

The Effects of Economic and Political Shocks on Bilateral Trade Flows

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Abstract – We analyse trade dynamics following episodes of economic recession and various non-economic shocks on bilateral trade flows in the period 1948-2017. We use an augmented gravity model with 190 countries, and we find sharp declines in trade in the immediate years following recessions, coups, war, and moments of political instability. Our research was unable to detect significant trade impacts of ethnic warfare, and we register small impacts for government crises, political revolutions and major epidemics. For the detected impacts, effects on the importer and exporter differ markedly, with generally greater effects if the importer is struck by a shock, indicating that the demand side is the primary driver of bilateral trade flows.

Keywords – trade, recession, gravity, political shock

1 Introduction

Financial crises are a phenomenon that has been consistently present in the economic landscape. Just in the past 25 years we have experienced five major financial crisis: The European Monetary System crisis in 1992, The Mexican crisis in 1994, the Asian Crisis in 1997, the dot-com crisis in 2000, and the global financial crisis of 2008. [Cerra & Saxena \(2008\)](#) using panel data analysis and controlling for country fixed effects find a loss in output averaging about 4 % following a currency crisis, and around 8 % following a banking crisis, with an output loss exceeding 6 % at a ten year horizon. These effects would be deeper if dealing with a "twin crisis" reaching and remaining at 10 %, three years after the crisis. [Reinhart & Rogoff \(2009\)](#) estimate severe consequences to the economy following a financial crisis: average fall in output of 9%, unemployment rate increment of 7% , and real value of government debt rising on average 86%. As a consequence of a financial crisis, we would expect to see a recession in the economy accompanied by a drop of imports. Exports, however, may rise due to a devaluation of the domestic currency or a decline in domestic demand or may decrease if the impact to the financial system is so great as to weaken its capability to export.

Next to financial crisis, wars and political violence are frequent events with the potential to cause long term political and economic distortions. In 2008 alone, the year the Global Financial Crisis started, [M. Marshall \(2009\)](#) reports 25 major conflicts, mostly in Africa and Asia, 20 of which involved interstate warfare. Naturally, the infrastructure destruction, the lower investments, the physical and human capital losses translate into serious economic costs. As case illustrations, The World Bank reports, for 1992, high transport costs from Burundi to Kenya

due to the war between Uganda and Tanzania. The IMF WEO database shows a 10 % reduction in total trade in Syria in 2003 due to the war in neighbouring Iraq. In contrast to the high persistence following a financial crisis, [Cerra & Saxena \(2008\)](#) find that following a civil war, output declines by 6 % initially but half the loss is recuperated after four years.

Trade can play an important role in the "contagious effect" of the crisis, as financial crises or political shocks may be transmitted through trade linkages from an affected country to others despite the latter's relatively good fundamentals. Political instability in neighbouring countries could have similar negative effects on economic performance partly due to disruption of trade flows. Using a probit model with data for 20 countries span, [Eichengreen & Rose \(1999\)](#) find that the probability of a financial crises occurring in a country increases on average by 8% if the country has high bilateral trade linkages with countries in crises. In the case of political shocks, [Qureshi \(2013\)](#) find a 7% bilateral trade reduction as a result of spillovers from conflict in neighbouring countries. [Blomberg & Hess \(2006\)](#) calculate that the presence of terrorism together with internal and external conflict is equivalent to as much as a 30% tariff on trade.

The degree of recovery following a crisis has not been at all the same for all countries. Regarding the aftermath of the 2008 Global financial crisis [Baldwin \(2009\)](#) finds that while the collapse of trade in 2008-2009 was very severe for countries that had recently had a banking crisis; for countries that did not have a banking crisis, they reached their pre-crisis levels of trade by the first quarter of 2010.

This paper uses the gravity model to estimate the bilateral trade value. The idea is that trade between any pair of countries is positively related to their economic size but inversely related to the distance between them. This approach has been widely used to study the impact of various types of shocks to an economy on trade. Investigating the effects of war on trade using a gravity model with country fixed effects, [Glick & Taylor \(2010\)](#) find large, negative, and persistent impacts of wars on trade: an 80% reduction between two adversaries relative to its peacetime prewar counterfactual level, and trade returning to its peacetime level only about a decade later. Analysing the aftermath of financial crises using a gravity model, [Abiad et al. \(2014\)](#) find a 19 % decline in imports the year following the crisis, with imports recovering only 10 years after. For the period 1981-1988, [Ma & Cheng \(2005\)](#) use a gravity model with crisis dummies to estimate a decline of a country's imports of 9.7% during the crisis, 13% in the first year after the crisis, and 14.5% in the year after. Exports would increase by 8.8% during the crisis, by 5% the first year after the crisis, but would decrease by 2% in the second year after the crisis.

Our paper adds to the existing literature on several counts. First, as opposed to previous studies which have considered primarily financial crisis, this paper looks at the effect of general downturns defined when GDP per capita growth drops below -2%. We also consider a large number of non-economic shocks including revolutions, coups, major constitutional changes, government crises, civil-, ethnic- and international-warfare, riots and demonstrations and major epidemics. For each of these shocks we compute point estimates and 4-period impulse response functions, while assessing robustness using a large number of different specifications with different covariates and varying levels of fixed-effects. We conduct a rigorous variable-selection exercise to assess the importance of these shocks vis-a-vis other standard and non-standard predictors in gravity models explaining bilateral trade flows.

2 Data and Methodology

Our research employs trade data from the CEPII Tradehist v4 database compiled by [Fouquin & Hugot \(2016\)](#). Although this data stretches from 1827-2014, we only use data from 1948 onwards, of which more than 98% is taken from the IMF Direction of Trade Statistics Database complemented by a few primary and secondary sources for certain countries. The original dataset records about 2 million bilateral trade observations from 1948 onwards, 885,609 of which are non-0. Since we wish to study the effect of various shocks on actual trade flows, we use the truncated sample for the remainder of this paper. In total we have data on 206 countries, some of which ceased to exist and were newly founded throughout the period. Figure (19) in the Appendix provides a detailed overview over the country-coverage in our data. Figure (1) shows the data coverage by continent. Whereas for Africa, Asia and the Pacific data coverage increases monotonically over the sample period, for Europe and Asia we see a jump following then end of the Cold War, reflecting the addition of post-USSR countries in eastern Europe and central Asia.

Figure 1: Data Coverage by Year and Continent
Non-0 Trade flows | *N. Obs.*: 885,609

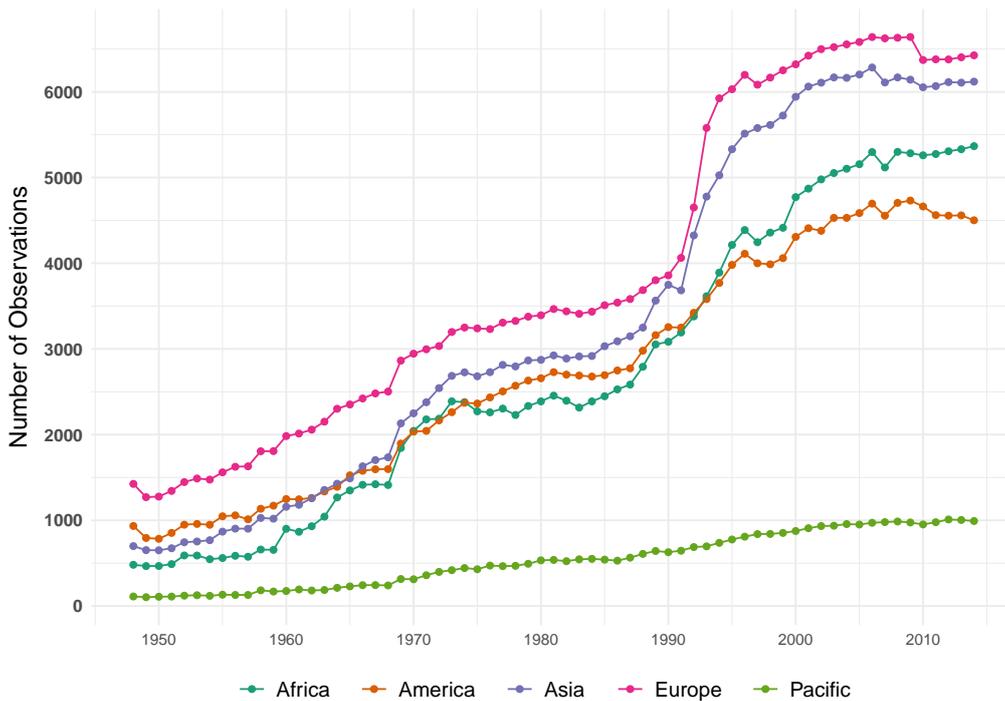


Figure (2) shows the increase in nominal trade volumes over time¹. Tradehist records bilateral trade volumes in current British Pounds, where one observation represents the value of the trade flow from the origin (exporter) country to the destiny (importer) country in a given year². Bilateral trade flows have risen dramatically following 1975, with the average bilateral trade volume peaking around 700 million pounds in 2013 for Europe or Asian origin countries, while remaining much lower in Africa and the Pacific. The Effects of the 2008 global financial crisis are also visible in Figure (2). For Europe and Asia, the crisis led to an average decrease of 50 million pounds in bilateral trade volumes.

¹For Figure (2), the dataset was collapsed by continent of origin and year.

²Internal trade flows e.g. from the UK to the UK in the year 2000 are not recorded in Tradehist

Figure 2: Average Nominal Bilateral Trade Volumes by Year and Continent Collapsed $N. Obs.: 885,609$

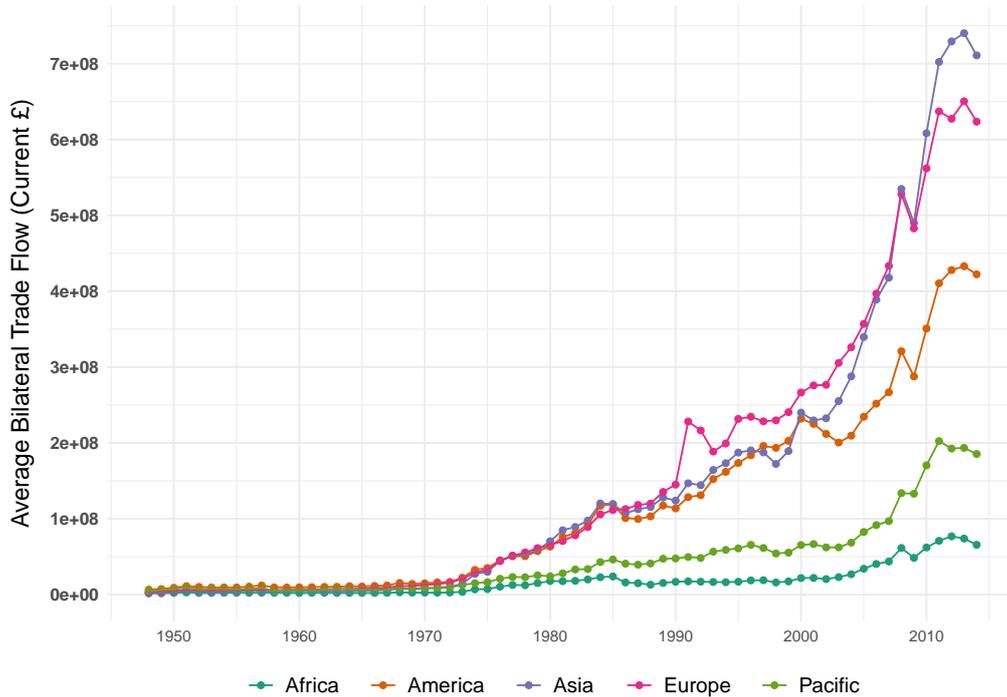
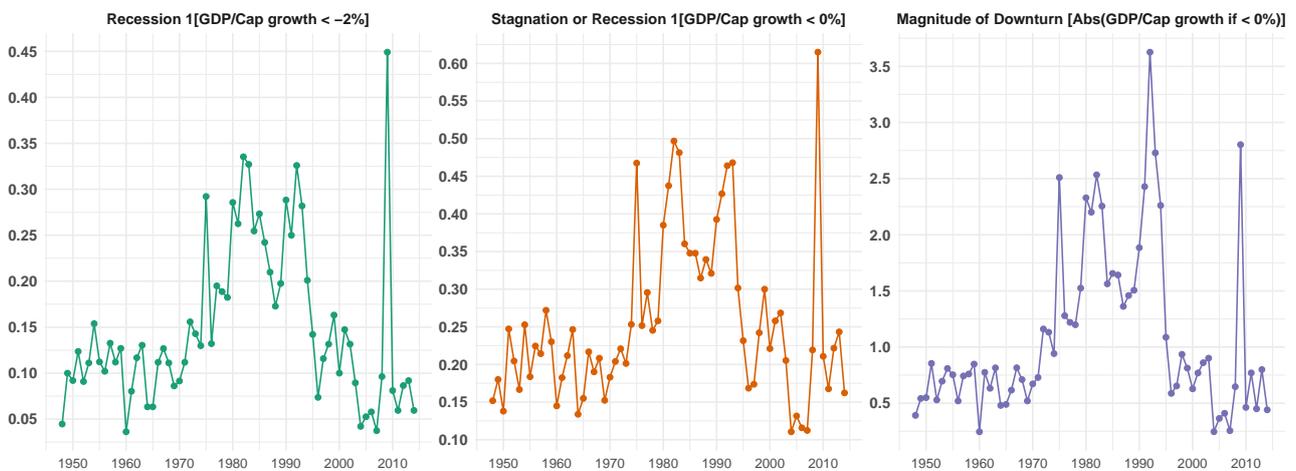


Figure (3) shows the temporal frequency of recessions based on GDP per capita PPP \$ inflation-adjusted data from the Gapminder Foundation ([Gapminder, 2018](#)). We define a recession when GDP per capita growth drops below -2%, and a stagnation when GDP per capita growth is between 0% and -2%. The graphs show the expected sharp spike in 2008, although the average severity of recession was greater in 1992 as the last plot shows. Importantly, Figure (3) shows that there is no pronounced linear increase or decrease in the incidence of recessions,

Figure 3: Temporal Frequency of Recessions

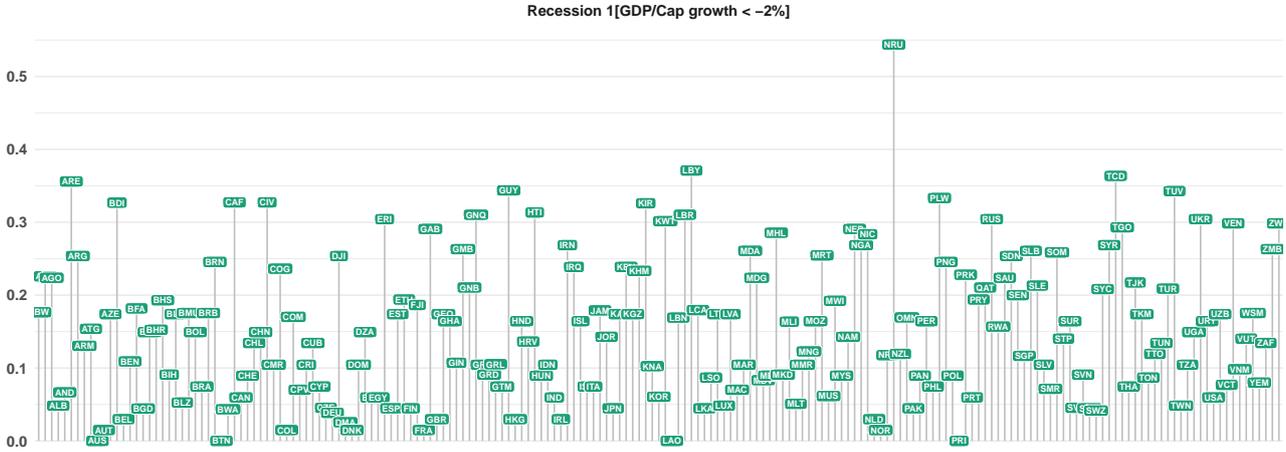
Based on a Cross-Country Average for all Country-Years Represented in the Trade Data



although the "lost decade" of the 1980's has left it's mark. Figure (4) shows the incidence of recession for each country, taken as a country-average over the entire 1948-2014 period. The incidence of economic recession differs substantially for different countries, with especially Sub-Saharan African, Latin-American and Polynesian states suffering from a high incidence

of recessions. We note an exceptional incidence of recession for Nauru, whose GDP shrunk continuously between 1974 and 2006.

