Bound by Ancestors:

Immigration, Credit Frictions, and Global Supply Chain Formation*

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Abstract

This paper shows that the ancestry composition shaped by century-long immigration to the US can explain the current structure of global supply chain networks. Using an instrumental variable strategy, combined with a novel dataset that links firm-to-firm global supply chain information with a US establishment database and historical migration data, we find that co-ethnic networks formed by immigration have a positive causal impact on global supply chain relationships between foreign countries and US counties. Such a positive impact not only exists in conventional supplier-customer relationships but also extends to strategic partnerships and trade in services. Examining causal mechanisms, we find that the positive impact is stronger for counties in which more credit-constrained firms are located, and such a stronger effect becomes even more pronounced for foreign firms located in countries with weak contract enforcement. Collectively, the results suggest that co-ethnic networks serve as social collateral to overcome credit constraints and facilitate global supply chain formation.

JEL Codes: F14, F22, F36, F60, G30, J61, L14

Keywords: Immigration, Global Supply Chain, Global Value Chain, Network Formation, Co-ethnic Networks, Social Ties, Trade Credit, Credit Constraints.

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1 Introduction

During the past decade, the global economy has experienced a series of events that triggered disturbances in global supply chains and immigration. For instance, the reorganization of the global supply chains has been at the center of economic and political debates following the 2018 US-China trade war, the Covid-19 pandemic, and the Russo-Ukrainian War, which all severely disrupted the global supply chain networks. Despite decades of movements toward global integration through global value chains, the recent Covid-19 pandemic, for example, has ignited a movement toward "renationalization" under the premise that global integration has exacerbated the negative impacts of the pandemic.[1] And just as importantly, these events also triggered disruptions in immigration across borders. For example, the Trump administration tightened visa access for high-skilled foreign workers in 2020 as part of its protectionist policies, and the COVID-19 pandemic led many countries to implement various types of border restrictions and halt immigration processes.

The increased attention to the global supply chain reorganization following the massive disruption in global supply chains and immigration then raises the following questions: What determines the global supply chain network structure? Does immigration, among its potential determinants, affect the formation of global supply chains across countries? If so, through what mechanisms does immigration shape the global supply chain structure? In this article, we address these questions by establishing a causal linkage between immigration and global supply chain formation: Immigration from a given country to a given US county has a positive causal impact on firm-to-firm global supply chain relationships between these two regions.[2] In terms of underlying economic mechanisms, we provide novel evidence that co-ethnic networks across borders play an important role in facilitating trade credit provision by mitigating credit constraint problems, which fosters global supply chain formation.

Understanding the role of immigration in the formation of global supply chain networks is contemporaneously relevant because if immigration affects global supply chain formation, then it implies that the recent decline in immigration due to the pandemic could have long-lasting impacts on the global supply chain structure above and beyond the direct impact of the pandemic. Moreover, investigating the interdependence between two seemingly unrelated networks — co-ethnic and global supply chain networks — and their interaction with credit frictions can deepen our understanding

[1] The United Nations Department of Economic and Social Affairs reported in April 2020 that "*The adverse effects of prolonged restrictions on economic activities in developed economies will soon spill over to developing countries via trade and investment channels. ⋯ In addition, global manufacturing production could contract significantly amid the possibility of extended disruptions to global supply chains.*"— World Economic Situation And Prospects: April 2020 Briefing, No. 136.

[2] Researchers have typically considered the structure of supply chains or production networks as exogenously given. A few recent studies (Lim, 2018; Acemoglu and Azar, 2020; Kopytov et al., 2022; Taschereau-Dumouchel, 2022) develop a tractable framework to investigate the *endogenous* determination of the production network, but mostly focus on *domestic* firm-to-firm networks. Our work is differentiated from these studies as we empirically explore the determination of *global* firm-to-firm supply chain networks.

of the complexities of global supply chains, including credit provision across borders, in the era of globalization of trade and finance with rising interplay between the two.

To this end, we first explore whether the co-ethnic networks between US counties and foreign countries, which are formed by century-long immigration from foreign countries to the United States, have *causally* shaped the current landscape of the global supply chain networks between these locations. However, establishing the causal relationship is empirically challenging as it requires exogenous variation in ethnic composition that is unrelated to the global firm-to-firm supply chains. Certain characteristics such as climate similarity between two places may induce more immigrants from a given country to reside in a particular area and, at the same time, create more global supply chain networks between the two locations. Furthermore, past supply chain networks between an origin country and a destination county may have induced more immigration.

We solve these issues by adopting a "leave-out push-pull" approach, an instrumental variable technique pioneered by Burchardi et al. (2019), which exploits unique US migration history for more than a century to construct an instrument for the present-day distribution of ancestry composition. The US experienced successive waves of immigration from many different origin countries. The immigrants settled at different destinations within the US depending on the relative attractiveness in each period. Three factors, (i) a push factor, (ii) a pull factor, and (iii) a recursive factor, summarize time-series variation in the relative attractiveness of different destinations within the US combined with staggered arrival of migrants from different origins. The push factor measures the total number of migrants arriving in the US from origin o in time t; the pull factor captures the relative economic attractiveness of destination d to migrants arriving in time t; and the recursive factor gauges the relative size of the pre-existing local population of the ancestry of origin country o in destination d at time t. The instrumental variable is constructed as the full set of simple and higher-order interactions of these pull and push factors.

Equipped with the empirical strategy, we assemble a unique and comprehensive dataset that links US firms' global supply chain relationships from the FactSet Revere with their establishment-level information from the National Establishment Time Series (NETS) database. We then relate the global supply chain relationships to migration networks data (i.e., century-long data on historical migration from foreign countries to US counties). Using the novel datasets combined with the identification strategy, we found a positive impact of co-ethnic networks on the current structure of global supply chain networks. Quantitatively, doubling the number of residents with ancestry from a given origin relative to the sample mean (from 320 to 640) increases by 4.9 (or 4.5) percentage points the probability that at least one firm in destination d has suppliers (or customers) headquartered in origin o. We also find that the positive impact of co-ethnic networks on global supply chain linkages operates at the intensive margin: the number of suppliers and customers.

We conduct various robustness checks to corroborate the key empirical findings. We show

that global supply chain formation is a distinct phenomenon from foreign direct investment (FDI): Controlling for FDI and strictly ruling out any potential within-multinational linkages do not alter our result. We conduct a placebo test and find that the impact of ancestry composition on global supply chain linkages only works through trade-engaging establishments — which directly engage in firm-to-firm trade with foreign companies — and not through non-trade-engaging establishments. The core results are also robust to restricting firms to single-establishment firms or defining firms' US county locations based on headquarter locations. Finally, neither using ancestry compositions prior to 2010 (i.e., 1980, 1990, and 2000) nor restricting supply chain linkages to those newly formed after 2010 affects our main results, reassuring that the reverse causality is not driving our core results.

We further explore whether the positive impact of co-ethnic networks goes beyond conventional supplier-customer relationships in the literature. First, using a strategic relationship variable (e.g., joint ventures, research collaboration, etc.) in FactSet Revere, we uncover that co-ethnic networks have a positive impact on such a broader concept of relationships — strategic partnerships. Next, we find that the effect of ancestry composition on global supply chain formation is positive for both manufacturing and non-manufacturing, and the effects are stronger for non-manufacturing establishments. Collectively, the first key finding of our paper provides evidence that co-ethnic networks play an important role in shaping the current global supply chain networks, and that such effect operates mainly through trade-engaging establishments and extends further to non-conventional supply chain relationships such as strategic partners and non-manufacturing industries.

Finally, we explore the mechanisms responsible for the key findings. It has been well documented that business across borders, compared to within-border business, entails considerable barriers such as poor enforcement of international contracts, incomplete information about foreign partners, cultural and language differences. In these frictional environments, Rauch (2001) noted that co-ethnic networks might help mitigate these informal barriers. Therefore, we posit that the role of co-ethnic networks in forming global supply chain relationships becomes more important under circumstances where credit and contractual friction issues are more serious.[3]

Using firms' trade credit performance information, we validate the hypothesis that the positive impact of co-ethnic networks on global supply chain relationships becomes stronger for US counties in which more credit-constrained firms are located. Furthermore, using a triple-interaction of co-ethnic networks, credit constraints, and judicial quality of origin countries, we further show that such a stronger effect becomes even more pronounced for origin countries with weak contract enforcement.

[3]Because two or more unrelated firms engage in firm-to-firm global supply chains, unlike environments in which firms can internalize the issue of financial problems (e.g., FDI through multinationals, which is a within-firm activity), firms rely heavily on informal finance such as trade credit to fill a mismatch between payment and delivery. It has been noted that trust plays a major role in granting and receiving trade credit, especially when there are no formal contractual enforcement mechanisms in place because implicit financing contracts naturally involve default risks. Karlan et al. (2009) argue that social networks facilitate informal borrowing by enhancing trust. We argue that a co-ethnic network is one such social network that enables each involved party to build trust in trade credit relationships.

The results, taken together, suggest that co-ethnic networks serve as social collateral to overcome credit constraints and facilitate global supply chain formation.

Related Literature

Our paper studies the interplay between immigration, global supply chains, and credit constraints under incomplete contract enforcement. The first strand of related literature is a series of research that investigated the relationship between immigration and trade. Gould (1994) and Head and Ries (1998) are the early two examples that use a gravity model to uncover the positive impact of immigration on trade for US and Canada, respectively. More recent studies have attempted to establish more rigorous causal effect of immigration on international trade (Rauch and Trindade, 2002; Aleksynska and Peri, 2014; Cohen et al., 2017; Parsons and Vézina, 2018; Cardoso and Ramanaryanan, 2019; Bonadio, 2020) and FDI (Javorcik et al., 2011; Burchardi et al., 2019). Our paper contributes to the literature by providing a causal linkage between immigration and firm-to-firm global supply chain relationships and the underlying economic mechanism.

It is worth emphasizing the distinction between global supply chain networks — which involve firm-to-firm relationships between distinct firms — and within-firm activities such as FDI. The distinction between firm-to-firm and within-firm activities has been a central topic in the theory of the firm. For instance, as the seminal work of Coase (1937) emphasized, within-firm activities are governed by organizational rules, whereas firm-to-firm transactions are mediated by prices (i.e., market mechanisms). Therefore, the issues involving prices, trade credit, and trade under incomplete contracting are more pronounced in firm-to-firm transactions than in within-firm movement of factors (Williamson, 1975; Hart and Moore, 1988).[4] Also, perhaps more importantly, by focusing on global supply chain relationships, we could explore trade credit and its incomplete contracting environments, which is not directly applicable in the case of FDI (e.g., Burchardi et al., 2019).

This paper also complements the literature on the nexus between social networks and credit constraints under incomplete contracting. It has been noted that social networks play an essential role in building trust in relationships in sociology literature (e.g., Putnam et al., 2000). Following this insight, in the economics literature, Karlan et al. (2009) developed a theory of trust based on informal contract enforcement in social networks. They found that social networks create trust when agents use connections as social collateral to facilitate informal borrowing.[5] As such, social networks can build trust that serves as social collateral to facilitate trade credit (Fafchamps, 2000; Karlan,

[4] In particular, this distinction matters more in international trade due to the difficulties of formal contractual enforcement in international transactions. As a result, a domestic firm faces an important choice problem of whether to trade with a separate foreign firm or to own a subsidiary in the foreign country, and this choice problem has been among the most active research agenda in the international trade literature (Antras and Helpman, 2004).

[5] In Karlan et al. (2009), they noted that "*The possibility of losing valuable friendships secures informal transactions in the same way that the possibility of losing physical collateral can secure formal lending.*"

2005; Wu et al., 2014; Levine et al., 2018).[6] Although our credit friction mechanism is in the spirit of these papers, we find this channel in the reciprocal relationship between immigration and global supply chain relationships — which has not been investigated before. Furthermore, consistent with Antras and Foley (2015), we find that the role of social networks in alleviating credit constraints is more pronounced for foreign countries with weak enforcement of contracts.

Finally, there is also active research on the role of financial frictions or credit shocks on international transactions. Amiti and Weinstein (2011) and Niepmann and Schmidt-Eisenlohr (2017) find that exogenous financial shocks result in the decline of trade activities by firms. Antras and Foley (2015) study the financing terms that support international trade and find that the choice of trade finance shapes the impact of crises. Our paper complements this literature by showing that the co-ethnic networks could potentially alleviate such credit frictions and facilitate global firm-to-firm transactions.

The paper is organized as follows. Section 2 introduces the datasets for our main analysis. Section 3 presents the estimation model. Section 4 presents the main results. Section 5 provides evidence on the credit constraints mechanism. Section 6 concludes.

2 Data

We construct a unique dataset of US firms' global supply chain relationships merged with their establishment-level information. The global supply chain networks come from the FactSet Revere database where we are able to identify customer-supplier relationships between US firms and foreign firms. The US firms in FactSet Revere might have multiple establishments (i.e., multiple locations) across the US. The National Establishment Time Series (NETS) database contains the precise location information of all establishments, which enables us to identify global firm-to-firm supply chain relationships between US county d and foreign country o. The global supply chain relationships are then linked to migration networks between US county d and foreign country o, wherein the immigration and ancestry data come directly from Burchardi et al. (2019).

