Appendix (Not For Publication)

A Data Construction Appendix

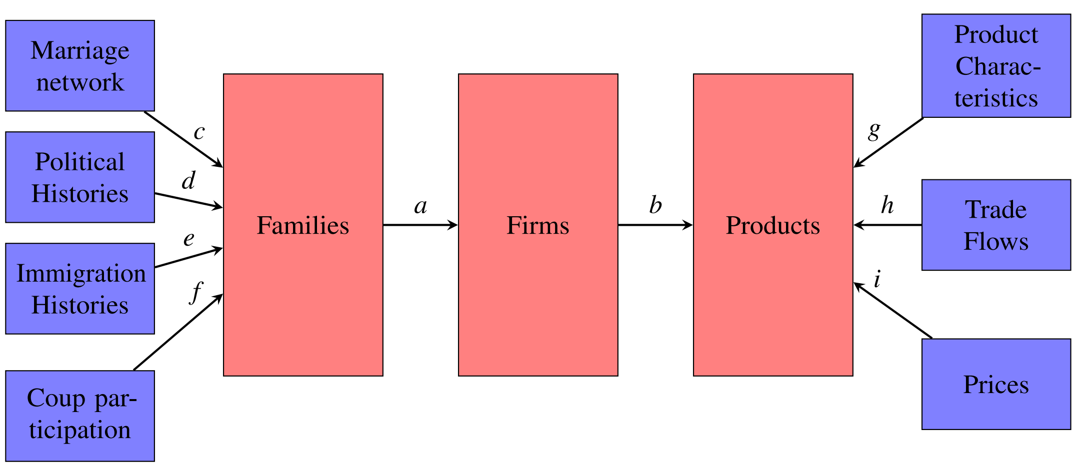
In this Appendix we provide an overview of how we constructed these datasets and describe the source and construction of each variable. The core of our dataset is a linkage between families, the firms they own, and the products that they import into Haiti. To this base, we draw in additional information on the political and social histories of Haitian families, as well as the characteristics of products. Figure A2 provides an overview of our data structure.

Figure A1: Import quotas for 19 major families, 1984-1985 (Fass, 1988)

	SHARE OF QUOTA ALLOCATED TO IMPORTER (%)																			Total Share (%)	Total Importers
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S		
Household utensils, metal	7	92																		99	2
Household utensils, plastic	2	2	15	26	49															94	5
Shoes						70														70	1
Slippers	92																			92	1
Nails						65														65	1
V-8 juice	29							71												100	2
Vegetable and fruit juices	48							48												96	2
Toothpaste	3								62											65	2
Liquid disinfectant	11				14			14		39										78	4
Wrapping paper, cardboard	66							16												82	2
Paper and plastic bags	94																			94	1
Irons for pressing clothes		43		28			28													99	3
Paint											44	22	22							88	3
Hand soap	10		18						45											73	3
Candies	65							32												97	2
Textiles														31	12	37				80	3
Milk																	63	28		91	2
Spaghetti, macaroni, etc.	44																		56	100	2

Source: Reveco (1984).

Figure A2: Diagram of dataset construction



We first link families to firms (link a in Figure A2) with three databases of contemporary firm ownership. The first, a commercial dataset called Orbis produced by the Bureau van

Dijk corporation, has information on 626 unique families that own 345 Haitian corporations; however, the majority of these are not importing firms.[8] The second is a database of Haitian firms assembled by a nonprofit organization called Haiti Building Markets after the 2010 earthquake to encourage aid agencies to buy goods and services from local firms.[9] This data includes information on more than 3,400 firms owned by 1,951 unique families. Third, we draw on information in an online database of firms registered with the Haitian Ministry of Commerce and Industry.[10] In a few cases, when a firm did not appear in any of these databases but is a major importer of a staple good in Haiti, we also use public information on the web or the knowledge of experts on Haiti's import sector. We conducted this additional research for all of the firms that import one of the 18 products on which we have consumer price data, if the owners were not identified in one of the three existing databases. From these four sources, we constructed a table of which families owned each firm that appears in our data.

The second key link in our data is from firms to products (link b in Figure A2). To make this link, we use data on shipping patterns by firm in 2009 and 2011 provided by AGEMAR, a Haitian shipping firm that collects and sells data from the port authority. We exclude the year of 2010 because the catastrophic earthquake that hit Port-au-Prince in January 2010 dramatically changed shipping patterns by shocking demand, changing the most common suppliers of many goods (in particular, causing an influx of goods imported by NGOs), and destroying the primary Haitian port. We also exclude the bottom 10% of firms importing each product to ease the matching process and to exclude tiny or one-off shipments of goods. Using the 2009 and 2011 data, we construct a measure of the portion of trade in each good that is controlled by specific firms. Each of our products is ultimately identified by a four-digit Harmonized System (HS) code. In later robustness checks in Appendix E.3 we test whether our results are robust to down-weighting data for products that have lower levels of consistency in shipments between 2009 and 2011.

Linking the two datasets involves merging by firm name. To accurately match firms across multiple sources, we use a combination of approximate string matching and manual identification of alternative spellings. We first strip out some words and standardize spelling, including accents on French words, and common terms.[11] We also eliminate NGOs using a combination of key word search (ex. firm names that include "foundation") and manual identification (ex. large, well-known NGOs such as "World Vision"). Next we strip out individuals only shipping items for personal use, marked by a special tariff code. After this first round of processing, we implement an approximate string matching algorithm across all the firm names with more than eight letters to match firms with a generalized Levenshtein edit distance of two or lower. Last, we identify a number of alternative spellings manually.

From this base, we merge in additional data at the level of the family and product. Our data on the social structure is taken from the *Association Généalogique d'Haïti*, a nonprofit effort to collect genealogical data from Haitian and American archives and the personal records

[8]Accessed through a Columbia University Library portal at `https://orbis.bvdinfo.com/version-2014812/home.serv?product=orbisneo`.

[9]Accessed at `http://haiti.buildingmarkets.org/en_af/supplier-search`.

[10]Accessed at `http://registre.mci.gouv.ht/`.

[11]For example, "shpg" becomes "shipping", and words like "S.A.", the abbreviation of "societé anonyme", a type of Haitian corporation, are stripped.

of Haitian families run by a business leader in Haiti.[12] We use the Collective Genealogy of Haitian Families, which includes information on more than 64,000 individual members of Haitian families beginning in the 17th century. We restrict this data to cohorts born between 1850 and 1975 to ensure that our measure of the social network is relatively complete, and also show robustness to earlier cohorts. We collapse the genealogical data into a network of marriage links between families. Our unit of analysis for the family data is the last name, which we take to represent a family dynasty. Women are entered into the dataset based on their father's name (97% of the women in our dataset have the same last name as their father), which makes it possible for us to easily identify marriage links between two families. This also implies that the marriage ties of a woman's children are coded as second-degree rather than first-degree ties between her family and the family of her children's spouse.[13]

This process produces a set of 1040 families in our all-elite sample, and 301 in the sample that is restricted to importing families. In the all-elite sample, families have on average 21 members born during the cohorts in our main sample (1850-1975), and 15 marriage ties. In the importer sample, the average family has 26 members and 20 marriages in the 1850-1975 cohorts.

We also draw in data on the history of political and military service of each family, as well as the date and country of immigration for families that immigrated to Haiti after independence in 1804, using data collected by Daniel Supplice. This researcher and politician published a *Dictionnaire biographique des personnalités politiques de la République d'Haïti* that includes dictionary entries for all known individuals who held political office in Haiti, from executives to citizens who served single terms in constituent assemblies or were rewarded with titles of nobility during the 19th century. We coded all of the entries of Supplice (2001) and then restricted this data to individuals who served prior to the end of the Duvalier regime in 1986 in the executive, legislative, or judicial branch.[14] From this, we created binary variables for whether any member of a family served in any of the three main branches of government, and whether any member of a family held a commanding role in the military between 1804 and 1986. Political histories are linked to our other family-level data by last name (link d in Figure A2).

Immigration histories are coded from another of Supplice's books and also linked by last name (link e in Figure A2) (Supplice, 2009). This 750-page tome notes the date of naturalization and country of origin of foreign immigrants who took Haitian nationality after independence. We coded it to create an indicator variable noting whether a family immigrated to Haiti from a foreign country post-independence, and whether they immigrated from a Middle Eastern country including Syria, Lebanon, Palestine, or Egypt. Haitians reclaiming Haitian nationality after marriages to foreigners or being stripped of their nationality are not coded as immigrants.