Figure 4: Country Frequency of Recessions
Based on a Time Average for all Country-Years Represented in the Trade Data



With Figures (20) and (21) in the Appendix, we provide analogs to Figures (3) and (4) for 12 non-economic shock variables. Of these, magnitude scores for civil-, ethnic-, and international warfare are taken from the Quality of Government Standard Dataset (Teorell et al., 2017), and made available by the Center for Systemic Peace (M. G. Marshall, 2010), epidemics data is taken from the International Disaster Database (CRED, 2017), and the remaining data on domestic turmoil and political events is taken from the Cross-National Time-Series Data Archive (Banks & Wilson, 2001).

2.1 Model Selection

As a first step of analysis, we would like to find out how important these shock variables are in explaining bilateral trade flow vis-a-vis standard predictors. A simple OLS regression of Log trade on all shock variables yields an R^2 of 4.7%, with the R^2 for any individual shock never above 0.6% (the R^2 for recession is 0.3%). We proceed by taking a large pool of proven and potential predictors of trade, including population, area, membership in OECD or EU, free trade agreements and GATT membership, various pair characteristics like colonial, cultural, linguistic or systemic ties, and number of further country characteristics like landlockedness, latitude and longitude of country centroid, GDP shares in primary and secondary sector, time and cost for business startup procedures, religious, ethnic and language fractionalization etc., yielding, together with the shock variables, a maximum model size of 90 variables³. The data herefore is mostly taken from 3 further CEPII datasets: Gravity Data (Head & Mayer, 2013), GeoDist (Mayer & Zignago, 2011) and Language data (Melitz & Toubal, 2012). We perform variable selection on this extended set of predictors using 3 different algorithms: Backwards Selection, Forward Selection and LASSO regression. Backwards selection considers first the full model and then eliminates variables one by one, each time eliminating the variable that least reduces the fit, as measured by the R^2 . Forward selection starts with a constant and

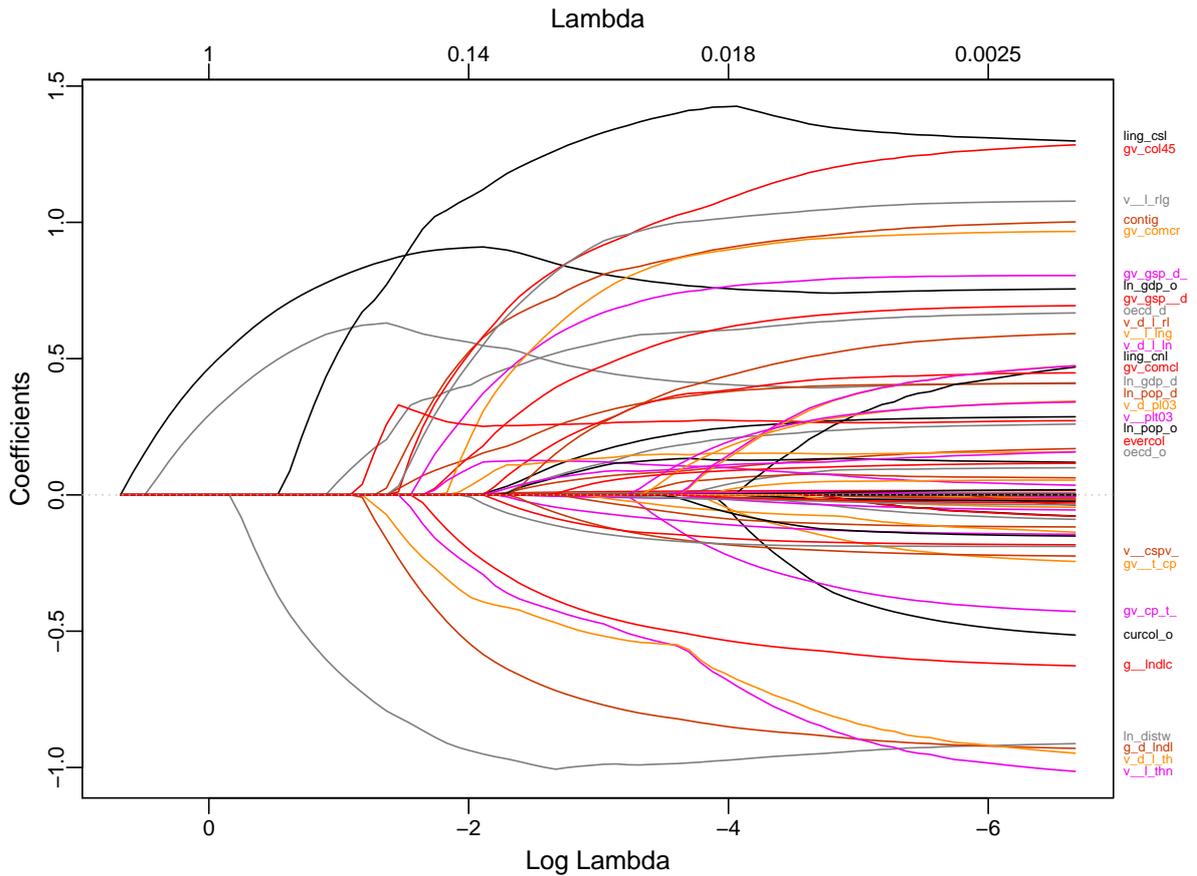
³It must be noted that all variables except for pair characteristics are included twice, once for the origin and once for the destiny country. Thus technically we only have around 50 unique predictors. We omit available data on tariffs and exchange rates because of insufficient data coverage on these variables.

adds variables one by one, each time adding the variable that gives the greatest increase in R^2 . LASSO regression is a so-called shrinkage method which is performed on standardized data (so as to yield standardized coefficients) and minimizes

$$\min_{\beta} \sum_{i=1}^n \left(y_i - \beta_0 - \sum_{j=1}^k \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^k |\beta_j| \quad (1)$$

The first term in Eq. (1) is just the residual sum of squares and the second term is a penalty on the sum of the absolute values of the standardized coefficients. The effect of increasing the penalty parameter λ is to shrink the coefficient estimates towards 0. Shrinkage methods are mainly used to improve the fit of a regression as shrinking the coefficient estimates can significantly reduce their variance (James et al., 2013). They have however also proven themselves a powerful variable selection tool since the coefficients of less important variables shrink to 0 earlier as λ increases. We perform the LASSO regression for 80 different λ values. Figure (5) shows the standardized coefficients plotted against λ^4 . A ranking of the top 30 predictors based on all 3 methods is reported in Table (1).

Figure 5: LASSO Regression Result



We are pleased to note that both LASSO and forward selection select the basic gravity variables as the most important variables. Figure (5) shows that the two GDP's have quite an edge over all other variables, followed by distance and common spoken language. Table (1) shows that in all three methods the most important shock variables are epidemics and civil

⁴Table (1) matches the variable names to their labels and is thus helpful in interpreting Figure (5).

Table 1: Best Predictors of Bilateral Trade Flows

#	Backwards Selection	R^2	Forwards Selection	R^2	LASSO	LASSO Varname
1	Log GDP (Current £), Origin	0.292	Log GDP (Current £), Origin	0.292	Log GDP (Current £), Origin	ln_gdp_o
2	1[OECD Member], Destiny	0.413	Log GDP (Current £), Destiny	0.514	Log GDP (Current £), Destiny	ln_gdp_d
3	Log Population (Millions), Destiny	0.496	Log Population-weighted-great-circle Distance (km)	0.588	Log Population-weighted-great-circle Distance (km)	ln_distw
4	Log Population-weighted-great-circle Distance (km)	0.562	Common Spoken Language (% of Pop.)	0.598	Common Spoken Language (% of Pop.)	ling_csl
5	Share of Primary Sector (% GDP), Destiny	0.594	Longitude in Degrees, Origin	0.606	1[OECD Member], Destiny	oecd_d
6	Common Spoken Language (% of Pop.)	0.604	Longitude in Degrees, Destiny	0.611	1[Landlocked], Destiny	geo_d_landlocked
7	1[Landlocked], Destiny	0.613	1[Landlocked], Destiny	0.616	1[Ever in a Colonial Relationship]	evercol
8	Longitude in Degrees, Origin	0.620	1[ODA Donor], Destiny	0.622	Ethnic Fractionalization	vi_d_al_ethnic
9	1[ODA Donor], Destiny	0.626	Log Population (Millions), Destiny	0.627	Longitude in Degrees, Origin	geo_o_lon
10	Religion Fractionalization	0.630	Religion Fractionalization	0.630	1[Contiguity]	contig
11	Longitude in Degrees, Destiny	0.633	1[Landlocked], Origin	0.633	Log Population (Millions), Destiny	ln_pop_d
12	Log GDP (Current £), Destiny	0.635	1[Colonial Relationship Post 1945]	0.635	Longitude in Degrees, Destiny	geo_d_lon
13	1[Landlocked], Origin	0.638	1[Epidemic], Destiny	0.638	1[Colonial Relationship Post 1945]	gv_col45
14	1[ODA Donor], Origin	0.640	1[Common Currency]	0.640	Religion Fractionalization	vi_o_al_religion
15	1[Contiguity]	0.642	Share of Primary Sector (% GDP), Destiny	0.642	Ethnic Fractionalization	vi_o_al_ethnic
16	1[Colonial Relationship Post 1945]	0.644	1[OECD Member], Destiny	0.644	1[ODA Donor], Destiny	gv_gsp_d_d
17	1[Common Colonizer Post 1945]	0.646	1[Contiguity]	0.646	1[Landlocked], Origin	geo_o_landlocked
18	Share of Secondary Sector (% GDP), Origin	0.648	1[ODA Donor], Origin	0.648	1[ODA Donor], Origin	gv_gsp_o_d
19	Ethnic Fractionalization	0.649	Share of Secondary Sector (% GDP), Origin	0.649	1[Common Language >9% of Pop. in Both Countries]	comlang
20	Log Population (Millions), Origin	0.650	1[Common Colonizer Post 1945]	0.650	Share of Secondary Sector (% GDP), Origin	sh_sec_o
21	1[Common Currency]	0.651	Ethnic Fractionalization	0.651	1[Common Currency]	gv_comcur
22	Civil Warfare (Magnitude Score, 0-10), Origin	0.652	Log Population (Millions), Origin	0.653	1[Regional Trade Agreement] (WTO, 2015)	gv_fta_wto
23	Ethnic Fractionalization	0.653	Share of Primary Sector (% GDP), Origin	0.654	Share of Secondary Sector (% GDP), Destiny	sh_sec_d
24	Religion Fractionalization	0.654	International Warfare (Magnitude Score, 0-10), Origin	0.655	1[Epidemic], Destiny	vi_d_occurrence
25	1[Epidemic], Destiny	0.655	1[Epidemic], Origin	0.656	Log Population (Millions), Origin	ln_pop_o
26	Latitude in Degrees, Origin	0.656	Civil Warfare (Magnitude Score, 0-10), Origin	0.656	1[Common Colonizer Post 1945]	gv_comcol
27	1[Epidemic], Origin	0.657	Ethnic Fractionalization	0.657	1[Ever in a Sibling Relationship]	gv_sibling
28	International Warfare (Magnitude Score, 0-10), Origin	0.658	Religion Fractionalization	0.658	1[Epidemic], Origin	vi_o_occurrence
29	Share of Primary Sector (% GDP), Origin	0.659	Latitude in Degrees, Origin	0.659	1[OECD Member], Origin	oecd_o
30	Adjusted Value of Linguistic proximity (ASJP)	0.659	Adjusted Value of Linguistic proximity (ASJP)	0.659	Adjusted Value of Linguistic proximity (ASJP)	ling_lp2

warfare, entering around the 20'th rank⁵. Most of the shock variables are however concentrated at the bottom of the variable ranking, suggesting that they are not very important in predicting trade flows. It remains to ascertain whether a model predicting trade can possibly gain by the inclusion of these shock variables. We answer this question by using 10-fold cross-validation (CV) to predict out of sample with models of different sizes.

Figure 6: Evaluation of Forward Selection Ranking using 10-Fold Cross-Validation

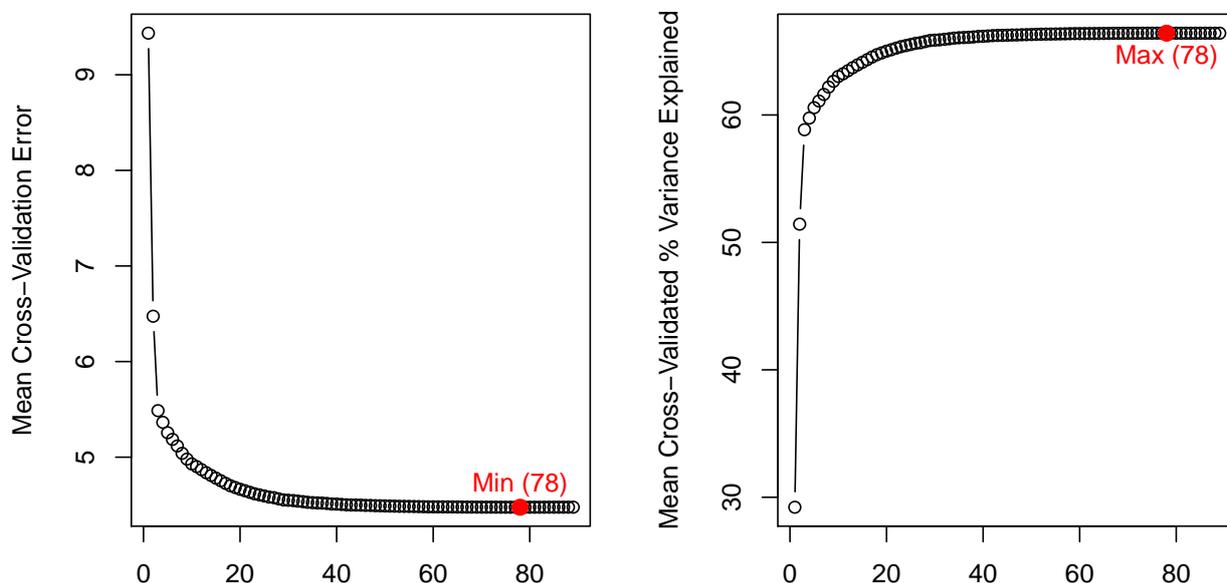


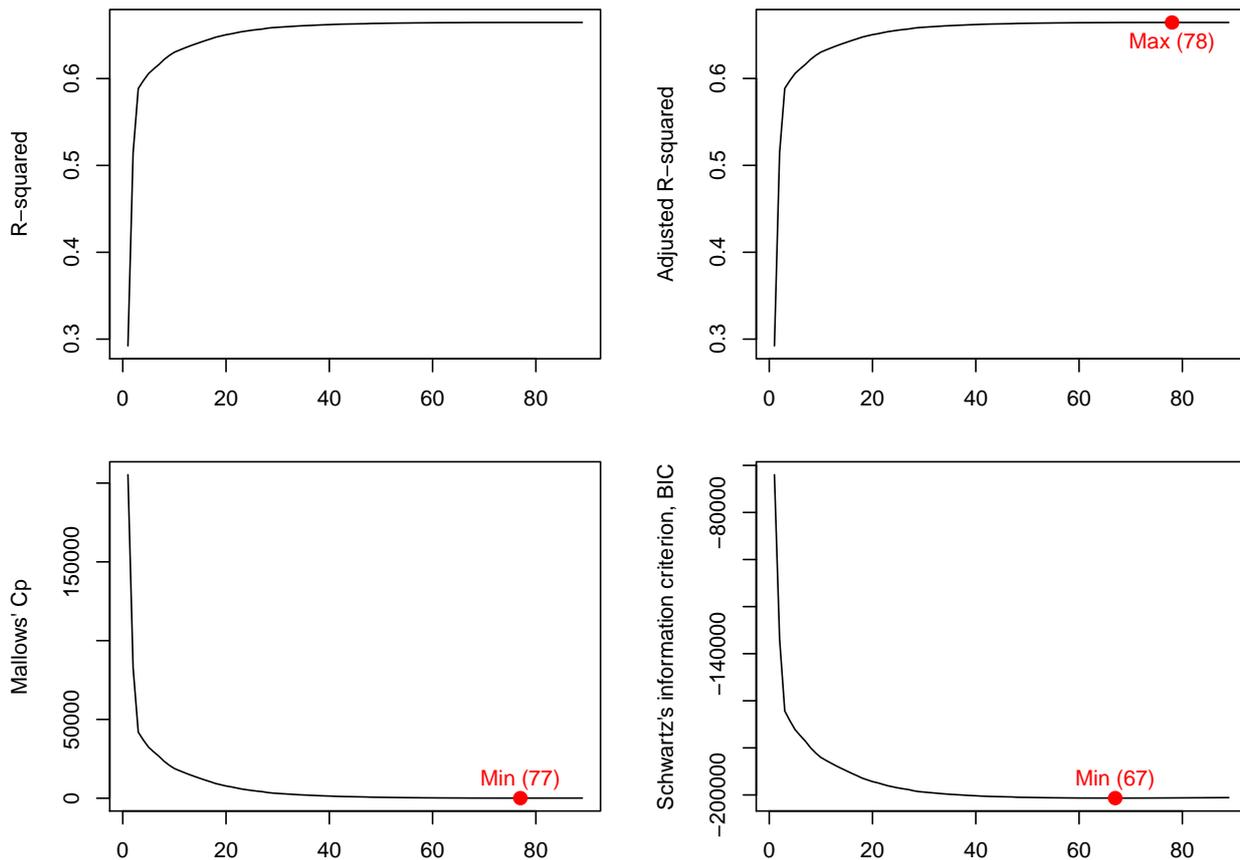
Figure (6) shows the cross-validation results for the Forward selection algorithm where we calculate the mean CV error and the CV R^2 for a model of each size⁶. The best predictive performance according to this metric is obtained by a large model of 78 variables, which for that matter would include most of the shock variables. The figure however also shows that

⁵Which is contradictory to what we find later when we introduce FE.