2.1 Global Supply Chain Relationships

FactSet Revere database is designed to uncover business relationship interconnections among companies globally. FactSet analysts systematically collect companies' relationship information from primary public sources such as SEC 10-K annual filings, investor presentations, and press releases. They provide four normalized relationship types: (i) customers, (ii) suppliers, (iii) competitors, and (iv) strategic partners. We identify a firm's supplier and customer firms using relationship types

[6] Using Chinese firm-level datasets, Kong et al. (2020) find that CEOs' hometown connections, one example of network connections between individuals, increase access to trade credit.

categorized as "suppliers" and "customers."

FactSet Revere supply chain relationships database covers approximately 200,000 firms including more than 30,000 publicly listed firms around the world, comprising over 725,000 unique business relationships, with historical data going back as far as 2003.[7] Importantly, FactSet Revere database includes both publicly listed and private firms, provides both important and less important relationships, and incorporates relationship information obtained from both direct disclosure from a source company and reverse disclosure from another company regarding the source company.

These features allow researchers to better capture the complete picture of network structure in the economy. They provide an important advantage compared to other firm-level supply chain data sources used in US studies such as Compustat Segment database, which primarily relies on SEC 10-K filings that require publicly listed firms to disclose customers consisting more than 10% of the firms' revenue.[8] Also, to give a concrete example of the importance of reverse disclosure, FactSet Revere Data and Methodology Guide states that there are 22 suppliers directly disclosed by an exemplary firm — Walmart — while as a result of the reverse relationships methodology, an additional 293 companies disclose Walmart as a customer, therefore providing a more comprehensive suppliers network for the exemplary firm — Walmart. Finally, a linkage weight between supplier and customer is disclosed, whenever available, which is measured as the percentage of supplier's revenue arising from the relationship with that customer.

2.2 National Establishment Time Series Database

National Establishment Time Series (NETS) database is an annual panel of a near universe of US establishments. NETS tracks firm structures systematically. NETS assigns each establishment a unique identifier called DUNS number, which is unchanged even after M&As, and is not reused after an establishment exit. Each establishment is also assigned the identifier of its headquarter establishment. Using this feature of NETS, we group together all the establishments under the same firm, and match them to the corresponding firm in FactSet Revere.

Importantly for our purpose, NETS includes establishment-level information about an exact address and a precise location at the longitude and latitude level. Since the NETS links each establishment to its headquarter establishment, we can identify potentially multiple locations of a firm that can be matched to the FactSet Reserve database.

The location information in NETS is obtained from telephone book Yellow Pages, public records,

[7] Company information is fully reviewed annually, and changes based on corporate actions are monitored daily. Thus it provides a detailed and up-to-date dataset — including information on inter-company relationships. The coverage statistics are based on the authors' own calculations.

[8] Therefore, Compustat Segment database only captures important relationships directly disclosed by publicly listed firms. In contrast, Factset Revere database collects information not only from SEC 10-K filings but also from many other sources such as investor presentations and press releases, and incorporates reverse disclosure by other firms, allowing researchers to capture less important relationships and relationships that involve private firms.

and other wide-ranging data verification efforts. A number of studies have demonstrated the accuracy of location information in NETS. For example, Barnatchez et al. (2017) find that the county-level correlation between NETS and the Census Bureau's County Business Patterns (CBP) is above 0.99 regarding both employment counts and establishment counts. Based on the documented indication for data accuracy, a number of recent studies utilized the location information in NETS as the main dataset (e.g., Gray et al., 2015; Rossi-Hansberg et al., 2021; Behrens et al., 2022; Hyun and Kim, 2022; Hyun et al., 2022; Oberfield et al., 2022).

The source of NETS is Dun & Bradstreet (D&B), which has a strong incentive to collect accurate data as a credit rating company. Using reports from firms' trade credit suppliers, D&B calculates PayDex Score, a 100 point credit score measure for the overall manner of trade credit payment, which is widely used as a measure of creditworthiness (e.g., Kallberg and Udell, 2003; Borisov et al., 2021; Avramidis et al., 2022). We use PayDex Scores — both the yearly maximum and the minimum PayDex scores — to investigate whether co-ethnic networks help mitigate credit constraints in global supply chains.

2.3 Immigration and Ancestry

The immigration and ancestry data come directly from Burchardi et al. (2019) where they used the individual files of the Integrated Public Use Microdata Series (IPUMS) samples of 1880, 1900, 1910, 1920, 1930, 1970, 1980, 1990, and 2000 waves of the US census, and the 2006-2010 five-year sample of the American Community Survey. For each wave, the largest available sample is chosen; observations are weighted by the personal weights to get a representative sample. The individual-level data are then aggregated to the level of historic US counties and foreign countries and then are transformed into the 1990 country-county level using various transition matrices.[9]

For our empirical analysis, the flow of immigrants, $I^t_{o,d}$, is measured as the number of migrants from foreign origin country o to US destination county d between $t-1$ and t (the interval between two consecutive census waves).[10] The stock of ancestry information, $A^t_{o,d}$, is measured as the number of respondents in US county d who report the first ancestry as foreign origin country o at time t. The dyadic dataset covers 3,141 US counties, 195 foreign countries, and 10 census waves.

In the baseline analyses, we exploit the first 9 waves (1880-2000) of migrations and exclude the 2000-2010 wave, following Burchardi et al. (2019).[11] We show, however, that the inclusion of the 10th wave barely affects our main result.

[9] For a more detailed procedure, please refer to Burchardi et al. (2019).

[10] In the first sample, i.e., the 1880 census, the variable, $I^{1880}_{o,d}$, is defined as the number of residents who were either born in o or whose parents were born in o.

[11] As well documented in Jensen et al. (2015) and Burchardi et al. (2019), the number of foreign-born first-generation immigrants in the 2010 American Communities Survey is somewhat understated. So we exclude the 2000-2010 wave in the baseline regression.

2.4 Other Datasets

We use geographic distances, absolute latitude differences, and measures of agricultural similarity between country-of-origin o and US county d as a set of control variables.[12] The distance variables are measured as the distance between the coordinates for all postal codes within a US county and the coordinates of the main city for a foreign country.[13] The agricultural similarity between each origin country o and county d is measured as the difference in crop suitability of the country and county for a select group of crops.[14]

We also use an industry-level measure of external finance dependency from Rajan and Zingales (1998). Specifically, this widely used measure captures an industry's need for external finance, which is defined as the difference between investments and internal cash generated from operations, originally sourced from data on U.S. firms. In addition to the PayDex Score measures, the industry-level measure will complement the analysis in investigating the credit constraint channel. Lastly, to gauge the extent to which countries enforce contracts pursuant to an agreement, we use a measure of judicial quality from Nunn (2007), which is originally drawn from the "rule of law" from Kaufmann et al. (2004). The judicial quality measure enables us to examine further the credit constraint mechanism by exploiting institutional differences across countries.

2.5 Summary Statistics

Table 1 provides basic summary statistics of the datasets, for four different levels of the unit: (i) Origin-Destination level; (ii) Origin level; (iii) Destination level; and (iv) Firm level.

In Panel A, one notable pattern in the global supply chain relationships (the outcome variables of our interest) is that only 3% of the origin-destination pairs have at least one linkage between foreign suppliers (in origin) and US customers (in destination) in 2011-2014. A similar pattern holds for foreign-customer-and-US-supplier linkages. This means that most of the variation in global supply chain relationships is along the extensive margin. Along the same line, conditional on having at least one foreign-supplier-and-US-customer linkage, the average number of foreign suppliers within an origin-destination pair is 2.54 with a standard deviation of 4.27. We find a similar pattern for foreign-customer-and-US-supplier linkages.

Turning our attention to the key independent variable (i.e., the ancestry variable) in Panel A, the average number of residents with ancestry from a particular origin country is 320 in the year 2010. The standard deviation of the ancestry variable is 5,960, which provides us with sufficient variation for our empirical analysis.

[12] The three measures come directly from Burchardi et al. (2019).

[13] If a US county has multiple postcodes, then one of them was randomly selected. The geo-coordinates can be downloaded from GeoNames (geonames.org) and CEPII (cepii.fr), respectively.

[14] The raw data come from the Food and Agriculture Organization of the United Nations Global Agro-Ecological Zones (FAOGAEZ) data.

Panel A also provides credit-related variables and a measure of judicial quality, which are converted into the origin-destination level.[15] PayDex Score measures display sufficient variations across origin-destination pairs, which enables us to investigate the role of credit constraints in exploring mechanisms. The measure of judicial quality, which is converted from the origin level to the origin-destination level, also has sufficient variation across observations with a mean of 0.50 and a standard deviation of 0.21.

Panels B and C of Table 1 provide summary statistics for origin countries and destination counties, respectively. In Panel B (origin level), the average origin country is connected to 105 US counties by having suppliers headquartered in the origin country who supply to US firms in those counties. Similarly, the average origin country is connected to 118 US counties through customer linkages. The distribution is highly skewed, which is also confirmed by Figure A.1. Panel C summarizes similar information at the destination level. We find a highly skewed distribution of the number of origins connected through global supply chains, which is visualized in Figure A.2. Panel C additionally provides summary statistics of the number of establishments as well as the number of establishments that engage in trade between 2011-2014. On average, there are 220 establishments, among which 10 establishments engage in trade. This is consistent with the well-established fact in the literature that only a few businesses engage in foreign transactions (e.g., Bernard et al., 2007).

Lastly, Panel D shows summary statistics at the firm level. The total number of firms in our sample is 48,458 and an average firm has about 14 establishments. However, an average firm has less than one (0.66) trade-engaging establishments, which is again consistent with the well-established fact in trade. Among 48,458 firms, 3,306 (2,954, respectively) firms supply to (buy from, respectively) at least one foreign company.

3 Empirical Strategy

Our aim is to estimate the causal impact of immigration on global supply chain relationships. Specifically, we would like to evaluate whether the presence of descendants of migrants from an origin country o within US county d induces more US firms in county d to have a global supply chain link (either as a supplier or a customer) with foreign firms based in the origin country o. To do so, we set up the following structural gravity equation:

$$Y_{o,d} = \delta_o + \delta_d + \beta A_{o,d}^{2010} + X'_{o,d}\gamma + \varepsilon_{o,d} \tag{3.1}$$

[15] D&B provides PayDex Score information at the establishment level. We average the scores of the establishments within a county. After the procedure, at the origin-destination level (the unit of analysis), the number of observations shrinks to 592,995 due to some non-reporting observations.

Table 1: Summary Statistics

Panel A	**Origin-Destination Level**					
Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
I(N.Supp>0)	612495	0.03	0.18	0.00	0.00	0.00
I(N.Cust>0)	612495	0.04	0.19	0.00	0.00	0.00
N.Supp (>0)	20385	2.54	4.27	1.00	1.00	5.00
N.Cust (>0)	22968	2.44	4.29	1.00	1.00	5.00
Ancestry 2010 (in thousands)	612495	0.32	5.96	0.00	0.00	0.08
Distance (km)	612495	9122.39	3802.10	3358.40	9330.90	14027.00
Latitude Difference (degree)	612495	19.44	11.31	3.92	19.53	34.52
100-PayDexMax	592995	24.65	3.53	20.57	24.36	28.47
100-PayDexMix	592995	30.26	5.62	23.15	30.15	36.13
Judicial Quality	452304	0.50	0.21	0.29	0.45	0.86
Panel B	**Origin Level**					
Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
N.Destination - Supplier Linkage	195	104.54	213.18	0.00	0.00	448.00
N.Destination - Customer Linkage	195	117.78	223.95	0.00	1.00	506.00
Avg. Ancestry 2010 (in thousands) across Destination	195	0.32	1.30	0.00	0.01	0.48
Avg. Distance (km) across County	195	9122.39	3711.71	3658.20	9279.65	14006.68
Avg. Latitude Difference (degree) across Destination	195	19.44	10.19	5.39	20.29	33.79
Judicial Quality	144	0.50	0.21	0.29	0.45	0.86
Panel C	**Destination Level**					
Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
N.Origin - Supplier Linkage	3141	6.49	11.56	0.00	0.00	24.00
N.Origin - Customer Linkage	3141	7.31	12.92	0.00	0.00	26.00
Avg. Ancestry 2010 (in thousands) across Origin	3141	0.32	1.13	0.01	0.07	0.63
Avg. Distance (km) across Origin	3141	9122.39	443.46	8592.80	9062.89	9722.44
Avg. Latitude Difference (degree) across Origin	3141	19.44	3.28	15.71	19.08	23.55
N.Establishment	3141	219.64	701.33	9.00	46.00	437.00
N.Establishment (Trade-engaging)	3141	9.99	46.41	0.00	1.00	16.00
100-PayDexMax	3103	24.76	3.74	20.57	24.40	28.73
100-PayDexMix	3103	30.49	6.05	23.15	30.25	36.59
Panel D	**Firm Level**					
Variable	Obs.	Mean	Std. Dev.	P10	P50	P90
N.Supp (>0)	3306	2.83	3.86	1.00	1.00	6.00
N.Cust (>0)	2954	3.97	5.13	1.00	2.00	11.00
N.Establishment	48458	14.35	169.98	1.00	2.00	13.00
N.Establishment (Trade-engaging)	48458	0.66	3.38	0.00	0.00	1.00
100-PayDexMax	36813	25.28	8.81	20.00	22.24	33.45
100-PayDexMix	36813	31.39	12.59	20.00	28.15	46.00

