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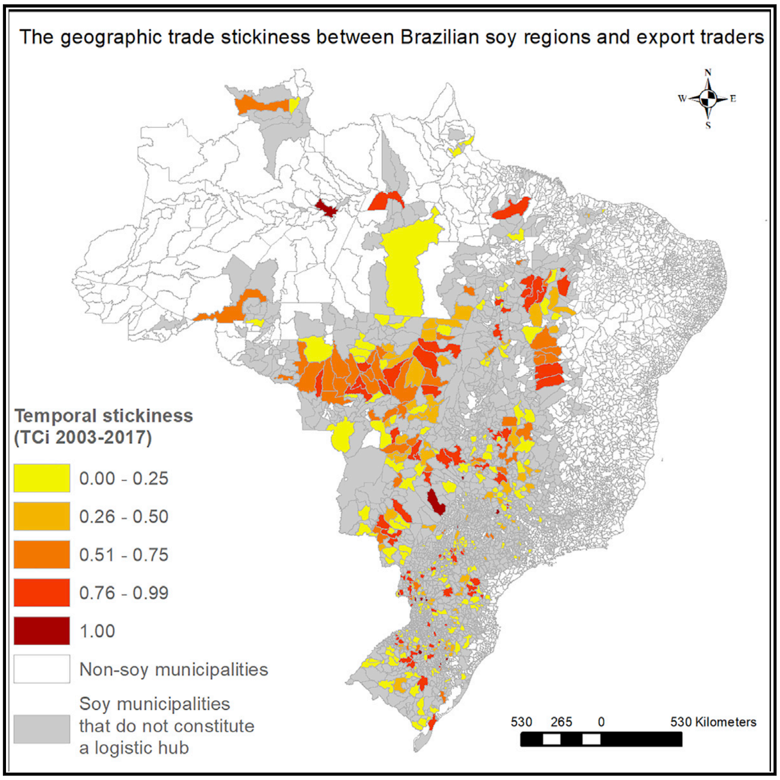
Understanding the Stickiness of Commodity Supply Chains Is Key to Improving Their Sustainability

Graphical Abstract



Highlights

- Stickiness is key for accountability of supply-chain actors
- The soy traders with the largest market share are geographically stickier
- Stickier traders also show higher soy-deforestation risk
- Stickier traders are also signatories of zero-deforestation commitments

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In Brief

Geographic trade stickiness is related to the stability of commercial relationships between companies and regions. Stickiness patterns may influence how companies attain zero-deforestation commitments and how places manifest different development trajectories. This occurs because non-sticky companies may move geographically, not committing to achieving long-term sustainability or contributing to local development pathways. Here, we show how to analyze supply chain stickiness and explain why it is essential to increase sustainability.

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Understanding the Stickiness of Commodity Supply Chains Is Key to Improving Their Sustainability

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SCIENCE FOR SOCIETY Consumption of food in locations far from production is a cause of forest loss, especially in developing countries that lack the resources, capacity, or political will to distinguish legal from illegal deforestation. In response, civil society and consumers have pushed companies to make zero-deforestation commitments. For these commitments to be effective, supply chain transparency is crucial, but stickiness also plays a key role. Stickiness refers to stable and consistent commercial relationships between companies and regions. Stickiness may influence how companies attain zero-deforestation commitments.

For instance, companies with non-sticky sourcing patterns may move geographically, not committing to achieving long-term sustainability. Here, we look at the soy trade in Brazil, the world's largest exporter, to analyze supply chain stickiness and explain why it is essential to curb deforestation. We show that stickiness is associated with deforestation risk.

SUMMARY

Commodity trade is central to the global economy but is also associated with socio-environmental impacts, for example, deforestation, especially in producer countries. It is crucial to understand how geographic sourcing patterns of commodities and commercial relationships between places and actors influence land-use dynamics, socio-economic development, and environmental degradation. Here, we propose a concept and methodological approach to analyze the geographic stickiness of commodity supply chains, which is the maintenance of supply network configurations over time and across perturbations. We showcase policy-relevant metrics for all Brazilian soy exports between 2003 and 2017, using high-resolution supply chain data from www.trase.earth. We find that the Brazilian soy traders with the largest market share exhibit stickier geographic sourcing patterns, and that the supply network configurations between production places and traders become increasingly sticky in subsequent years. Understanding trade stickiness is crucial for supply chain accountability, because it directly affects the effectiveness of zero-deforestation commitments.

INTRODUCTION

Over recent decades, the growth in agricultural trade has promoted economic development and food security but also resulted in negative socio-economic and environmental impacts.[1–4] Trade and consumption of agricultural commodities are critical drivers of land-use change, deforestation, biodiversity loss,[5,6] and carbon emissions.[7,8]

The production of internationally traded and financed commodities, such as soy (see Supplemental Experimental

Procedures, The Soy Supply Chain in Brazil), beef, and palm oil, dominates land use in many agricultural regions. It is responsible for over 27% of recent global forest loss.[6] Supply chain actors, such as food processors, slaughterhouses, traders, and retailers, including countries that purchase these commodities, play a crucial role in shaping land-use dynamics by influencing demand, investments in infrastructure, financing, and government decisions.[9–11]

An increasing number of governance interventions target these supply chain actors, including pushes for zero-deforestation commitments (ZDC). ZDCs aim to zero the deforestation driven by commodity supply chains, such as palm oil, beef, or soy. There are ZDCs signed by individual companies, but also by multi-stakeholder coalitions, including national and subnational governments and non-government organizations (NGOs), where each stakeholder assumes a specific role. For example, companies implement ZDCs, NGOs monitor compliance, and governments provide the tools. Examples of ZDCs can be in the form of sustainability roundtables (e.g., Roundtable on Sustainable Palm Oil), and broader governance fora (e.g., Tropical Forests Alliance).[12]

The Amazon Soy Moratorium (ASM), another ZDC example, was the first voluntary ZDC in the tropics. It was a response from soy traders to pressure from retailers and NGOs, resulting in the agreement to not purchase soy from areas deforested after July 2006 in the Brazilian Amazon. The ASM is reputed to have reduced direct deforestation to soy fields from 30% to 1% of annual soy expansion in the Brazilian Amazon.[13] ZDCs, combined with public policies, are crucial to address deforestation, as commodity supply chains drive about 5 million hectares of forest loss every year.[6]

ZDCs result from consumer demand and NGO pressure,[12,14,15] but also from corporate recognition that sustainability commitments may increase both supply chain control and reputation.[16] The accountability and engagement of supply chain upstream actors are thus critical for these initiatives to be successful and deliver the expected impacts. In agricultural supply chains, for example, implementing ZDCs requires the engagement between food buyers, processors, and farmers.[14,17–19] Understanding the geographic patterns of supply chain relationships can contribute to holding corporations accountable for what happens in the production regions to which they are linked.[14,18,20]

Supply chain transparency is a prerequisite for corporate land use accountability[14] and the monitoring of ZDCs,[18] such as through the accountability framework initiative (https://accountability-framework.org/). Knowledge of how much, how, and why supply chain actors engage with each other and with specific sourcing regions remains limited. Moreover, we need an improved understanding of how and why actors shift sourcing locations over time and how this influences land-use dynamics and socio-environmental outcomes.[12,15,19,21]

Researching the patterns of relationships between actors and regions over time is critical to understand different development trajectories in rural landscapes, as these trajectories are shaped by the responses of supply chain actors to biophysical, policy, logistic, or socio-economic shocks and changes.[12,22,23] Examining the spatial-temporal connections between commodity buyers and sourcing regions can support governance and accountability processes by informing on the potential effectiveness of ZDCs,[12,15] and on indirect and leakage effects where sourcing relationships are displaced in response to policy interventions.[24]

Markets are not entirely integrated and exhibit some stickiness, i.e., some trading relationships persist under changing conditions or show inertia in responding to price and other shocks.[25] This persistence is related to various factors, such as supply chain infrastructures in production regions and traders' local expertise.[26] Agricultural traders that have volatile geographic sourcing patterns likely have weaker connections, credibility, and engagement with farmers, and thus less capacity to transmit the zero-deforestation signal or demand to their suppliers. Volatile traders can move from high to low deforestation risk regions after signing a ZDC, thereby mitigating the direct risks in their supply chains, but failing to improve the overall outcome. Traders with more enduring commercial relationships may have enhanced relevance and impact in their actions. Trade persistence justifies robust accountability frameworks to reduce deforestation in specific supply chains, as it increases the likelihood that these supply chain actions will send a strong and sustained signal to the actors in the production landscapes.[14,16–18,27,28]

Nevertheless, to date, research has mostly focused on country-to-country persistence of trade relations. Current research lacks a clear conceptual model for defining the relationship between production landscapes, commodity traders, and consuming markets, as well as empirical measures of it, mostly because of insufficiently detailed and subnational data on supply chains.

The objectives of this paper are to develop (1) a conceptual framework to analyze the geographic stickiness in global commodity trade, conceived as a measure of the stability and rigidity over time of supply chain configurations, i.e., of the network of trade linkages and flows between specific regions and actors; (2) metrics to operationalize this framework and to measure stickiness empirically; and (3) hypotheses on how stickiness influences the existence and effectiveness of supply chain ZDCs, and, more broadly, the governance of supply chains for socio-environmental sustainability. We focus on agricultural commodities and their relation to land use, but the notion has broader relevance for other supply chains and sustainability issues.