⁶Model size is on the x-axis.

gains in predictive power are very marginal beyond 40 variables, and there seems to be a predictive bottleneck at a CV R^2 of around 70. We complement the CV criterion with other standard information criteria used to select model size: The adjusted R^2 , the Schwartz Bayesian Information Criterion (BIC) and Mallows' CP. These are shown in Figure (7), and all together also suggest large models, with the BIC giving the most conservative estimate of optimal model size (67).

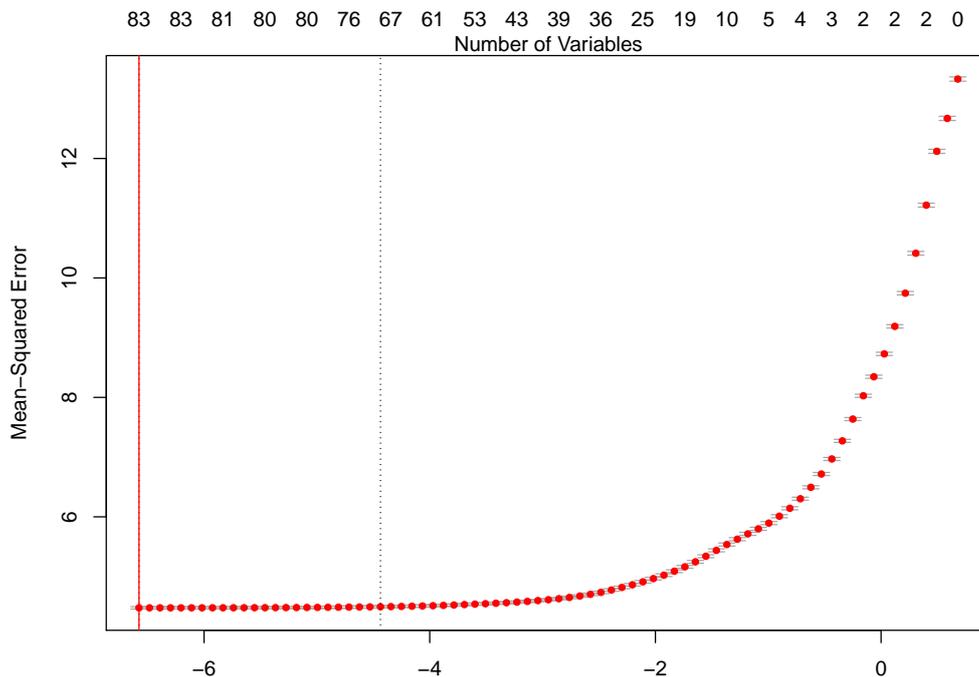
Figure 7: Information Criteria on Forward Selection Result



We also perform CV on the LASSO results (shown in Figure (8)⁷), which suggests an even larger optimal model size of 83 variables. Taken together these results suggest that although shock variables explain very little variance vis-a-vis standard predictors, including them in a regression predicting trade does generally improve predictive performance, thus they are not irrelevant.

⁷Log λ on the x-axis.

Figure 8: LASSO Regression 10-Fold Cross-Validation Result



2.2 Empirical Approach

Our empirical methodology is inspired by the structural gravity literature and the existing literature on financial crisis and trade. The structural gravity approach stipulates the estimation of gravity equations with various levels of fixed-effects (FE) to account for omitted determinants of bilateral trade, which could otherwise render gravity estimates subject to omitted variable bias. The most conservative specifications generally include a set of exporter-year, importer-year and exporter-importer (pair) fixed effects to account for all effects that occur in each of the two countries at a given time, and all time-invariant pair characteristics (such as a common colonizer). In these specifications only time-varying pair characteristics, for example regional trade agreements being concluded, are entered as predictors in the regression.

This approach will not work for us, because our country-level shocks would be collinear with the country-year FE. [Abiad et al. \(2014\)](#) solve this problem by estimating a specification with pair FE and time FE, in which they control for log GDP (which is curious since it surely takes away some of the impact of financial crisis) and further pair level time-varying controls such as currency unions and free trade agreements. [Ma & Cheng \(2005\)](#) take a different approach in which they include, next to log GDP and population and a number of time-invariant country and pair characteristics and several lags of currency devaluation relative to the dollar, a lagged dependent variable into their gravity estimation to account for the underlying continuity of trade relationships. They also include a global time-trend to account for the global increase in trade-volumes over time.

Since it is unclear to which extent economic recession and our other non-economic shocks are correlated with omitted determinants of trade, we consider both kinds of specification in addition to specifications that allow for country FE and country specific time-trends, and

specifications with differenced log trade as the dependent variable. Equation (2) shows our (hypothetical⁸) unrestricted model (o subscript for origin or exporter, d for destiny or importer):

$$\begin{aligned} \ln T_{od,t} = & \beta_0 + \beta_1 \ln T_{od,t-1} + \sum_{s=-1}^3 \beta_{so} shock_{o,t-s} + \sum_{s=-1}^3 \beta_{sd} shock_{d,t-s} + \mathbf{X}_o \gamma_1 + \mathbf{X}_d \gamma_2 \\ & + \mathbf{X}_{o,t} \gamma_3 + \mathbf{X}_{d,t} \gamma_4 + \mathbf{X}_{od} \gamma_5 + \mathbf{X}_{od,t} \gamma_6 + \alpha_o + \alpha_d + \alpha_{ot} + \alpha_{dt} + \alpha_{od} + \pi_t + \theta t + \epsilon_{od,t}. \end{aligned} \quad (2)$$

In Eq. (2), β_0 denotes a constant term, $\ln T_{od,t-1}$ is the trade flow in the previous period, $\sum_{s=-1}^3 \beta_{so} shock_{o,t-s} + \sum_{s=-1}^3 \beta_{sd} shock_{d,t-s}$ are the shock variables for the origin and destiny country where we add 1 lead and 3 lags to the contemporaneous effect. \mathbf{X}_o and \mathbf{X}_d are row-vectors of time-invariant country characteristics (like landlockedness or area), $\mathbf{X}_{o,t}$ and $\mathbf{X}_{d,t}$ are time-varying country characteristics (like GDP or population), \mathbf{X}_{od} are time-invariant pair characteristics (like distance or common colonizer) and $\mathbf{X}_{od,t}$ are time-varying pair characteristics (like regional trade agreement or monetary union). These vectors come with associated coefficient vectors γ_i . Furthermore α_o and α_d are exporter and importer FE, α_{ot} and α_{dt} are exporter and importer specific time-trends, α_{od} are pair FE, π_t are time FE, t is a global time-trend and $\epsilon_{od,t}$ the idiosyncratic error term. Eq. (2) cannot be estimated in practice, since α_o and α_d would wipe out X_o and X_d , and α_{od} would eliminate X_{od} . We instead estimate variants of Eq. (2) where we assess the effect of imposing different types of restrictions on it. Table (2) provides an overview over the 14 different specifications we proceed to estimate.

Table 2: Models Estimated

#	Name	Restrictions Imposed on Eq. (2)	Description
1.	RAW	$\beta_1 = \gamma_i = \alpha_i = \pi_t = \theta = 0 \forall i$	Log trade regressed on the shocks
2.	ST-GR	$\beta_1 = \gamma_{1,2} = \alpha_i = \pi_t = 0 \forall i$	A standard gravity specification ^a
3.	EX-GR	$\beta_1 = \alpha_i = \pi_t = 0 \forall i$	Extended gravity with all predictors ^b
4.	IMF	$\beta_{0,1} = \gamma_{1,2,5,6} = \alpha_{o,d,ot,dt} = \theta = 0$	Model of Abiad et al. (2014)
5.	FE-1	$\beta_{0,1} = \gamma_{1,2,3,4} = \alpha_{ot,dt,od} = \theta = 0$	EX-IM FE + TFE
6.	FE-2	$\beta_{0,1} = \gamma_{1,2,5} = \alpha_{ot,dt} = \pi_t = 0$	EX-IM FE + PFE + global trend
7.	FE-3	$\beta_{0,1} = \gamma_{1,2,5} = \pi_t = \theta = 0$	EX-IM FE + PFE + country trends
8.	FE-4	$\beta_{0,1} = \gamma_{1,2,3,4,5,6} = \theta = 0$	Full set of FE's, no covariates
9.	LD-1	$\gamma_{1,2,5} = \alpha_i = \pi_t = \theta = 0 \forall i$	Simple lagged dependent (LD), no FE
10.	LD-2	$\beta_0 = \gamma_{1,2,5} = \alpha_{ot,dt} = \pi_t = \theta = 0$	LD with EM-IM FE + PFE
11.	LD-3	$\beta_0 = \gamma_{1,2,3,4,5,6} = \theta = 0$	LD with full set of FE's, no covariates
12.	FD-1	$\gamma_{1,2,5} = \alpha_i = \pi_t = \theta = 0 \forall i, \beta_1 = 1$	Simple first-difference (FD), no FE
13.	FD-2	$\beta_0 = \gamma_{1,2,5} = \alpha_{ot,dt} = \pi_t = \theta = 0, \beta_1 = 1$	FD with EM-IM FE + PFE
14.	FD-3	$\beta_0 = \gamma_{1,2,3,4,5,6} = \theta = 0, \beta_1 = 1$	FD with full set of FE's, no covariates

Note: For gravity we use log GDP in current £. A recession dummy computed from this data is sufficiently dissimilar to the dummy computed using Gapminder GDP per capita data ($corr = 0.3$), thus we are not too worried that the inclusion of log GDP will downward bias our recession estimates. Below we also demonstrate robustness of the findings to the choice of GDP series.

^a This specification just includes the 2 countries GDP's, distance, and dummies for contiguity, common language, ever in colonial relationship and regional trade agreement + a global time trend.

^b We take the union of the top 50 predictors from all 3 model selection methods in section 2.1, and exclude shock variables from these, yielding 32 unique covariates in the EX-GR model (unique in the sense of not double-counting country-characteristics).

Table (3) summarizes all variables used in the different models as they are referred to in Eq. (2). Codebook descriptions for the political shock variables are provided in Table (5) in the Appendix. Figure (9) shows a correlation matrix of the natural log of trade flow, the log of GDP and the log of the population-weighted distance between two trading partners with all

⁸It is Hypothetical because it cannot be estimated since the FE will wipe out some of the X_k included

shock variables⁹.