Notes: This table presents the number of observations (Obs), mean, standard deviation, tenth (P10), fiftieth (P50), and ninetieth (P90) percentiles of the variables. Panel A refers to our main sample of (origin) country and (destination) county pairs. Panels B and C refer to the origin country sample and the destination county sample, respectively. Panel D refers to the sample of firms in US counties. I(N.Supp>0) is a dummy variable that equals one if any firm whose trade-engaging establishments located in destination d has supplier firms headquartered in origin o between 2011 and 2014, and zero otherwise. I(N.Cust>0) is similarly defined, where we use customer firms headquartered in origin o instead of supplier firms. N.Destination - Supplier (Customer) Linkage in Panel B indicates the number of destination counties for each origin country, where destination counties have firms whose supplier (customer) firms are headquartered in origin o. N.Origin - Supplier (Customer) Linkage in Panel C indicates the number of origin countries for each destination county, whose supplier (customer) firms are headquartered in origin countries. Averaged variables (Avg.) in Panel B and Panel C are simple averages of respective variables in Panel A.

where $Y_{o,d}$ is the outcome of interest such that if any US firm in destination d has a global supply chain linkage with a foreign firm in origin country o between 2011 and 2014. We construct both a dummy variable and the number of linkages to explore extensive and intensive margins, respectively, and consider supplier linkages and customer linkages separately. Specifically, I(N.Supp>0) is a dummy variable that equals one if any firm whose trade-engaging establishments located in destination d has supplier firms headquartered in origin o between 2011 and 2014, and zero otherwise.[16] I(N.Cust>0) is similarly defined, where we use customer firms headquartered in origin o instead of supplier firms. We also consider the log of the number of linkages to explore intensive margin. For the intensive margin, we use a logarithm of the number of supplier firms (Log N.Supp) and the number of customer firms (Log N.Cust).

$A_{o,d}^{2010}$ is defined as the log of one plus the number of residents in US county d that report having ancestors in origin country o in 2010. $X'_{o,d}$ is a set of control variables that include the geographic distance, the differences in latitude, and agricultural similarity between o and d. δ_o are origin country fixed effects; δ_d are destination county fixed effects. Standard errors are clustered at the origin-country level. The key coefficient of our interest, β, captures the causal impact of immigration on a global supply chain relationship between firms in o and d.

The standard OLS estimation applied to Equation (3.1) will be biased if the migration network term, $A_{o,d}^{2010}$, and the error term, $\varepsilon_{o,d}$, are correlated, even after controlling for origin and destination fixed effects and a set of control variables. For instance, origin-destination-specific omitted factors such as climate affinity or other characteristics can simultaneously affect global supply chain networks today and historical migration flows. Or, perhaps, the direction of causality can be the opposite such that past global supply chain relationships might drive migration.

To address these challenges, we adopt a "leave-out push-pull" approach (a variant of IV strategy), originally developed by Burchardi et al. (2019), which enables us to identify the causal impact of immigration on global supply chain networks. In a nutshell, the "leave-out push-pull" approach is based on a simple dynamic model of migrations that comprise three factors: (i) a push factor; (ii) a pull factor; and (iii) a recursive factor. Migrations from a given origin country o to a given US county d in period t, $I_{o,d}^t$, depend on the total number of migrants arriving in the US from o in t (I_o^t: the push factor), the relative economic attractiveness of d to migrants arriving in t ($\frac{I_d^t}{I^t}$: the pull factor), and the relative size of the pre-existing local population of ancestry o in d at t ($\frac{A_{o,d}^{t-1}}{A_o^{t-1}}$: the recursive factor).

Solving the model recursively, Burchardi et al. (2019) show that the first-stage specification can

[16] Trade-engaging establishments are defined using NETS data, which provides information on trade activity for each establishment. We define establishments to be engaged in trade if they report being active in trade at least once between 2011 and 2014.

be expressed as follows:[17]

$$A_{o,d}^{2010} = \delta_o + \delta_d + \sum_{t=1880}^{2000} \alpha_t I_{o,-r(d)}^t \frac{I_{-c(o),d}^t}{I_{-c(o)}^t} + \sum_{n=1}^{5} \delta_n PC_n + X_{o,d}'\gamma + \eta_{o,d} \tag{3.2}$$

where $I_{o,-r(d)}^t$ captures the push factor, excluding migrants to d's census region; $\frac{I_{-c(o),d}^t}{I_{-c(o)}^t}$ measures the pull factor, excluding migrants from o's continent. Excluding migrants to d's census region and migrants from o's continent further ensure that $I_{o,d}^t$ and $\varepsilon_{o,d}$ are uncorrelated. PC_n denotes the n-th principal component summarizing the information contained in the higher-order terms $I_{o,-r(d)}^s \cdots I_{o,-r(d)}^t \frac{I_{-c(o),d}^t}{I_{-c(o)}^t}, \forall t < s \leq 2010$.

The key identifying assumption is that conditional on the control variables and the fixed effects, $I_{o,-r(d)}^t \frac{I_{-c(o),d}^t}{I_{-c(o)}^t}$ and $\varepsilon_{o,d}$ are uncorrelated. In the empirical procedures, we further relax this assumption and include the destination x continent-of-origin fixed effects ($\delta_d \times \delta_{c(o)}$) and origin x destination's census region fixed effects ($\delta_o \times \delta_{r(d)}$). Those fixed effects can even control for any confounding factors that operate within an origin-continent and destination-census-region pair.

4 Main Results

This section shows that the ancestry composition shaped by immigrants to the US for more than a century can causally explain the current structure of global supply chain networks. We first present the instrumental variable regression results and then provide various robustness checks to corroborate our findings.

4.1 Instrumental Variable Regressions

Table 2 presents the estimated results of Equation (3.1) using IV regression, where we consider $Y_{o,d} \equiv$ I(N.Supp>0) and $Y_{o,d} \equiv$ I(N.Cust>0), respectively, as dependent variables. We present the standard OLS regression results in Table B.1 of Appendix B, in which we find similar but slightly smaller coefficients compared to the IV results, assuring that the IV strategy mitigates potential downward bias of simple OLS regressions created by measurement errors or confounding factors.[18]

In Panel A of Table 2, we use I(N.Supp>0) as the dependent variable. In column (1), we regress I(N.Supp>0) on the log of ancestry in 2010 instrumented by the leave-out push-pull IVs from nine

[17] Please refer to Burchardi et al. (2019) for a more detailed derivation of the first-stage specification.

[18] Burchardi et al. (2019) argue that the endogenous assignment of migrants within the US could create a downward bias of the OLS coefficient on FDI flow. A similar logic holds on the relationship between the endogenous assignment of migrants and global supply chain relationships, which could create a downward bias in the OLS estimates: migrations could be driven by differences in factor endowments (i.e., differences in wages between o and d), while global supply chain linkages could be driven by similarities in factor endowments.

waves of US census data (1880-2000 waves) and control for origin and destination fixed effects. We find a statistically significant and positive causal impact of immigration from origin o to destination d on global supply chain creation between firms located in d and supplier firms headquartered in o: a 10 percent increase of ancestry from origin o to destination d results in 2.42 percentage points increase in the probability that at least one firm in destination d has a connection with origin o through supplier linkages.

From column (2) to column (7), we show the robustness of the result by adding various controls and more granular fixed effects. In column (2), we add the first five principal components of the higher-order interactions to the set of instruments. We find a slightly smaller magnitude but still a highly statistically significant positive impact of immigration on the global supply chain connection. In column (3) we add destination x continent-of-origin fixed effects ($\delta_d \times \delta_{c(o)}$) and origin x destination's census region fixed effects ($\delta_o \times \delta_{r(d)}$), exploiting only variation within continents and within census regions. Therefore, any common factors that operate within an origin-continent and destination-census-region pair are absorbed by these fixed effects.[19] The estimate in column (3) shows that a 10 percent increase of ancestry from origin o to destination d results in 2.24 percentage points increase in the probability that at least one firm in destination d has a connection with origin o through supplier linkages. Put another way, doubling the number of residents with ancestry from a given origin relative to the sample mean (from 320 to 640) increases by 4.9 percentage points the probability that at least one firm engages in global supply chain relationship with a supplier company headquartered in that origin.[20]

In column (4) we add an instrument constructed by using the 2000-2010 wave of migration. Column (5) adds the third-order polynomials of distance and latitude difference to capture any non-linear relationship between global supply chain connection and distance, and column (6) adds measures of agricultural similarity between US counties and foreign countries to control for the country-county specific attractiveness driven by agricultural similarity, which could jointly affect migration and supply chain linkages between origin countries and destination counties. Finally, in column (7), we include more stringent fixed effects by including origin x destination's state fixed effects, exploiting only variation within US states. Across all the specifications, we find a statistically significant and positive causal impact of the ancestry composition in 2010 on global supply chain connections through supplier-firm linkages for the period 2011-2014. We obtain similar first-stage results as in Burchardi et al. (2019), confirming the relevance of the instruments: The Kleibergen-Papp

[19] For instance, migrants from Asia have tended to settle in certain places such as the Pacific census division. If we were to observe larger global supply chain relationships between Asian countries and US counties in the Pacific census division, then one may argue that any confounding pair-specific factors could drive the result. The destination x continent-of-origin fixed effects ($\delta_d \times \delta_{c(o)}$) and origin x destination's census region fixed effects ($\delta_o \times \delta_{r(d)}$) can alleviate this concern.

[20] With $\hat{\beta} = 0.224$ from column (3) in Table 2: I(N.Supp>0|Ancestry$_{o,d} = 640$)−I(N.Supp>0|Ancestry$_{o,d} = 320$)=$0.224 \left[\ln\left(1+\frac{640}{1000}\right) - \ln\left(1+\frac{320}{1000}\right)\right] \approx 0.049$.

first-stage F-statistics strongly reject the null of weak instruments across all specifications at the conventional level, where the F-statistics range from 11 to 2448.

Panel B of Table 2 repeats the exercise by using I(N.Cust>0) as the dependent variable. Again, we find a statistically significant and positive causal impact of the ancestry composition on global supply chain connections through customer-firm linkages across all the specifications. Table B.2 of Appendix B further shows the robustness of our results. Here we consider a union of supplier-firm and customer-firm linkages, I(N.Link>0), which is formally defined as a dummy variable that equals to one if any firm whose trade-engaging establishments located in destination d has *either* supplier firms *or* customer firms headquartered in origin o. Based on column (7) of Table B.2, our estimate of interest shows that a 10 percent increase of ancestry from origin o to destination d results in 2.03 percentage points increase in the probability that at least one firm in destination d has a connection with origin o through customer or supplier linkages. This implies that doubling the number of residents with ancestry from a given origin relative to the sample mean (from 320 to 640) increases by 4.5 percentage points the probability that at least one firm engages in a global supply chain relationship with the customer- or supplier-firm headquartered in that origin.

In Table B.3 of Appendix B, we explore the impact of ancestry on global supply chain linkages at the intensive margin. To do so, we consider new dependent variables — log of the number of supplier linkages (Log N.Supp) and customer linkages (Log N.Cust), respectively, conditional on having positive supply chain network connections between origin o and destination d. Across all specifications, we find a strong causal impact of ancestry composition on global supply chain formation even at the intensive margin. Based on column (3) (column (10)), the estimate implies that doubling the number of residents with ancestry from a given origin relative to the sample mean (from 320 to 640) increases the number of supplier (customer) linkages by 5.5 percent (5.5 percent).

4.2 Robustness and Placebo Tests

In this section, we conduct further robustness checks to corroborate our findings. We first show that global supply chain formation is a distinct phenomenon from foreign direct investment (FDI): Directly controlling for FDI and strictly ruling out any potential within-multinational linkages do not alter our result. Second, we conduct a placebo test and show that the impact of ancestry composition on global supply chain linkages only works through trade-engaging establishments — which directly engage in firm-to-firm trade with foreign companies — and not through non-trade-engaging establishments. Third, we show that the result is robust to restricting firms to single-establishment firms or defining firms' US county locations based on headquarter locations. Finally, using ancestry compositions prior to 2010 (i.e., 1980, 1990, and 2000), the core results were barely changed, reassuring the role of historical migration in the formation of global supply chain networks.

