateral conflicts. All specifications are run at the country-pair level and include single countries $\times$ year, country-pair, and year fixed effects. Standard errors are in parentheses and are clustered at the country-couple level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-13: Heterogeneity Results: Conflicts and Entrepreneurship by Age

DV:	(1) Entry	(2) Entry
	Young Founding Teams	Old Founding Teams
Conflict	-0.147*	-0.227***
	(0.084)	(0.078)
N	38,578	35,701

Notes: This table shows estimates from a Poisson regression where the number of new businesses is regressed on a dummy variable taking the value one if the country couple is in conflict in a given year or zero otherwise, split by the median age of the founding team. Column (1) considers young founding teams, while column (2) considers older founding teams. All regressions control for the relevant firm stock and past bilateral conflicts. All specifications are run at the country-pair level and include single countries $\times$ year, country-pair, and year fixed effects. Standard errors are in parentheses and are clustered at the country-couple level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-14: Conflicts and Business Entry by Type of Team

DV:	(1) Entry	(2) Entry	(3) Entry
Team Type:	2 Founders 2 Nationalities	2+ Founders 2 Nationalities	$>$ 2 Founders $>$ 2 Nationalities
Conflict	-0.275***	-0.317***	0.166
	(0.062)	(0.080)	(0.154)
N	44,846	45,553	19,323

Notes: This table reports estimates from a Poisson regression in which the number of new firms is regressed on a dummy variable equal to one if the country pair is in conflict in a given year, split by team composition. Column (1) considers entry of teams founded by two individuals, column (2) considers entry of teams with two or more founders (but only two nationalities), and column (3) takes into account the entry of teams with at least three founders (with at least three nationalities). All regressions control for the relevant firm stock and past bilateral conflicts. All regressions include single countries $\times$ year, country-pair, and year fixed effects. Standard errors are in parentheses and are clustered at the country-pair level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-15: Heterogeneity Results: Expected and Unexpected Conflicts

DV:	(1) Entry
Expected Conflict	-0.807*** (0.286)
Unexpected Conflict	-2.658*** (0.566)
N	52,988

Notes: This table reports estimates from a Poisson regression where the number of new businesses is regressed on two mutually exclusive dummy variables that capture whether a country couple is in conflict in a given year. Specifically, Expected Conflict takes the value one if a couple is in conflict and has experienced at least the median number of past conflicts (calculated from 1850 to 2001 among couples with at least one past conflict), while Unexpected Conflict takes the value one if a couple is in conflict but has experienced fewer than the median number of past conflicts. Untreated observations serve as the omitted baseline category. Because expected and unexpected conflict are defined using a time-invariant measure of past conflicts at the couple level, single country–year and country-pair fixed effects are not included in the regression. The regression controls for the stock of existing businesses and includes year fixed effects. Standard errors are in parentheses and are clustered at the country-couple level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-16: Conflicts and Business Exits by Industry Capital Intensity

DV:	(1) Exit of Existing Businesses	(2) Exit of Existing Businesses
Type of Industry:	High Capital Intensity	Low Capital Intensity
Conflict	-0.414	-0.041
	(0.331)	(0.080)
N	6,476	38,460

Notes: This table reports estimates from a Poisson regression in which the number of business exits is regressed on a dummy variable equal to one if the country pair is in conflict in a given year, and zero otherwise. Results are reported separately for high- and low-capital-intensive industries, where capital intensity is measured by industry-level capital expenditures (Sutton, 1991). Industries are classified as high or low relative to the median value in the baseline year 2002. Capital expenditure data are drawn from the U.S. Census Bureau. All regressions control for the stock of firms and past bilateral conflicts. All regressions are run at the country-pair-year level and include single countries × year, country-pair, and year fixed effects. Standard errors are in parentheses and are clustered at the country-pair level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-17: Conflicts and Business Exits by Sector

DV: Exit	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Manufacturing	Construction	Wholesale and Retail Trade	Hotel and Restaurant	Transport and Storage	Finance	Real Estate and Business	Education, Health, and Social Work
Conflict	-0.028	-0.630	-0.249	0.199	0.166	0.005	0.073	-0.243
	(0.303)	(0.427)	(0.153)	(0.152)	(0.236)	(0.355)	(0.107)	(0.157)
N	7,828	5,729	16,355	9,305	7,607	6,182	25,427	15,071

Notes: This table shows estimates from a Poisson regression where the number of business exits by industry is regressed on a dummy variable taking the value one if the country couple is in conflict in a given year or zero otherwise. All regressions control for the relevant firm stock and past bilateral conflicts. All specifications are run at the country-pair level and include single countries × year, country-pair, and year fixed effects. Standard errors are in parentheses and are clustered at the country-couple level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-18: Bilateral Trade Split-Sample Analysis

DV	(1) High-Trade Dyads Entry	(2) Low-Trade Dyads Entry
Conflict	-0.233***	-0.271**
	(0.083)	(0.107)
N	24,451	23,177

Notes: This table examines whether the effect of conflict on business entry varies with the intensity of bilateral trade (sourced from the CEPII Gravity Database) between two countries. Columns (1) and (2) split the sample into dyads with above-median and below-median bilateral trade in 2002, respectively. All regressions control for the stock of firms and past bilateral conflicts. All regressions include the full set of controls and are run at the country-pair-year level with single countries × year, country-pair, and year fixed effects. Standard errors are in parentheses and are clustered at the country-pair level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-19: Geographic Distribution of Countries and Diaspora

Continent	Share of Countries (%)	Share of Diaspora (%, 2013)
Africa	26.56	16.7
Europe	24.48	37.0
Asia	23.44	35.2
North America	13.54	6.9
South America	6.77	1.8
Oceania	5.21	2.4

Notes: The table reports the distribution of countries and diaspora stocks across continents. The share of countries is calculated as the percentage of unique countries in the dataset belonging to each continent. The share of diaspora corresponds to the percentage of the migrant stock in 2013 originating from each continent.

Table A-20: Observed vs. Potential Country Pairs by Continent

Continent A	Continent B	Possible Pairs	Observed Pairs	Observed (%)
Africa	Africa	1,326	243	18.3
Africa	Europe	2,397	604	25.2
Africa	Asia	2,295	252	11.0
Africa	North America	1,326	96	7.2
Africa	South America	663	24	3.6
Africa	Oceania	510	29	5.7
Europe	Europe	1,128	750	66.5
Europe	Asia	2,115	787	37.2
Europe	North America	1,222	292	23.9
Europe	South America	611	193	31.6
Europe	Oceania	470	84	17.9
Asia	Asia	1,035	321	31.0
Asia	North America	1,170	129	11.0
Asia	South America	585	46	7.9
Asia	Oceania	450	52	11.6
North America	North America	351	62	17.7
North America	South America	338	35	10.4
North America	Oceania	260	22	8.5
South America	South America	91	34	37.4
South America	Oceania	130	11	8.5
Oceania	Oceania	55	10	18.2

Notes: The table reports the distribution of dyads present in the sample by continent.