Empirically, we use the first supply chain maps linking subnational producing regions of Brazilian soy to global markets, identifying trading companies, between 2003 and 2017, developed by the Trase initiative (www.trase.earth). In the international trade of Brazilian soy, we measure the trade stickiness between specific production and distribution places, companies engaged in trading, and consumption countries.[29] We apply temporal network analysis to measure the similarity of the export supply chain network over time, i.e., how stable are the commercial relationships.

RESULTS

Conceptualizing Stickiness in Commodity Supply Chains

We bridge theoretical and empirical approaches from three main fields, agricultural and trade economics, global commodity chains (GCCs) and global value chains (GVCs), and social-ecological resilience,[11,15,22,25,30–45,46–65,66–75] to propose a

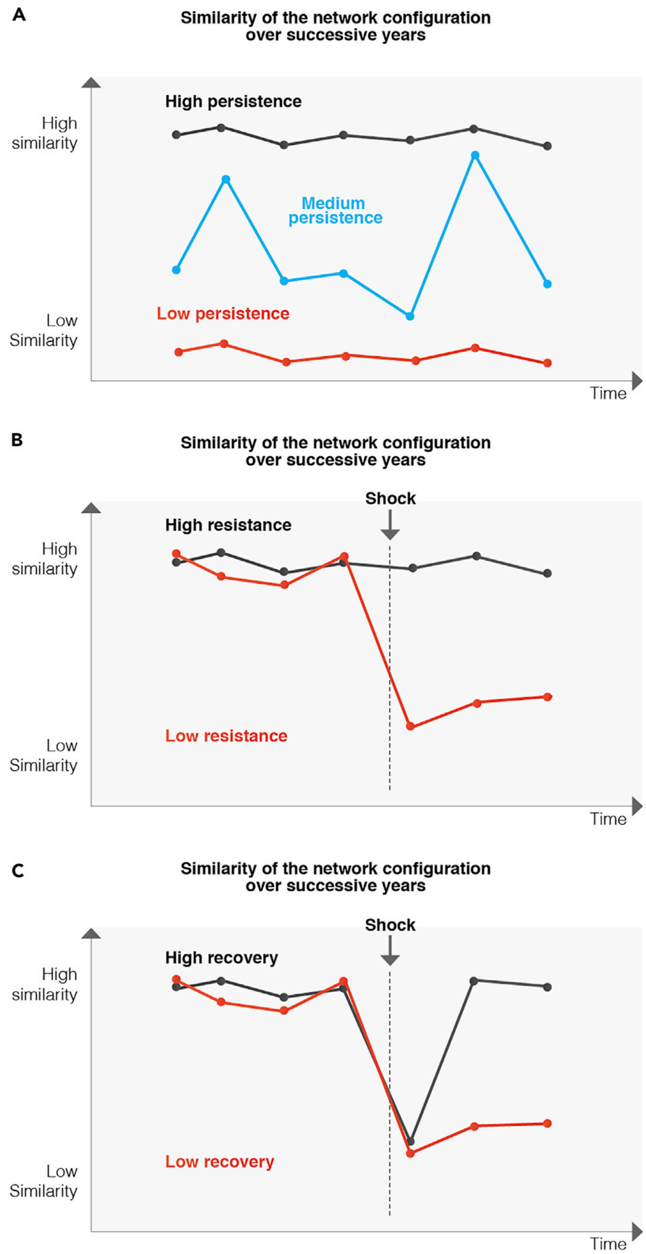

Figure 1. The Three Dimensions of Stickiness

(A) Persistence is the property of supply chains to have trade linkage configurations that remain highly similar over time. Medium persistence may characterize networks that have a medium similarity of trade linkages over time or that oscillate between low and high similarities across pairs of successive years.

(B) Resistance is the property of maintaining linkages unaltered in relation to a given shock.

(C) Recovery corresponds to the reestablishment of stable network configurations after a shock, either with the same previous configuration or the stabilization of a new configuration. The last two dimensions are assessed based on an identified shock.

conceptualization of stickiness in global commodity supply chains (see Designing a Conceptual Framework for Stickiness in Experimental Procedures).

Based on this, we define stickiness in global commodity supply chains as the maintenance and recovery, over time and through shocks, of supply chains' geographic network configurations, i.e., the network of trade linkages and flows between specific places of production and consumption, and specific actors including producers, traders, retailers, and consumers. We distinguish three interlinked dimensions of stickiness: (1) the persistence of supply chain configurations over time, regardless of the identification of any shock, and their (2) resistance to and (3) recovery from shocks (Figure 1). These three dimensions can be used to characterize supply chains as a whole, as well as specific actors and places in a supply chain.

The first dimension, persistence, is directly observable. In contrast, assessing resistance and recovery requires the identification of a shock affecting supply chain relationships and an analysis of their capacity to remain unaffected by it or to return to their previous state. Thus, under an initial observation, "sticky" would correspond to "persistent." A lack of persistence likely reveals a lack of resistance. However, when analyzing the response to specific shocks, it is possible to further qualify the resistance or recovery to these specific shocks.

Persistence measures how much trade relations remain similar over time—e.g., as traders consistently source products from the same regions and sell to the same consumer markets—or not. Persistence describes the patterns observed, absent specific knowledge about factors (shocks, perturbations) that could have affected the supply chain configuration.

Resistance measures the persistence of supply chain configurations under specific shocks or perturbations. Perturbations may affect certain places and supply chain actors. Perturbations result from policy changes, natural phenomena (e.g., severe droughts, excessive rainfall), governance interventions (e.g., new ZDCs), shifts in land-use decision logics (e.g., exhaustion of suitable lands for expansion in a given geographic region), and market events (e.g., significant changes in commodity prices), among others.

Recovery measures how trade relations restore after having been disrupted by shocks in two ways. First, locations and actors that had stable relations can recover the same stable configuration of relations as before. Second, these locations or actors may recover by reconfiguring their network toward another set of persistent relationships, but with a different configuration of relations with different actors and places.

Metrics to Assess Stickiness in Brazil's Soy Exports

We represent the Brazilian soy export supply chain[29] as a temporal network[76,77] (see Experimental Procedures). This temporal network is the aggregate of soy transactions, or commercial relationships, between three levels of supply chain actors (nodes), over 2003–2017. These three levels of actors (n = 2,304) are logistics hubs (LHs; n = 468), exporting traders (n = 1,709), and importing countries (n = 127). LHs are jurisdictions (municipalities) of soy production and trade in Brazil (see Supplemental Experimental Procedures). LHs aggregate the behavior of soy farmers located within the logistic range of these logistics and commercial hubs for soy processing and export. They are regional market places for defining farm-gate soy prices, storage, and freight fees, acting figuratively as soy "drains."

Traders include exporters and importers, who buy soy directly from farmers or indirectly through local small cereals warehouses and cooperatives located in these LHs or neighboring municipalities. These traders export either raw or crushed beans into oil, meal, and cake, which are primary inputs for animal feed, biofuels, or cooking oils, for example. Our dataset comprises only export transactions, raw and crushed, thus excluding soy transactions destined for domestic consumption in Brazil.[29,78] The dataset covers the period 2003–2017, where each year is a snapshot of the network, aggregating all individual soy transactions that occurred over that year between two actors in annual transactions. We thus represent the entire movement of the supply chain over 2003–2017 as a set of 15 slices or snapshots. We then compare these snapshots to calculate the similarity of the supply chain network over time.

The network is directed, i.e., soy only flows in one direction, from LHs to traders, and then from traders to countries. Flows are either outgoing or incoming depending on the actor's position in the supply chain, i.e., while one actor is supplying soy (outgoing flow), the next one is sourcing it (incoming flow). We measure stickiness as the similarity or change in the configuration of trading partners around each actor between two points in time—i.e., two snapshots—employing metrics from temporal network analysis (C_i and TC_i; Equations 1 and 2 in Experimental Procedures). C_i is the topological overlap,[76] which measures how much the configuration of the supply chain network changes from the first snapshot compared with the second. TC_i is the temporal average topological overlap, which is the average of several consecutive C_is over time.

This measurement can be applied to the specific configuration of commercial relations around one specific region or actor (node), or at the overall network level. C_i, our primary stickiness metric, measures the topological overlap—i.e., how much the network configuration around each actor (node) changed between two snapshots. In other words, how much the commercial relationships of this actor changed, for example, from 2003 to 2004 (Equation 1 in Experimental Procedures). TC_i is the temporal average of C_i over a sequence of successive snapshots covering the analyzed period (2003–2017) for each actor or group of actors. C is the temporal correlation coefficient over the entire supply network (Equation 4 in Experimental Procedures), i.e., the aggregation of all individual C_is in varying time windows. A time window is an interval between two snapshots, which can be 1 year, e.g., 2003–2004, 14 years, e.g., 2003–2017, or any interval in between. C measures the stickiness of the overall supply chain network over all possible time windows, i.e., applied to varying time intervals between two snapshots. Equations 1, 2, and 3 (Experimental Procedures) are steps to calculate C.

These indices vary between zero (i.e., a complete reconfiguration of trade relationships between the two snapshots) and one (i.e., full stickiness, all trade relations observed remain identical). Zero includes situations where the supply network has no linkages in one of the observed years. In large and complex networks, such as Brazil's soy export supply chain, we hardly find either one or zero at the whole network level, meaning that at this level, some linkages are always maintained, and new linkages always appear.[76,77,79] However, when looking at specific network configurations around actors, we find zeros or ones.