Table 2: The Impact of Ancestry Composition on Global Supply Chain Linkages: IV Regression

Panel A	I(N.Supp>0)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log Ancestry 2010	0.242***	0.194***	0.224***	0.218***	0.224***	0.233***	0.234***
	(0.019)	(0.023)	(0.020)	(0.020)	(0.020)	(0.023)	(0.020)
Log Distance	0.016	0.012	0.055	0.053	0.033	0.067	-0.002
	(0.015)	(0.014)	(0.037)	(0.037)	(0.044)	(0.058)	(0.051)
First-stage F stat	11.0	2448.0	162.2	195.4	158.1	102.8	186.2
Destination FE	✓	✓	-	-	-	-	-
Origin FE	✓	✓	-	-	-	-	-
Principal Components	-	✓	✓	✓	✓	✓	✓
Destination x Continent FE	-	-	✓	✓	✓	✓	✓
Origin x Census Region FE	-	-	✓	✓	✓	✓	-
$I^{2010}_{o,-r(d)}(I^{2010}_{-c(o),d}/I^{2010}_{-c(o)})$	-	-	-	✓	-	-	-
3rd order poly in dist and lat	-	-	-	-	✓	✓	-
Agricultural Similarity	-	-	-	-	-	✓	-
Origin x State FE	-	-	-	-	-	-	✓
Observations	612495	612495	612495	612495	612495	459150	612300
Panel B	I(N.Cust>0)						
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Log Ancestry 2010	0.232***	0.196***	0.207***	0.208***	0.208***	0.209***	0.213***
	(0.018)	(0.022)	(0.019)	(0.019)	(0.019)	(0.023)	(0.021)
Log Distance	0.017	0.014	0.041	0.041	0.029	0.050	-0.022
	(0.018)	(0.017)	(0.040)	(0.041)	(0.045)	(0.060)	(0.070)
First-stage F stat	11.0	2448.0	162.2	195.4	158.1	102.8	186.2
Destination FE	✓	✓	-	-	-	-	-
Origin FE	✓	✓	-	-	-	-	-
Principal Components	-	✓	✓	✓	✓	✓	✓
Destination x Continent FE	-	-	✓	✓	✓	✓	✓
Origin x Census Region FE	-	-	✓	✓	✓	✓	-
$I^{2010}_{o,-r(d)}(I^{2010}_{-c(o),d}/I^{2010}_{-c(o)})$	-	-	-	✓	-	-	-
3rd order poly in dist and lat	-	-	-	-	✓	✓	-
Agricultural Similarity	-	-	-	-	-	✓	-
Origin x State FE	-	-	-	-	-	-	✓
Observations	612495	612495	612495	612495	612495	459150	612300

Note. This table presents coefficient estimates from IV regressions of Equation (3.1). The main dependent variables are I(N.Supp>0) and I(N.Cust>0). I(N.Supp>0) is a dummy variable that equals to one if any firm whose trade-engaging establishments located in destination d has supplier firms headquartered in origin o between 2011 and 2014, and zero otherwise. I(N.Cust>0) is similarly defined, where we use customer firms headquartered in origin o instead of supplier firms. The key variable of interest is Log Ancestry 2010, which is instrumented using various specifications of equation (3.2). All columns include $\{I^t_{o,-r(d)}(I^t_{-c(o),d}/I^t_{-c(o)})\}_{t=1880,\ldots,2000}$ as excluded instruments. Columns (1)-(7) focus on I(N.Supp>0). Column (1) includes destination fixed effects and origin fixed effects. In column (2), we additionally include the first five principal components of the higher-order interactions of push and pull factors as instruments. Column (3) includes "destination county"-by-continent fixed effects and "origin country"-by-"census region" fixed effects. Column (4) includes the interaction of the push and pull factor constructed using data from the 2006-2010 American Community Survey. Columns (5)-(6) add the 3rd order polynomials in distance and latitude, and the measure of agricultural similarity. Column (7) includes "origin country"-by-state fixed effects instead of "origin country"-by-"census region" fixed effects. Columns (8)-(14) repeat the analyses using I(N.Cust>0). All regressions control for log distance and latitude difference; standard errors are clustered at the origin country-level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.2.1 Controlling for FDI and Excluding Potential Multinational Linkages

The IV estimates above will yield a biased estimate of the causal effect of ancestry if global supply chain relationships disproportionately occur between origin o and destination d pairs that also have more foreign direct investment links. Then, the estimates could capture the impact of ancestry on FDI rather than global supply chain relationships. To check for this possibility, we additionally include an FDI dummy variable between origin o and destination d in equation (3.1) and repeat the analysis.[21]

Table 3: Controlling for FDI

	I(N.Supp>0)				I(N.Cust>0)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Ancestry 2010	0.177***	0.177***	0.188***	0.188***	0.162***	0.162***	0.165***	0.169***
	(0.020)	(0.020)	(0.022)	(0.020)	(0.018)	(0.018)	(0.021)	(0.019)
FDI Dummy	0.244***	0.244***	0.224***	0.226***	0.235***	0.235***	0.221***	0.221***
	(0.024)	(0.024)	(0.024)	(0.023)	(0.024)	(0.024)	(0.024)	(0.023)
First-stage F stat	69.4	69.2	56.2	77.4	69.4	69.2	56.2	77.4
Principal Components	✓	✓	✓	✓	✓	✓	✓	✓
Destination x Continent FE	✓	✓	✓	✓	✓	✓	✓	✓
Origin x Census Region FE	✓	✓	✓	-	✓	✓	✓	-
3rd order poly in dist and lat	-	✓	✓	-	-	✓	✓	-
Agricultural Similarity	-	-	✓	-	-	-	✓	-
Origin x State FE	-	-	-	✓	-	-	-	✓
Observations	612495	612495	459150	612300	612495	612495	459150	612300

Note. This table presents coefficient estimates from IV regressions of Equation (3.1), where we additionally control for the FDI dummy from Burchardi et al. (2019). FDI dummy has value one if at least one firm in destination d has at least one parent or subsidiary in origin o in 2014. Columns (1)-(4) use specifications in columns (4)-(7) in Table 2; columns (5)-(8) use specifications in columns (11)-(14) in Table 2.

Table 3 presents the estimation results. We first find that FDI linkages between origin o and destination d, which are by nature intra-firm linkages through parents and subsidiaries, are positively associated with inter-firm linkages through global supply chain networks. The positive correlation between FDI and global supply chain relationships thus provides us a rationale for controlling for FDI. Despite this positive correlation, even after controlling for the FDI dummy, we find a statistically significant positive impact of ancestry composition on global supply chain linkages across all columns in Table 3. The magnitudes are somewhat smaller than the corresponding results in Table

[21] We use the FDI dummy provided by Burchardi et al. (2019), which has value one if at least one firm in destination d has at least one parent or subsidiary in origin o in 2014. We thank the authors who publicly share their datasets on their webpages and the journal's data archive.

2, potentially reflecting the confounding effects between FDI and global supply chain relationships. All in all, we fail to reject the null impact of ancestry on global supply chain relationships.

Based on column (1) (column (5)), doubling the number of residents with ancestry from a given origin relative to the sample mean (from 320 to 640) increases by 3.8 percentage points (3.5 percentage points) the probability that at least one firm engages in global supply chain relationship with a supplier (customer) company headquartered in that origin.[22]

In Table B.4 of Appendix B, we further show the robustness of our results by strictly restricting US firms to those who have headquarters located in the US. Therefore, in this exercise, we restrict supplier-customer relationships to those between foreign firms whose headquarters are located *outside the US* and US firms whose headquarters are located *in the US*.[23] Since foreign suppliers or foreign customers of these firms have headquarters outside the US, we strictly rule out any potential supplier-customer linkages that might capture within-multinational relationships between headquarters and their foreign subsidiaries.

4.2.2 Placebo Test: Non-trade-engaging Establishments

In our baseline analyses, to measure the location of firms in US counties, we restricted establishments to those who engage in international trade between 2011 and 2014. Given that our firm-to-firm global supply chain information is provided at the firm level — and not the establishment level, the presumption we made is that a firm's establishments who engaged in international trade between 2011 and 2014 (trade-engaging establishments) are more likely to be connected with foreign firms through global supply chain relationships between 2011 and 2014, compared to the same firm's establishments who did not engage in trade between 2011 and 2014 (non-trade-engaging establishments).[24] For example, if a firm that has a supplier firm in Italy has establishments in Sacramento county (California) and San Augustine county (Texas), and if the establishment in Sacramento engaged in international trade while the one in San Augustine did not, we would expect that the establishment in Sacramento is more likely to be connected with the firm's supplier in Italy.

This provides us with a natural placebo test, where we measure firms' US county locations solely based on non-trade-engaging establishments. Table 4 presents the estimation results. Columns (1)-(4) show that there is no impact of ancestry composition on supplier linkages between origin o and

[22] Specifically, with $\hat{\beta} = 0.177$ from column (1) in Table 3: $\text{I(N.Supp}>0|\text{Ancestry}_{o,d} = 640) - \text{I(N.Supp}>0|\text{Ancestry}_{o,d} = 320) = 0.177 \left[\ln\left(1+\frac{640}{1000}\right) - \ln\left(1+\frac{320}{1000}\right)\right] \approx 0.038$.

[23] In the baseline analysis, we define US firms as companies who have establishments located in the US, regardless of their headquarter location. Therefore, it is possible that these firms have headquarters outside the US. In the data, among all firms that have at least one trade-engaging establishment in the US, only 16% have headquarters outside the US. Table B.4 shows that our results are robust to strictly restricting US firms to those who have headquarters in the US.

[24] Such complication does not exist if a firm has a single establishment. We show the robustness of our results (i) by restricting firms to single-establishment firms and (ii) by measuring the location of firms using the county location of headquarter establishments. See Table B.5 of Appendix B.

Table 4: Placebo Test: Establishments Not Engaging in Trade between 2011-2014

	I(N.Supp>0)				I(N.Cust>0)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Ancestry 2010	0.014	0.014	0.022	0.011	0.039*	0.039*	0.021	0.031
	(0.022)	(0.022)	(0.026)	(0.022)	(0.023)	(0.023)	(0.025)	(0.023)
First-stage F stat	69.4	69.2	56.2	77.4	69.4	69.2	56.2	77.4
Principal Components	✓	✓	✓	✓	✓	✓	✓	✓
Destination x Continent FE	✓	✓	✓	✓	✓	✓	✓	✓
Origin x Census Region FE	✓	✓	✓	-	✓	✓	✓	-
3rd order poly in dist and lat	-	✓	✓	-	-	✓	✓	-
Agricultural Similarity	-	-	✓	-	-	-	✓	-
Origin x State FE	-	-	-	✓	-	-	-	✓
Observations	612495	612495	459150	612300	612495	612495	459150	612300

Note. This table presents the regression results of the placebo test. Specifically, we present coefficient estimates from IV regressions of Equation (3.1), where we measure firms' US county location solely based on non-trade-engaging establishments. Columns (1)-(4) use specifications in columns (1)-(4) in Table 3; columns (5)-(8) use specifications in columns (5)-(8) in Table 3.

destination d if we measure firms' US county location using non-trade-engaging establishments. This means that, for example, even if a firm has an establishment in San Augustine, if that establishment does not engage in trade, an (exogenous) increase in Italian ancestry in San Augustine does not increase global supply chain linkages between that county (d) and Italy (o) through supplier linkages.

Columns (5)-(8) repeat the exercise using customer linkages. Although columns (5) and (6) give weakly positive coefficients, the effects are economically small. Also, controlling for the agricultural similarity (column (7)) and more granular fixed effects (column (8)) make the estimates statistically insignificant, confirming that the impact of ancestry composition on firm-to-firm supply chain linkages works primarily through trade-engaging establishments in the US and their connection with the foreign customer- or supplier-firms.

4.2.3 Alternative Ways of Defining Firms' US County Locations

Given that our firm-to-firm global supply chain information is provided at the firm-level while location information for US firms are at the establishment level, multi-establishment firms create complication on how we should assign firm-to-firm linkages to each establishment. Our baseline analyses used trade-engaging establishments to measure firms' US county locations.

As a robustness check, we investigate whether our results are robust to (i) restricting firms to single-establishment firms and (ii) measuring the location of firms using the county location of headquarter establishments. As Table B.5 in Appendix B shows, we find robust results on these

specifications.

4.2.4 Reverse Causality

We also directly address the potential reverse causality concern in two ways. First, we use ancestry compositions prior to 2010 that go back to 1980, therefore, only exploiting exogenous variations in immigration prior to 1980. Second, we strictly restrict global supply chain linkages in 2011-2014 to those that did not exist in 2010 but were newly formed in 2011-2014. Together, the robustness of our results under these alternative specifications reassures that the core results are not driven by reverse causality.

Using Ancestry Compositions Prior to 2010 We also show that our results are robust to using ancestry compositions prior to 2010. Global supply chain linkages between 2011 and 2014 might have existed for a prolonged time period, potentially prior to 2010. Our main specification in Table 3.1 therefore uses IVs that exploit historical migration spanning from 1880 to 2000 (except for columns (4) and (11) which use the 2006-2010 wave). We additionally show that the ancestry composition that goes back to 1980 can explain the current global supply chain linkages, reassuring the role of historical migration in the formation of global supply chain connections.