In addition to this family-level data, we also use data at the level of the product. Product information is linked to our product data by four-digit HS Code or six-digit Standard Industrial Classification (SIC) codes. We use the HS-SIC crosswalk developed by Pierce and Schott (2009) as a base for merging information by SIC and HS codes (Pierce and Schott, 2009). For data that

[12]Accessible at `http://www.agh.qc.ca/`.

[13]To see why, consider that a woman from family A marries a man from family B and has children who inherit the last name B. If one of those children marries someone from family C, that would be coded as a direct link between family B and C, and an indirect link between A and C that goes through B.

[14]We excluded the categories of nobility, constituent assembly, party leadership, and "other", which often denoted voluntary or unofficial positions.

does not include HS or SIC codes, we match text product descriptions based on a combination of an exact match to a key word, approximate string matching among the possible matches, and hand matching the most common products by volume and value.

Our primary source of price data comes from the *Institut Haïtien des Statistiques et Information* (IHSI), the Haitian statistical bureau. IHSI publishes a monthly price bulletin that includes individual prices of around 20 of the top goods in the Haitian consumption basket that go into the consumer price index. We link the text descriptions of these products to 4-digit HS Codes with the help of the Office of the *Direction des Statistiques* in the *Administration Generale des Douanes*, or Haitian customs bureau. We exclude goods like public transportation fees, water provisions, and manufactured textiles that are typically not imported. This data ultimately includes monthly consumer prices of 18 goods from 2001 to 2012.

We also include product-level data on trade flows from two primary sources: first, information by product on the volume of trade between Haiti and the rest of the world collected by the Haitian shipping firm AGEMAR. As mentioned above, this data is used to link products to specific Haitian firms. Second, we draw in information on goods traded between the U.S. and Haiti from the international trade database maintained by the U.S. Census Bureau. We use this information on trade flows to construct measures of supply prices of goods traded between the U.S. and Haiti, and the U.S. and the rest of the world. Our measures are indexed to August 2004 and standardized to ease interpretation.

We also draw in information on product characteristics that may shape the incentives of firm owners to put a sympathetic autocrat in power. First, we proxy for the inelasticity of demand, which affects the extent to which monopolists could increase their profits by raising prices, using the share of the average Haitian's consumption that goods make up. Under constant elasticity of substitution preferences, consumption share and demand elasticity are inversely related. We measure consumption share using household expenditure data collected by Jensen, Johnson and Stampley (1990). Other research has shown that elite resistance to democracy is shaped in part by the ease with which a democratic government can tax and redistribute assets (Acemoglu and Robinson, 2006). We draw from this insight, plus the literature on corruption, to identify characteristics that might make certain imported goods easier for the government to effectively tax. First, we use data from PIERS to construct measures of the bulkiness and divisibility of each product to test the prediction that products that are harder to move or easier to divide should be easier to informally tax. Divisibility is measured as units per twenty-foot equivalent unit (TEU), while bulkiness is measured as value per TEU to test the prediction that bulkier products, which may be easier to identify and tax, should be associated with more resistance to democracy. Second, we merge our products with existing product-level datasets of product complexity from Hausmann et al. (2013), time sensitivity from Hummels (2007), and scope for quality differentiation from Rauch (1999). These measures will be used as controls for the differential vulnerability to tariffs based on specific-skills, high discount rates, and custom agent discretion.

From this linkage, we construct two primary datasets: family-level and product-level. In our family data, we aggregate the product characteristics up to the level of the family (for families who are involved in importing more than one product) by calculating a weighted sum based on the value of a family's trade in each product. This weighted sum takes into account the price and volume of the trade by each firm that the family owns as well as the number of other owners. Thus, our measure of product-level data by family is determined by:

$$x_i = \frac{\sum\limits_{j=1}\sum\limits_{k=1} \frac{value_{jk}}{nown_j} x_k}{\sum\limits_{j=1}\sum\limits_{k=1} \frac{value_{jk}}{nown_j}}$$

where i represents each unique family in our family-level dataset, j represents each business that they own, and k represents each product that they import. In this formula x_k is the value of the product characteristic such as divisibility for each product k and x_i is the average product characteristic for each family.

For our product-level data, we aggregate family-level characteristics up to the level of the firm using a similar weighted measure that takes into account the share of trade in each product that is owned by a particular family. Again, this takes into account the share of imports controlled by a firm and the number of families that own each firm. In this way, we calculate measures of the proportion of firm owners who participated in the 1991 coup and the average network centrality by product.

$$x_k = \frac{\sum\limits_{j=1}\sum\limits_{i=1} \frac{value_{ij}}{nown_j} x_i}{\sum\limits_{j=1}\sum\limits_{i=1} \frac{value_{ij}}{nown_j}}$$

where i again represents each family, j each firm, and k each product. In this case, because values are calculated using a monthly, product-level price, using the value or weight of each good results in the same product-level average. Ultimately the product-level values take into account the share of imports controlled by each firm and the share of each firm controlled by a particular family.

Table A1 provides the names of the top 25 families in terms of our preferred centrality measure along with information on the products they are associated with.

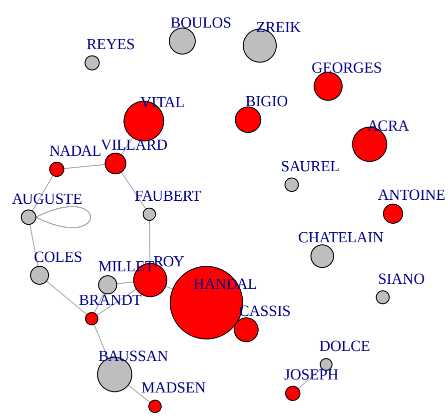
The penultimate column in Table A1 shows the 2-digit HS Codes that each family is associated with, with HS Codes that are worth less than 1% of the value of each family's trade excluded. The last column shows approximate text descriptions of the 2-digit HS Codes. Many families are associated with machinery (including generators, refrigerators, dishwashers, etc) and transportation (automobiles, locomotives, containers). Some of the most central individual families are also associated with HS Codes that capture consumer items including basic foods like cereals (rice, wheat) and cooking oils, fuel, pharmaceutical products, and home goods.

Figure A3 shows a plot of the top 25 families and the direct links between them, with those on the U.S. Treasury Department coup list in red. Many of the top most central families, including many of those identified by the coup list, are connected to each other by direct marriage ties.