From a network perspective, we decompose trade relations in commodity supply chains in "linkages" and "flows," corresponding to the presence of a commercial relationship between two partners, and the volume of commodities exchanged between them, respectively, over discrete periods. These two approaches provide complementary information, allowing analysis of changes in the presence and intensity of trade relations and verification of whether a linkage reconfiguration is related to an increase or decrease in specific flows.

For example, an LH may trade slightly varying soy volumes every year with the same set of exporters. The stickiness measured on linkages will be 1 over these years, while indices on flows will be slightly below 1, as the changes in volume imply that some linkages are trading more or less soy than the year before, thus changing the flow configuration. Note that these stickiness metrics measure the absolute magnitude of changes in network configuration, notwithstanding their direction (appearance or disappearance of linkages, increases, or decreases in flows). Although this information is partly independent, changes in linkages and flows are strongly correlated (Figure S1). For clarity, the main text presents only results on linkages. We replicate all analyses in flows in the Supplemental Information.

These indices are scaled from 0 to 1 and are independent of the size of the network, making it possible to compare indices within groups, e.g., among traders. Although the different types of supply chain relationships have a distinct nature and correspond to groups of actors with a distinct agency, the scaling of the indices also makes it possible to compare the values observed across groups, e.g., comparing traders with LHs. Here, we explore the six types of supply chain relationships present in our Brazil's soy export data: (A) logistics hubs (LHs) supplying traders, (B) LHs supplying countries, (C) traders sourcing from LHs, (D) traders supplying countries, (E) countries sourcing from traders, and (F) countries sourcing from LHs (Figure 2). Yet, we focus our discussion on traders in their sourcing relationships with LHs and supplying relationships with countries. Other datasets might include other types of supply chain relationships, such as retailers selling to consumers or farmers buying fertilizers from input suppliers.

The Stickiness of Brazil's Soy Export Supply Chain

Observing the first dimension of the stickiness (i.e., persistence) of different sets of actors in the Brazilian soy export supply chain reveals that traders overall have relatively low stickiness. LHs and import countries have somewhat moderate stickiness levels. However, each group is heterogeneous (Figure 3). The soy supply chain is highly concentrated, with 31 traders (of 1,709 in total) accounting for 82% of the total soy traded. Traders with the largest market shares have higher average stickiness (Figure 3, t test, $p = 9.107 \times 10^{-13}$). A large group of small traders (1,678 companies) is comparatively non-sticky and represents 18% of the total soy exported. A few LHs ($n = 35$) were the source of 62% of the total exported soy volume, while the 29 largest consuming countries imported 97% of total soy in the analyzed period. Both groups have higher average stickiness than the average LHs (t test, $p < 2.2 \times 10^{-16}$) and countries (t test, $p = 2.208 \times 10^{-14}$) analyzed here (Figure 3).

We correlated the temporal average stickiness (TC_i) with soy-deforestation risk from Trase.[18,29] "Soy deforestation risk (hectares) is the soy deforestation allocated to the actors along the supply chain in proportion to the volume of soy that they export

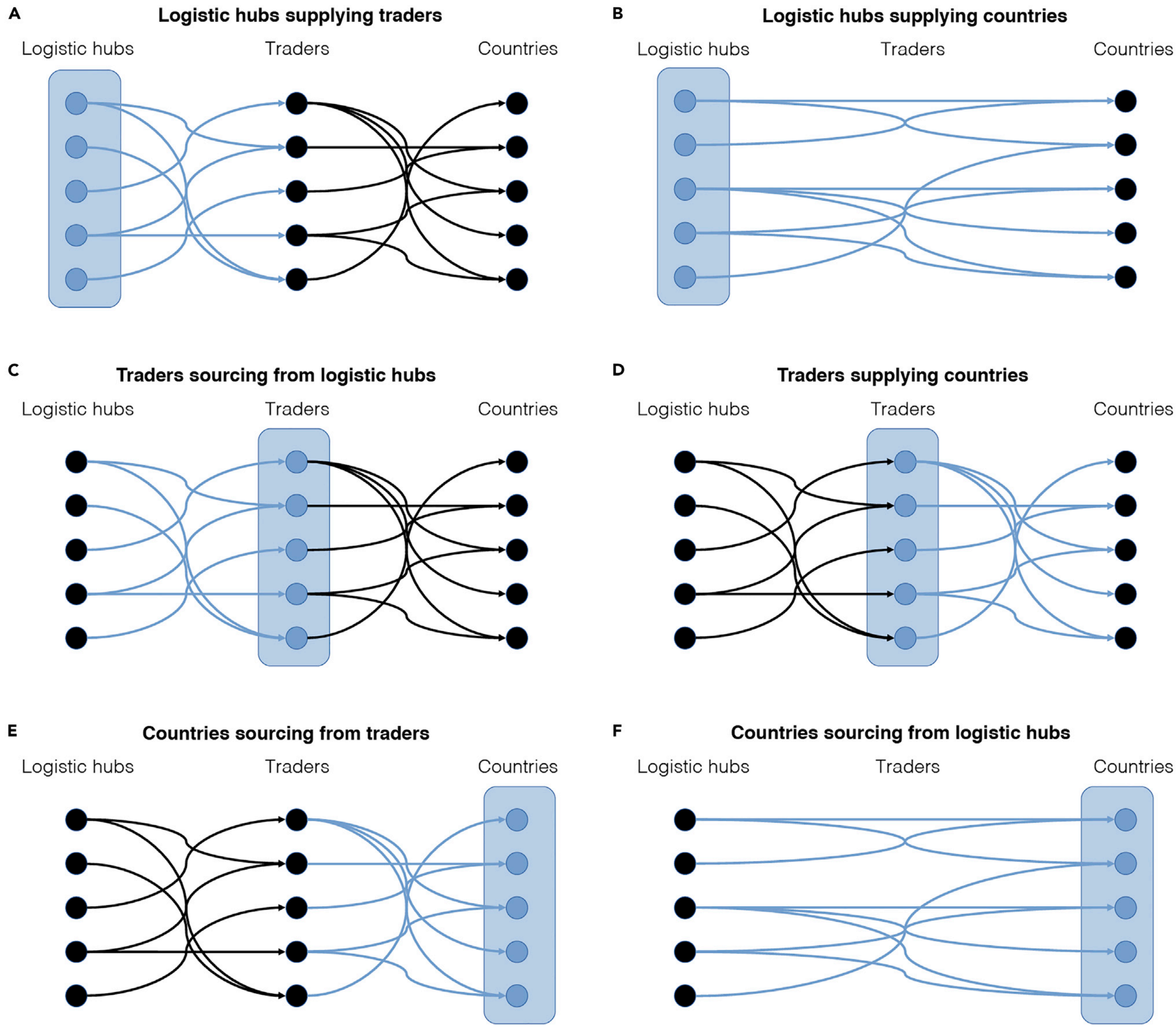

Figure 2. The Six Types of Brazil's Soy Supply Chain Relationships

The measurement of stickiness focuses on the set of linkages and the changes in their configurations around each actor in the network. The blue color denotes the focal group of actors (i.e., the nodes from whose perspective the analysis is being done). The blue arrows denote the linkages of the supply chain being analyzed. (A) Logistics hubs (LHs) supplying traders; (B) LHs supplying countries; (C) traders sourcing from LHs; (D) traders supplying countries; (E) countries sourcing from traders; and (F) countries sourcing from LHs.

from a given jurisdiction, relative to the total production of soy (by all producers) in the same jurisdiction. Deforestation risk for a given year of export is based on deforestation that occurred in the previous five years, during which time the soy that is being exported was planted and harvested."[78]

When observing the network of traders sourcing from LHs and supplying countries (Figures 2A and 2B), we found that stickier traders also exhibit higher soy-deforestation risk ($r = 0.22$ and 0.27; t test, $p < 1.98 \times 10^{-9}$ and $p < 1.51 \times 10^{-14}$, respectively). This correlation suggests that traders who have been stably sourcing from a set of LHs or supplying to a stable set of countries also present higher soy-deforestation risks. Moreover, the stickiness measurements on these two types of supply chain relationships, i.e., traders sourcing from LH (Figure 2C) and supplying countries (Figure 2D), are also strongly correlated ($r = 0.95$ and $p < 0.001$), indicating that traders who have stable relationships with their suppliers also have stable relationships with their customers. This association suggests a high potential for signal transmission from consumers to producers in the supply chain, including a signal demanding to reduce deforestation.

Testing the difference in the temporal average stickiness (TC_i) between ZDC signatory and non-signatory traders,[18] we found that ZDC traders are significantly stickier than non-ZDC, both when measuring their stickiness in sourcing from LHs (Figure 2C; t test, $p = 1.042 \times 10^{-8}$) and in supplying countries (Figure 2D; t test, $p = 1.765 \times 10^{-8}$).