Specifically, in Table B.6 of Appendix B, we consider log of ancestry in 2000, 1990, and 1980, respectively, where we exclude IVs that are constructed by using waves 1990 and 2000 (as well as principal components). We find robust results under these alternative specifications.[25]

Restricting Global Supply Chains to Newly Formed Linkages After 2010 We further show the robustness of our results by restricting global supply chain connections to those newly formed after 2010. Specifically, we measure linkages based on global supply chain connections that did not exist in 2010 but were newly formed between 2011-2014. Table B.7 presents the results and confirms the robustness of our findings.

4.3 Beyond Conventional Perspectives on Supply Chain Relationships

In this section, we present two novel results that go beyond conventional perspectives on supply chain network relationships. First, we show that the impact of ancestry composition extends to strategic partners, which is a broader concept of relationships that is related to but does not coincide with conventional supplier-customer relationships in global supply chains. Second, we show that the impact of ancestry composition on global supply chain linkages operates not only through manufacturing industries but also through non-manufacturing industries and that the impact through non-manufacturing industries is stronger.

[25] We tend to get slightly low F statistics (around 11) mainly because we do not use the principal components.

4.3.1 The Impact on Strategic Partners

Our baseline analyses focus on conventional global supply chain linkages: firm-to-firm networks that capture supply of goods and services from one firm to the other. FactSet Revere database, however, provides relationship information that goes beyond conventional global supply chain networks: strategic partner relationships.[26] Strategic partnerships — (e.g.,) joint venture, research collaboration, marketing, integrated product offering, in- and out-licensing, etc. — could be viewed as a broader concept of firm-to-firm relationships (i.e., partnership) that partially overlap with but do not exactly fall into supplier-customer relationships.[27]

Columns (1)-(4) in Table 5 reveal that there is a statistically significant and positive causal impact of ancestry composition on strategic partnership between origin o and destination d.[28] Thus, our main results extend to a broader concept of relationships beyond the conventional global supply chains.

4.3.2 Manufacturing vs. Non-manufacturing Industries

In our main analysis, we do not distinguish between (trade-engaging) manufacturing and non-manufacturing establishments. We explore whether our results are driven by (trade-engaging) manufacturing establishments or non-manufacturing establishments or both. To this end, we perform separate analyses by restricting establishments to manufacturing (SIC 2-digit 20-39) and non-manufacturing, respectively.

Despite the fact that the literature primarily focused on goods trade in manufacturing industries (potentially due to limited data accessibility to service trade), we find the impact of ancestry composition on global supply chain formations for both manufacturing and non-manufacturing industries. In fact, the impact is greater for non-manufacturing industries.

[26] FactSet Revere also provides disclosed competitors of a firm, through which we can identify competitors relationships. We present results for competitor relationships in Table B.8 of Appendix B. Although it may be plausible that an increase of ancestry in a given county creates competition among firms — by making competitor firms in origin o to join markets in destination d, we do not find a strong evidence for this. The estimates are positive — consistent with such view — but small and indistinguishable from zero. However, this does not necessarily mean that an increase of ancestry does not create any competitive pressure on firms; instead it may reflect larger measurement errors in competitor information relative to other types of relationships information. First, competitor relationships reported by FactSet Revere are relatively small compared to other types of relationships: more than 50% are supplier-customer relationships, 30% are strategic partner relationships, and less than 20% are competitor relationships. Second, in contrast to supplier-customer relationships, where SEC 10-K fillings — one of important sources from which FactSet Revere collects supply chain relationship information — mandate publicly listed firms to disclose major customers who consist more than 10% of their revenues, information on competitor relationships is collected purely based on voluntary disclosure through public sources, investor presentations and press releases. Therefore, there can be competitor relationships that are not captured by the dataset. This could create downward bias of estimates due to measurement errors.

[27] We follow the classification provided by FactSet Revere and define two firms having a strategic partnership if one of them report the other as having the following relationship types — joint venture, research collaboration, marketing, integrated product offering, in- and out-licensing, equity investment, and manufacturing and distribution of products.

[28] As in Table 2, we use trade-engaging establishments to identify county locations of each firm in the US.

Table 5: The Impact of Ancestry Composition on Strategic Partner Relationships

	I(N.Link>0)			
	(1)	(2)	(3)	(4)
Log Ancestry 2010	0.039**	0.039**	0.040**	0.042**
	(0.018)	(0.018)	(0.019)	(0.019)
First-stage F stat	69.4	69.2	56.2	77.4
Principal Components	✓	✓	✓	✓
Destination x Continent FE	✓	✓	✓	✓
Origin x Census Region FE	✓	✓	✓	-
3rd order poly in dist and lat	-	✓	✓	-
Agricultural Similarity	-	-	✓	-
Origin x State FE	-	-	-	✓
Observations	612495	612495	459150	612300

Note. This table presents coefficient estimates from IV regressions of Equation (3.1), where we use a linkage dummy based on strategic partner relationships as a dependent variable. Columns (1)-(4) use specifications in columns (1)-(4) in Table 3, where only the dependent variable is replaced with the linkage dummy based on strategic partner relationships.

Panel A in Table 6 measures firms' US county location solely based on the location of trade-engaging *manufacturing* establishments. That is, the dependent variable I(N.Supp>0) (similarly, I(N.Cust>0)) is equal to one if any firm whose trade-engaging *manufacturing* establishments located in destination d has supplier (customer) firms headquartered in origin o. Similarly, panel B measures firms' US county location using the location of trade-engaging *non-manufacturing* establishments. We find that the impact of ancestry on global supply chain relationships works through both manufacturing and non-manufacturing establishments and that the impact is stronger for non-manufacturing establishments.

5 Exploring Mechanisms

So far, we have found robust evidence that the presence of co-ethnic networks that have been shaped by immigrants to the US for more than a century can causally explain the current structure of global supply chain relationships. A natural follow-up question is then *why* firm-to-firm networks are more prevalent between a US county and a foreign country when co-ethnic networks are more predominant between them. In this section, we now delve into the specific mechanisms responsible for the linkage between global supply chain and co-ethnic networks.

Table 6: (i) Manufacturing Establishments, (ii) Non-manufacturing Establishments

Panel A	Manufacturing Establishments							
	I(N.Supp>0)				I(N.Cust>0)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Ancestry 2010	0.157***	0.157***	0.170***	0.170***	0.144***	0.145***	0.155***	0.153***
	(0.019)	(0.019)	(0.021)	(0.020)	(0.021)	(0.021)	(0.023)	(0.024)
First-stage F stat	69.4	69.2	56.2	77.4	69.4	69.2	56.2	77.4
Principal Components	✓	✓	✓	✓	✓	✓	✓	✓
Destination x Continent FE	✓	✓	✓	✓	✓	✓	✓	✓
Origin x Census Region FE	✓	✓	✓	-	✓	✓	✓	-
3rd order poly in dist and lat	-	✓	✓	-	-	✓	✓	-
Agricultural Similarity	-	-	✓	-	-	-	✓	-
Origin x State FE	-	-	-	✓	-	-	-	✓
Observations	612495	612495	459150	612300	612495	612495	459150	612300
Panel B	Non-manufacturing Establishments							
	I(N.Supp>0)				I(N.Cust>0)			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Log Ancestry 2010	0.198***	0.198***	0.209***	0.209***	0.193***	0.193***	0.201***	0.203***
	(0.020)	(0.020)	(0.024)	(0.021)	(0.020)	(0.020)	(0.023)	(0.021)
First-stage F stat	69.4	69.2	56.2	77.4	69.4	69.2	56.2	77.4
Principal Components	✓	✓	✓	✓	✓	✓	✓	✓
Destination x Continent FE	✓	✓	✓	✓	✓	✓	✓	✓
Origin x Census Region FE	✓	✓	✓	-	✓	✓	✓	-
3rd order poly in dist and lat	-	✓	✓	-	-	✓	✓	-
Agricultural Similarity	-	-	✓	-	-	-	✓	-
Origin x State FE	-	-	-	✓	-	-	-	✓
Observations	612495	612495	459150	612300	612495	612495	459150	612300

Note. This table presents coefficient estimates from IV regressions of Equation (3.1), where Panel A measures firms' US county location using trade-engaging manufacturing establishments and Panel B measures location using trade-engaging non-manufacturing establishments. Columns (1)-(4) in Panel A and columns (9)-(12) in Panel B use specification in columns (1)-(4) in Table 3; columns (5)-(8) in Panel A and columns (13)-(16) in Panel B use specifications in columns (5)-(8) in Table 3.

5.1 Barriers in International Firm-to-Firm Relationships

It is well documented in the literature that international transactions, including global supply chain relationships, are riskier than domestic transactions. For instance, international transactions usually involve greater geographical distances than domestic transactions, which require more working capital for firms engaged in international transactions due to longer transportation times. Moreover, language

barriers, and information and contractual frictions are more severe than domestic transactions. Thus, firms need to put extra effort to understand differences in institutional contexts across countries in international transactions. In these frictional environments, Rauch (2001) noted that co-ethnic networks that operate across national borders may help mitigate these kinds of barriers.[29]

Among many types of international transactions, a firm-to-firm supply chain relationship has unique features that distinguish itself from within-firm transactions such as foreign direct investment (FDI) — the subject of the study in Burchardi et al. (2019). While the global supply chain network is characterized by an arm's-length firm-to-firm relationship, the FDI is conducted within the firm boundary. That is to say, the boundaries of a firm are defined in a different manner (Coase, 1937; Grossman and Hart, 1986; Hart and Moore, 1990). It has been well documented that the friction of incomplete contracts can be more severe in an arm's-length relationship than in integrated companies (Williamson, 1975, 1985; Antras and Helpman, 2004). Furthermore, financial or credit constraints may hamper firms' participation in global supply chain networks (Kim and Shin, 2012; Carluccio and Fally, 2012; Basco, 2013; Choi, 2020), which can be internalized in the case of FDI. Despite the important differences, as Antras (2005) noted, usual FDI data may not capture firm-to-firm global supply chains.

5.2 Co-ethnic Networks, Trust, and Credit Constraints in Global Supply Chains

Due to an arm's length transactions in global supply chains, international firm-to-firm relationships rely heavily on informal finance such as trade credit in order to fill a mismatch between payment and delivery in international transactions.[30] The mismatch can arise in global supply chain relationships because a supplier (i) can require the customer to pay for goods before they are loaded for shipment or (ii) can allow the customer to pay at some time after the goods have arrived at their destination (Antras and Foley, 2015). While domestic transactions also involve financial claims between firms through trade credit, cross-border financial claims are associated with more risks owing to longer transportation times and different institutional contexts across countries.[31]

An important feature of informal finance, such as trade credit, is that social trust plays a major role in granting and receiving trade credit,[32] especially when there are no formal contractual

[29] Please refer to Rauch (2001) for a comprehensive review on the informal trade barriers and the role of business and social networks in international trade.

[30] Trade credit is non-financial firm-to-firm borrowing and lending such that credits are extended bilaterally between firms in transactions. Ahn (2021) reviewed the related literature and summarized major payment methods in international transactions. Among the major payment methods, trade credit accounts for 65 to 96 percent of international transactions: (i) 65% in IMF-BAFT Survey from Asmundson et al. (2011); (ii) 94% in U.S.-based food exporter from Antras and Foley (2015); (iii) 85% in Turkey from Turkcan (2016); (iv) 96% in Colombia and 90% in Chile from Ahn (2015).

[31] It is also worth reiterating that cross-border financial claims can arise in firm-to-firm relationships (i.e., global supply chain relationships). On the other hand, foreign direct investment (FDI) is conducted within the same entity. Thus, the issue of credit constraints would be less concern in the case of FDI.

[32] Fukuyama (1996) described social trust as *"the expectation that arises within a community of regular, honest,*

enforcement mechanisms in place (Fafchamps, 2000; Karlan, 2005; Wu et al., 2014; Levine et al., 2018).[33] The mismatch between payment and delivery is key to understanding the link between social trust and trade credit relationship. The mismatch in trade credit relationships gives rise to an implicit financing contract such that one party promises to pay later. This implicit financing contract naturally involves default risks because there are typically no collateral or guarantees from formal financial institutions. Social trust thus plays an important role in facilitating trade credit.[34] Furthermore, unlike in domestic relationships, in global supply chain relationships, social trust could be more important when a firm interacts with other firms in countries with poorly functioning institutions (e.g., poor enforcement of contracts).

Karlan et al. (2009) argue that network connections between individuals can be used as social collateral (or network-based trust) to secure informal borrowing. We argue that one such social network that enables each involved party to build trust is a co-ethnic network. One reason co-ethnic networks facilitate trust might be that they communicate more effectively within co-ethnic societies. For instance, Ederer and Schneider (2022) show that communication raises trust in their laboratory and online trust experiment. Therefore, co-ethnic networks may facilitate trade credit provision by enhancing trust in trade credit relationships (Fafchamps, 2000).[35]

To summarize, international firm-to-firm transactions rely heavily on trade credit — which is riskier than a domestic transaction due to longer times and the potential absence of formal contract enforcement procedures. Social networks (such as co-ethnic networks) can enhance trust that serves as social collateral to grease the wheels of granting and receiving trade credit in global supply chain relationships.