Table A1: Statistics for top 25 most central families

Family	# Individuals	# Marriage Ties	Business Elite	Military Elite	Political Elite	Coup	Immigrant	Middle Eastern	HS-2 Codes	Descriptions
HANDAL	5	5	1	0	0	1	1	1	84; 85; 86; 87	Heavy machinery; Transportation
VITAL	29	25	1	0	0	1	1	0	30; 69; 84; 85; 86; 87	Pharmaceuticals; Ceramic products; Heavy machinery; Transportation
BAUSSAN	46	41	1	1	1	0	0	0	44; 84; 86; 87	Wood products; Heavy machinery; Transportation
ACRA	8	5	1	0	0	1	1	1	86; 87; 94	Heavy machinery; Transportation; Furniture
ROY	148	128	1	0	1	1	1	0	84; 85; 86; 87	Heavy machinery; Transportation
ZREIK	1	1	1	0	0	0	1	1	84; 86; 87	Heavy machinery; Transportation
GEORGES	19	15	1	1	1	1	1	1	84; 85; 86; 87	Heavy machinery; Transportation
BOULOS	2	2	1	0	1	0	1	1	28; 30; 84; 85; 86	Chemicals; Pharmaceuticals; Heavy machinery; Transportation
BIGIO	1	1	1	0	0	1	1	1	27; 48; 84; 86	Fuels; Paper products; Heavy machinery; Transportation
CASSIS	12	11	1	0	0	1	1	1	44; 84; 86	Wood products; Heavy machinery; Transportation
CHATELAIN	26	24	1	0	1	0	0	0	84	Heavy machinery
VILLARD	24	18	1	0	1	1	0	0	84; 86	Heavy machinery; Transportation
ANTOINE	43	38	1	1	1	1	1	1	84; 86	Heavy machinery; Transportation
MILLET	25	23	1	0	0	0	1	0	86	Transportation
COLES	37	32	1	0	0	0	0	0	15; 23; 39; 84; 94	Cooking oils; Food waste; Plastic products; Heavy machinery; Furniture
AUGUSTE	98	75	1	1	1	0	1	0	84; 85; 86; 87	Heavy machinery; Transportation
JOSEPH	52	44	1	1	1	1	1	1	10; 84; 86	Cereals; Heavy machinery; Transportation
NADAL	24	23	1	0	0	1	1	0	40; 69; 84; 85; 86; 87	Rubber products; Ceramic products; Heavy machinery; Transportation
REYES	1	1	1	0	0	0	1	1	84; 86	Heavy machinery; Transportation
SAUREL	34	30	1	0	0	0	0	0	84; 85; 86; 87	Heavy machinery; Transportation
SIANO	4	2	1	0	0	0	1	0	84; 86; 87	Heavy machinery; Transportation
MADSEN	13	10	1	0	0	1	1	0	70; 84; 86; 87	Glass products; Heavy machinery; Transportation
BRANDT	26	27	1	0	0	1	1	0	15; 23; 28; 38; 84; 87	Cooking oils; Food waste; Chemicals; Heavy machinery; Transportation
FAUBERT	24	21	1	1	1	0	0	0	84; 86; 87	Heavy machinery; Transportation
DOLCE	29	21	1	0	0	0	0	0	10; 15; 84; 86	Cereals; Cooking oils; Heavy machinery; Transportation

Figure A3: Plot of Most Central 25 Families and Their Direct Marriage Connections



A.1 Summary Statistics

Family data summary statistics

Tables A2 and A3 show the means and standard deviations of the variables in our family datasets for the importers and all elites samples, respectively.

Table A2: Summary Statistics: Family-level data - Importer sample

		Coup			Non-coup		
		N	Mean	St. Dev.	N	Mean	St. Dev.
Social	Immigrant	76	0.38	0.49	225	0.17	0.38
	Middle Eastern	76	0.22	0.42	225	0.08	0.27
	Political elite	76	0.46	0.50	225	0.21	0.41
	Military elite	76	0.24	0.43	225	0.08	0.28
	Bonacich centrality	73	144.24	245.28	144	78.23	116.83
	Degree	73	26.37	29.59	144	16.60	19.81
	Family size	73	33.93	39.41	144	22.18	27.87
	Reachability	73	0.36	0.28	144	0.57	0.30
Economic	Market share	76	0.07	0.11	225	0.08	0.12
	Value (mil USD)	76	19.05	48.47	225	13.42	38.19
	Consumption share	52	0.46	0.63	131	0.37	0.56
	All inputs	76	0.87	0.28	225	0.87	0.27
	Bulkiness	76	3.62	2.99	225	3.98	2.83
	Divisibility	76	4.90	2.23	225	4.98	2.20
	Reference price	76	1.32	0.55	225	1.25	0.53
	Time sensitivity	76	0.00	0.01	225	0.00	0.01
	Complexity	76	1.66	1.69	225	1.72	1.77

Table A3: Summary Statistics: Family-level data - All elite sample

		Coup			Non-coup		
		N	Mean	St. Dev.	N	Mean	St. Dev.
Social	Political elite	212	0.71	0.45	828	0.62	0.49
	Military elite	212	0.42	0.49	828	0.29	0.45
	Business elite	212	0.43	0.50	828	0.34	0.47
	Immigrant	212	0.22	0.42	828	0.08	0.27
	Middle Eastern	212	0.10	0.31	828	0.02	0.15
	Bonacich centrality	202	53.11	162.10	514	23.02	70.69
	Degree	202	19.23	21.89	514	13.54	16.55
	Family size	202	25.38	29.78	514	18.84	24.73
	Reachability	202	0.35	0.27	514	0.53	0.30

Product data summary statistics

Table A4: Summary Statistics: Product data

Product	Firms	Fams	Coup	Cent.	Middle Eastern	Share Consumption
	N			Weighted Mean		Percent
Beauty care	56	42	0.57	11.00	0.81	0.20
Bread	18	14	0.58	10.82	0.83	0.53
Chicken	12	9	0.92	3.15	0.92	0.22
Cigarettes	2	6	1.00	8.77	1.00	0.37
Cola	12	17	0.69	4.82	0.60	0.16
Corn meal	6	6	0.66	3.97	0.36	0.45
Dry peas	5	6	0.55	13.55	0.88	0.00
Edible oil	5	10	0.43	6.08	1.00	3.10
Evaporated milk	10	12	0.49	14.83	0.59	0.38
Fabric	23	15	0.52	7.89	0.67	1.15
Fresh fish	10	7	0.42	9.55	0.67	1.28
Furniture	19	19	0.38	11.10	0.63	0.01
Kerosene	5	3	0.76	7.65	1.00	0.85
Laundry soap	24	19	0.35	7.42	0.81	0.00
Medicine	11	12	0.31	5.10	0.50	0.73
Raw sugar	8	6	0.70	7.35	0.85	0.51
Rice	7	6	0.88	5.51	1.00	2.26
Sandals	23	7	0.65	0.63	0.00	0.00

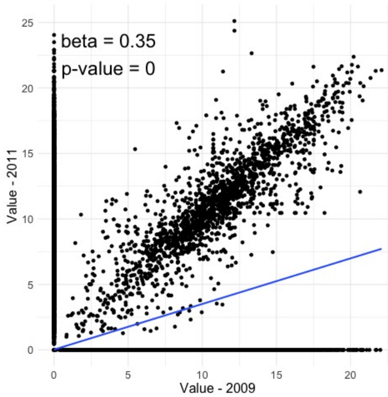
A.2 Analysis of trading patterns

We use data from the Haitian shipping firm AGEMAR to link Haitian families to firms and imported products. We were able to obtain this data for 2009-2011. Our analysis relies on the assumption that shipping interests are stable over time. In this section, we present an analysis of stability of shipping interests during the years for which we have data. We exclude 2010 from this analysis because in January 2010 Haiti was hit by a magnitude 7.0 earthquake that destroyed the main port of Port-au-Prince and massively disrupted shipping patterns with a huge influx of aid.

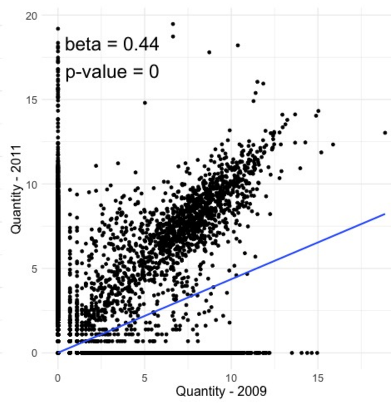
To assess the plausibility of this assumption we analyze the relationship between the log-transformed value and quantity of trade by firm and four-digit HSCODE in 2009 and 2011. We examine this relationship in three different samples: first, we look at the full sample of trade data, including all firms. Second, we look at the sample of trade data for which we can match families to the importing firms. This is the relevant sample for the analysis of coup participation by family.