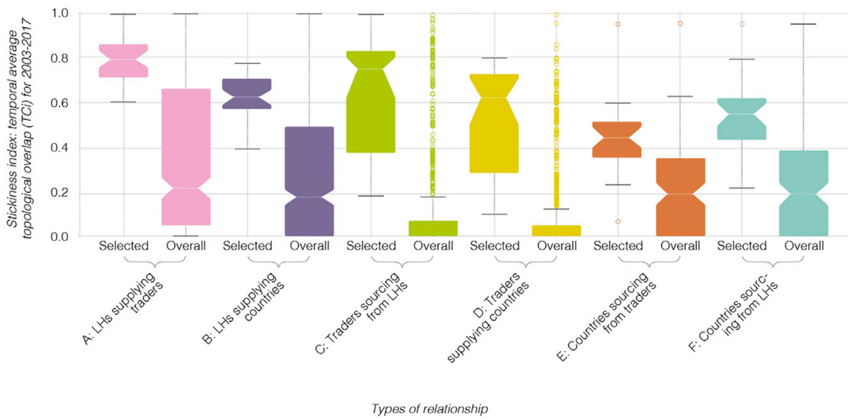

Figure 3. Overall Distribution of the First Dimension of Stickiness (Persistence)

Measured on the configuration of commercial linkages (TC*i*, Equation 2 in Experimental Procedures). Over the whole dataset ("Overall"), traders are the least sticky group in the Brazilian soy supply chain. "Selected" includes only logistics hubs and traders that commercialized at least 1% of the total soy volume in any year after 2008 and countries that imported at least 0.5% of the total soy volume in the same period. These selected traders, logistics hubs, and countries are stickier overall. (See the equivalent on flows in Figure S2). The bars in the boxplots represent quartiles. The horizontal bar inside the colored range indicates the median. The upper and lower ranges indicate the 25% and 75% quartiles, respectively. The upper and lower black lines indicate the max and min values.

A temporal profile of stickiness between consecutive snapshots also confirms that traders and LHs with large market shares (Figures 4B1 and 4B2) are stickier than their respective overall groups (Figures 4A1 and 4A2).

For most types of supply chain relationships, especially the linkages between LHs and traders (Figures 2A and 2C), the inter-annual stickiness increases over time. When comparing the 2003 snapshot directly with 2017, all relationships become less sticky (Figures 4A1, 4A2, 4B1, and 4B2). Thus, even if supply chain configurations appear relatively stable year to year, small step-by-step reconfigurations over short time intervals lead to major overall changes in the long term.

This difference in the measured time frame may reflect various processes, including expansion into new frontiers, and newcomers. Calculating the temporal correlation coefficient (C; Equations 1, 2, 3, and 4 in Experimental Procedures) shows that, when observing the mean value of stickiness for all possible time windows, the overall stickiness of the entire supply chain network decreases the longer the time window is (Figure 5). For example, the stickiness will be higher when comparing the supply network over two consecutive years, such as 2003 versus 2004, in contrast with comparing more temporally distant configurations, such as 2003 versus 2017.

The geographic analysis of the stickiness of LHs in their supplying relationships with traders shows that certain LHs have been supplying soy to exactly ($TCi = 1$, $n = 13$) or mostly the same ($0.76 \leq TCi \leq 0.99$, $n = 75$) set of traders over time (Figure 6). Showing the various levels of engagement between regions of production and distribution and soy traders reveals the potential land use accountability of traders operating in these places. Some LHs in two important agricultural frontiers in Brazil—Northern Mato Grosso and the "Matopiba" (Maranhão, Tocantins, Piauí, and Bahia) frontier in the Cerrado—present high stickiness with traders, suggesting that impacts of soy production and trade can be consistently associated with these specific traders in those regions.

Stickiness Dimensions in Brazil's Soy Exports

Here, we illustrate how the three dimensions of stickiness (persistence, resistance, and recovery) manifest in relation to shocks and other factors using exemplary cases in traders (Figure 7). We use the stickiness of soy linkages (C*i*), the temporal average stickiness (TC*i*), and the stickiness measured on the longest time window (the supply network configuration for 2003 compared with 2017) (see Experimental Procedures). Formally, attributing a causal relation to specific factors requires further analyses beyond the scope of this paper.

Bunge, the single largest soy trader in Brazil, had a persistent configuration of soy linkages from LHs (Figure 7). In contrast with Santa Rosa Agroindustrial and Agrenco, Bunge also appears to have had a more resistant configuration to the various shocks that occurred during 2008–2010, including the global financial crisis and the Amazon Soy Moratorium (ASM), which all three companies signed in 2006. Santa Rosa Agroindustrial had a persistent pattern until 2008, and then experienced a profound reconfiguration of its sourcing linkages, with a period of high instability between 2008 and 2010, and then recovered a sticky pattern from 2011 onward. Despite the collapse of Santa Rosa's linkages configuration in 2008–2010, the configuration of the first snapshot (2003) and the last (2017) were quite similar (index, ~0.62) (Figure 7A2). This long-term similarity indicates that after having been disrupted for several years, Santa Rosa Agroindustrial recovered a similar network of sourcing LHs to a greater extent than Bunge. Agrenco, in contrast, exemplifies a non-persistent pattern, with stable linkages configurations sometimes lasting for two consecutive years, but then strongly reorganizing, and being unable to recover any stable sourcing pattern after 2009.

A proper causal analysis to explain why different traders present distinct patterns is beyond the scope of this paper. Nevertheless, these examples illustrate that small local traders like Santa Rosa Agroindustrial are subject to particular circumstances that may affect the observed stickiness patterns. Depending on market circumstances, these small local traders may venture into direct exports. However, they may also decide to sell their stocks for other traders to export or for local demand, thereby disappearing from the export registry in a given year. Indeed, Santa Rosa appears with zero exports in 2009, leading to the stickiness metric dropping to zero when comparing the similarity of Santa Rosa's supply network in 2008 with 2009. In 2010, Santa Rosa resumed exporting, so that this new network configuration also produced a stickiness value of zero when comparing 2009 with 2010. Then the 2010–2011 measurement

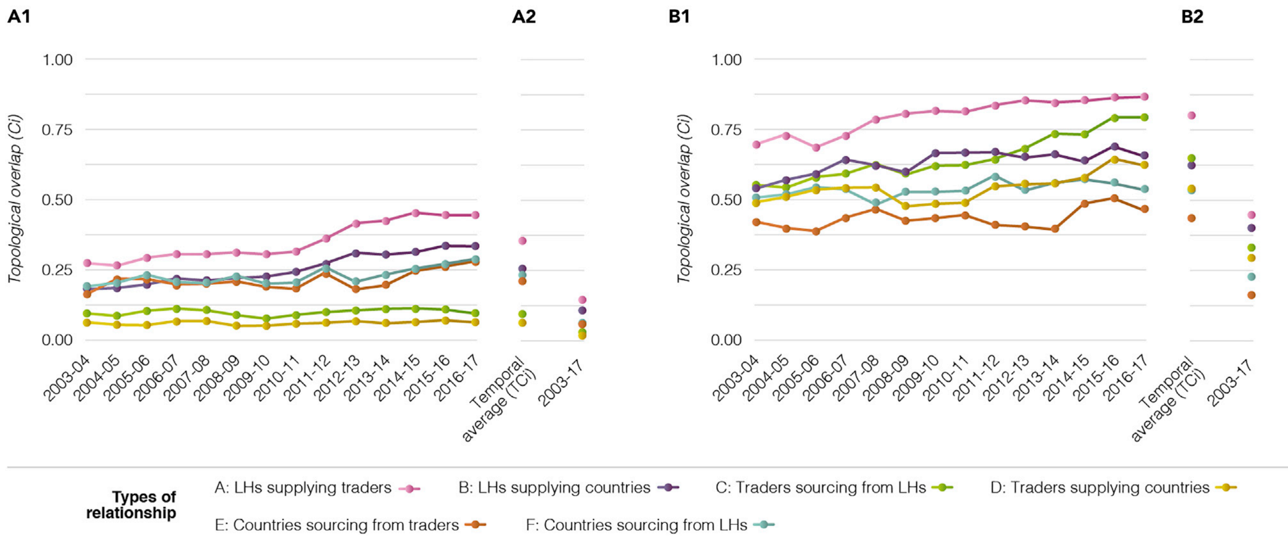

Figure 4. Temporal Stickiness Profile in the First Dimension of Stickiness (Persistence)
Measured on the configuration of commercial linkages (Ci and Cm; Equations 1 and 3 in Experimental Procedures). In (A1) and (A2), LHs are stickier than other actors' group in both types of relationships. Nonetheless, in (B1) and (B2) the selected traders sourcing from LHs show higher stickiness than the overall group in (A). (A2) and (B2) complement the temporal profiles by showing the temporal average (TCi; Equation 2) and the Ci calculated for the comparison directly between 2003 and 2017, instead of for each consecutive biannual snapshots compared. See the equivalent figure measured on flows in Figure S3. Also see a complementary Figure S4 zooming in on the relationships of different categories of traders (overall, small, and large).

goes up to 0.7, indicating that the supply network of 2011 was around 70% similar to that in 2010.