5.2.1 Testable Hypothesis

Therefore, we would expect to observe that the positive impact is stronger for US counties in which more credit-constrained firms are located. If so, the presence of co-ethnic networks can serve as social collateral to overcome the credit constraints of customer- and supplier-firms in global supply chain

cooperative behavior, based on commonly shared norms, on the part of other members of that community."

[33]Trust may also facilitate the bilateral financial infrastructure itself so that firms can get cheaper trade credit. Taylor and Wilson (2011) find that countries that trade more tend to have larger financial transactions, and argue that one of the potential explanations is that bilateral financial infrastructure may lead to cheaper trade credit.

[34]In a related manner, Guiso et al. (2004) noted that *"Since financial contracts are the ultimate trust-intensive contracts, social capital should have major effects on the development of financial markets. Financing is nothing but an exchange of a sum of money today for a promise to return more money in the future. Whether such an exchange can take place depends not only on the legal enforceability of contracts but also on the extent to which the financier trusts the financee."*

[35]In various contexts, the literature documents that co-ethnicity matters for the formation of business relationships such as those between founders and venture capitalists (Bengtsson and Hsu, 2015), between inventors and foreign country with which the inventors' firm builds a multinational affiliate or engages in business cooperation (Foley and Kerr, 2013; Xie et al., 2022), and between Indian hirers and workers on an online outsourcing platform (Ghani et al., 2014).

relationships. To test our hypothesis, we set up the following empirical specification:

$$Y_{o,d} = \delta_o + \delta_d + \beta A_{o,d}^{2010} + \gamma A_{o,d}^{2010} \times CC_d + X'_{o,d}\eta + \varepsilon_{o,d} \tag{5.1}$$

where CC_d denotes destination-level credit constraints, which measures the average credit constraint of establishments located in destination county d.[36] A higher value of CC, i.e., credit constraint, indicates *worse* trade credit solvency. To be more specific, CC is measured by (100-PayDex) so that higher CC indicates lower PayDex scores, and thus, higher credit constraints. For the measures of PayDex, we use PayDexMax and PayDexMin, which stand for yearly maximum and minimum PayDex scores, respectively.[37] To facilitate the interpretation of coefficients, we standardize CC so that the sample mean equals zero and the sample standard deviation equals one.

5.2.2 Validating the Hypothesis: Co-ethnic Networks Serve as Social Collateral

Table 7 confirms the hypothesis. The interaction term in the second row is the main focus of the empirical analysis. All coefficients are positive and statistically significant, meaning that when the credit constraints are more serious, the positive impact of ancestry on foreign supply chain relationships becomes stronger. The result is consistent with our hypothesis that co-ancestral connections help mitigate credit constraints in global supply chain relationships. In Table B.9 of Appendix B, we use the external financial dependence indicator by Rajan and Zingales (1998) as an alternative variable to capture the destination-level credit constraints (i.e., CC_d). The coefficients of the interaction term in the second row are all positive and statistically significant, which means that when a county's industries are more dependent on external finance, the positive impact of co-ethnic networks on global supply chain networks becomes more pronounced, which corroborates the main result in Table 7.

We employ a battery of robustness checks to strengthen the hypothesis. In Tables B.10 and B.11 of Appendix B, we further show that the results hold robustly under various subsamples splitted based on the quartiles of county-level characteristics, such as a county's average establishment size and final goods sector share, to control for the role of these other characteristics. In Table B.12 of Appendix B, we allow for a firm dimension. That is, we perform analysis at the firm-origin-destination

[36] CC_d is obtained by calculating a weighted average of establishment-level credit constraint measures, averaged across establishments within each destination. We use establishments' employment as the weights of each establishment.

[37] We use business PayDex score information in NETS, which is originally derived from D&B. PayDex information from NETS is particularly well-suited to test our hypothesis since it is directly based on actual trade credit performances at the establishment level. PayDex score for a business plays a similar role as FICO Score for an individual. Suppliers of goods and services around the world report to D&B their trade credit experiences with each business, and D&B — from which NETS data is derived from — constructs PayDex score based on this information. Since D&B is one of the largest credit rating companies in the world, it has a strong incentive to construct accurate credit ratings, and suppliers around the world use the PayDex score of their potential trading partners to decide whether to extend trade credit to them. For this reason, PayDex information in NETS data has been fruitfully used in the context where trade credit solvency may matter (e.g., Akey and Appel, 2021; Borisov et al., 2021).

Table 7: Heterogeneous Treatment Effect: Credit Constraints

	100-PayDexMax		100-PayDexMin	
	I(N.Supp>0)	I(N.Cust>0)	I(N.Supp>0)	I(N.Cust>0)
	(1)	(2)	(3)	(4)
Log Ancestry 2010	0.054	0.084**	0.065*	0.098***
	(0.039)	(0.042)	(0.039)	(0.037)
Log Ancestry 2010 x CC	0.186***	0.131**	0.158***	0.099**
	(0.056)	(0.060)	(0.050)	(0.044)
First-stage F stat	567.7	567.7	468.9	468.9
Destination FE	✓	✓	✓	✓
Origin FE	✓	✓	✓	✓
Principal Components	✓	✓	✓	✓
Observations	592995	592995	592995	592995

Note. This table presents heterogeneous treatment effect results by including the interaction of Log Ancestry 2010 with credit constraint measures. The regression equation is given by Equation (5.1). Columns (1) and (3) use specifications in panel A in Table 2 and columns (2) and (4) use specifications in panel B in Table 2, where we add interaction of Log Ancestry 2010 and the measure of credit constraints (CC). CC, which is defined at the destination level, measures the average credit constraint of establishments within each destination county. Columns (1)-(2) define CC using 100-PayDexMax; columns (3)-(4) define CC using 100-PayDexMin. All regressions control for FDI dummy as in Table 3. To facilitate the interpretation of coefficients, all credit constraint variables are standardized so that the sample mean equals to zero and the sample standard deviation equals to one.

level.[38] The results are still robust under this firm-level specification, meaning that when a *firm's* credit constraints are more serious in a given county, the positive impact of co-ethnic networks on the *firm's* foreign supply chain relationships becomes stronger.

5.2.3 Solidifying the Mechanism: The Role of Contractual Enforcement

Furthermore, in global supply chain relationships, we would expect to observe that the positive impact is not only stronger for credit-constrained firms in US counties, but this stronger effect would

[38] Specifically, we run the following regression:

$$Y_{f,o,d} = \delta_f + \delta_{o,s} + \delta_{d,s} + \beta A^{2010}_{o,d} + \gamma A^{2010}_{o,d} \times CC_{f,d} + X'_{o,d}\eta + \varepsilon_{f,o,d}$$

$Y_{f,o,d}$ can take I(N.Supp>0), I(N.Cust>0), and I(N.Link>0). I(N.Supp>0) and I(N.Cust>0) are dummy variables that equal one if firm f, who has a trade-engaging establishment in destination county d, has suppliers (customers) headquartered in origin country o. I(N.Link>0) is a linkage dummy that incorporates both supplier and customer linkages as in Table B.2. $CC_{f,d}$ measures firm-destination-level credit constraints, which is obtained by calculating the weighted average of "100-PayDex" across trade-engaging establishments within each firm-destination, weighted by establishments' employment. δ_f indicates firm fixed effects. $\delta_{o,s}$ ($\delta_{d,s}$) indicates origin (destination)-by-sector fixed effects, where sector is defined as a firm's primary SIC 4-digit industry. These fixed effects absorb any firm-specific or origin (destination)-by-sector-specific (un)observed components. The goal of the exercise is to check if higher ancestry composition from origin country o to destination county d increases the probability that firm f — who has a trade-engaging establishment in destination d — has supply chain linkages with origin o between 2011-2014.

be more amplified if US firms interact with firms in foreign countries with weak enforcement of contracts. To test this additional hypothesis, we set up the following empirical specification:

$$\begin{aligned} Y_{o,d} = \delta_o + \delta_d + \beta_1 A_{o,d}^{2010} + \beta_2 A_{o,d}^{2010} \times CC_d + \beta_3 A_{o,d}^{2010} \times CC_d \times JQ_o \\ + \beta_4 A_{o,d}^{2010} \times JQ_o + \beta_5 CC_d \times JQ_o + X'_{o,d}\eta + \varepsilon_{o,d} \end{aligned} \tag{5.2}$$

where JQ_o denotes the origin-level judicial quality, which measures the degree of contractual enforcement at the country o. A higher value of JQ indicates *better* institutional quality.[39]

Table 8 reports the results on the role of judicial quality of origin countries and its interaction with credit constraints in destination US counties. To start with, we reconfirm the key estimation results in Table 7 such that the coefficients of the double-interaction term between the co-ethnic network and the destination-level credit constraint are all positive and statistically significant. Then, turning our attention to the role of contractual enforcement in origin countries, the coefficients of the triple-interaction term in the third row are all negative with statistical significance, which means that the *stronger* effect of co-ethnic networks on global supply chain relationships in more credit-constrained destination counties is *alleviated* if origin countries have better judicial quality. To put it another way, the role of co-ethnic networks in relaxing credit constraints of firms in a destination US county for global supply chain formation becomes even more important if the origin country has weaker institutions (i.e., lower judicial quality). By including an additional dimension of the role of judicial quality, the results reinforce the credit constraint mechanism that we hypothesized. Furthermore, the results are consistent with Antras and Foley (2015), which shows that the establishment of trading relationships between exporters and importers mitigates credit constraints in international transactions, especially for countries with weak enforcement of contracts.

6 Conclusion

This article has advanced our understanding on the formation of global supply chain networks by exploring the role of immigration and its interaction with credit frictions. Our main findings are summarized as follows: (i) co-ethnic networks formed by century-long immigration to the US causally explain the present-day structure of global supply chains; (ii) the positive impact of immigration on global supply chain relationships becomes stronger for US counties with more credit-constrained firms, and that such a stronger effect becomes even more elevated for foreign firms operating in countries with weak contract enforcement.

These findings provide new insights and predictions on the interdependencies between global

[39] More specifically, we use a measure of judicial quality from Nunn (2007). This measure is originally drawn from the "rule of law" from Kaufmann et al. (2004), which is a weighted average of a number of variables that measure individuals' perceptions of the effectiveness and predictability of the judiciary and the enforcement of contracts in each country.

Table 8: Heterogeneous Treatment Effect:
The Role of Judicial Quality Interacting with Credit Constraints

	100-PayDexMax		100-PayDexMin	
	I(N.Supp>0)	I(N.Cust>0)	I(N.Supp>0)	I(N.Cust>0)
	(1)	(2)	(3)	(4)
Log Ancestry 2010	-0.004	0.014	-0.069***	-0.034
	(0.023)	(0.030)	(0.026)	(0.035)
Log Ancestry 2010 x CC	0.285***	0.234***	0.397***	0.311***
	(0.035)	(0.053)	(0.046)	(0.056)
Log Ancestry 2010 x CC x JQ	-0.095***	-0.113***	-0.175***	-0.165***
	(0.025)	(0.037)	(0.030)	(0.038)
Log Ancestry 2010 x JQ	0.057***	0.071***	0.104***	0.103***
	(0.016)	(0.020)	(0.018)	(0.023)
CC x JQ	0.002	0.007**	0.005*	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)
First-stage F stat	22.4	22.4	145.7	145.7
Destination FE	✓	✓	✓	✓
Origin FE	✓	✓	✓	✓
Principal Components	✓	✓	✓	✓
Observations	437904	437904	437904	437904

Note. This table presents heterogeneous treatment effect results by including the interaction of Log Ancestry 2010 with credit constraint measures (destination level) and the measure of judicial quality (origin level). We use the same specifications as in Table 7, where we additionally include the triple interaction of Log Ancestry 2010, credit constraints, and judicial quality (Log Ancestry 2010 x CC x JQ), the interaction of Log Ancestry 2010 and judicial quality (Log Ancestry 2010 x JQ), and interaction of credit constraints and judicial quality (CC x JQ). The measure of credit constraints (CC) is obtained as the average credit constraint of establishments within each destination county, and the measure of judicial quality (JQ), which comes from Nunn (2007), is defined at the origin country level. To facilitate the interpretation of coefficients, credit constraint variables and the measure of judicial quality are standardized so that the sample mean equals zero and the sample standard deviation equals one.

linkages of supply chains, cross-border credit provision, and immigration. First, our findings imply that the Covid-19 pandemic and the Russo-Ukrainian War can reshape the future structure of global supply chain relationships for several decades or even a century since they have altered the pattern of migrations. Whether this prediction holds will be an important avenue for rigorous future work.

Second, the finding that co-ethnic networks mitigate credit-constraint problems in global supply chain networks indicates the tight inter-linkages between trade and finance in global supply chains. Particularly, it implies that credit provision across borders is crucial in fostering global supply chain relationships. Further research is warranted to dissect the interdependencies between global supply chains and finance — especially using global firm-to-firm trade credit provision data when such data

become easily accessible to researchers interested in this topic.