Figure A4: Relationship between 2009 and 2011 trade for firm-product dyads

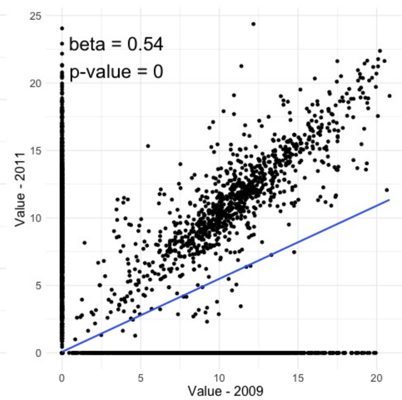
(a) Value - All firm-product dyads



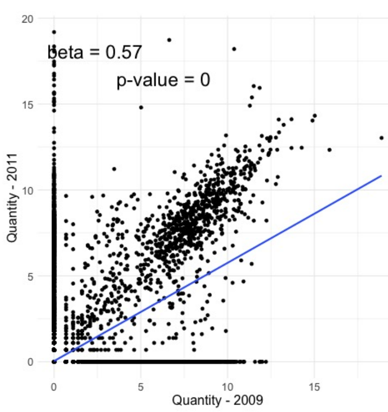
(b) Quantity - All firm-product dyads



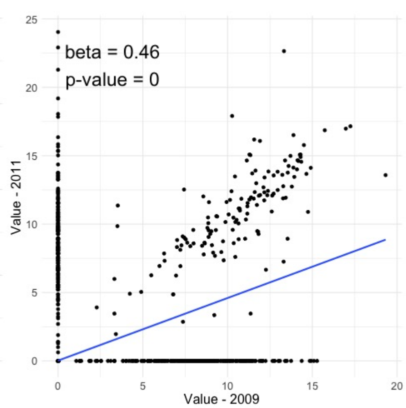
(c) Value - Family matched firm-product dyads



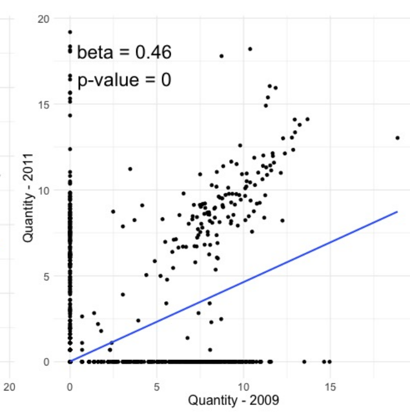
(d) Quantity - Family matched firm-product dyads



(e) Value - Family matched firm-product dyads for products with retail prices



(f) Quantity - Family matched firm-product dyads for products with retail prices



This analysis suggests that, while there are some firms that only import a product in one of the two years, there is a strong relationship ($p < 0.001$ for all six samples) between the amount of a product a firm imports in 2009 and 2011. This relationship is particularly strong for firms that can be matched to families in our genealogical data and matched to retail price data from the Haitian consumer price index.

B Determinants of Centrality

In Table A5 we regress family centrality on a variety of covariates to examine possible sources of endogeneity. As per our model, we use a measure of centrality in which nodes are weighted by the value of their business interests, and we also weight edges by family size to take into account the fact that larger families have more opportunities to form marriage ties. characteristics that might independently predict coup participation, such as being a military or political elite, seem to be uncorrelated with centrality. Nonetheless, we control for all covariates in our specifications.

Table A5: Determinants of Centrality

	Dependent variable: Centrality					
	(1)	(2)	(3)	(4)	(5)	(6)
Middle Eastern	0.29	0.31*	0.20	0.22	0.32**	0.33**
	(0.18)	(0.18)	(0.15)	(0.15)	(0.14)	(0.14)
Immigrant	0.21**	0.20**	0.21**	0.19**	0.08**	0.08**
	(0.09)	(0.09)	(0.08)	(0.08)	(0.04)	(0.04)
Reachability	0.10	0.10	0.13	0.10	0.04	0.04
	(0.10)	(0.09)	(0.09)	(0.09)	(0.03)	(0.03)
Military	0.01	−0.01	−0.05	−0.09	−0.01	−0.01
	(0.08)	(0.08)	(0.07)	(0.07)	(0.02)	(0.02)
Political	0.08	0.05	0.04	0.04	−0.004	−0.01
	(0.06)	(0.06)	(0.06)	(0.05)	(0.03)	(0.03)
Business					0.16***	0.15***
					(0.02)	(0.02)
Family Size (Log)		0.02	0.02	0.02		0.01
		(0.02)	(0.02)	(0.02)		(0.01)
Business Value (Mil USD)			0.005***	0.004***		
			(0.001)	(0.001)		
Consumption Share				0.01		
				(0.02)		
All Inputs				−0.05		
				(0.11)		
Reference Price				−0.03		
				(0.02)		
Complexity				0.01		
				(0.03)		
Time Sensitivity				0.05***		
				(0.02)		
Bulkiness				−0.06**		
				(0.02)		
Divisibility				−0.06**		
				(0.03)		
Constant	−0.69***	−0.74***	−0.79***	−0.80***	−0.79***	−0.80***
	(0.06)	(0.08)	(0.07)	(0.10)	(0.04)	(0.04)
Observations	217	217	217	217	716	716
R^2	0.14	0.15	0.31	0.37	0.24	0.24
Sample	Importers				All Elite	

*p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses.

C Two Technical Issues

We here discuss the conditions under which a_e is interior and no elite producer is rationed.

Recall that we required that $a_e \in [0,1]$ and assumed that the elite's first-order condition was interior. By Theorem 1 of Ballester, Calvó-Armengol and Zenou (2006) it must be that $a_e > 0$. Thus we only need to ensure that $a_e < 1$. A sufficient condition for this is that the following inequality holds

$$\gamma + \delta > \max_e \left\{ \sum_{e' \neq e} \omega_{e'e} \mathbf{1} + \frac{1}{E} \left[\sum_{m=1}^{M} w_{em} \left(\bar{\tau}_m - 1\right) q \kappa \right] \right\} \tag{10}$$

where $\mathbf{1}$ is a vector of ones and $\max \omega_{e'e}$ is the maximum degree. The inequality says that γ must be sufficiently large that at $a_e = 1$ even if all other agents set their actions at one, the marginal benefit is less than the marginal cost for the agent who has the endowment that maximizes the sum of the degree and the share of total elite profits. A weaker condition would be to evaluate the network effects at the candidate Nash Equilibrium action vector for the other agents. In addition to make sure there is no equilbrium where elites set $a_e > 0$ even when there are no incentives we require that γ be sufficiently large, a sufficient condition being $\gamma > max_e \sum_{e' \neq e} \omega_{e'e} \mathbf{1}$.

Finally, we need to make sure that elites are not demand constrained. Since the competitive price is lower than the post-coup prices it suffices to assume that elites are not demand constrained at the prices determined by the maximal (exogenous) tax rate which implies that the following inequality holds

$$qM\kappa\bar{\tau}_m \leq LY. \tag{11}$$

C.1 Alternative Version of Proposition 2

For proposition 2 we can make a weaker assumption that $\frac{\gamma}{q\kappa}$ is sufficiently large relative to the maximum tariff exposure of each elite e, given by $\tau_m \sum_m w_{em}$, rather than the more transparent assumption in the main text that $E[\tau_m]$ is sufficiently close to 1.

Proposition 2': If for all e we have $(1 - \tau_m) \sum_m w_{em} + \frac{\gamma}{q\kappa} > 0$ then $Cov(\tau, \sum_e w_{em} a_e) > 0$

Proof: Let W denote the $E \times M$ matrix of ownership shares, and $\Omega \equiv (I - \frac{1}{\delta}\omega)^{-1}$. Multiply both sides of the equilibrium condition (9) by the transpose of $\Pi = W(\tau - \mathbf{1_M})q\kappa - \gamma 1_E$ to get

$$(W(\tau - \mathbf{1_M})q\kappa - \gamma 1_E)' \Omega W((\tau - \mathbf{1_M})q\kappa - \gamma 1_E) = (W(\tau - \mathbf{1_M})q\kappa - \gamma 1_E)' a$$

Note that the left hand side is greater than 0 by Ω being positive definite. We can then expand the right hand side to get:

$$0 < W(\tau - \mathbf{1_M})q\kappa - \gamma 1_E)' a = q\kappa \tau' W' a - q\kappa \mathbf{1_M}' W' a - \gamma 1_E' a$$

Which implies

$$0 < \tau' W' a - \mathbf{1_M}' W' a - \frac{\gamma}{q\kappa} 1_E' a$$

Now by assumption $(1-\tau_m)\sum_m w_{em} + \frac{\gamma}{q\kappa} > 0$ for every e and a being interior we have:

$$(1-\tau_m)\sum_m w_{em} a_e + \frac{\gamma}{q\kappa} a_e > 0$$

Which, since $E[\tau] = \frac{1_M' \tau}{M} \leq \tau_m$ implies for every e that:

$$\sum_m w_{em} a_e + \frac{\gamma}{q\kappa} a_e > \tau_m \sum_m w_{em} a_e > E[\tau] \sum_m w_{em} a_e$$

Summing over e we get:

$$\sum_e \sum_m w_{em} a_e + \sum_e \frac{\gamma}{q\kappa} a_e > E[\tau] \sum_e \sum_m w_{em} a_e$$