DISCUSSION

Stickiness as a Conceptual and Methodological Tool

Our results reveal key insights into Brazilian soy supply chains: stickiness is higher for large traders, and increases over time, which may reflect the progressive consolidation of the relationships between traders and specific regions of production through investments in infrastructures or business relations. Further, stickiness typically decreases when the time interval observed becomes longer. From one year to the next, the configuration of the Brazilian soy network presents only small changes. However, these changes accumulate over time so that within the 15 years covered by our assessment, the supply chain has substantially reconfigured, as observed for a pig supply chain in Germany.[77]

Our results reflect three characteristics of Brazil's soy supply chain: (1) market concentration, including potential infrastructure lock-in of large traders in some regions, e.g., through the ownership of port terminals and export corridors; (2) the strategy of large traders to diversify their sourcing regions to mitigate supply risks, and therefore a tendency to have relatively high stickiness given their ubiquity; (3) the existence of many small traders (1,678 companies) that engage in intermittent trading and brokerage, without strong geographic dependency, following market circumstances and opportunities.

Our proposed metrics allow characterizing the whole network, specific linkages, and flows, as well as the behavior of actors; i.e., decision-making entities (companies and regions of production, distribution, and consumption, representing the aggregate of individual producers' and consumers' trade behaviors). These metrics can apply to different types of relations across supply and value chains—i.e., material flows such as soy volumes here, but also financial flows or others—to investigate the existence and changes in linkages configuration and their intensity (e.g., volumes traded). Examples from the Brazilian soy supply chain suggest that the three dimensions capture the dynamics of trade relationships and can be approached with our method.

Beyond our set of indices (Equations 1, 2, 3, 4, 5, and 6 in Experimental Procedures), other metrics can be used to measure the similarity of the network around specific nodes over time or the frequency or persistence of specific linkages. Our dataset on Brazilian soy has a fine granularity (i.e., subnational production areas and distribution points, importing and exporting companies), but the same approach can also be applied over country-to-country data or other levels of detail.

Further methodological research would help to refine the indices and their information content, the measurement of the different stickiness dimensions and quantitative thresholds to characterize them, and specific procedures for supply chains covering distinct products, scales, and types of flows. Additional investigations are needed to formally define and identify shocks and analyze their impacts on trade linkages and flows.[68] The stickiness concept can further our understanding of various processes across commodity supply or value chains ranging from development,[80] macroeconomics, and political economy[81] to supply chain management and business strategies.[82] Here, we focus on appraising the potential effectiveness of supply chain ZDCs and other similar interventions.[15]

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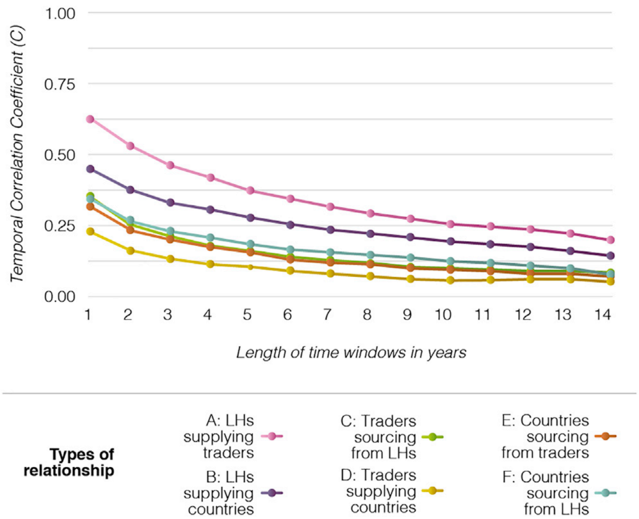

Figure 5. Overall Stickiness (Persistence) of Brazil's Export Soy Supply Chain

Calculated over all different configurations of comparisons between years separated by increasing time intervals.

Understanding Stickiness for Sustainability Governance

Analyzing stickiness in commodity trade can contribute to improve territorial and supply chain governance for sustainability, including reducing deforestation, carbon emissions, and biodiversity loss.

First, understanding stickiness can contribute to explaining and projecting the restructuring of trade flows under changing governance contexts or other shocks.[24] Past stickiness patterns can inform on which trade relations are more likely to persist over time, be resistant to shocks, or recover from them. Changes in deforestation regulations alter soy and cattle expansion and exports, but the mediating role of specific supply chain actors remains unclear.[24] Identifying areas and actors with low stickiness can help to understand their instability under changing policy or market conditions, as well as supply chains', companies', or regions' vulnerabilities to shocks such as newcomers or climatic changes.

Second, there is a growing momentum of supply chain interventions, such as ZDCs, to improve the sustainability of land use and other dimensions of supply chains.[12,38] In 2006, Greenpeace launched a campaign blaming McDonald's consumers in Europe for causing deforestation in the Brazilian Amazon.[13] In response, soy companies and environmental NGOs established the Amazon Soy Moratorium (ASM) to address this growing awareness of corporate accountability for unsustainable commodity production and tackle reputational risks.[13,16] Other related initiatives ensued, including the New York Declaration on Forests, the Amsterdam Declarations, Tropical Forests Alliance 2020, and companies' pledges.[12] Assessments of the effectiveness, coverage, and benefit to corporate actors of these zero-deforestation initiatives[15,19,83–85] rest on a poor understanding of how strongly actors are connected to production places and how supply chain configurations are affected by these initiatives. We hypothesize that the relations between stickiness and supply chain governance are multiple. If supply chains are not geographically sticky, these commitments may be less effective, as traders will lack a sufficient engagement with producing regions to influence changes in their suppliers. In the reverse direction, supply chain interventions can also create, increase, or decrease stickiness.

We hypothesize that the ASM may have consolidated the export relationships between places with already deforested available lands, signatory traders, and European countries. However, it may have also created instability in other places by creating market space for non-signatory traders supplying the growing Chinese soy demand from municipalities where expansion was still occurring. About 350,000 tons of soy were harvested in the 2016/2017 season in violation of the ASM,[28] suggesting that non-signatory companies entered this market and bought this soy. We speculate that the entry of these non-signatory companies decreased stickiness in these municipalities.

Consequently, the strength of actor-geography connections is likely to have important implications for actors' accountability. Traders sourcing in spot markets with low stickiness may be held more hardly accountable for the impacts associated with soy production than actors with consistent sourcing patterns. Further, stickiness may not only influence the effectiveness of ZDCs and other interventions but also condition their emergence and signing in the first place. Our results show that ZDC signatories, for example, also have the largest market shares and the highest stickiness scores for their sourcing places and supplying countries. This higher stickiness may reflect not only the investments and facilities installed in these places but also the long-term trust relationships and the role of embeddedness[49] in shaping social-economic relations. Traders with such embeddedness and long-term engagement may be in a favorable position to sign and implement ZDCs.

Monitoring the stickiness and deforestation risk exposure of each company over time[18] allows for targeted efforts on specific regions in the supply chain. Companies with non-sticky patterns may require more robust monitoring and verification tools than sticky companies sourcing consistently from the same locations. In contrast, sticky actors may constitute stronger levers to influence their sourcing regions with more additionality in curbing deforestation, not only in their direct suppliers.[11,13–15,18]

Stickiness may also affect the mechanisms through which interventions are transmitted along supply chains: strategies of sticky and non-sticky traders to achieve a ZDC may differ, with different overall impacts on the sector. Non-sticky traders may easily achieve targets related to their own embedded deforestation by shifting their sourcing to compliant suppliers. Nevertheless, this approach may have less effect on territorial deforestation overall, in contrast with sticky traders that have to steer changes on the ground to achieve a commitment.[27] These different approaches may have distinct implications for socioeconomic development and the spatial distribution of ZDC effectiveness.

Stickiness reflects stable long-term relations between actors. We hypothesize that the level of stickiness may thus also relate to and inform on the level of trust between regions of production and distribution, traders, and consuming countries.[50] Trust may be crucial for the success of supply chain interventions, and gaining insights on this level of trust may thus inform the sustainability strategy to be implemented and the likelihood of its