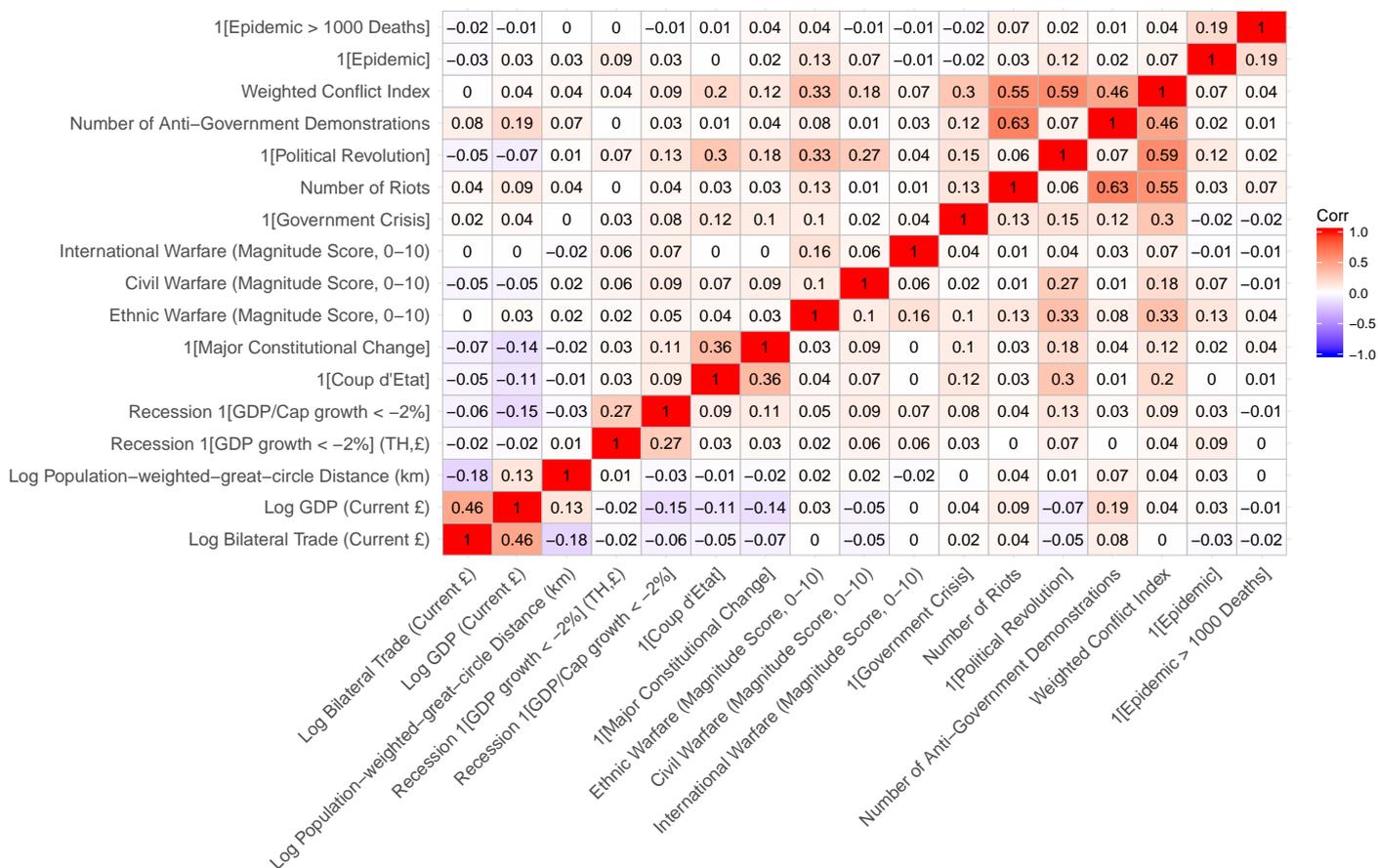
Table 3: Summary Statistics

Country characteristics are largely symmetric and reported for the exporter only

<i>Variable</i>	<i>N</i>	<i>Distinct</i>	<i>Mean</i>	<i>Median</i>	<i>SD</i>	<i>Min</i>	<i>Max</i>
Panel ID	885609	32611	19852.29	18951	11512.76	1	40476
Pair ID (α_{od})	885609	17330	10481.61	10305	5934.45	1	21219
Country Code (α_o and α_d)	885609	206					
Year (t or π_t)	885609	67	1991.27	1995	16.77	1948	2014
<i>Trade ($T_{od,t}$)</i>							
Bilateral Trade Flow (Current £)	885609	623863	173e ⁶	989e ³	2127e ⁶	1	283660e ⁶
Log Bilateral Trade Flow (Current £)	885609	604374	13.74	13.8	3.66	-17.56	26.37
<i>Time-Varying Country Characteristics ($\mathbf{X}_{o,t}$ and $\mathbf{X}_{d,t}$)</i>							
Log GDP (Current £)	847451	9804	23.3	23.24	2.39	15	30
Log Population (Millions)	881054	10933	2.13	2.26	1.95	-5.46	7.22
Share of Primary Sector (% GDP)	643507	6635	13.69	8.95	12.95	0.03	93.98
Share of Secondary Sector (% GDP)	643189	6617	28.51	26.78	11.44	1.88	90.51
1[OECD Member]	832485	2	0.26	0	0.44	0	1
1[EU Member]	885609	2	0.14	0	0.34	0	1
1[ACP (Africa, Caribbean, Pacific) to EU]	885609	2	0.04	0	0.19	0	1
1[ODA Donor]	885609	2	0.1	0	0.3	0	1
1[GATT/WTO Member]	885609	2	0.73	1	0.45	0	1
<i>Time-Invariant Country Characteristics (\mathbf{X}_o and \mathbf{X}_d)</i>							
Internal Distance ($0.67 \times \sqrt{Area/\pi}$)	885609	206	298.85	199.82	324.98	1	1853.8
1[Landlocked]	885609	2	0.14	0	0.34	0	1
Latitude in Degrees	885609	211	22.05	25.08	25.8	-51.7	64.18
Longitude in Degrees	885609	213	19.08	18.08	63.8	-175.23	179.2
Ethnic Fractionalization	808921	181	0.4	0.41	0.26	0	0.93
Language Fractionalization	790673	175	0.35	0.32	0.28	0	0.92
Religion Fractionalization	812358	184	0.43	0.43	0.24	0	0.86
<i>Time-Varying Pair Characteristics ($\mathbf{X}_{od,t}$)</i>							
1[Common Currency]	885609	2	0.02	0	0.14	0	1
1[Currently in Colonial Relationship]	885609	2	0	0	0.06	0	1
1[Foreign Trade Agreement] (Head et al., 2010)	682627	2	0.04	0	0.21	0	1
1[Regional Trade Agreement] (WTO, 2015)	885609	2	0.08	0	0.27	0	1
Shortest Bilateral Sea Distance (km)	637886	6364	10211.45	9537.8	5843.11	61.12	29533.84
<i>Time-Invariant Pair Characteristics (\mathbf{X}_{od})</i>							
Log Population-weighted-great-circle Distance (km)	885609	17285	8.61	8.82	0.83	4.11	9.89
1[Common Language >9% of Pop. in Both Countries]	885609	2	0.18	0	0.38	0	1
1[Contiguity]	885609	2	0.03	0	0.16	0	1
1[Ever in a Colonial Relationship]	885609	2	0.02	0	0.16	0	1
1[Colonial Relationship Post 1945]	885609	2	0.02	0	0.12	0	1
1[Common Colonizer Post 1945]	885609	2	0.09	0	0.29	0	1
1[Ever in a Sibling Relationship]	885609	2	0.19	0	0.39	0	1
Common Native Language (% of Pop.)	754699	863	0.05	0	0.18	0	0.99
Common Spoken Language (% of Pop.)	754699	3064	0.16	0.02	0.26	0	1
Adjusted Value of Linguistic proximity (ASJP)	740953	2425	0.7	0.62	0.81	0	7.46
<i>Shock Variables ($shock_{o,t}$ and $shock_{d,t}$)</i>							
Recession 1[GDP/Cap growth <-2%]	854114	2	0.12	0	0.33	0	1
Stagnation or Recession 1[GDP/Cap growth <0%]	854114	2	0.23	0	0.42	0	1
Magnitude of Downturn [Abs(GDP/Cap growth if <0%)]	854114	2703	0.88	0	2.91	65.03	0
Recession 1[GDP growth <-2%] (TH,£)	838366	2	0.15	0	0.35	0	1
1[Coup d'Etat]	643006	2	0.02	0	0.13	0	1
1[Major Constitutional Change]	643006	2	0.06	0	0.24	0	1
Ethnic Warfare (Magnitude Score, 0-10)	772186	9	0.27	0	1.01	0	10
Civil Warfare (Magnitude Score, 0-10)	772186	9	0.15	0	0.79	0	10
International Warfare (Magnitude Score, 0-10)	772186	9	0.05	0	0.47	0	9
1[Government Crisis]	684500	2	0.14	0	0.35	0	1
Number of Riots	684377	25	0.5	0	2.01	0	55
1[Political Revolution]	684406	2	0.13	0	0.33	0	1
Number of Anti-Government Demonstrations	684475	25	0.64	0	2.02	0	60
Weighted Conflict Index	684118	191	927.36	0	1978.55	0	51625
Asinh Weighted Conflict Index	684118	191	3.64	0	3.89	0	11.54
1[Epidemic]	875734	2	0.11	0	0.31	0	1
1[Epidemic >1000 Deaths]	875734	2	0	0	0.07	0	1

⁹All variables in Figure (9) are the measures for the origin country. Log GDP is a measure of nominal GDP in current British Pounds supplied with the Tradehist database, as is the distance variable.

Figure 9: Correlation Matrix Of Shocks and Gravity Variables
N. Obs.: 580,476



In contrast to [Abiad et al. \(2014\)](#), who compute impulse response functions (IRF's) with 10 lags, we restrict ourselves to 3 lags (in line with [Ma & Cheng \(2005\)](#)) because the estimates show we don't need more than that for the effects of our shocks to fully materialize, and because [Ma & Cheng \(2005\)](#) argue that some financial shocks may not be too far apart, for example, the EMS crisis (1992–1993), the Mexican crisis (1994–1995), and the Asian crisis (1997–1998). They argue that lags in excess of two years would run into an identification problem whether an observed effect was caused by the current or a previous crisis.

With further reference to the specifications, our choice for in some specifications replacing time FE with a global time-trend and country specific time trends, the latter clearly constituting the less restrictive choice, is motivated by the consideration that some shocks, notably recessions and international warfare, take global dimensions in certain years. Time FE eliminate the impact global shocks in the data, which in these cases may be undesirable. We add three specifications with differenced log trade as the dependent variable because these curb all potential remaining serial correlation in the errors, and, together with the lagged dependent variable specifications, yield better behaved impulse response functions than the rest of the specifications.

3 Estimation Results

We begin the presentation of the results by showing in Table (4) point estimates for the contemporaneous effects of economic recessions on trade¹⁰. The first horizontal block in the table shows the impact estimates obtained when we compute the recession dummy with the [Gapminder \(2018\)](#) GDP per capita 2011 PPP \$ inflation adjusted data. The second block serves as a robustness check and shows the impact estimates when we compute the dummy from the nominal GDP in current British Pounds series that comes with the Tradehist v4 database. Overall the two series of estimates are very similar. We thus conclude that the estimates are robust to the choice of data¹¹, and leave the second block to the reader while we focus increased attention on the first.

The raw impact (1) shows a very large negative impact of economic recessions on trade flows. The estimates suggest that the bilateral trade flow contemporaneously drops by 48% in the incidence of crisis in the exporting country, and by 33% for a crisis the importing country. These impact estimates drop to -15% and -20% respectively in the standard gravity model (2) and further down to -4% and -15% in the extended gravity model (3). When moving to the specification of [Abiad et al. \(2014\)](#) with pair and time FE and log GDP in column (4), the impact of a crisis in the exporter country drops to 0 while the importer effect drops to -6%. Specification 5 with country FE, time FE and all pair characteristics included gives very similar estimates. In specification (6) which imposes country and pair FE together with a global time trend while controlling for time-varying country and pair characteristics, the exporter recession estimate remains insignificant while the importer impact increases to -11.5%. This suggests that time FE slightly depress the effects of recessions for reasons of collinearity with global financial breakdowns. In specification (7) we just replace the global trend from (6) with country specific time-trends. This pushes the importer impact down to -7% again, while the exporter impact remains insignificant. In specification (8), we impose country, pair and time FE in addition to country specific time trends, while omitting all covariates. The importer impact rises slightly to -7.7%, and we again measure an small exporter effect of -3%. Specification (9) is the simple lagged dependent variable model where we control for time-varying country and pair level covariates but do not impose fixed effects. The estimated exporter impact is -7.4% and the importer impact -12%. Specification (10) adds to this simple LD model country and pair FE. The impact estimates drop to -4.2% and -11.8% respectively. In (11) we estimate the LD model with the full set of FE while omitting all covariates. The impacts are quite steady compared to the previous 2 models, with -5.1% for exporter recession and -10.4% for importer recession. The final 3 columns of Table (4) show the first-difference specifications, which, apart from the dependent variable being replaced by its first difference, are identical to the LD specifications. Compared to the LD estimates, the FD estimates are slightly larger, with [X -7.3%, M -12.1%] (12), [X -7.2%, M -12.6%] (13) and [X -6.3%, M -11.5%] (14).

Of all these models, we strongly favor the LD and FD models since they most effectively deal with issues of time-series correlation (as will be visible shortly when we present the IRF's),

¹⁰That is the contemporaneous effects obtained when we estimate the models without lags and leads for the shocks.

¹¹The Tradehist GDP data is very clearly of worse quality than the Gapminder data, which can be checked by computing a figure analogous to Figure (3) and observing the stark dissimilarity between the time-frequency of major historical crisis periods and the crisis-pattern shown in these plots

Table 4: Trade Response to Recession

Variables	RAW	ST-GR	EX-GR	IMF	FE-1	FE-2	FE-3	FE-4	LD-1	LD-2	LD-3	FD-1	FD-2	FD-3
Lagged Log Bilateral Trade (Current $\$$)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Recession I[GDP/Cap growth < -2%] _t , Origin	-0.475*** (0.020)	-0.154*** (0.013)	-0.043*** (0.021)	0.000 (0.010)	0.016 (0.011)	-0.013 (0.010)	-0.012 (0.009)	-0.027*** (0.007)	-0.074*** (0.005)	-0.049*** (0.005)	-0.051*** (0.005)	-0.073*** (0.005)	-0.072*** (0.006)	-0.063*** (0.006)
Recession I[GDP/Cap growth < -2%] _t , Destiny	-0.334*** (0.020)	-0.198*** (0.012)	-0.148*** (0.020)	-0.059*** (0.009)	-0.053*** (0.011)	-0.115*** (0.009)	-0.069*** (0.008)	-0.077*** (0.007)	-0.120*** (0.005)	-0.118*** (0.005)	-0.104*** (0.005)	-0.121*** (0.005)	-0.126*** (0.005)	-0.115*** (0.005)
Constant	13.918*** (0.028)	174.456*** (1.535)	131.726*** (4.160)						1.312*** (0.014)			0.147*** (0.003)		
Observations	820,812	780,818	203,814	780,396	414,447	498,463	498,463	820,383	697,757	697,351	737,793	697,757	697,351	737,793
R^2	0.003	0.611	0.678	0.767	0.688	0.802	0.814	0.789	0.857	0.874	0.881	0.001	0.015	0.019
Lagged Log Bilateral Trade (Current $\$$)									0.906*** (0.001)	0.711*** (0.002)	0.632*** (0.002)			
Recession I[GDP growth < -2%] _t , Origin	-0.060*** (0.013)	-0.032*** (0.008)	-0.036*** (0.013)	0.033*** (0.007)	-0.114*** (0.010)	-0.006 (0.007)	-0.026*** (0.007)	-0.079*** (0.006)	-0.068*** (0.005)	-0.042*** (0.005)	-0.055*** (0.005)	-0.085*** (0.005)	-0.084*** (0.005)	-0.043*** (0.005)
Recession I[GDP growth < -2%] _t , Destiny	-0.001 (0.013)	-0.085*** (0.008)	-0.080*** (0.013)	-0.051*** (0.007)	-0.095*** (0.009)	-0.051*** (0.007)	-0.020*** (0.007)	-0.108*** (0.006)	-0.123*** (0.005)	-0.096*** (0.004)	-0.106*** (0.005)	-0.140*** (0.005)	-0.142*** (0.005)	-0.104*** (0.005)
Constant	13.911*** (0.028)	171.999*** (1.519)	129.577*** (4.150)						1.301*** (0.014)			0.147*** (0.003)		
Observations	796,604	796,604	202,464	796,126	390,697	502,613	502,613	796,126	693,047	692,599	726,130	693,047	692,599	726,130
R^2	0.000	0.611	0.678	0.768	0.698	0.802	0.814	0.796	0.858	0.876	0.882	0.002	0.016	0.020
<i>Controls and Fixed-Effects</i>														
Time-Varying Country Characteristics ($\mathbf{X}_{c,t}$, $\mathbf{X}_{d,t}$)	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time-Invariant Country Characteristics (\mathbf{X}_c , \mathbf{X}_d)	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time-Varying Pair Characteristics ($\mathbf{X}_{cd,t}$)	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time-Invariant Pair Characteristics (\mathbf{X}_{cd})	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Importer-Exporter Fixed-Effects (α_{oi} , α_{od})					YES									
Pair Fixed-Effects (α_{od})				YES										
Global Time Trend (t)		YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time Fixed-Effects (τ_t)				YES										
Country-Specific Time Trends (α_{oi} , α_{od})					YES									

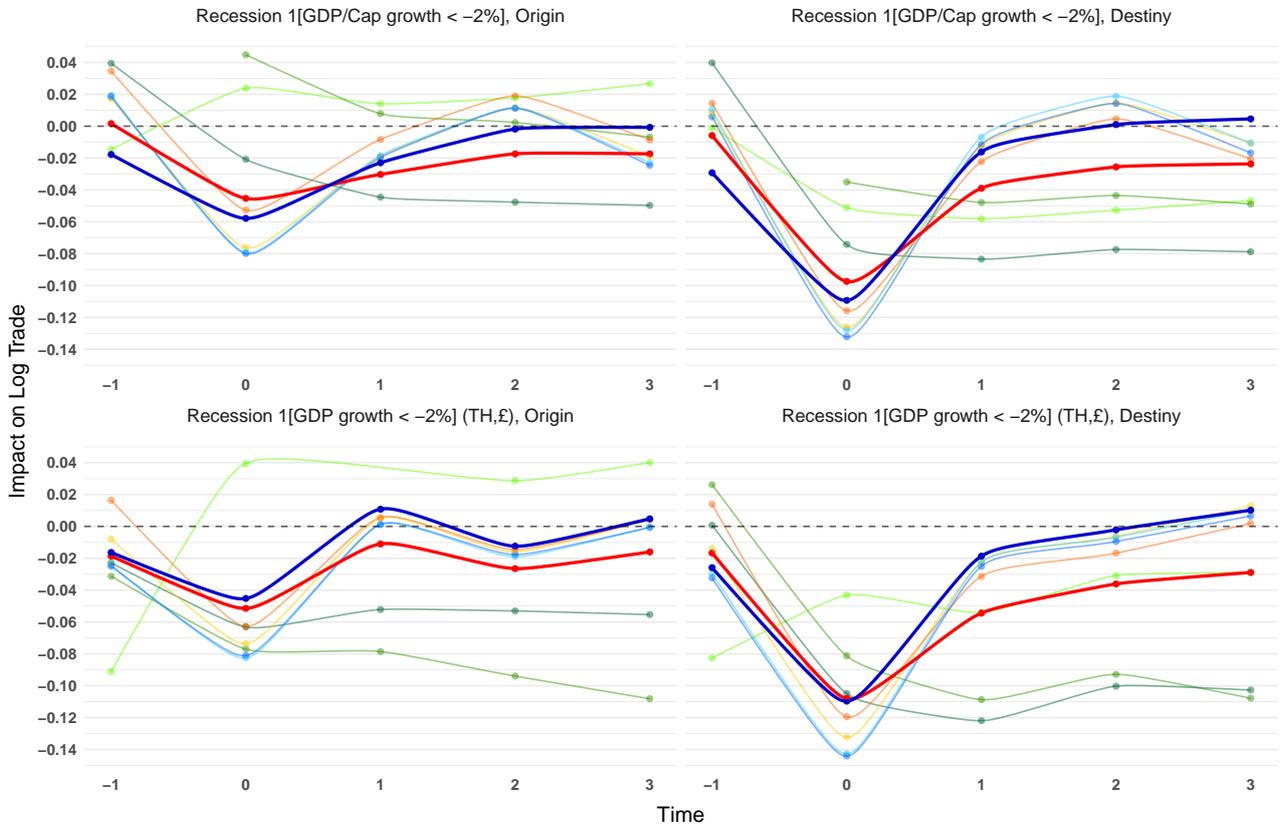
Robust standard errors clustered at the pair level in parentheses
 *** p<0.01, ** p<0.05, * p<0.1

and yield balanced estimates for both importer and exporter recession that are in line with the previous literature on financial crises and trade. Our preferred specifications are LD-3 (11) and FD-3 (14) because they are estimated with the full set of FE and produce conservative and well behaved estimates (also for all the other shocks we will discuss shortly). Across the board we are pleased to note that at least when it comes to point estimates, the majority of specifications¹² deliver closely aligned point estimates ranging from -3% to -7% for the exporter and from -8% to -15% for the importer. It is also especially noteworthy that the inclusion of sufficient control variables as we do in the extended gravity model (which is estimated with 32 covariates, not double-counting country characteristics), we are able to bring the estimates down to a sensible range commensurate with FE estimates. The R^2 of the EX-GR regression is 0.68, while the R^2 in the FE models does not rise above 0.81 (and the FE models with high R^2 all include time FE or country specific time trends). This, together with the proximity of estimates, suggests that the EX-GR model suffers from very little omitted variable bias in terms of important omitted country and pair-level determinants of trade. The latter is also in line with the predictive bottleneck at an R^2 of around 0.70 we observed in the model selection. Nevertheless, it is evident especially then comparing the IRF's from standard FE models with those from LD and FD models, that time-series correlation remains a big source of bias in gravity equations.