Which in matrix form:

$$\mathbf{1_M}' W' a + \frac{\gamma}{q\kappa} 1_E' a > E[\tau] 1_M' W' a$$

This inequality together with the inequality in C.1 gives:

$$0 < \tau' W' a - \mathbf{1_M}' W' a - \frac{\gamma}{q\kappa} 1_E' a_e < \tau' W' a - E[\tau](\mathbf{1_M}' W' a) = M \times Cov(\tau, W' a)$$

Where we recall that the sample covariance of two vectors x and y is $Cov(x,y) = E[xy] - E[x]E[y] = \frac{x \cdot y}{M} - \frac{(1_M \cdot x)}{M} \frac{(1_M \cdot y)}{M}$, gives the result. ■

D Robustness checks: Coup participation

D.1 Methodology to determine weighting parameter

In order to calculate our measure of Bonacich centrality, we need to set a parameter that weights the importance of close versus distant network ties. Bonacich (1987) shows that for a network with complementarities, $\frac{1}{\delta}$ can be in the range $(0, \frac{1}{\lambda})$ where λ is the largest eigenvalue of the adjacency matrix. We work with a baseline parameter of $\frac{1}{\delta} = \frac{1}{5\lambda} = .1$. As an auxiliary check, we regress coup participation on the number of connections that a family has to coup participators. The coefficient on this measure of coup degree is a rough check on the general quantitative range within which an appropriate weighting parameter $\frac{1}{\delta}$ could lie. Table A6 shows the results of this analysis, with an implied coefficient on $\frac{1}{\delta}$ of 0.23 to 0.25, close to our baseline choice and well within the range of the robustness exercises we conduct.

Table A6: Centrality in the Network of Coup Participators

	(1)	(2)
Coup Degree	0.253*	0.229**
	(0.146)	(0.089)
Observations	217	716
R^2	0.015	0.011
Sample	Importers	All elite

Robust standard errors in parentheses.
*p<0.1; **p<0.05; ***p<0.01
The outcome variable is a binary measure of whether a family participated in the coup, as measured by whether the family is on the 1991 U.S. Treasury targeted sanctions list. The measure Coup Degree is the number of connections that a family has to coup participators. Models are estimated using OLS.

D.2 Robustness to weighting by measures of data quality

One source of noise in our data comes from misattribution of families with the same last name to family dynasties. We have interpreted all individuals with the same last name as members of the same dynasty. However, in some cases common names can be shared across families.

To examine robustness to the possibility that last names are not capturing family dynasties, we calculate an additional statistic using the subgraph of individuals that share a last name as a measure of data quality, which we call reachability. Reachability is the probability that an individual with a certain last name is connected through some path of marriage or parentage to another individual with the same last name. We calculate this probability for each node in a last-name subgraph and then take the average across all nodes in the subgraph to get a family reachability. Reachability is a good measure of the quality of our network data because it picks up two types of measurement error in the social network: first, if there are two separate family dynasties in Haiti that share the same last name but are not actually connected by kinship. Second, if we are missing marriage links between some individuals due to missing data.

Figures A5a and A5b show examples of dynasties with high and low measures of reachability using data from actual families in our database that have the same number of individual members but differ in their reachability. The size of the nodes shows the cohort of each individual, with smaller nodes indicating earlier family members. Links represent parent-child relationships.

Figure A5: Examples of Reachability in the Haitian Marriage Network

(a) Low reachability family (b) High reachability family

We deal with this measurement error by testing whether our coefficients are robust to least squares regression weighted by the quality of the network data, as measured by each family's reachability score. Table A7 shows the results of this analysis. In this table, we use the standardized weighted Bonacich centrality with $\frac{1}{\delta} = \frac{1}{5\lambda}$ as our independent variable of interest and an adjacency matrix that takes into account the size of each family.

Table A7: Robustness to weights based on quality of network data

	Dependent variable:									
	Coup									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Centrality	0.234***	0.214**	0.206**	0.155	0.152	0.195**	0.233***	0.219***	0.175**	0.175**
	(0.083)	(0.085)	(0.098)	(0.101)	(0.101)	(0.088)	(0.076)	(0.077)	(0.079)	(0.079)
Family Size		0.049**	0.043**	0.042	0.038	0.050		0.024*	0.026*	0.026*
		(0.021)	(0.022)	(0.026)	(0.025)	(0.031)		(0.013)	(0.014)	(0.014)
Economic Characteristics			✓	✓	✓	✓				
Social Characteristics				✓	✓	✓		✓	✓	✓
Product Characteristics					✓	✓				
Community FE						24				35
Observations	217	217	217	217	217	217	716	716	716	716
R^2	0.050	0.078	0.098	0.121	0.157	0.253	0.022	0.030	0.096	0.096
Sample	Importers						All elite			

Robust standard errors in parentheses.

*p<0.1; **p<0.05; ***p<0.01

Data quality weights are constructed using network data from all time periods and represent for each last name the average proportion of other nodes with that last name that can be reached from a single node of that last name, or the reachability within each last name across nodes. Models are estimated using OLS.

Table A7 shows that the relationship between centrality and coup participation is similar in magnitude and significance once we take variation in data quality into account.

D.3 Robustness to varying weights in centrality calculation

We also assess the robustness of our results to various ways of calculating centrality. As discussed in Section 5.1, our main results are based on a measure of centrality that is calculated using weights for both the nodes and the edges. Our theory implies that an agent's action should be increasing in his Bonacich centrality, where nodes are weighted by the profits that the agent would make during autocracy. To take into account the fact that the probability of a link between two families is also a function of the number of members in each family, we down-weight large families by also weighting the network edges by the inverse of the product of each family's size, $\frac{1}{size_e * size_m^{\frac{1}{2}}}$. In this section we recreate our analysis of the determinants of coup participation in Table 1 using various alternative node and edge weights to calculate centrality.

Table A8: Robustness to varying node and edge weights in the centrality measure

Weights		Specification									
Nodes	Edges	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$log(value_{2002})$	$\frac{1}{(size_e * size_m)^{\frac{1}{2}}}$	0.19***	0.21***	0.21***	0.14*	0.14*	0.17**	0.21***	0.19***	0.1	0.09
		(0.06)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.06)	(0.05)	(0.06)	(0.06)
$log(value_{2002})$	None	0.19***	0.21***	0.22***	0.14*	0.14*	0.17**	0.21***	0.19***	0.1	0.09
		(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.05)	(0.06)	(0.06)
None	$\frac{1}{(size_e * size_m)^{\frac{1}{2}}}$	0.07***	0.07***	0.06**	0.04*	0.01	0	0.06***	0.02	0.01	0.01
		(0.02)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)	(0.02)	(0.03)	(0.03)	(0.03)
None	None	0.1***	0.1***	0.09***	0.07*	0.03	0.03	0.09***	0.05	0.03	0.02
		(0.03)	(0.03)	(0.03)	(0.04)	(0.05)	(0.06)	(0.02)	(0.04)	(0.04)	(0.04)
$log(value_{2002-12})$	$\frac{1}{(size_e * size_m)^{\frac{1}{2}}}$	0.19***	0.21***	0.21***	0.14*	0.14*	0.17**	0.21***	0.19***	0.1	0.09
		(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.05)	(0.06)	(0.06)
$log(value_{autocracy})$	$\frac{1}{(size_e * size_m)^{\frac{1}{2}}}$	0.19***	0.21***	0.21***	0.14*	0.14*	0.17**	0.21***	0.19***	0.1	0.09
		(0.06)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.06)	(0.05)	(0.06)	(0.06)
$log(price_{2002})$	$\frac{1}{(size_e * size_m)^{\frac{1}{2}}}$	0.14***	0.15***	0.16***	0.12**	0.11*	0.14**	0.16***	0.14***	0.09*	0.08
		(0.05)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.05)	(0.05)	(0.05)	(0.05)
$log(value_{2002})$	$\frac{1}{(size_e + size_m)/2}$	0.19***	0.21***	0.21***	0.14*	0.14*	0.17**	0.21***	0.19***	0.1	0.09
		(0.06)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.06)	(0.05)	(0.06)	(0.06)
truncated($log(value_{2002})$)	$\frac{1}{(size_e * size_m)^{\frac{1}{2}}}$	0.19***	0.21***	0.21***	0.14*	0.14*	0.17**	0.21***	0.19***	0.1	0.09
		(0.06)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.06)	(0.05)	(0.06)	(0.06)
binary($log(value_{2002})$)	$\frac{1}{(size_e * size_m)^{\frac{1}{2}}}$	1.19**	1.13**	1.19**	0.79	0.04	0.32	0.04**	0.03*	0.02	0.03
		(0.52)	(0.53)	(0.54)	(0.59)	(0.79)	(0.85)	(0.02)	(0.02)	(0.03)	(0.03)
rank($log(value_{2002})$)	$\frac{1}{(size_e * size_m)^{\frac{1}{2}}}$	0.24***	0.23***	0.22**	0.15	0.01	0.02	0.05***	0.03*	0.03	0.03
		(0.08)	(0.08)	(0.09)	(0.09)	(0.13)	(0.14)	(0.02)	(0.02)	(0.03)	(0.03)
e = 0;	$\frac{1}{(size_e * size_m)^{\frac{1}{2}}}$	0.09***	0.08**	0.08**	0.06**	0.05	0.06*	0.05***	0.03	0.01	0.01
m = $log(value_{2002})$		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
Observations		217	217	217	217	217	217	716	716	716	716
Sample		Importers						All elite			