Finally, by combining our work with the existing research on the consequences of supply chain networks, we can predict the far-reaching implications of immigration. For example, global supply chain networks have been shown to lead to cross-country transmission of shocks (e.g., Boehm et al., 2019; Hyun et al., 2020; Carvalho et al., 2021). Combining it with our results, we can hypothesize that immigration from a foreign country will lead to economic shock synchronization with that country. Hence, the nexus between immigration and business cycle co-movement will be another fruitful research topic that deserves special attention.

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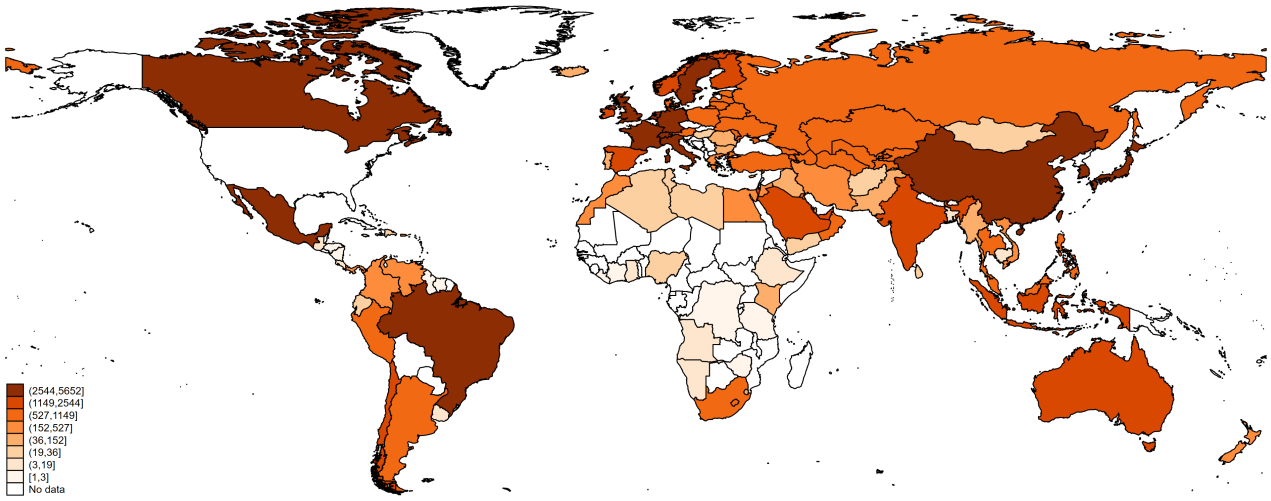
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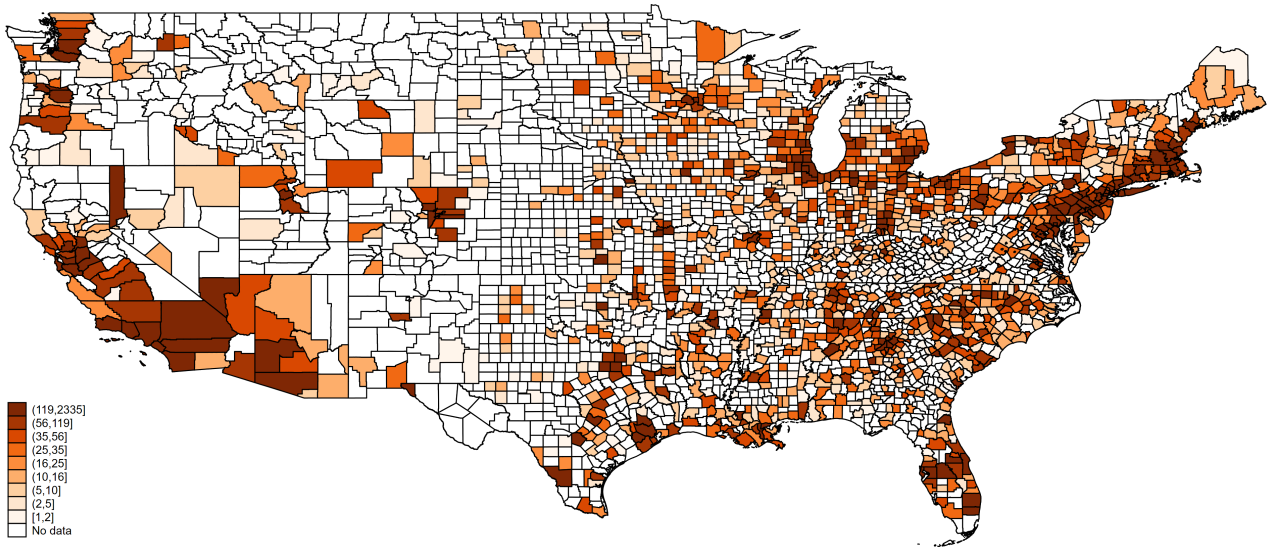
Appendix A Additional Figures

Figure A.1: Global Supply Chain Linkages by Origin Country



Note. The world map shows the origin-country variation in the global supply chain linkages with US firms. A darker red indicates that a country has more connections with US suppliers and/or US customers; the figure shows a significant variation in the total number of global supply chain relationships with the US across foreign countries.

Figure A.2: Global Supply Chain Linkages by Destination County



Note. The US map shows the county variation in the global supply chain linkages within the US. A darker red indicates that a county has more connections with foreign suppliers and/or foreign customers; the figure shows a significant variation in the total number of global supply chain relationships across counties within the US.

Appendix B Additional Tables

Table B.1: The Impact of Ancestry Composition on Global Supply Chain Linkages: OLS Regressions

Panel A	I(N.Supp>0)				
	(1)	(2)	(3)	(4)	(5)
Log Ancestry 2010	0.196***	0.184***	0.183***	0.182***	0.195***
	(0.014)	(0.016)	(0.016)	(0.017)	(0.017)
Log Distance	0.012	0.045	0.022	0.051	-0.008
	(0.015)	(0.034)	(0.040)	(0.051)	(0.051)
Destination FE	✓	-	-	-	-
Origin FE	✓	-	-	-	-
Destination x Continent FE	-	✓	✓	✓	✓
Origin x Census Region FE	-	✓	✓	✓	-
3rd order poly in dist and lat	-	-	✓	✓	-
Agricultural Similarity	-	-	-	✓	-
Origin x State FE	-	-	-	-	✓
Observations	612495	612495	612495	459150	612300
Panel B	I(N.Cust>0)				
	(6)	(7)	(8)	(9)	(10)
Log Ancestry 2010	0.189***	0.173***	0.173***	0.172***	0.184***
	(0.014)	(0.016)	(0.016)	(0.017)	(0.017)
Log Distance	0.014	0.033	0.020	0.038	-0.027
	(0.018)	(0.038)	(0.042)	(0.056)	(0.071)
Destination FE	✓	-	-	-	-
Origin FE	✓	-	-	-	-
Destination x Continent FE	-	✓	✓	✓	✓
Origin x Census Region FE	-	✓	✓	✓	-
3rd order poly in dist and lat	-	-	✓	✓	-
Agricultural Similarity	-	-	-	✓	-
Origin x State FE	-	-	-	-	✓
Observations	612495	612495	612495	459150	612300

Note. This table presents the OLS regression results that correspond to the IV regression results in Table 2. Columns (1)-(5) correspond to columns (1), (3), (5), (6), and (7) in Table 2; columns (6)-(10) correspond to columns (8), (10), (12), (13), and (14) in Table 2.

Table B.2: Using Linkage Dummy

	I(N.Link>0)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log Ancestry 2010	0.228***	0.194***	0.198***	0.193***	0.198***	0.198***	0.203***
	(0.019)	(0.026)	(0.019)	(0.020)	(0.019)	(0.022)	(0.020)
Log Distance	0.017	0.014	0.039	0.038	0.018	0.048	-0.033
	(0.019)	(0.018)	(0.039)	(0.039)	(0.043)	(0.055)	(0.063)
First-stage F stat	11.0	2448.0	162.2	195.4	158.1	102.8	186.2
Destination FE	✓	✓	-	-	-	-	-
Origin FE	✓	✓	-	-	-	-	-
Principal Components	-	✓	✓	✓	✓	✓	✓
Destination x Continent FE	-	-	✓	✓	✓	✓	✓
Origin x Census Region FE	-	-	✓	✓	✓	✓	-
$I^{2010}_{o,-r(d)}(I^{2010}_{-c(o),d}/I^{2010}_{-c(o)})$	-	-	-	✓	-	-	-
3rd order poly in dist and lat	-	-	-	-	✓	✓	-
Agricultural Similarity	-	-	-	-	-	✓	-
Origin x State FE	-	-	-	-	-	-	✓
Observations	612495	612495	612495	612495	612495	459150	612300

Note. This table presents coefficient estimates from IV regressions of Equation (3.1), where we use a union of supplier-firm and customer-firm linkages, I(N.Link>0), as the dependent variable. I(N.Link>0) is formally defined as a dummy variable that equals to one if any firm whose trade-engaging establishments located in destination d has *either* supplier firms *or* customer firms headquartered in origin o. Columns (1)-(7) use specifications in columns (1)-(7) in Table 2, where only the dependent variable is replaced with the linkage dummy.

Table B.3: Intensive Margin: Log Number of Linkages

Panel A	Log N.Supp						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log Ancestry 2010	0.309***	0.213***	0.253***	0.318***	0.254***	0.248***	0.262***
	(0.110)	(0.067)	(0.074)	(0.062)	(0.074)	(0.091)	(0.075)
First-stage F stat	10.2	84.3	26.8	26.1	26.3	21.4	22.7
Destination FE	✓	✓	-	-	-	-	-
Origin FE	✓	✓	-	-	-	-	-
Principal Components	-	✓	✓	✓	✓	✓	✓
Destination x Continent FE	-	-	✓	✓	✓	✓	✓
Origin x Census Region FE	-	-	✓	✓	✓	✓	-
$I^{2010}_{o,-r(d)}(I^{2010}_{-c(o),d}/I^{2010}_{-c(o)})$	-	-	-	✓	-	-	-
3rd order poly in dist and lat	-	-	-	-	✓	✓	-
Agricultural Similarity	-	-	-	-	-	✓	-
Origin x State FE	-	-	-	-	-	-	✓
Observations	20385	20385	20385	20385	20385	18949	20340
Panel B	Log N.Cust						
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Log Ancestry 2010	0.341***	0.204***	0.255***	0.279***	0.254***	0.279***	0.265***
	(0.094)	(0.054)	(0.069)	(0.055)	(0.068)	(0.085)	(0.072)
First-stage F stat	14.9	67.7	16.2	31.3	17.0	21.5	18.4
Destination FE	✓	✓	-	-	-	-	-
Origin FE	✓	✓	-	-	-	-	-
Principal Components	-	✓	✓	✓	✓	✓	✓
Destination x Continent FE	-	-	✓	✓	✓	✓	✓
Origin x Census Region FE	-	-	✓	✓	✓	✓	-
$I^{2010}_{o,-r(d)}(I^{2010}_{-c(o),d}/I^{2010}_{-c(o)})$	-	-	-	✓	-	-	-
3rd order poly in dist and lat	-	-	-	-	✓	✓	-
Agricultural Similarity	-	-	-	-	-	✓	-
Origin x State FE	-	-	-	-	-	-	✓
Observations	22968	22968	22968	22968	22968	20551	22931

Note. This table presents coefficient estimates from IV regressions of Equation (3.1), where we consider the intensive margin of global supply chain linkages as dependent variables. Specifically, we use log of the number of supplier linkages (Log N.Supp) and customer linkages (Log N.Cust), respectively, as dependent variables. Columns (1)-(7) use specifications in columns (1)-(7) in Table 2, where only the dependent variable is replaced with Log N.Supp; columns (8)-(14) use specifications in columns (8)-(14) in Table 2, where only the dependent variable is replaced with Log N.Cust.

Table B.4: Strictly Restricting US Firms to Those Who Have Headquarters Located in the US

	I(N.Supp>0)				I(N.Cust>0)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Ancestry 2010	0.175***	0.175***	0.187***	0.187***	0.159***	0.160***	0.164***	0.166***
	(0.019)	(0.019)	(0.022)	(0.020)	(0.018)	(0.018)	(0.022)	(0.020)
First-stage F stat	69.4	69.2	56.2	77.4	69.4	69.2	56.2	77.4
Principal Components	✓	✓	✓	✓	✓	✓	✓	✓
Destination x Continent FE	✓	✓	✓	✓	✓	✓	✓	✓
Origin x Census Region FE	✓	✓	✓	-	✓	✓	✓	-
3rd order poly in dist and lat	-	✓	✓	-	-	✓	✓	-
Agricultural Similarity	-	-	✓	-	-	-	✓	-
Origin x State FE	-	-	-	✓	-	-	-	✓
Observations	612495	612495	459150	612300	612495	612495	459150	612300

Note. This table presents coefficient estimates from IV regressions of Equation (3.1), where we strictly restrict US firms to those who have headquarters located in the US. Therefore, in this exercise, global supply chain linkages capture relationship between foreign firms whose headquarters are located outside the US and US firms whose headquarters are located in the US. This exercise strictly rules out any potential supplier-customer linkages that might capture within-multinational relationships between headquarters and their subsidiaries. Columns (1)-(4) use specification in columns (1)-(4) in Table 3; columns (5)-(8) use specifications in columns (5)-(8) in Table 3.