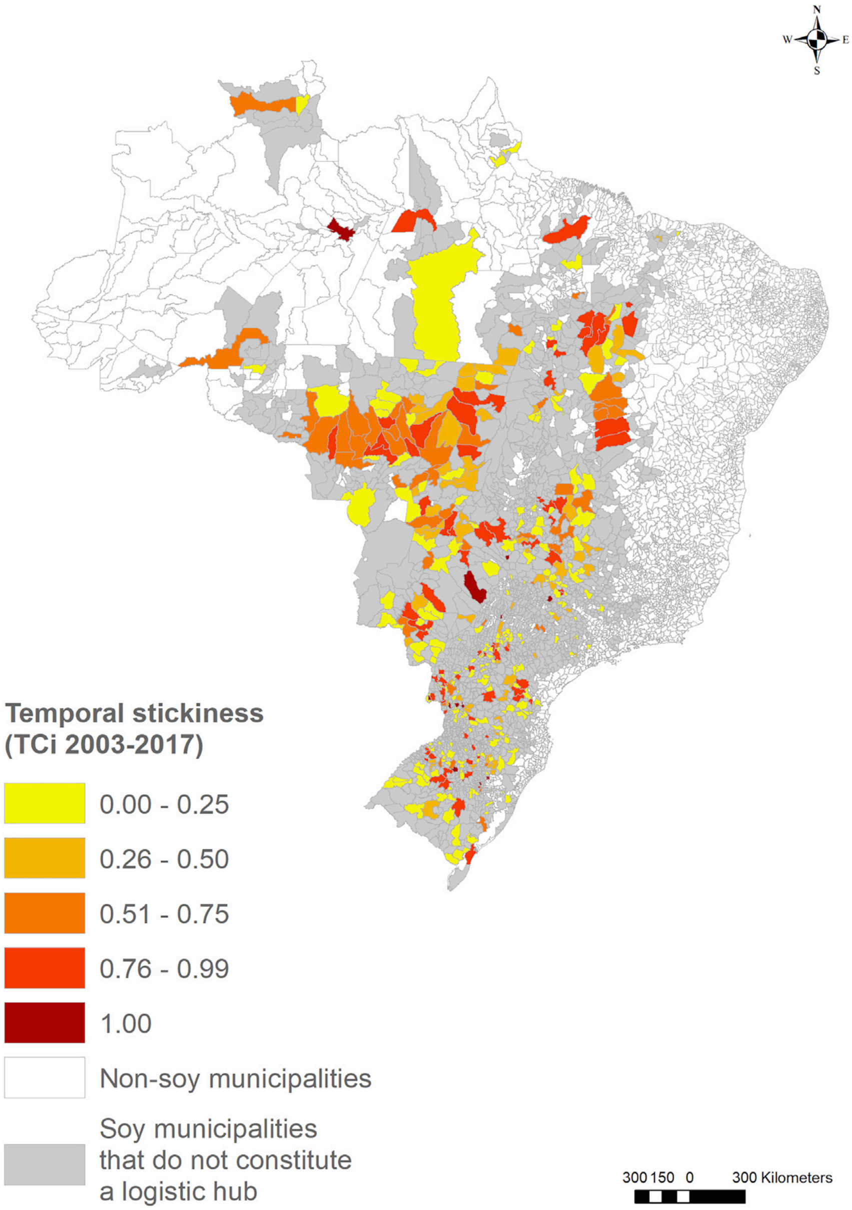

Figure 6. Spatial Distribution of Stickiness (Persistence) of Traders to Sourcing Areas

A map with stickiness measured on soy flow configuration displays similar patterns (Figure S5). Municipalities in gray produce soy, but this soy is bought by traders through one of the logistics hub municipalities. Note that local soy transactions destined for local consumption in poultry or pork facilities are not captured by this dataset.

success. Further works could explore these various hypotheses empirically.

Third, by informing on how supply chains behave, adapt over time, and react to shocks, analyzing stickiness can further our understanding of deforestation leakage and other complex land-use spillover dynamics stemming from territorial interventions and other regulatory changes.[27,28,86,87] The stickiness of consolidated traders in already-cleared regions in the Amazon may have facilitated their decision to sign the ASM agreement, acknowledging that they could expand into the neighboring Cerrado.[84,85,88]

Leakage across supply chains (e.g., deforestation being displaced from soy to beef[27,89]) and regions (e.g., displacement of deforestation from the Amazon to the Cerrado[13,84]) is likely to follow the patterns of sticky relationships.[25] Traders facing an intervention that curbs deforestation and agricultural expansion (e.g., in the Amazon) may seek room for expansion in regions unaffected by the intervention (e.g., in the Cerrado) where they already have sticky relationships. Stickiness analyses might have informed on which Cerrado municipalities were more likely to experience increased soy deforestation after the ASM implementation.[84]

Stickiness levels can also result from anticipation behaviors. Companies can enhance their fluidity by building new assets in places they expect to remain unaffected by interventions, or outsourcing logistics and storage services in locations targeted by interventions. In ASM procedures, soy purchased by indirect suppliers in the Amazon, i.e., local cooperatives or small grain warehouses, are not subject to the verification procedures applied when traders source directly from farmers.[90] Traders have thus an incentive to become more fluid and outsource their facilities, while possessing physical assets in places targeted by interventions may become a competitive hindrance.

Fourth, stickiness can inform on trade dependency and market concentration. At the country level, dependency theory suggests that developing countries face reinforcing feedback loops between the creation of strong export linkages with wealthy countries and the expansion of land use with detrimental environmental impacts.[91] The stickiness concept and method can improve the understanding of how agricultural supply chains and land use determine each other. This reciprocal dynamic includes legacies of past investments, infrastructure decisions,[23] corporate strategies to increase market share, and positioning in distinct market segments.[92]

A Research Agenda on Stickiness in Commodity Trade

Two key questions may constitute a research agenda for stickiness in commodity supply chains, particularly concerning sustainability.

First, how sticky are various trading relationships, and what are the factors and mechanisms that explain variations in stickiness between specific actors and locations? These factors likely

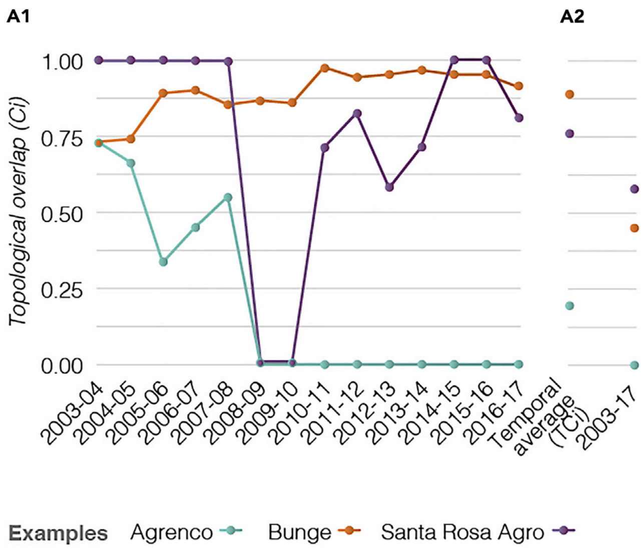

Figure 7. Temporal Stickiness (Persistence) Measured on Selected Traders

Traders' sourcing linkages from logistics hubs. See the same graphs with measurements on trade flows in Figure S6. (A2) complements the temporal profiles by showing the temporal average stickiness (TC*i*; Equation 2, Experimental Procedures) and the C*i* calculated for the direct comparison between 2003 and 2017, instead of for each subsequent biannual snapshot.

vary at different levels (e.g., company to company, or country to county), and steps in the supply chain. The concept of territoriality, i.e., how global production networks are spatially dispersed, can contribute to explaining the level of supply chain stickiness, as clustered actors tend to have more rigid relationships than dispersed ones.[93]

Producer-driven commodity chains—i.e., those in which large transnational manufacturers or processors play the central roles—are expected to have high barriers to entry for new producers, such as the soy industry for new producers of soy outputs such as oil and cake.[36,59,60] These high barriers, due to the need for appropriate capital and expertise, may lead producer-driven chains to be relatively sticky, as downstream actors such as feed companies and food retailers depend on a concentrated set of processors. In contrast, buyer-driven chains, such as vegetables retailed by supermarkets, have lower barriers to entry and may be less sticky. In this case, large-branded supermarkets can easily change their suppliers drawing from a dynamic pool of vegetable producers. New buyers can also enter the market and compete for a pool of producers by offering more advantageous purchasing conditions.[94]

The governance structure of value chains—i.e., how authority and power relationships, such as through market shares and price-setting power, determine the allocation of benefits and resources across chains—also influences the options and bargaining power of actors and thus their stickiness.[61] Social networks and embeddedness[95] also likely influence stickiness. Geographic factors, including the availability of land for further expansion, may influence the involvement of supply chain actors with specific places. Producers' stickiness can be tied to the presence of infrastructures from one versus different companies, or preferential contracts, while consumers' stickiness depends on their attachment to brands.[37]

Countries may shift sourcing across other countries while a local trader may be tied to a place where it has a silo or other infrastructure. Stickiness may also be influenced by policies that increase traceability or compliance with specific sanitary norms or preferences—such as the EU refusal of genetically modified (GMO) crops—or provide preferential market access.[32,92] Over the long term, environmental and other policies affect infrastructure development and production factors such as labor force, which in turn determines land-use displacement across geographies.[23]

Second, how does an actor's stickiness influence patterns of land use in the geographies where they engage, and more broadly, the socio-environmental impacts of commodity production? Further, how does stickiness interact with various governance interventions, i.e., territorial or jurisdictional interventions, supply chain, or public policy interventions, aiming to manage land use more sustainably, and does this influence their effectiveness?

Formulating and testing more specific hypotheses relating to the relationship between stickiness and land-use governance can help to design more effective interventions. In the specific context of ZDCs, we propose that (1) stickier companies are more likely to implement ZDCs by requesting changes in their suppliers' practices as opposed to shifting their sourcing patterns, and (2) interventions on stickier companies or territories are less likely to result in leakage. Testing these hypotheses requires further work beyond the scope of this study.

Conclusion

We presented the notion of stickiness to measure and characterize the level of stability and rigidity of supply chain relations, decomposed into the persistence, resistance, and recovery of these relations. Metrics from network analysis can measure these dimensions for both the presence of linkages and the intensity of flows.

Understanding stickiness can inform policies and initiatives to address deforestation, in particular, to assess the potential effectiveness of supply chain ZDCs. If supply chains are not geographically sticky, these commitments may be less effective, and less likely to be signed, as companies may lack the capacity to influence their suppliers downstream. This relationship between stickiness and ZDCs requires further investigation.

Analyzing stickiness revealed insights into the behavior of production places and traders active in the Brazilian soy supply chain. Brazilian soy traders with the largest market share and with ZDCs exhibit stickier geographic sourcing patterns. Soy-deforestation risk among traders is correlated with stickiness. The linkages between production places and traders become increasingly sticky over time. Specific regions, in particular current agricultural and deforestation frontiers, have higher stickiness. The cause-effect relationships behind these patterns require further investigations.