Robust standard errors in parentheses.
*p<0.1; **p<0.05; ***p<0.01
This table presents the coefficients on centrality calculating using different node and edge weights from ten specifications (controls not shown). Models are estimated using OLS.

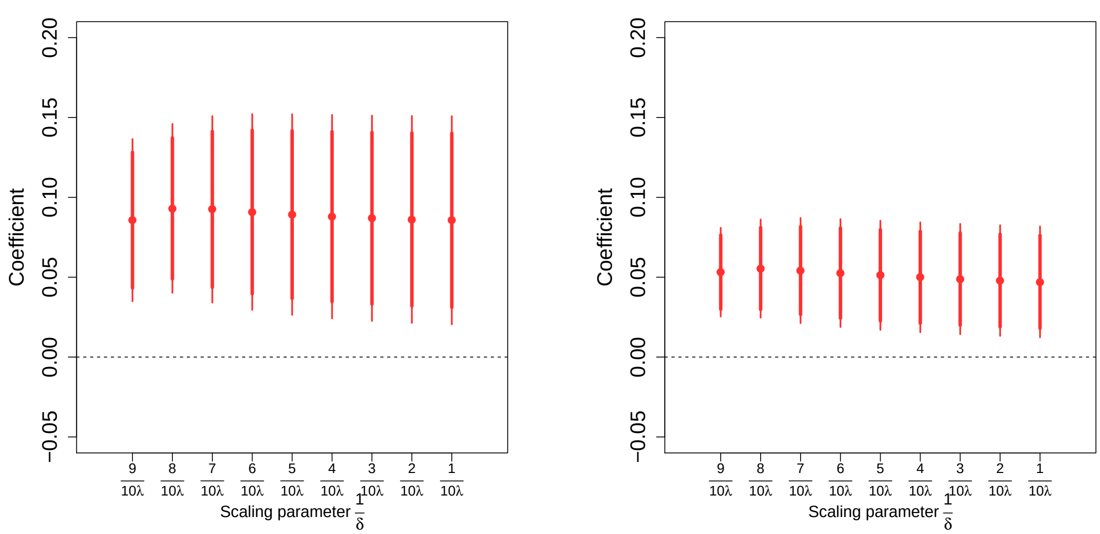
Table A8 presents the coefficients on the centrality measure from regressions that also include all of the controls from the corresponding specifications in Table 1. It shows that the results on centrality are similar in magnitude, and in most cases remain significant, when we vary the node and edge weights used to calculate centrality. The second row of results present the coefficient on centrality calculated with no node or edge weights. The third and fourth row vary the node weights by calculating the value of a family's trade using the average prices between 2002 and 2012, or during the autocratic period from March 2004 to January 2006, respectively. The penultimate set of results replace the edge weights based on the product of the two family sizes with the inverse sum. Finally, in the last row, we recalculate centrality after setting each family's own node weight to 0 (i.e., assuming that the family has no trade). This last estimate is designed to probe whether our results are being driven by a family's own profits as opposed to the peer effects coming through the network.

For this last specification, where own profits are set to 0 before we calculate each family's centrality, we can also test whether results are still robust to various choices of the weighting parameter $\frac{1}{\delta}$. This is a particularly hard test of robustness across a range of $\frac{1}{\delta}$ parameters because the influence of own profits might be stabilizing these estimates. Figure A6 shows that the correlations are similar in magnitude across a range of $\frac{1}{\delta}$ parameters in both the all-elite and importer samples, even when own wealth is set to 0 while calculating centrality.

Figure A6: Coefficients on centrality placing increasing weight on close ties, with own profits set to 0

(a) Importers

(b) All elite



D.4 Sensitivity Analysis

One concern in this analysis is that network centrality is endogenous. We have controlled for a range of economic and social characteristics that should influence network centrality and coup participation, as well as community fixed effects that take into account unobserved characteristics that might be shared by connected families. However, to the extent that we have missed factors that influence both selection into centrality and coup participation our specifications would be biased.

To assess the sensitivity of the results to omitted variable bias, we use a method identified by Altonji, Elder and Taber (2005) and elaborated by Oster (2017). This method uses information provided by coefficient and R^2 movements, with identifying assumptions about the relative explanatory power of unobserved factors relative to observed and the maximum R^2 value of a regression that includes the unobservables. This method scales coefficient movements by the change in the R^2 when the observed controls are introduced, and uses this to predict additional coefficient movements if unobserved controls that were similarly related to the main explanatory variable were added.

We apply this method to assess the sensitivity of our analysis of the relationship between network centrality and coup participation to unobserved confounding variables. There are two key parameters that must be set by assumption. First, you must set the maximum R^2 in a regression that includes the independent variable, observed controls, and unobservables, called R_{max}. Oster (2017) uses data from experiments to set a standard for robustness of $R_{max} = 1.3\tilde{R}$, where $\tilde{R}$ is the R^2 from a regression including the observed controls (Columns 6 and 10 in Table 1).

The second key parameter that must be set by assumption is δ, or the proportion of selection into treatment on unobservables to unobserved controls. When $\delta = 1$, the unobservables and observed controls are equally important in explaining selection into treatment. Both Altonji, Elder and Taber (2005) and Oster (2017) suggest that this is an appropriate threshold for robustness.

We set R_{max} at $1.3\tilde{R}$ and vary δ between 0.1 and 1. Figure A7 presents the adjusted coefficients on centrality from the importers sample and all elite samples as δ increases from 0.1 to 1. Standard errors on the adjusted coefficients are calculating using the Oster (2017) bootstrapping method.

Figure A7: Coefficients on centrality after adjusting as per Altonji, Elder and Taber (2005)-Oster (2017) sensitivity analysis

(a) Importers (b) All elite

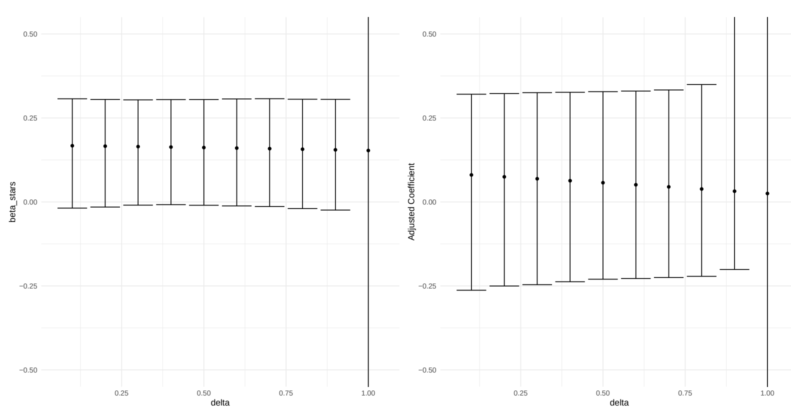


Figure A7 shows that the coefficients on both samples cannot be explained by unobservables that are equally important in explaining selection into the main treatment variable, under the recommended assumptions regarding R_{max}. The coefficient in the importers sample moves very little in this exercise: under the equal selection assumption ($\delta = 1$), the adjusted coefficient is 0.153, very close to our coefficient of 0.169 in the model with full controls. In the all elite sample the adjusted coefficient moves further towards zero, but still remains positive up to $\delta = 1$. Ultimately, it would take unobservables of 2.79 to explain the coefficient in the importers sample, and 1.34 to explain the all elite coefficient. Both exceed the threshold suggested by Altonji, Elder and Taber (2005) and Oster (2017).