Figure 10: Impulse Responses, Recession

Top: GDP Per Capita shock, Bottom: GDP Shock (GDP Series from Trade Hist, in cur. £)

Specification: IMF FE-1 FE-4 LD-1 LD-2 LD-3 FD-1 FD-2 FD-3

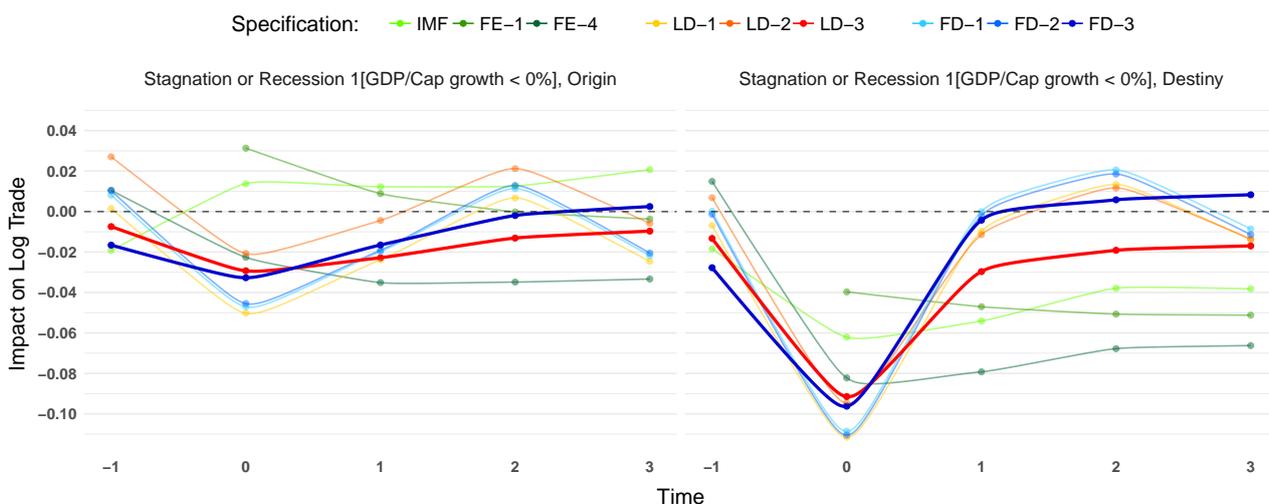


¹²With exception of the RAW impact and the standard gravity model that clearly give to large estimates and the FE models (4) through (7) that give us a 0-impact of the exporter which we are unwilling to believe.

Figure (10) shows the 4 period IRF'S (with contemporaneous impact at time 0) for a selected set of specifications. As noted before, we focus ourselves on the LD and FD specifications since the IRF's produced by these models are well behaved and closely aligned, while the other specifications generally provide much worse behaved IRF's. Our preferred two specifications LD-3 and FD-3, each featuring the full set of FE with no additional covariates, are highlighted in red and blue respectively. As we would expect, the IRF's from the FD-3 decay faster than those of the LD-3, and provide slightly more conservative estimates of the delayed shock impacts. The FE specifications, of which FE-4 is most conservative with the full set of FE, generally suffer from time-series correlation, that is, they fail to decay fast enough. The IRF's sometimes exhibit slight oscillations, which however remains confined in the range of $\pm 2\%$ and therefore does not interfere too gravely with significant impacts. Regarding statistical significance, we note that that the standard errors for dummy coefficients very rarely exceed 0.01. Thus impacts above $\pm 2\%$ can be considered statistically significant.

Having provided all these qualifications, Figure (10) shows in the top panel a contemporaneous impact between -4.5% and -6% and a 1-period delayed impact between -2% and -3% for an economic recession in the exporting country (according to our preferred 2 specifications). For the importing country the IRF's show a contemporaneous impact between -9.5% and -11% and a first-order lagged impact between -2% and -4% . The bottom panel of Figure (10) shows the IRF's if we use the Tradehist nominal GDP series to compute recession dummies, yielding identical results. The IRF's suggest that the cumulative impact of economic recessions on bilateral trade flows is around -8% if the recession occurs in the exporting country and around -14% if the recession occurs in the importing country. These cumulative impact estimates only marginally exceed the point estimates obtained in Table (4). The estimates are sensible in light of both economic theory and the existing literature on financial crises and trade¹³, which suggest that recessions have a stronger impact on the domestic demand for imports than on domestic production and export capacities.

Figure 11: Impulse Responses, Stagnation or Recession

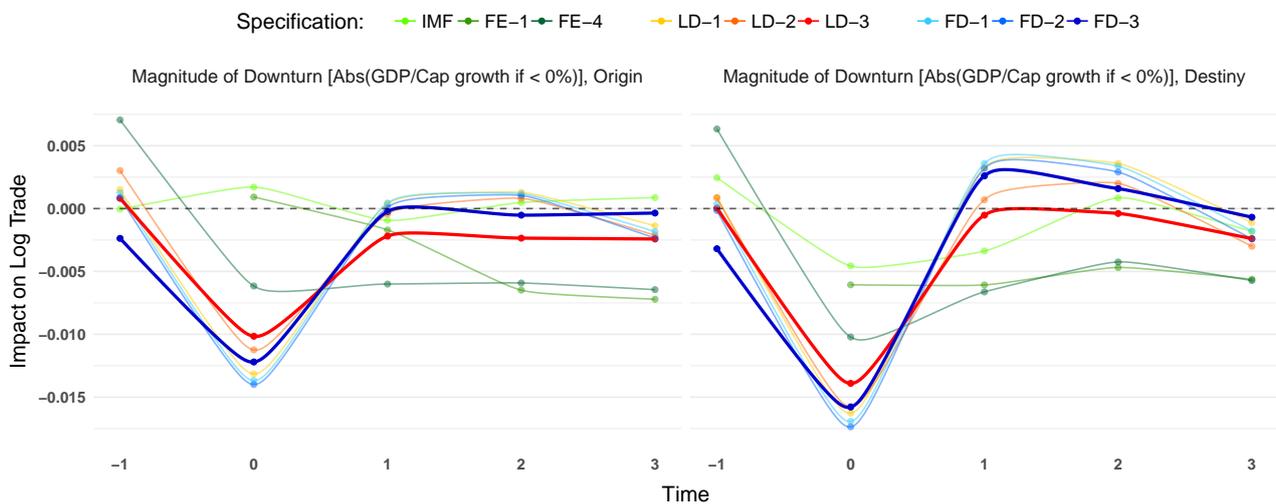


We further examine the robustness of our findings by computing "stagnation or recession"

¹³The estimates in the literature, e.g. [Abiad et al. \(2014\)](#) are generally a bit larger (with cumulative impacts ranging around 20% for the importing country) since these authors restrict themselves to well defined incidences of financial or currency crisis instead of studying the general impact of economic recessions as we do.

dummies indicating whenever per capita GDP growth dropped below 0%. The results are shown in Figure (11). As hoped for, We find IRF's of identical shape to Figure (10), but slightly smaller in magnitude (peak impact is around -3% for the exporter and around -8% for the importer). So as to round things off, we present in Figure (12) IRF's sensitive to the magnitude of the economic downturn. The shock here is simply the GDP per capita growth rate if growth is negative, and 0 otherwise. The estimates in Figure (12) suggest that economic downturns in the exporting country translate approximately 1:1 into trade flows (e.g. a 1% decrease in the growth rate below 0 yields a 1% decrease in export volumes), while an economic downturn in the importing country translates approximately 1.5:1 into trade flows (e.g. a 1% decrease in the growth rate below 0 yields a 1.5% decrease in import volumes). This again nicely aligns with economic theories prediction that the demand-side effects of economic recessions are stronger than the supply-side effects, and also with the stylized fact that the elasticity of trade to growth is about 1.5:1.

Figure 12: Impulse Responses, Magnitude of Downturn



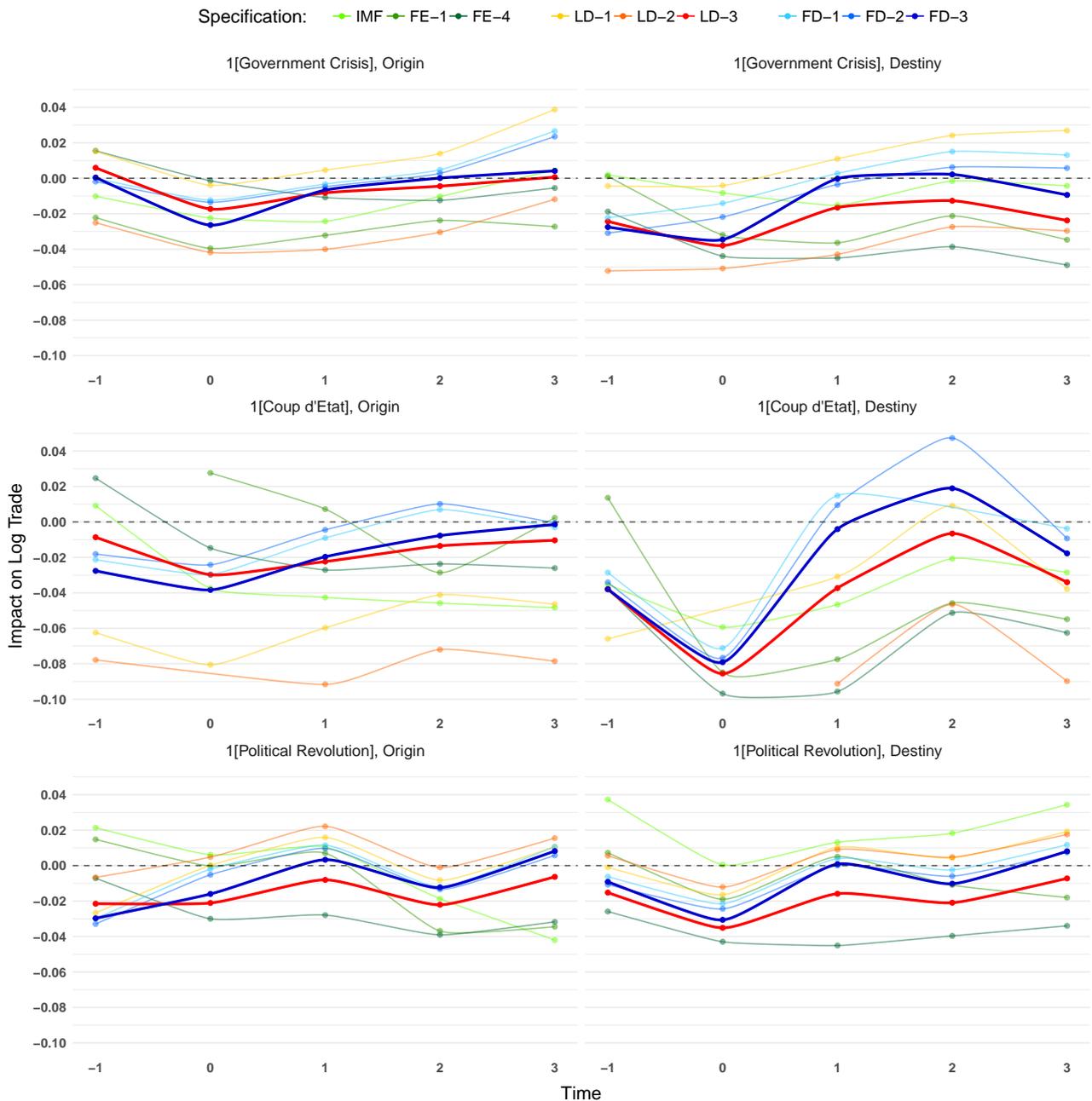
We proceed to discuss non-economic shocks. In order to avoid a repetitive and coarse investigation of over-sized regression tables, we provide the tables containing point estimates in the Appendix and focus on the IRF's, although we will keep referring to these tables.

Figure (13) shows the IRF's for 3 types of domestic political shocks: Government crises, coups d'etat and political revolutions. According to the first set of IRF's, the impact of a government crisis on trade is quite small, around -2% for the exporter and -3% for the importer. This impact is fully realized within one period, although the forward lag for the destiny country is significant, casting doubt on the sensitivity of the estimates. Table (7) provides the corresponding point-estimates. A few specifications yield insignificant coefficients for either exporter or importer. Our two preferred specifications estimate an impact of [X -1.9%, M -4.3%] (LD-3) and [X -2%, M -3.6%] (FD-3), which we think are reasonably precise estimates for the impact of government crises on trade.

The second panel of Figure (13) shows the IRF's documenting the average impact of a coup d'etat on bilateral trade. For the exporter we observe a small impact of -3 to -4% contemporaneously and approx. -2% in the first period following the coup. For the importer this effect

is much larger, with a contemporaneous impact of -8% and lagged impact of -4% according to the LD-3. The point estimates from Table (7) are [X -2.9%, M -8.1%] (LD-3) and [X -4.4%, M -7.6%] (FD-3), with a consistent series of point estimates in that range provided by all three FD specifications, whereas all specifications in levels provide widely differing estimates.