Further research could improve the methodological tools for empirically assessing the different dimensions of stickiness, especially related to the identification of supply chain shocks and their effects. These improvements can enhance our understanding of the factors that influence stickiness patterns, the impacts of supply chain dynamics, and the mediating role of actors on socio-environmental dimensions. Research on stickiness can inform the development of solutions for curbing deforestation and promoting sustainable land use and supply chains.

EXPERIMENTAL PROCEDURES

Resource Availability

Lead Contact

Further information and requests for resources and reagents should be directed to and will be fulfilled by the Lead Contact, Tiago Nogueira Pimenta dos Reis (tiago.reis@uclouvain.be/tiagopimentadosreis@gmail.com).

Materials Availability

This study did not generate new unique materials.

Data and Code Availability

The datasets and code generated during this study are available at Zenodo repository: https://doi.org/10.5281/zenodo.3901699.

Designing a Conceptual Framework for Stickiness

Several fields have explored how to describe the stability and rigidity of supply chain patterns and trade networks, and the processes that underpin them. First, agricultural economics investigates stickiness in international trade, showing, under the so-called "Armington assumption," that in global markets with free trade, agricultural products from one place are not fully substitutable with products from another place, even after accounting for price differences.[25,30] The often-used gravity model explains the amount of country-to-country flows as a function of economy sizes, i.e., gross domestic product (GDP) and geographic distance.[54,55] However, this literature says little about geographic stickiness between places and actors, except for clustering in manufacturing supply chains,[58] and lacks explicit articulation of the role of stickiness in sustainability governance of supply chains, particularly for ZDCs.[15] Second, research on GCCs,[59] GVCs,[60] and production networks (GPNs)[62] show how actors, including raw material producers, traders, and retailers, create and maintain specific trade networks. This research remains based on specific case studies, lacking the large datasets linking localized production, supply chain actors, and consumption places that are necessary to explore quantitatively how supply chain configurations react to various changes in markets and policies.[66] Third, studies on social-ecological resilience and biosphere stewardship[71,72] have analyzed how social-ecological systems resist, adapt, transform, and recover from external shocks.[96–98] They distinguish the two dimensions of resistance (i.e., the ability of a system to withstand shocks by maintaining its functions) and recovery (i.e., the ability of a system to bounce back to its previous state after being perturbed).[68,98,99] In the next paragraphs, we explain in more detail how these three streams of literature contribute to designing a conceptual framework for stickiness.

Agricultural economics studies show that in global markets with free trade, agricultural products from one place are not fully substitutable with products from another place, even after accounting for price differences.[31–33] Standard econometric studies and economic models use empirically calibrated "Armington trade substitution elasticities."[30] These studies account for the differentiation of products based on production place, and for the fact that price shocks occurring in one country do not spread homogenously in the global market, but predominantly affect the key trade partners of that country.[30,34,73,75]

For example, a drought in a few specific municipalities of Brazil, as a soy exporting country, will affect local producers and traders by impairing their capacity to deliver future contracts. As a result, this local shortage of supply may increase regional soy prices, but this will not affect global markets, as most traders can change sourcing to other regions not affected by this local shock. In global commodities, for global prices to be affected, there need to be higher scale shocks. In this sense, a local price shock caused by local climate variability will differentiate soy according to its production location because municipalities that did not suffer from this drought will have more supply and lower prices to feed global demand.

For supply chains at firms level, the economic literature identifies some factors influencing stickiness, mainly input and output specificity.[34,35] Input and output specificity refers to the properties and characteristics of materials used in manufacturing and the resulting products that differentiate them. For example, soy farmers who use specific breeds of GMO seeds are highly sticky to the companies that supply the specific set of agrochemicals that function with those seeds. By acquiring certain types of GMO seeds, a farmer may establish an enduring commercial relationship with the suppliers of an adequate and specific set of inputs.[36,92]

The actor's relative position in the supply chain, which is dependent on the elasticity of demand faced by the consumer-facing company,[11,37,38] also influences stickiness because of the embeddedness nature of some commodities in food systems.[11] For example, soy is used for multiple purposes that are opaque to consumers, such as animal feed and biofuel; only a small fraction of soy goes to direct human consumption. This opacity means that it is relatively easy for intermediate companies, such as traders and processors, to be non-sticky with their suppliers. These intermediate companies have a distant relative supply chain position from end consumers. This distance implies they can shift sourcing places from time to time, as they do not receive direct consumer pressure for accountability.

Geographic proximity influences the country-to-country trade patterns[25,39,42] significantly. However, the literature also shows other more qualitative factors influencing international trade, such as ethnic networks,[40] colonial linkages and common language,[41,42] piracy,[43] governance regimes,[44] institutional quality and differences between countries,[45] and the countries' capacity to enforce contracts.[46] The social economy concept of embeddedness[47,48] complements our review of stickiness by acknowledging the social structure and trust of interfirm networks and commercial relationships.[49] Understanding the embeddedness of social relations[50] in supply chain economic and geographic relationships is crucial to advance the stickiness research agenda.

Lock-in effects are equally important factors of stickiness in supply chains, mainly technological,[51] the fixing of relative preferences over time,[52] social dependence, and investments.[53] The gravity model explains the amount of country-to-country flows as a function of economy sizes, i.e., GDP, and geographic distance,[54,55] which can also partially explain stickiness or, in other words, why some country-to-country flows persist over time. Furthermore, the Melitz model[56] suggests that stickiness depends on a country's exposure to international trade, where more productive firms would access foreign markets, thus having more volatile supply chains. In contrast, less productive firms would be sticky to domestic consumers. Varying levels of trade openness would cause different supply chain responses and more or less volatility in sourcing and supplying patterns.[57]

These economic studies focus on providing robust estimates of trade substitution elasticities for different commodities, and on explaining stickiness in interfirm and country-to-country trade. Nonetheless, they say little about geographic stickiness between places and actors, except for clustering in manufacturing supply chains.[58] This literature also lacks explicit articulation of the role of stickiness in sustainability governance of supply chains, particularly for ZDCs.[15]

Research on GCCs[59] and GVCs[60] provides a complementary perspective. They move beyond structural country-to-country relations and show that various actors such as raw material producers, traders, processors, and retailers play a role in creating and maintaining specific trade networks. The notion of GPNs[62] highlights that companies and non-state actors exercise power and agency to shape the legal, governance, and policy frameworks and contexts in which they operate.[61–64] Most quantitative research on supply chain configurations investigates structural factors at the country-to-country level.[65] As far as we know, research on GCCs, GVCs, and GPNs remains based on specific case studies. It lacks the large datasets linking localized production, supply chain actors, and consumption locations that are necessary to explore quantitatively how supply chain network configurations react to various changes in markets and policies.[66]

Here, we bridge these theoretical and empirical approaches by analyzing supply chains as a network.[69,70] We extend the notion of stickiness formulated in economics through the analysis of supply chains as proposed in GCC, GVC, and GPN research. We consider stickiness as a moderating factor of the existence, and the potential effectiveness, of supply chain sustainability initiatives,[15] particularly ZDCs. The notion of resilience in social-ecological systems and biosphere stewardship[71,72] inspires us to define the dimensions or characteristics of stickiness, namely resistance and recovery. Extensive inquiry on network approaches[22,68] and in supply chains[74] is also crucial for our stickiness approach. Nonetheless, here we do not aim to characterize all the aspects of resilience of production, consumption locations, and networks, as well as of actors in the supply chains, and the capacity of these actors to adapt and transform. We simply aim to provide a concept and methodological approach to initiate those types of enquiry.

Assessing Stickiness in the Brazilian Soy Supply Chain

Network analyses are applied to various sustainability issues, including social-ecological, biological, food webs,[68] supply chain,[100] land acquisitions,[101] and virtual water trade.[102] In many cases, they aim to describe and understand the persistence and reconfigurations of these networks. These studies offer inspirations for our methodology for characterizing trade stickiness.

The Brazilian soy trading data from Trase version 2.3 (Supplemental Experimental Procedures, Data and Methods) includes transactions of soy exported as raw beans, oil, meal, or cake.[29] We assembled this dataset as a network linking LHs, traders, and countries of consumption. We did not measure stickiness on all soy-producing municipalities. The allocation of soy flows from the logistic hubs (LHs) to the municipalities of production in the Trase data is the result of linear programming. This method may create artifacts in the measurements of the inter-annual stability of the network configuration at the municipality level.[78] LH-level data rely directly on official trade records and are representative of a set of soy farms within the municipal boundaries in which they are located, but also for neighboring municipalities, as these LHs gather soy produced in a surrounding region with viable logistic connectivity. We also clarify that we do not consider trade linkages with local feed companies and processors that supply soy for Brazilian domestic consumption. All soy consumed internally is treated as a single node called "domestic consumption" in the LHs and traders network levels, and as "Brazil" at the country destination network level.

We transformed the raw data (in the format of edges lists) into adjacency matrices. Each aggregate year of trade data between 2003 and 2017 became one adjacency matrix, representing one snapshot of the network. We call each year's aggregate transaction data a snapshot because our network comprises 15 snapshots or annual aggregate transaction data. Each stickiness measurement implies comparing two snapshots. In one set of adjacency matrices, we replaced entries by 1, representing the existence of a linkage between two adjacent nodes, and 0 when no link existed, thus creating an unweighted adjacency matrix (or binary interaction matrix). We used this to measure stickiness on trade linkages. All measurements presented here in the main text use this unweighted adjacency matrix.