D.5 Robustness to alternative periods of the network data

In this section we test whether our results are robust to stricter temporal cutoffs. One source of concern in our analysis is that reverse causality could be driving our results if families that participate in the coup are more likely to marry into each other post-coup. Using older versions of the network data that are more likely to temporally predate the coup mitigates against the risk of such reverse causality. Table A9 re-estimates the coefficients in Table 1 using earlier versions of the network. Panel B presents results using a version of the network that is truncated at cohorts born in 1950, and Panel C truncates the network at cohorts born in 1925.

Table A9: Robustness to earlier versions of the network

	Dependent variable:									
	Coup									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: 1850-1975 Marriage Network										
Centrality	0.188***	0.206***	0.214***	0.141*	0.136*	0.169**	0.209***	0.193***	0.099	0.086
	(0.06)	(0.067)	(0.068)	(0.075)	(0.073)	(0.071)	(0.055)	(0.054)	(0.064)	(0.064)
R^2	0.033	0.038	0.057	0.115	0.132	0.232	0.016	0.033	0.071	0.112
Observations	217	217	217	217	217	217	716	716	716	716
Panel B: 1850-1950 Marriage Network										
Centrality	0.178***	0.202***	0.213***	0.127	0.12	0.149**	0.205***	0.183***	0.082	0.076
	(0.062)	(0.069)	(0.07)	(0.077)	(0.076)	(0.073)	(0.057)	(0.055)	(0.066)	(0.065)
R^2	0.028	0.034	0.049	0.115	0.13	0.249	0.015	0.031	0.073	0.114
Observations	209	209	209	209	209	209	699	699	699	699
Panel C: 1850-1925 Marriage Network										
Centrality	0.126**	0.155**	0.173**	0.117	0.108	0.141*	0.156***	0.13**	0.068	0.06
	(0.061)	(0.071)	(0.074)	(0.075)	(0.076)	(0.072)	(0.053)	(0.055)	(0.058)	(0.058)
R^2	0.021	0.028	0.05	0.127	0.13	0.258	0.014	0.024	0.073	0.11
Observations	191	191	191	191	191	191	659	659	659	659
Sample	Importers						All elite			

Robust standard errors in parentheses.
*p<0.1; **p<0.05; ***p<0.01

D.6 Robustness to removing outliers

Our measure of network centrality has a long right tail, indicating that some members of the network are extremely central and there are many members with essentially zero centrality. Skewness is a common feature of social network data, and theory and history suggests that we should be precisely interested in the influence of a couple of key players in the organization of elite collective action. However, when running ordinary least squares on skewed data there is the possibility that observations might have extreme influence on the coefficients. Table A10 presents robustness checks testing various ways to reduce the influence of outliers.

Table A10: Robustness to transformations and censoring outliers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Centrality	0.19***	0.21***	0.21***	0.14*	0.14*	0.17**	0.21***	0.19***	0.1	0.09
	(0.06)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)	(0.06)	(0.05)	(0.06)	(0.06)
Observations	217	217	217	217	217	217	716	716	716	716
Centrality >3 SD Censored	0.19**	0.22**	0.23**	0.13	0.12	0.16	0.22***	0.19**	0.09	0.06
	(0.09)	(0.1)	(0.1)	(0.12)	(0.11)	(0.11)	(0.08)	(0.07)	(0.09)	(0.09)
Observations	216	216	216	216	216	216	715	715	715	715
Centrality >1 SD Censored	0.21*	0.25*	0.28*	0.14	0.13	0.12	0.25**	0.21**	0.07	0.01
	(0.12)	(0.14)	(0.15)	(0.16)	(0.15)	(0.18)	(0.1)	(0.1)	(0.11)	(0.12)
Observations	211	211	211	211	211	211	710	710	710	710
Log(Centrality)	0.06*	0.08	0.08	0.03	0.01	0.04	0.05***	0.03*	0	0
	(0.03)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.02)	(0.02)	(0.03)	(0.03)
Observations	217	217	217	217	217	217	716	716	716	716
Rank(Centrality)	0.04	0.04	0.05	0	-0.02	0.01	0.04**	0.02	-0.02	-0.02
	(0.03)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.02)	(0.02)	(0.03)	(0.03)
Observations	217	217	217	217	217	217	716	716	716	716
Sample			Importers					All elite		

Robust standard errors in parentheses.
*p<0.1; **p<0.05; ***p<0.01

The first panel of Table A10 reproduces our main result for comparison. Panels 2 and 3 of Table A10 show that the results are not driven by the highest observations. In these specifications, we censor data points that are 3 standard deviations above the mean (Panel 2) or 1 standard deviation above the mean (Panel 3). The results in the importers only sample are very similar after dropping these highest observations, suggesting that they are not exerting outsize influence on the coefficients. In the all elite sample the coefficients with controls drop in magnitude when the highest observations are censored, but the specifications without controls and with only family size as a control are unchanged. The results are less robust to transformations meant to reduce the skew, including a log and rank transformation. These robustness checks suggest that the variation at the upper echelons of the centrality distribution is meaningful, but the few most central families are not driving the relationship between centrality and coup participation.

E Robustness Checks: Prices

E.1 Serial Correlation

Our preferred specification includes four lags of the dependent variable. These lags take into account dynamic processes in prices, but under some circumstances they can raise difficulties in estimation. In this section we discuss potential estimation problems and present the results of empirical tests of our additional assumptions.

One concern when estimating models with both fixed effects and lagged dependent variables is Nickell bias (Nickell, 1981; Alvarez and Arellano, 2003). This bias decreases as the number of time periods in a model go up: Judson and Owen (1999) show that this bias is around 1% when $T = 30$, so in our case with around 140 time periods it will be negligible. An alternative is the GMM estimators that are consistent in the presence of a lagged dependent variable, but become biased for large T as they run into the "many instruments" problem. This can be overcome by restricting the number of moments used in the estimation which we do in Table A12. Again results are consistent than our main OLS specification.

Models with lagged dependent variables can also be biased if the lagged dependent variable is a unit root. In these cases, the sampling distributions of the coefficients are not normal. To test whether our time series has a unit root, we test for whether the linear combination of the lags is equal to one. The lags in columns 2-5 of Table 2 add up to 0.96 (with only one lag), 0.946, 0.945, and 0.944, respectively. The coefficients from tests of whether the linear combination of the coefficients on the lagged dependent variables equal one are significant at the 1% level, which means that we can reject the null hypothesis that there is a unit root in all four of the specifications in Columns 2-5 of Table 2.

Last, we test whether our coefficient of interest is robust to assuming autocorrelation parameters between 0.9 and 1. Assuming an autocorrelation coefficient eliminates the threat of bias that exists in the specifications where we estimate both the autocorrelation and our coefficient of interest. In Table A11 we test whether our preferred specification of Column 5 in Table 2 is robust to autocorrelation coefficients in this range of parameters around our estimated getting increasingly close to 1.

Table A11 shows that the estimate of the coefficient of interest on $Coup_i \times Autocracy_t$ remains statistically significant up to an imposed autocorrelation of 1 (equivalent using the price growth rates as the dependent variable). This is well above our estimated autocorrelation of around 0.945. At an imposed autocorrelation of 0.95, our estimated coefficient is statistically indistinguishable from the result reported in Column 5 of our main Table 2.

E.2 Robustness to inclusion of product controls

Table A13 tests whether the price regressions shown above are robust to including the interactions of product characteristics and autocracy.