Figure 13: Impulse Responses, Domestic Political Shocks

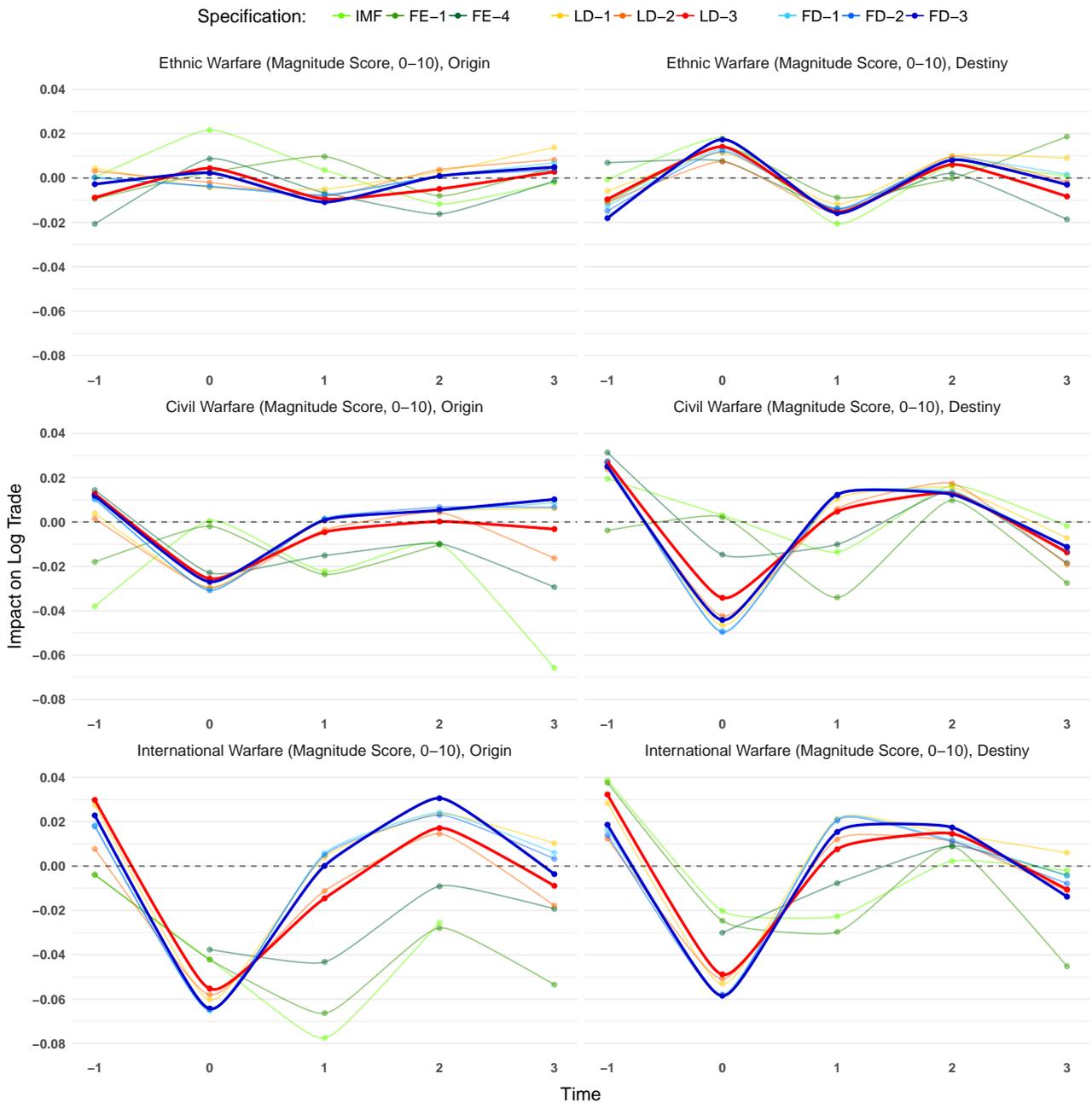


The third panel of Figure (13) indicates that political revolutions hardly impact trade. Since the IRF's here are meandering a lot we move straight to Table (7) for the estimates: [X -3.5%, M -4.7%] (LD-3) and [X -3.1%, M -3.1%] (FD-3). The estimates in the table differ quite a bit, a large part of them insignificant although our preferred specifications are somewhat similar. We conclude (with little confidence) that the impact of a revolution on trade is on average around -3% for both exporter and importer. We explain this symmetry by suggesting that in

most revolutions a little bit of capital gets destroyed, and that destruction is equally likely to afflict consumers of foreign goods and producers for export.

Figure (14) shows the IRF's for ethnic civil and international warfare. A first point to make is that the measures are coded on ordinal scales (0-10) thus the impulse corresponds to a 1-point increase in the magnitude score for these events. This certainly limits our ability to compare their effects with other (dummy) shocks, but we can interpret them relative to one-another.

Figure 14: Impulse Responses, Warfare



The first panel of Figure (14) indicates that ethnic warfare does not have an impact on trade, or at least that impact is in the wrong direction. Table (8) reports the corresponding point-estimates. The point estimates for the LD-3 are [X -1.7%, M -0.9%], and [X -1.1%, M -0.8%]

for FD-3. All point estimates are significant at the 1% level, implying that there is still a small effect in the right direction, but clearly the IRF's are unable to display the temporal structure of this effect.

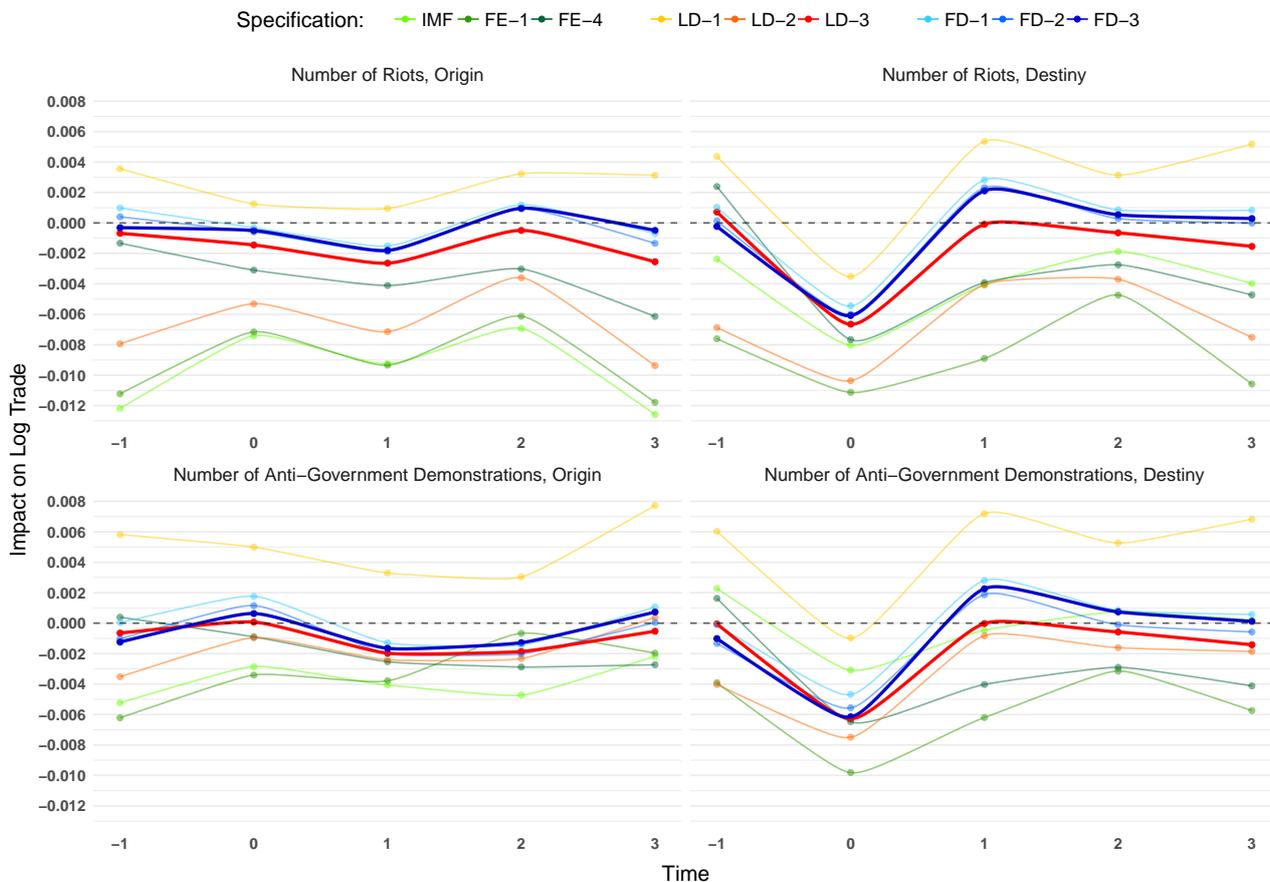
The picture alters for civil and international warfare in the second and third panel of Figure (14), where the IRF's do demonstrate up a sizable shock impact. A 1-point increase in the magnitude of civil war in the exporting country has an average impact on trade is around -2.5%, whereas if that increase is in the importing country, trade flow decreases by 3.5-4.5%. Similarly during a 1-point increase in the magnitude of international war involving the exporting country, trade decreases by 5.5-6.5%, while an aggravation of international war involving the importing country decreases trade by 5-6%. For either type of conflict the impact has fully decayed after one period propounding that unilateral warfare (within the limits of our empirical analysis) has no prolonged impact on bilateral trade¹⁴. Nevertheless the contemporaneous trade impact of unilateral warfare can be quite large. The average magnitude of civil warfare in our sample is 3.7, which would produce an average decline in trade of around [X -9.3%, M -15%]. Likewise the average magnitude of international warfare in our sample is 3.8, producing an average trade impact of [X -23%, M -21%]. We explain the symmetry of impact between exporting and importing countries by the same argument advanced earlier in the context of political revolutions: These events generally destroy capital in a manner equally impacting both consumers and producers.

In Figure (15) we present impulses for two further (softer) measures of domestic political instability: The number of Riots and the number of Anti-Government Demonstrations taking place in a given year¹⁵. The impacts are of an order of magnitude smaller than the impacts previously considered. The IRF's show that both events have no impact in trade when taking place in the exporting country. The impact of an additional riot or anti-government demonstration in the importing country is estimated to yield a 0.6% reduction in the trade flow. This effect alone is surely not attributable solely to the demonstrations, but both measures proxy for an array of possible sources of political instability. For example France is contemporaneously (April 2018) witnessing an increasing amount of anti-government demonstrations triggered by economic reforms. These demonstrations have gone hand-in hand with prolonged strikes against major affected corporations (SNCF and Air France amongst others). While SNCF operates across central Europe, Air France operates worldwide, thus these strikes will have had an impact on trade. On average, 16.9% of importer-years are experiencing riots with an average number of 2.73 riots in positive-riot years, and 22.8% of importer-years are experiencing anti government demonstrations with an average of 2.6 demonstrations in positive years. This purports that countries experiencing these events incur on average 1.5-2% losses in trade as a consequence of the domestic political tensions proxied for by these variables.

¹⁴This excludes of course situations of bilateral warfare where both trading partners are at war with one-another. In that case the impact on bilateral trade is very large. Glick & Taylor (2010) estimate a 80-90% reduction in trade during a war between belligerents, and trade only returns to its pre-war level after 10 years on average.

¹⁵See Table (5) for precise definitions of these variables.

Figure 15: Impulse Responses, Political Instability



In Figure (16), we have regressed log trade on the inverse hyperbolic \sin^{16} of a weighted domestic conflict index (WCI) provided by Banks & Wilson (2001). The index is computed as follows:

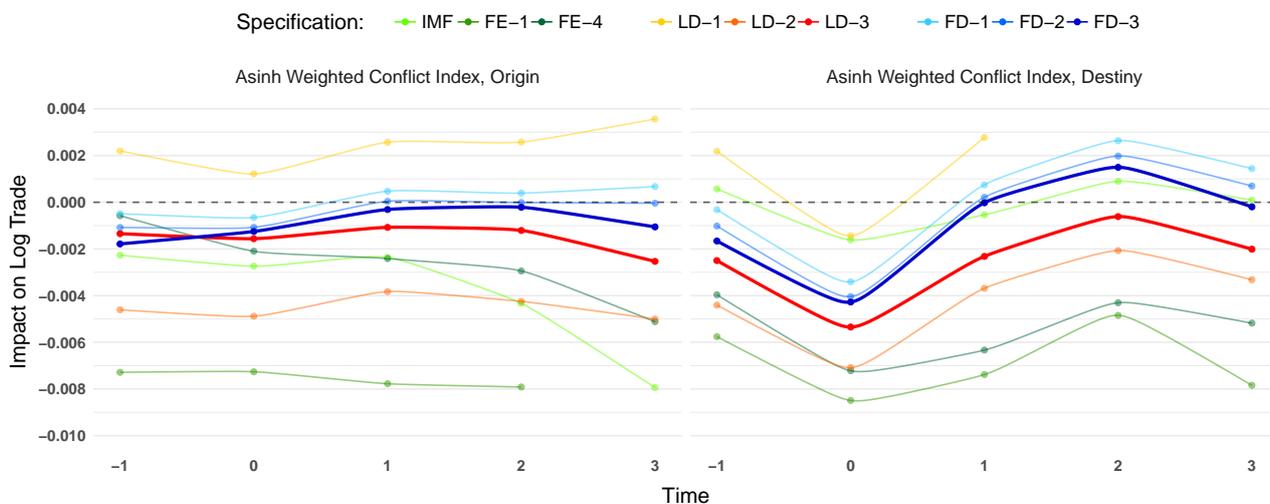
$$\text{WCI} = \left(\begin{array}{l} 25 \times \text{Assassinations} + 20 \times \text{Strikes} + 100 \times \text{Guerrilla Warfare} + 20 \times \text{Government Crises} \\ + 20 \times \text{Purges} + 25 \times \text{Riots} + 150 \times \text{Revolutions} + 10 \times \text{Anti-Government Demonstrations} \end{array} \right) \times \frac{100}{8}$$

The IRF's show not much of an impact of domestic conflict for the exporter country, but a 100% increase in domestic conflict in the importer country yields a contemporaneous 0.4-0.55% decrease in the bilateral trade flow, with a 1-period lagged impact of up to -2%. The corresponding point-estimates are shown in Table (10) and confirm the results (for the importer Table (10) yields LD-3 -0.6% and FD-3 -0.4%).

Finally, we report in Figure (17) the IRF's for epidemics. Although this variable showed up among the top 30 variables in Table (1), it turns out that the correlation of this variable with trade totally breaks down after controlling for various fixed effects. The second panel shows that very large epidemics might have a small effect on trade when taking place in the origin country. The corresponding point-estimates are shown in Table (11) and are -8.9% (LD-3) and -4.7% (FD-3). For the destiny country the effects of even very large epidemics are insignificant. This is a curious result. A possible explanation could be that large epidemics do not impede

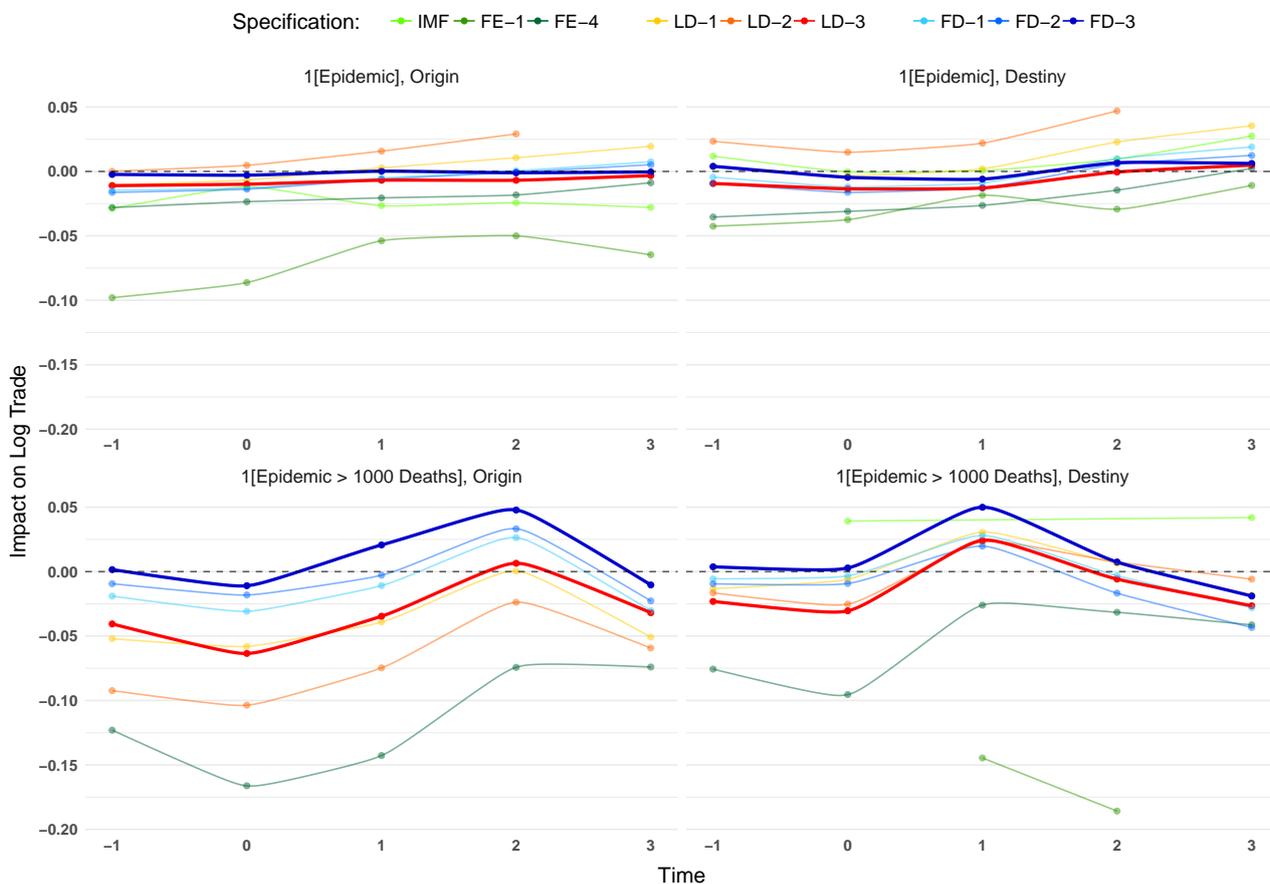
¹⁶Given by $\text{arsinh}(x) = \ln(x + \sqrt{x^2 + 1})$. We use this transformation to be able to estimate a constant elasticity model without losing 0-observations.