Table B.5: Restricting Establishments:
(i) Single-establishment Firms, (ii) Headquarter Establishments

Panel A	Single-establishment Firms							
	I(N.Supp>0)				I(N.Cust>0)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Ancestry 2010	0.091***	0.091***	0.099***	0.100***	0.104***	0.104***	0.109***	0.111***
	(0.022)	(0.022)	(0.024)	(0.022)	(0.020)	(0.020)	(0.022)	(0.020)
First-stage F stat	69.4	69.2	56.2	77.4	69.4	69.2	56.2	77.4
Principal Components	✓	✓	✓	✓	✓	✓	✓	✓
Destination x Continent FE	✓	✓	✓	✓	✓	✓	✓	✓
Origin x Census Region FE	✓	✓	✓	-	✓	✓	✓	-
3rd order poly in dist and lat	-	✓	✓	-	-	✓	✓	-
Agricultural Similarity	-	-	✓	-	-	-	✓	-
Origin x State FE	-	-	-	✓	-	-	-	✓
Observations	612495	612495	459150	612300	612495	612495	459150	612300
Panel B	Headquarter Establishments							
	I(N.Supp>0)				I(N.Cust>0)			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Log Ancestry 2010	0.136***	0.136***	0.143***	0.148***	0.146***	0.146***	0.155***	0.159***
	(0.026)	(0.026)	(0.028)	(0.027)	(0.022)	(0.022)	(0.026)	(0.024)
First-stage F stat	69.4	69.2	56.2	77.4	69.4	69.2	56.2	77.4
Principal Components	✓	✓	✓	✓	✓	✓	✓	✓
Destination x Continent FE	✓	✓	✓	✓	✓	✓	✓	✓
Origin x Census Region FE	✓	✓	✓	-	✓	✓	✓	-
3rd order poly in dist and lat	-	✓	✓	-	-	✓	✓	-
Agricultural Similarity	-	-	✓	-	-	-	✓	-
Origin x State FE	-	-	-	✓	-	-	-	✓
Observations	612495	612495	459150	612300	612495	612495	459150	612300

Note. This table presents coefficient estimates from IV regressions of Equation (3.1), where Panel A measures firms' US county location only using (trade-engaging) single-establishment firms and Panel B measures location using (trade-engaging) headquarter establishments. Columns (1)-(4) in Panel A and columns (9)-(12) in Panel B use specification in columns (1)-(4) in Table 3; columns (5)-(8) in Panel A and columns (13)-(16) in Panel B use specifications in columns (5)-(8) in Table 3.

Table B.6: Using Ancestry Compositions Prior to 2010

	I(N.Supp>0)	I(N.Cust>0)	I(N.Supp>0)	I(N.Cust>0)	I(N.Supp>0)	I(N.Cust>0)
	(1)	(2)	(3)	(4)	(5)	(6)
Log Ancestry 2000	0.223***	0.205***				
	(0.023)	(0.023)				
Log Ancestry 1990			0.238***	0.219***		
			(0.026)	(0.026)		
Log Ancestry 1980					0.261***	0.240***
					(0.032)	(0.032)
First-stage F stat	10.9	10.9	10.7	10.7	12.1	12.1
Destination x Continent FE	✓	✓	✓	✓	✓	✓
Origin x Census Region FE	✓	✓	✓	✓	✓	✓
Observations	612495	612495	612495	612495	612495	612495

Note. This table presents coefficient estimates from IV regressions of Equation (3.1), where we use log of Ancestry in 2000, 1990, and 1980, respectively. Columns (1), (3), (5) and columns (2), (4), (6) use specifications in columns (3) and (10) in Table 2, respectively, except that principal components are excluded. We additionally exclude IVs that are constructed by using waves 1990 and 2000.

Table B.7: Restricting Global Supply Chains to Newly Formed Linkages After 2010

	I(N.Supp>0)				I(N.Cust>0)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Ancestry 2010	0.160***	0.160***	0.168***	0.172***	0.165***	0.165***	0.172***	0.175***
	(0.028)	(0.028)	(0.027)	(0.029)	(0.018)	(0.018)	(0.020)	(0.019)
First-stage F stat	69.4	69.2	56.2	77.4	69.4	69.2	56.2	77.4
Principal Components	✓	✓	✓	✓	✓	✓	✓	✓
Destination x Continent FE	✓	✓	✓	✓	✓	✓	✓	✓
Origin x Census Region FE	✓	✓	✓	-	✓	✓	✓	-
3rd order poly in dist and lat	-	✓	✓	-	-	✓	✓	-
Agricultural Similarity	-	-	✓	-	-	-	✓	-
Origin x State FE	-	-	-	✓	-	-	-	✓
Observations	612495	612495	459150	612300	612495	612495	459150	612300

Note. This table presents coefficient estimates from IV regressions of Equation (3.1), where we measure linkages based on global supply chain connections that did not exist in 2010 but were newly formed between 2011-2014. Columns (1)-(4) use specification in columns (1)-(4) in Table 3; columns (5)-(8) use specifications in columns (5)-(8) in Table 3.

Table B.8: The Impact of Ancestry Composition on Competitor Relationships

	I(N.Link>0)			
	(1)	(2)	(3)	(4)
Log Ancestry 2010	0.028	0.028	0.027	0.030
	(0.017)	(0.017)	(0.019)	(0.018)
First-stage F stat	69.4	69.2	56.2	77.4
Principal Components	✓	✓	✓	✓
Destination x Continent FE	✓	✓	✓	✓
Origin x Census Region FE	✓	✓	✓	-
3rd order poly in dist and lat	-	✓	✓	-
Agricultural Similarity	-	-	✓	-
Origin x State FE	-	-	-	✓
Observations	612495	612495	459150	612300

Note. This table presents coefficient estimates from IV regressions of Equation (3.1), where we use a linkage dummy based on competitor relationships as a dependent variable. Columns (1)-(4) use specifications in columns (1)-(4) in Table 3, where only the dependent variable is replaced with the linkage dummy based on competitor relationships.

Table B.9: Heterogeneous Treatment Effect:
The External Finance Dependence Indicator (Rajan and Zingales, 1998)

	External Finance Dependence	
	I(N.Supp>0)	I(N.Cust>0)
	(1)	(2)
Log Ancestry 2010	0.038	0.058**
	(0.027)	(0.025)
Log Ancestry 2010 x CC	0.206***	0.175***
	(0.043)	(0.043)
First-stage F stat	485.3	485.3
Destination FE	✓	✓
Origin FE	✓	✓
Principal Components	✓	✓
Observations	498615	498615

Note. This table repeats the exercise in Table 7, where we use an alternative measure of credit constraints: the external finance dependence indicator from Rajan and Zingales (1998). To facilitate the interpretation of coefficients, the credit constraint variable is standardized so that the sample mean equals to zero and the sample standard deviation equals to one.

Table B.10: Heterogeneous Treatment Effect: Credit Constraints - Split-sample based on County's Average Establishment Size

Split-Sample: County's Avg. Establishment Size				
	100-PayDexMax		100-PayDexMin	
	I(N.Supp>0)	I(N.Cust>0)	I(N.Supp>0)	I(N.Cust>0)
	(1)	(2)	(3)	(4)
1st Quartile				
Log Ancestry 2010 x CC	-0.020	0.075	0.042***	0.107**
	(0.018)	(0.056)	(0.012)	(0.046)
First-stage F stat	140.0	140.0	306.0	306.0
Observations	148395	148395	148395	148395
2nd Quartile				
Log Ancestry 2010 x CC	0.276***	0.034	0.260***	0.114**
	(0.059)	(0.030)	(0.048)	(0.045)
First-stage F stat	145.5	145.5	90.6	90.6
Observations	148200	148200	148200	148200
3rd Quartile				
Log Ancestry 2010 x CC	0.144***	0.197***	0.114***	0.142***
	(0.044)	(0.044)	(0.040)	(0.050)
First-stage F stat	86.5	86.5	85.6	85.6
Observations	148200	148200	148200	148200
4th Quartile				
Log Ancestry 2010 x CC	0.115***	0.087	0.129***	0.075
	(0.039)	(0.059)	(0.047)	(0.054)
First-stage F stat	367.9	367.9	368.0	368.0
Observations	148200	148200	148200	148200

Note. This table repeats the heterogeneous treatment effect results in Table 7, where we split the sample into four subsamples based on the quartiles of county-level average establishment size (measured by the number of employees) and run separate regressions for each subsample.

Table B.11: Heterogeneous Treatment Effect: Credit Constraints - Split-sample based on County's Final Goods Sector Share

Split-Sample: County's Avg. Final Goods Sector Share				
	100-PayDexMax		100-PayDexMin	
	I(N.Supp>0)	I(N.Cust>0)	I(N.Supp>0)	I(N.Cust>0)
	(1)	(2)	(3)	(4)
1st Quartile				
Log Ancestry 2010 x CC	0.134**	0.120*	0.199***	0.210*
	(0.052)	(0.066)	(0.071)	(0.112)
First-stage F stat	652.8	652.8	918.4	918.4
Observations	148395	148395	148395	148395
2nd Quartile				
Log Ancestry 2010 x CC	0.131***	0.088**	0.129***	0.089**
	(0.036)	(0.036)	(0.038)	(0.037)
First-stage F stat	479.0	479.0	710.2	710.2
Observations	148200	148200	148200	148200
3rd Quartile				
Log Ancestry 2010 x CC	0.171**	0.118	0.141*	0.082
	(0.083)	(0.085)	(0.078)	(0.075)
First-stage F stat	478.3	478.3	329.6	329.6
Observations	148200	148200	148200	148200
4th Quartile				
Log Ancestry 2010 x CC	0.180***	0.121**	0.173***	0.113**
	(0.038)	(0.050)	(0.041)	(0.045)
First-stage F stat	732.5	732.5	412.0	412.0
Observations	148200	148200	148200	148200

Note. This table repeats the heterogeneous treatment effect results in Table 7, where we split the sample into four subsamples based on the quartiles of county-level average final goods sector share and run separate regressions for each subsample.

Table B.12: Heterogeneous Treatment Effect at the Firm-Origin-Destination-level: Credit Constraints

	100-PayDexMax			100-PayDexMin		
	I(N.Supp>0)	I(N.Cust>0)	I(N.Link>0)	I(N.Supp>0)	I(N.Cust>0)	I(N.Link>0)
	(1)	(2)	(3)	(4)	(5)	(6)
Log Ancestry 2010	-0.007**	0.006**	-0.003	-0.004	0.008***	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Log Ancestry 2010 x CC	0.072***	0.038*	0.088***	0.072***	0.033*	0.091***
	(0.018)	(0.020)	(0.018)	(0.022)	(0.019)	(0.023)
First-stage F stat	145.7	145.7	145.7	124.4	124.4	124.4
Destination x Sector FE	✓	✓	✓	✓	✓	✓
Origin x Sector FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Principal Components	✓	✓	✓	✓	✓	✓
Observations	4699364	4699364	4699364	4699364	4699364	4699364

Note. This table presents results of running regressions at the firm-origin-destination-level. The goal of the exercise is to check if higher ancestry composition from origin country o to destination county d increases the probability that firm f — who has a trade-engaging establishment in destination d — has supply chain linkages with origin o between 2011-2014. The regression specification is $Y_{f,o,d} = \delta_f + \delta_{o,s} + \delta_{d,s} + \beta A^{2010}_{o,d} + \gamma A^{2010}_{o,d} \times CC_{f,d} + X'_{o,d}\gamma + \varepsilon_{f,o,d}$, where $Y_{f,o,d}$ can take I(N.Supp>0), I(N.Cust>0), and I(N.Link>0). I(N.Supp>0) and I(N.Cust>0) are dummy variables that equal one if firm f, who has a trade-engaging establishment in destination county d, has suppliers (customers) headquartered in origin country o. I(N.Link>0) is a linkage dummy that incorporates both supplier and customer linkages as in Table B.2. $CC_{f,d}$ measures firm-destination-level credit constraints, which is obtained by calculating weighted average of "100-PayDex" across trade-engaging establishments within each firm-destination, weighted by establishments' employment. δ_f indicates firm fixed effects. $\delta_{o,s}$ ($\delta_{d,s}$) indicates origin (destination)-by-sector fixed effects, where sector is defined as a firm's primary SIC 4-digit industry. All regressions control for log distance, latitude difference, and origin-destination-level FDI dummy; standard errors are clustered at the origin country-level; * p < 0.10, ** p < 0.05, *** p < 0.01.