Table A13 shows that the effect of coup participation during autocratic periods is robust to including the five product characteristics, in addition to the product-level measures of Consumption Share and Number of Firms, interacted with Autocracy. There are no robust relationships

Table A11: Robustness to imposed autocorrelation coefficients

	Imposed autocorrelation:				
	$\rho = 0.9$	$\rho = 0.925$	$\rho = 0.95$	$\rho = 0.975$	$\rho = 1$
	(1)	(2)	(3)	(4)	(5)
Coup × Autocracy	0.024***	0.021***	0.018**	0.016**	0.013
	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)
Coup × Quake	0.077*	0.073*	0.069*	0.065	0.061
	(0.041)	(0.041)	(0.041)	(0.040)	(0.040)
World Supply Price	0.005	0.004	0.002	0.0001	−0.002
	(0.006)	(0.004)	(0.003)	(0.002)	(0.003)
Number Firms × Autocracy	−0.004	−0.004	−0.003	−0.002	−0.002
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Consumption Share × Autocracy	−0.0005	−0.0004	−0.0002	−0.0001	−0.00001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Month FE	✓	✓	✓	✓	✓
Product FE	✓	✓	✓	✓	✓
Product × Conflict Events	✓	✓	✓	✓	✓
Observations	2,322	2,322	2,322	2,322	2,322
Clusters	18	18	18	18	18

Standard errors clustered at the product level in parentheses
* significant at $p < .10$; $^{**}p < .05$; $^{***}p < .01$

Table A12: Robustness to GMM estimators

	(1)	(2)	(3)	(4)	(5)
Coup × Autocracy	0.0251***	0.0382**	0.0266*	0.0330*	0.0281 *
	(0.00969)	(0.0177)	(0.0158)	(0.0188)	(0.0152)
Lags of prices	4	4	4	4	4
Lags used for instruments	All Lags	Lags 1-10	Lags 2-10	Lags 1-8	Lags 2-8
Month FE	✓	✓	✓	✓	✓
Product FE	✓	✓	✓	✓	✓
N	1278	1278	1278	1278	1278
Clusters	18	18	18	18	18

Robust standard errors in parentheses
$^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$

between the product characteristics and prices during autocracy.

E.3 Robustness to weights for data quality

We also assess the sensitivity of our results to non-random missingness. There are three kinds of missingness that one may be worried about. First, there is non-random missingness in our data on which firms import which products. For each product we have data on the firms that import around 90% of the volume of trade. Missingness is concentrated in products that are imported in bulk such as sugar, kerosene, rice, and edible oil. Second, there is non-random missingness in the extent to which we could identify the families that own each firm. For our CPI products, we are able to identify on average 64-65% of the importing families. Generally, we are less able to identify the owners of firms that import less. Last, we may have measurement error in the extent to which our data from 2009 and 2011 represents historical shipping patterns in Haiti, which we

Table A13: Robustness of price results to controls for product characteristics

	Dependent variable:				
	Haiti retail price				
	(1)	(2)	(3)	(4)	(5)
Coup × Autocracy	0.019**	0.015**	0.018***	0.015*	0.013*
	(0.008)	(0.007)	(0.007)	(0.009)	(0.008)
Coup × Quake	0.068*	0.068*	0.068*	0.068*	0.068*
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
World Supply Price	−0.0003	−0.001	−0.001	−0.0003	−0.0002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Number Firms × Autocracy	−0.003	−0.003	−0.002	−0.001	−0.003*
	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)
Consumption Share × Autocracy	−0.0005	−0.0003	−0.0004	−0.0005	−0.0005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bulkiness × Autocracy	0.0004				
	(0.002)				
Time Sensitivity × Autocracy		−0.001			
		(0.001)			
Complexity × Autocracy			−0.001		
			(0.002)		
Ref. Price × Autocracy				0.003	
				(0.004)	
Divisibility × Autocracy					0.002*
					(0.001)
Product × Conflict Events	✓	✓	✓	✓	✓
Lagged Dep. Var.	4	4	4	4	4
Month FE	✓	✓	✓	✓	✓
Product FE	✓	✓	✓	✓	✓
Clusters	18	18	18	18	18
Observations	2,214	2,214	2,214	2,214	2,214

Standard errors clustered at the product level in parentheses
* significant at $p < .10$; $^{**}p < .05$; $^{***}p < .01$

were unable to obtain. As a measure of this potential error, we calculate the volume of shipments by shipper in 2009 that also occurred in 2011.

Table A14 shows that our results are generally stronger when we weight the data by measures of our confidence in its quality. Column 1 presents the results from our preferred specification in our original table of results, Table 2, without any weights. Column 2 presents this specification estimated using weighted OLS with the proportion of the volume of trade in each product where we identified the family as the weight. Column 3 presents the results using the proportion of firms that we were able to identify in each product as the weight. In Column 4 we use a weighted specification where the weights are the proportion of firm-product trade in 2009 that is also imported in 2011. In the last column, we use a "combined weight" that is the product of the three weights in columns 2-4. Results are similar in size and significance to those in Table 2.

E.4 Test for sensitivity to dropping each product

Another concern is that the results in our analysis may be driven by one particularly influential product. To address this, we test whether the coefficient on $Coup_i \times Autocracy_t$ is also robust to dropping each product. Figure A8 plots the coefficients on $Coup_i \times Autocracy_t$ from regressions with all the controls in Column 5 of Table 2. The magnitude of the effect remains similar across

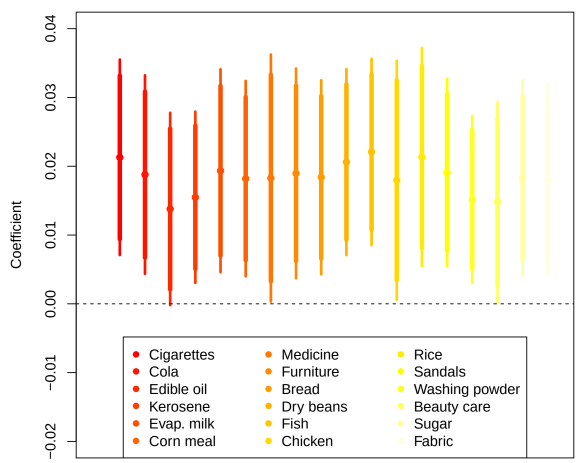
Table A14: Prices of goods imported by coup participators during autocratic periods using weights based on measures of data quality

	Weights:				
	None	Fams id'd (%)	Firms id'd (%)	$\frac{Import11}{Import09}$	Combined weights
	(1)	(2)	(3)	(4)	(5)
Coup × Autocracy	0.018**	0.017***	0.017**	0.025***	0.023**
	(0.007)	(0.006)	(0.007)	(0.009)	(0.009)
Coup × Quake	0.068*	0.060*	0.045	0.198***	0.077*
	(0.041)	(0.033)	(0.029)	(0.058)	(0.040)
World Supply Price	−0.0004	0.002	0.002	−0.002	0.004
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Number Firms × Autocracy	−0.003	−0.003	−0.003	−0.004	−0.005
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Consumption Share × Autocracy	−0.0005	−0.001	−0.0004	−0.0002	−0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lagged Dep. Var.	4	4	4	4	4
Month FE	✓	✓	✓	✓	✓
Product FE	✓	✓	✓	✓	✓
Observations	2,214	2,214	2,214	2,214	2,214
Clusters	18	18	18	18	18

Standard errors clustered at the product level in parentheses
* significant at $p < .10$; $^{**}p < .05$; $^{***}p < .01$

these product subsets.

Figure A8: Robustness: Coefficient on Coup × Autocracy dropping each product



F Historical Timeline

1956	Francois Duvalier seizes power in military coup
1971	Francois Duvalier is succeeded by his son Jean-Claude
1986	Jean-Claude Duvalier flees Haiti and is replaced by Lt-General Henri Namphy as head of governing council
1988	Leslie Manigat becomes president, but is ousted in a coup led by Brigadier-General Prosper Avril
1990	Jean-Bertrand Aristide (Lavalas) elected president in Haiti's first free and peaceful polls
1991	Aristide ousted in a coup led by Brigadier-General Raoul Cedras, triggering sanctions by the US and the OAS
1994	Military relinquishes power under threat of US invasion; US forces oversee transition to civilian government; Aristide returns
1995	Rene Preval (Lavalas) party elected president
2000	November - Aristide elected president
2001	July - attempted coup
2001	November - attempted coup
2001	Cross-border paramilitary campaign launches
2004	February - Aristide leaves Haiti after paramilitary offensive
2006	Rene Preval elected president