Figure 16: Impulse Responses, CNTS Weighted Conflict Index



domestic demand too much but curtail foreign demand for domestic goods for the fear of contamination with the disease. This interesting channel would demand further empirical investigation with more detailed data on epidemics and measures taken in response to it, which we will not indulge in at this point.

Figure 17: Impulse Responses, Epidemic



4 Conclusion

Our findings show that bilateral trade flows are quite elastic to various economic and political shocks. We identified the strongest trade impacts as being economic recessions, civil and international warfare, followed by coups and political instability. In addition we registered small trade responses to government crises and revolutions, and to major epidemics. With the exception of epidemics and warfare, we observe that shocks have a stronger effect on trade when occurring in the importer country, indicating a leading role for the domestic demand channel in driving bilateral trade flows. We also observe that all shocks considered appear to have no lasting impacts on trade flows, at least when they occur unilaterally as in our analysis framework: most IRF's calculated return to 0 after 1 or 2 periods.

Further research could take off from here and analyze regional and temporal heterogeneity in the impact estimates and study more carefully the various channels through which these shocks impact trade. An analysis of the determinants of impact estimates could be added as a second step in the analysis. An additional interesting trajectory for future research could be to extend the scope of this research and conduct a careful study of natural disasters and the potential impact of climate change on global trade patterns. Disaggregated datasets at the sectoral and/or regional level surface as particularly promising for such an analysis.

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Appendix

Table 5: Definitions of Political Shock Variables from Codebook

Variable Name	Codebook Definition	Source
Coup d'Etat	Extraconstitutional or forced changes in the top government elite and/or its effective control of the nation's power structure in a given year. The term "coup" includes, but is not exhausted by, the term "successful revolution". Unsuccessful coups are not counted.	Banks & Wilson (2001)
Major Constitutional Change	Basic alteration in a state's constitutional structure, the extreme case being the adoption of a new constitution that significantly alters the prerogatives of the various branches of government. Examples of the latter might be the substitution of presidential for parliamentary government or the replacement of monarchical by republican rule. Constitutional amendments which do not have significant impact on the political system are not counted.	Banks & Wilson (2001)
Government Crisis	Any rapidly developing situation that threatens to bring the downfall of the present regime - excluding situations of revolt aimed at such overthrow.	Banks & Wilson (2001)
Political Revolution	Any illegal or forced change in the top government elite, any attempt at such a change, or any successful or unsuccessful armed rebellion whose aim is independence from the central government.	Banks & Wilson (2001)
Number of Riots	Any violent demonstration or clash of more than 100 citizens involving the use of physical force	Banks & Wilson (2001)
Number of Anti-Government Demonstrations	Any peaceful public gathering of at least 100 people for the primary purpose of displaying or voicing their opposition to government policies or authority, excluding demonstrations of a distinctly anti-foreign nature.	Banks & Wilson (2001)

Figure 18: Country Frequency of Recessions: Robustness checks

Based on a Time Average for all Country-Years Represented in the Trade Data

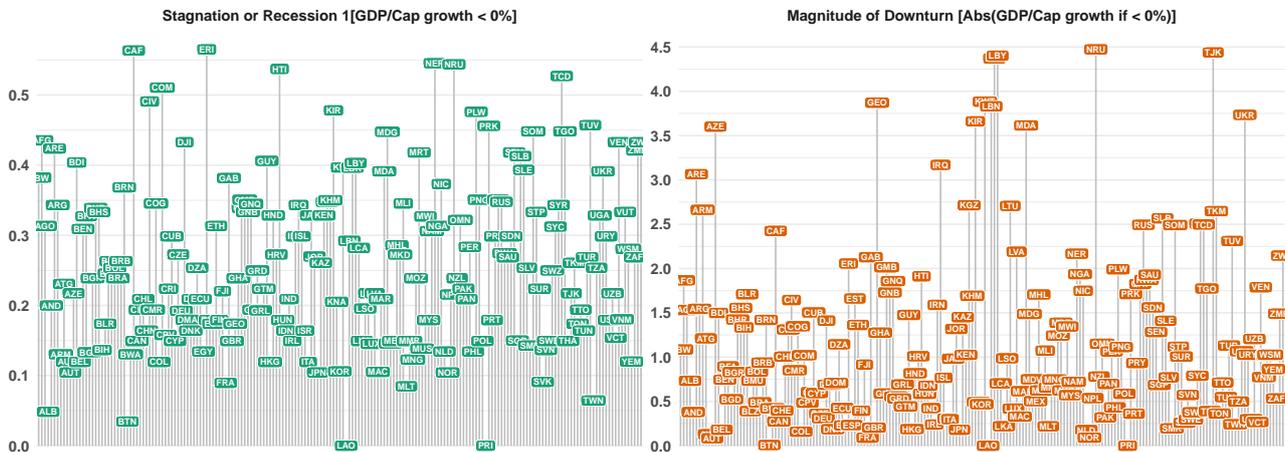


Figure 19: Country Coverage

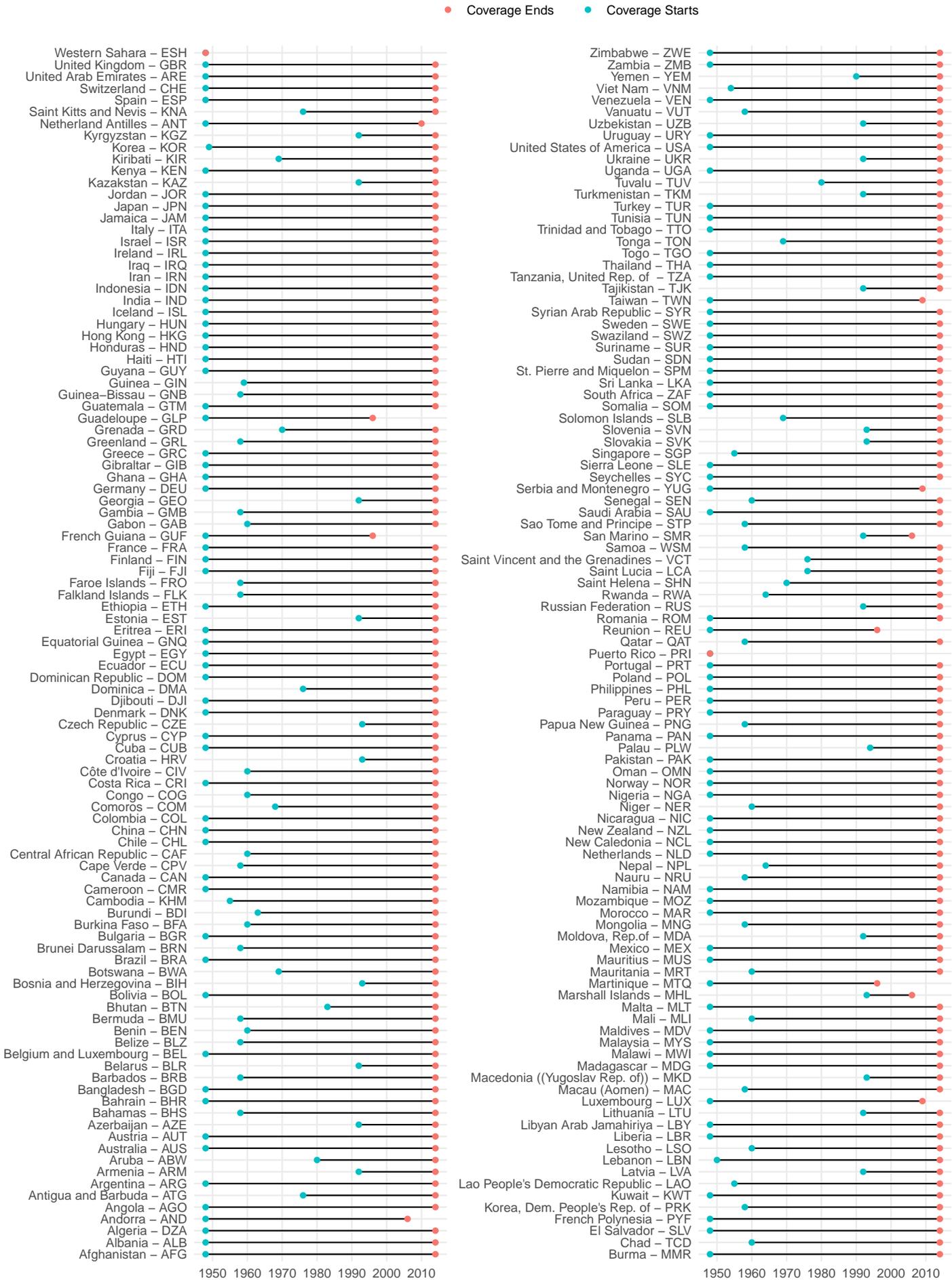


Figure 20: Temporal Frequency of Non-Economic Shocks
 Based on a Cross-Country Average for all Country-Years Represented in the Trade Data

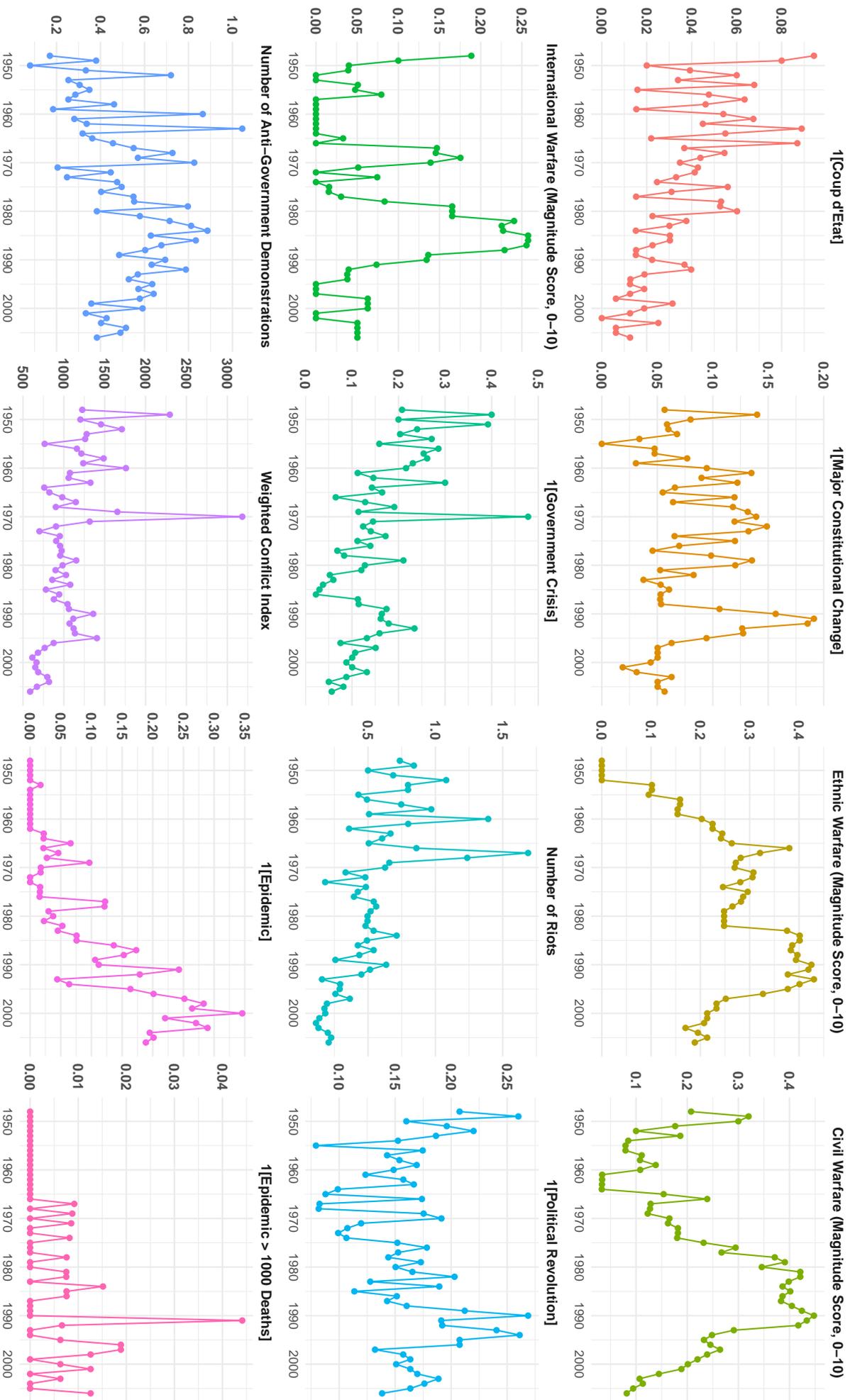


Table 6: Trade Response to Recession: Robustness Checks

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	RAW	ST-GR	EX-GR	IMP	FE-1	FE-2	FE-3	FE-4	LD-1	LD-2	LD-3	FD-1	FD-2	FD-3
Stagnation or Recession I[GDP/Cap growth < 0%], Origin	-0.376*** (0.015)	-0.114*** (0.009)	-0.059*** (0.016)	0.002 (0.007)	0.019** (0.009)	-0.015** (0.007)	-0.011* (0.007)	-0.031*** (0.006)	-0.058*** (0.004)	-0.016*** (0.004)	-0.035*** (0.004)	-0.047*** (0.004)	-0.042*** (0.004)	-0.037*** (0.004)
Stagnation or Recession I[GDP/Cap growth < 0%], Destiny	-0.298*** (0.015)	-0.183*** (0.009)	-0.176*** (0.016)	-0.073*** (0.007)	-0.058*** (0.008)	-0.113*** (0.007)	-0.064*** (0.006)	-0.086*** (0.006)	-0.108*** (0.004)	-0.093*** (0.004)	-0.096*** (0.004)	-0.099*** (0.004)	-0.101*** (0.004)	-0.096*** (0.004)
Observations	820,812 0.003	780,818 0.611	203,814 0.678	780,396 0.767	414,447 0.688	498,463 0.802	498,463 0.814	820,393 0.789	697,757 0.857	697,351 0.874	737,793 0.881	697,757 0.001	697,351 0.015	737,793 0.019
Magnitude of Downturn [Abs(GDP/Cap growth if < 0%)], Origin	-0.049*** (0.002)	-0.016*** (0.002)	0.012*** (0.003)	-0.002 (0.001)	-0.003 (0.002)	0.001 (0.001)	-0.001 (0.001)	-0.005*** (0.001)	-0.012*** (0.001)	-0.010*** (0.001)	-0.010*** (0.001)	-0.012*** (0.001)	-0.012*** (0.001)	-0.012*** (0.001)
Magnitude of Downturn [Abs(GDP/Cap growth if < 0%)], Destiny	-0.025*** (0.002)	-0.016*** (0.001)	-0.001 (0.003)	-0.003*** (0.001)	-0.006*** (0.001)	-0.010*** (0.001)	-0.005*** (0.001)	-0.008*** (0.001)	-0.014*** (0.001)	-0.015*** (0.001)	-0.014*** (0.001)	-0.015*** (0.001)	-0.016*** (0.001)	-0.016*** (0.001)
Observations	820,812 0.002	780,818 0.611	203,814 0.678	780,396 0.767	414,447 0.688	498,463 0.802	498,463 0.814	820,393 0.789	697,757 0.857	697,351 0.874	737,793 0.881	697,757 0.002	697,351 0.015	737,793 0.020
<i>Controls and Fixed-Effects</i>														
Time-Varying Country Characteristics	YES													
Time-Invariant Country Characteristics	YES													
Time-Varying Pair Characteristics	YES													
Time-Invariant Pair Characteristics	YES													
Importer-Exporter Fixed-Effects														
Pair Fixed-Effects		YES												
Global Time Trend														
Time Fixed-Effects														
Country-Specific Time Trends														

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Trade Response to Domestic Political Shocks

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	RAW	ST-GR	EX-GR	IMF	FE-1	FE-2	FE-3	FE-4	LD-1	LD-2	LD-3	FD-1	FD-2	FD-3
1[Government Crisis], Origin	0.439*** (0.027)	-0.013 (0.014)	0.147*** (0.021)	-0.021** (0.010)	-0.067*** (0.010)	0.008 (0.010)	0.006 (0.009)	-0.016** (0.007)	0.031*** (0.005)	-0.047*** (0.005)	-0.019*** (0.005)	-0.000 (0.005)	-0.003 (0.005)	-0.020*** (0.005)
1[Government Crisis], Destiny	0.420*** (0.028)	0.027* (0.015)	-0.004 (0.023)	-0.016 (0.010)	-0.032*** (0.011)	-0.033*** (0.010)	-0.028*** (0.009)	-0.051*** (0.007)	0.025*** (0.005)	-0.061*** (0.006)	-0.043*** (0.005)	-0.008 (0.005)	-0.019*** (0.006)	-0.036*** (0.006)
Observations	624,341	603,994	203,224	603,495	374,261	379,166	379,166	623,828	534,897	534,441	559,573	534,897	534,441	559,573
R ²	0.003	0.611	0.678	0.771	0.693	0.799	0.809	0.793	0.849	0.869	0.876	0.000	0.018	0.023
1[Coup d'Etat], Origin	-1.172*** (0.043)	-0.118*** (0.030)	0.176*** (0.051)	0.011 (0.022)	0.061** (0.025)	0.043 (0.029)	-0.004 (0.026)	-0.008 (0.017)	-0.099*** (0.016)	-0.113*** (0.015)	-0.029** (0.014)	-0.040** (0.016)	-0.038** (0.016)	-0.044*** (0.016)
1[Coup d'Etat], Destiny	-0.986*** (0.040)	-0.155*** (0.026)	0.109*** (0.041)	-0.031 (0.019)	-0.041* (0.021)	-0.027 (0.025)	-0.029 (0.022)	-0.074*** (0.015)	-0.123*** (0.014)	-0.173*** (0.014)	-0.081*** (0.012)	-0.072*** (0.014)	-0.078*** (0.015)	-0.076*** (0.014)
Observations	586,920	564,636	199,815	564,092	378,476	336,801	336,801	586,365	495,342	494,802	523,002	495,342	494,802	523,002
R ²	0.003	0.608	0.678	0.770	0.689	0.797	0.807	0.790	0.847	0.868	0.875	0.000	0.020	0.025
1[Political Revolution], Origin	-0.479*** (0.035)	-0.254*** (0.020)	-0.123*** (0.029)	-0.036** (0.014)	-0.037** (0.017)	0.022 (0.015)	-0.019 (0.012)	-0.048*** (0.010)	-0.016*** (0.006)	-0.002 (0.007)	-0.035*** (0.006)	-0.023*** (0.005)	-0.026*** (0.006)	-0.031*** (0.007)
1[Political Revolution], Destiny	-0.222*** (0.034)	-0.160*** (0.020)	-0.046* (0.027)	0.038*** (0.014)	-0.022 (0.016)	-0.013 (0.014)	-0.034*** (0.012)	-0.071*** (0.009)	0.002 (0.006)	-0.014** (0.007)	-0.047*** (0.006)	-0.017*** (0.005)	-0.030*** (0.006)	-0.031*** (0.006)
Observations	624,181	603,843	203,120	603,344	374,125	379,044	379,044	623,668	534,753	534,297	559,429	534,753	534,297	559,429
R ²	0.002	0.611	0.678	0.771	0.693	0.799	0.809	0.793	0.849	0.869	0.876	0.000	0.018	0.023
<i>Controls and Fixed-Effects</i>														
Time-Varying Country Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time-Invariant Country Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time-Varying Pair Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time-Invariant Pair Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Importer-Exporter Fixed-Effects														
Pair Fixed-Effects		YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Global Time Trend														
Time Fixed-Effects														
Country-Specific Time Trends														

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Trade Response to Warfare

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	RAW	ST-GR	EX-GR	IMF	FE-1	FE-2	FE-3	FE-4	LD-1	LD-2	LD-3	FD-1	FD-2	FD-3
Ethnic Warfare (Magnitude Score, 0-10), Origin	0.030* (0.016)	-0.047*** (0.009)	-0.061*** (0.014)	0.010 (0.008)	0.012 (0.012)	0.017* (0.010)	-0.022*** (0.008)	-0.023*** (0.007)	0.011*** (0.002)	-0.006* (0.003)	-0.017*** (0.003)	-0.007*** (0.001)	-0.012*** (0.002)	-0.011*** (0.002)
Ethnic Warfare (Magnitude Score, 0-10), Destiny	0.085*** (0.017)	-0.049*** (0.010)	-0.080*** (0.014)	0.001 (0.008)	0.008 (0.012)	-0.006 (0.009)	-0.002 (0.009)	-0.009 (0.007)	0.016*** (0.002)	-0.011*** (0.003)	-0.009*** (0.003)	-0.003*** (0.001)	-0.009*** (0.002)	-0.008*** (0.002)
Constant	14.215*** (0.031)	176.206*** (1.709)	133.567*** (4.306)						1.330*** (0.016)			0.126*** (0.003)		
Observations	660,666	642,606	189,404	642,391	343,346	425,153	425,153	660,460	579,221	579,005	603,815	579,221	579,005	603,815
R ²	0.001	0.617	0.679	0.770	0.694	0.804	0.817	0.795	0.861	0.877	0.884	0.000	0.012	0.018
Civil Warfare (Magnitude Score, 0-10), Origin	-0.300*** (0.017)	-0.168*** (0.011)	-0.154*** (0.018)	-0.119*** (0.009)	-0.133*** (0.010)	-0.094*** (0.012)	-0.054*** (0.010)	-0.062*** (0.008)	-0.020*** (0.002)	-0.042*** (0.004)	-0.026*** (0.004)	-0.011*** (0.002)	-0.012*** (0.002)	-0.007*** (0.003)
Civil Warfare (Magnitude Score, 0-10), Destiny	-0.087*** (0.015)	-0.029*** (0.010)	0.010 (0.014)	0.023*** (0.009)	-0.052*** (0.009)	0.023*** (0.011)	0.031*** (0.010)	0.001 (0.007)	-0.003 (0.002)	-0.015*** (0.003)	-0.005 (0.003)	-0.008*** (0.001)	-0.013*** (0.002)	-0.009*** (0.002)
Observations	660,666	642,606	189,404	642,391	343,346	425,153	425,153	660,460	579,221	579,005	603,815	579,221	579,005	603,815
R ²	0.005	0.618	0.680	0.770	0.695	0.805	0.818	0.795	0.861	0.877	0.884	0.000	0.012	0.018
International Warfare (Magnitude Score, 0-10), Origin	-0.062*** (0.026)	-0.243*** (0.019)	-0.251*** (0.031)	-0.195*** (0.015)	-0.159*** (0.018)	-0.141*** (0.018)	-0.057*** (0.016)	-0.048*** (0.011)	-0.018*** (0.004)	-0.072*** (0.005)	-0.039*** (0.006)	-0.029*** (0.004)	-0.035*** (0.004)	-0.035*** (0.004)
International Warfare (Magnitude Score, 0-10), Destiny	0.165*** (0.021)	-0.038*** (0.013)	-0.040* (0.023)	-0.008 (0.012)	-0.038*** (0.016)	-0.052*** (0.015)	-0.024* (0.013)	0.008 (0.010)	-0.000 (0.003)	-0.038*** (0.005)	-0.017*** (0.005)	-0.026*** (0.003)	-0.032*** (0.003)	-0.031*** (0.003)
Observations	660,666	642,606	189,404	642,391	343,346	425,153	425,153	660,460	579,221	579,005	603,815	579,221	579,005	603,815
R ²	0.001	0.618	0.680	0.770	0.694	0.805	0.817	0.795	0.861	0.877	0.884	0.001	0.012	0.018
<i>Controls and Fixed-Effects</i>														
Time-Varying Country Characteristics		YES	YES	YES		YES								
Time-Invariant Country Characteristics		YES	YES	YES		YES	YES	YES	YES	YES	YES		YES	YES
Time-Varying Pair Characteristics		YES	YES	YES		YES	YES	YES		YES	YES		YES	YES
Time-Invariant Pair Characteristics														
Importer-Exporter Fixed-Effects						YES	YES	YES	YES	YES	YES		YES	YES
Pair Fixed-Effects		YES	YES	YES	YES	YES	YES	YES	YES	YES	YES		YES	YES
Global Time Trend														
Time Fixed-Effects						YES	YES	YES	YES	YES	YES		YES	YES
Country-Specific Time Trends														YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Trade Response to Political Instability

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Number of Riots, Origin	0.092*** (0.005)	-0.036*** (0.003)	-0.041*** (0.005)	-0.028*** (0.002)	-0.025*** (0.002)	-0.026*** (0.003)	-0.002 (0.002)	-0.009*** (0.001)	0.008*** (0.001)	-0.017*** (0.001)	-0.004*** (0.001)	-0.001** (0.000)	-0.001*** (0.001)	-0.001*** (0.001)
Number of Riots, Destiny	0.097*** (0.005)	-0.019*** (0.003)	-0.041*** (0.006)	-0.014*** (0.002)	-0.024*** (0.002)	-0.022*** (0.004)	-0.006*** (0.003)	-0.012*** (0.002)	0.007*** (0.001)	-0.019*** (0.001)	-0.007*** (0.001)	-0.003*** (0.001)	-0.005*** (0.001)	-0.006*** (0.001)
Observations	624,108 0.005	603,763 0.611	203,224 0.679	603,264 0.771	374,261 0.694	378,943 0.799	378,943 0.809	623,505 0.792	534,667 0.849	534,211 0.869	559,343 0.876	534,667 0.000	534,211 0.018	559,343 0.023
Number of Anti-Government Demonstrations, Origin	0.179*** (0.005)	-0.022*** (0.003)	-0.002 (0.005)	-0.010*** (0.002)	-0.010*** (0.002)	-0.002 (0.003)	0.002 (0.002)	-0.004** (0.001)	0.017*** (0.001)	-0.003*** (0.001)	-0.001* (0.001)	0.000 (0.001)	-0.001 (0.001)	-0.000 (0.001)
Number of Anti-Government Demonstrations, Destiny	0.168*** (0.006)	-0.011*** (0.003)	-0.014*** (0.005)	-0.003 (0.002)	-0.015*** (0.002)	-0.009*** (0.003)	-0.006*** (0.003)	-0.009*** (0.002)	0.013*** (0.001)	-0.011*** (0.001)	-0.008*** (0.001)	-0.004*** (0.001)	-0.007*** (0.001)	-0.007*** (0.001)
Observations	624,299 0.017	603,957 0.611	203,171 0.678	603,459 0.771	374,184 0.693	379,153 0.798	379,153 0.809	623,787 0.793	534,869 0.849	534,414 0.869	559,546 0.876	534,869 0.000	534,414 0.018	559,546 0.023
<i>Controls and Fixed-Effects</i>														
Time-Varying Country Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time-Invariant Country Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time-Varying Pair Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time-Invariant Pair Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Importer-Exporter Fixed-Effects					YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Pair Fixed-Effects		YES		YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Global Time Trend			YES											
Time Fixed-Effects				YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country-Specific Time Trends					YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Trade Response to Weighted Conflict Index

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Asinh Weighted Conflict Index, Origin	0.068*** (0.003)	-0.026*** (0.002)	-0.012*** (0.003)	-0.009*** (0.001)	-0.017*** (0.001)	-0.002** (0.001)	0.000 (0.001)	-0.004*** (0.001)	0.008*** (0.000)	-0.008*** (0.001)	-0.002*** (0.001)	-0.001 (0.000)	-0.001* (0.001)	-0.001** (0.001)
Asinh Weighted Conflict Index, Destiny	0.071*** (0.003)	-0.014*** (0.002)	-0.007** (0.003)	-0.001 (0.001)	-0.013*** (0.001)	-0.007*** (0.001)	-0.005*** (0.001)	-0.009*** (0.001)	0.008*** (0.000)	-0.010*** (0.001)	-0.006*** (0.001)	-0.001** (0.000)	-0.003*** (0.001)	-0.004*** (0.001)
Observations	623,642	603,311	202,956	602,813	373,893	378,608	378,608	623,130	534,263	533,808	558,940	534,263	533,808	558,940
R^2	0.012	0.611	0.678	0.771	0.694	0.798	0.809	0.793	0.849	0.869	0.876	0.000	0.018	0.023
<i>Controls and Fixed-Effects</i>														
Time-Varying Country Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time-Invariant Country Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time-Varying Pair Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time-Invariant Pair Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Importer-Exporter Fixed-Effects					YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Pair Fixed-Effects		YES	YES	YES	YES	YES	YES	YES						
Global Time Trend					YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time Fixed-Effects					YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country-Specific Time Trends					YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
 *** p<0.01, ** p<0.05, * p<0.1

Table 11: Trade Response to Epidemics

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	RAW	ST-GR	EX-GR	IMF	FE-1	FE-2	FE-3	FE-4	LD-1	LD-2	LD-3	FD-1	FD-2	FD-3
1[Epidemic] _i , Origin	-0.303*** (0.028)	-0.178*** (0.017)	0.023 (0.017)	-0.044*** (0.012)	-0.127*** (0.014)	-0.019** (0.009)	0.003 (0.008)	-0.021*** (0.007)	0.006 (0.005)	0.027*** (0.005)	-0.010* (0.006)	-0.009* (0.005)	-0.008 (0.006)	0.003 (0.006)
1[Epidemic] _j , Destiny	-0.130*** (0.028)	-0.074*** (0.016)	0.019 (0.017)	0.034*** (0.012)	-0.051*** (0.013)	-0.011 (0.009)	-0.017** (0.008)	-0.043*** (0.007)	0.012** (0.005)	0.045*** (0.006)	-0.020*** (0.006)	-0.013** (0.005)	-0.019*** (0.006)	-0.008 (0.006)
Observations	867,644	794,746	203,814	794,285	427,321	499,321	499,321	867,110	735,314	734,814	777,501	735,314	734,814	777,501
R ²	0.001	0.610	0.678	0.767	0.683	0.802	0.814	0.786	0.856	0.873	0.879	0.000	0.014	0.019
1[Epidemic > 1000 Deaths] _i , Origin	-1.189*** (0.074)	-0.755*** (0.054)	-0.383*** (0.071)	-0.311*** (0.040)	-0.377*** (0.048)	-0.118*** (0.038)	0.006 (0.035)	-0.135*** (0.031)	-0.112*** (0.028)	-0.129*** (0.027)	-0.089*** (0.026)	-0.069** (0.028)	-0.061** (0.029)	-0.047 (0.029)
1[Epidemic > 1000 Deaths] _j , Destiny	-0.538*** (0.075)	-0.286*** (0.048)	-0.255*** (0.063)	0.122*** (0.036)	-0.208*** (0.043)	-0.031 (0.033)	-0.014 (0.031)	-0.057** (0.028)	-0.017 (0.025)	-0.007 (0.024)	-0.027 (0.024)	-0.018 (0.026)	-0.018 (0.027)	-0.003 (0.027)
Observations	867,644	794,746	203,814	794,285	427,321	499,321	499,321	867,110	735,314	734,814	777,501	735,314	734,814	777,501
R ²	0.001	0.610	0.678	0.767	0.683	0.802	0.814	0.786	0.856	0.873	0.879	0.000	0.014	0.019
<i>Controls and Fixed-Effects</i>														
Time-Varying Country Characteristics		YES	YES	YES		YES	YES		YES	YES	YES		YES	YES
Time-Invariant Country Characteristics			YES	YES		YES	YES			YES	YES		YES	YES
Time-Varying Pair Characteristics			YES	YES		YES	YES			YES	YES		YES	YES
Time-Invariant Pair Characteristics			YES	YES		YES	YES							
Importer-Exporter Fixed-Effects					YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Pair Fixed-Effects		YES	YES	YES		YES	YES	YES	YES	YES	YES	YES	YES	YES
Global Time Trend					YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time Fixed-Effects					YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country-Specific Time Trends					YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1