In the second set of matrices, we maintained the entries with the original values representing the volumes of soy traded. With this, we measured stickiness on trade flows. The measurements on flows that are equivalent to those on linkages presented here are shown in the Supplemental Information. Both measurements, on soy trade linkages and flows, are highly correlated. They are complementary indicators. While the measurements on linkages allow us to identify overall changes in the configurations of commercial relationships, the measurements on flows allow us to qualify these changes by indicating whether the configuration of volumes traded through each linkage increased or decreased.

For stickiness in trade linkages (unweighted networks), we used the temporal correlation coefficient (C)[76,103] and its intermediary steps for directed, temporal, and unweighted networks (as adapted by Büttner et al.[104] and Pigott and Herrera[105]). These intermediary steps are the topological overlap (C*i*), the temporal average topological overlap (TC*i*), and the graph average topological overlap (*Cm*; Equations 1, 2, 3, and 4). *Cm* is the average topological overlap, calculated not over time as TC*i*, but over groups of nodes. It is a necessary step to see the overall stickiness across groups and to calculate C. For stickiness in trade flows (weighted networks), we adapted the topological overlap (C*i*) to analyze directed, temporal, and weighted networks, transforming it into what we call weighted persistence of trade flows (WP*i*) and the temporal average weighted persistence (TWP*i*; Equations 5 and 6).

Metrics Used for Stickiness in Linkages

The temporal correlation coefficient and its intermediary steps were first designed as metrics for undirected and unweighted networks. Further adjustment corrected and adapted the metric for directed networks.[77,104,105] The temporal correlation coefficient "measures the overall average probability for an edge to persist across two consecutive snapshots."[76,77,103] The topological overlap (C*i*) of the surrounding links around a node in two time points is the first step to measure the temporal correlation coefficient (C) of a network. The C*i* allows us to quantify the temporal changes in the configuration of trading linkages of an actor in the supply chain.

We present the C*i* equation below, where C*i* is the topological overlap[76] of links around node *i*. t_m is the first snapshot of the temporal network, for example, the configuration of trade linkages of the soy supply chain in 2003. t_{m+1} is the second snapshot, in the same example, the configuration of trade linkages in 2004, the subsequent year with available data. We used the same metric to compare non-successive years, i.e., comparing the network configuration in 2003 with that of 2017. a_{ij} is a value (1 or 0) in the adjacency matrix representing the network. With the C*i* (Equation 1), we can observe and measure temporal changes in two snapshots with the selected time interval, in the trading relationships around any specific actor in the supply chain.

$$Ci\left(t_m,t_{m+1}\right)=\frac{\sum_j a_{ij}(t_m)a_{ij}(t_{m+1})}{\sqrt{\left[\sum_j a_{ij}(t_m)\right]\left[\sum_j a_{ij}(t_{m+1})\right]}}. \quad \text{(Equation 1)}$$

The C*i* in biannual snapshots allows the changes in the trade linkages configuration to be observed over two subsequent years around each node, e.g., 2003–2004, 2004–2005, …, 2016–2017. Based on this, we then computed the temporal average topological overlap[77] of the nodes (TC*i*, Equation 2) for all snapshots, where *M* is the total number of considered snapshots. In our study, the maximum snapshots we can have is 15, each year from 2003 to 2017.

$$TCi=\frac{1}{M-1}\sum_{m=1}^{M-1}Ci(t_m,t_{m+1}). \quad \text{(Equation 2)}$$

In practical terms, Equation 1 is calculated over two snapshots that may be successive years (e.g., 2003–2004) or non-successive years (e.g., 2003–2017), and Equation 2 is the mean of several C*i*s over time. Equation 2 shows the average variation in stickiness for every node in the complete length of the analyzed period and considering all biannual changes in between. With this C*i* temporal average (TC*i*), we can see the average changes in the trading relationships around any specific actor or region over a longer period, acknowledging several or all subsequent snapshots in between.

In the third step, we grouped the trade relationships in six types: logistics hubs (LHs) supplying (A) traders and (B) countries; (C) traders sourcing from LHs, and (D) supplying countries; (E) countries sourcing from traders, and (F) from LHs (Figure 2). We then calculated the mean of the biannual C*i*s for each type of relationship. Having the C*i*s of nodes, we also calculated the average topological overlap of the graph (entire supply network)[104] for two consecutive snapshots (*Cm*, Equation 3). The *Cm* is different from C*i* temporal average because TC*i* focuses on the trade linkages configuration around each node, while *Cm* describes the changes in the whole network configuration. The *Cm* is an intermediary step to get to the temporal correlation coefficient (C). Therefore, we did not present the results here. The equation used is

$$Cm=\frac{1}{\max[A(t_m),A(t_{m+1})]}\sum_{i=1}^{N}Ci(t_m,t_{m+1}). \quad \text{(Equation 3)}$$

In this equation, $\max[A(t_m),A(t_{m+1})]$ denotes the maximum number of active nodes of the graph at t_m and t_{m+1}. A node *i* is called "active" at time t_m if it has an edge with any other node.[77] This equation was presented by Büttner et al.[104] and Pigott and Herrera,[105] modifying Nicosia et al. s[76] equation to acknowledge only active nodes in the calculation rather than all nodes, i.e., even inactive nodes that did not trade anything in the two snapshots considered. We subset the network to compute *Cm* for specific groups of edges or, in our case, trade relationships, as described above.

Finally, the temporal correlation coefficient (C) (Equation 4) measures the overall average probability of an edge to persist between two consecutive snapshots.[76,77,103] It is the fourth step after computing Ci and Cm. M is the total number of considered snapshots. C is calculated as follows:

$$C = \frac{1}{M-1} \sum_{m=1}^{M-1} Cm. \tag{Equation 4}$$

The temporal correlation coefficient (Equation 4) summarizes the Cms, which we grouped by type of supply chain relationship, to demonstrate how much the trade configuration changes overall with the length of the time frame observed.

All these four metrics generate values ranging from 0 to 1, 0 being a complete change and 1 a complete maintenance of the trade configuration. As an illustration, if one actor in the supply chain displays Ci or TCi = 1, it means that this actor kept precisely the same trade linkages configuration throughout the period assessed. On the contrary, if the value is 0, the trade linkage configuration changed utterly. Any value in between implies some degree of reconfiguration. Looking at Cm and C, 1 means that the whole trade network remained completely unchanged over the assessed period, while 0 means a complete change. As can be expected, the longer the time interval, the more likely the network is to change, and therefore the less sticky it appears (Figure 4). Büttner et al.[77] found a slightly different trend in their pork supply chain analysis, as C increases sharply in the initial increments of the time frame, and then starts to fall slowly as time frame increases. Their time steps were very short (days) compared with ours, so their supply chain appears much more volatile in comparison with our soy supply chain, which is less volatile and measured in years.

Metrics Used for Stickiness in Flows

Despite the robustness of C and its sequential steps to measure stickiness in trade relationships, one primary limitation of this metric is its inability to account for the changes in volumes traded, as it was designed for unweighted networks (binary set of linkages). The Ci is calculated over a list of binary edges or pairs of adjacency matrices, where nodes are either connected by a trade relationship (1) or not (0). For our stickiness analysis of commodity trade, it is also important to gauge the variations in flows, i.e., the volumes of product traded in tons over the years through the linkages. Therefore, we devised an additional index modifying the Ci and C steps. The weighted persistence index (WPi) is the ratio between the absolute changes in the trade flows of a node i and the total volume of soy produced or distributed (if the node is a logistic hub), traded (if it is a trader), or imported (if it is a country) by this node i in the observed time window. The same interpretation of Ci applies to the WPi index, i.e., an actor having WPi = 1 reveals that, overall, its inflows or outflows of commodities remained unchanged over the observed period, whereas 0 indicates a complete change in flows. We calculated the weighted persistence (WPi, own formulation) as

$$WPi\left(t_{m,}t_{m+1}\right) = 1 - \frac{\sum_j \left|a_{ij}(t_m) - a_{ij}(t_{m+1})\right|}{\sum_j a_{ij}(t_m) + a_{ij}(t|m+1)}, \tag{Equation 5}$$

$$TWPi = \frac{1}{M-1} \sum_{m=1}^{M-1} WPi(t_m, t_{m+1}). \tag{Equation 6}$$

With these two equations, we demonstrate a way to measure stickiness and its three dimensions in commodity trading. Other metrics and approaches could be used. The WPi is only applicable to edges or flows aggregated by nodes or by types of trading relationships.

Measuring the Three Dimensions of Stickiness

Based on these indices, we explored the three dimensions of stickiness empirically, using the soy data, through the following questions (Figure 7):

Persistence

Which actors and locations have trade linkages and flows that are persistent over time? To answer this, we can look at trade linkages and flows with Ci, TCi, WPi, and TWPi close to 1. Those who kept biannual Cis and WPis at high values over the whole observed period are the most persistent. Actors and places that have values for these metrics closer to 0 have low persistence for the period considered.

Resistance

Which actors and locations have trade linkages and flows that are resistant over time? To answer this, we need to identify a potential or known shock, which can, among other things, be a drought, a new trade policy, a ban or moratorium, a sudden increase or decrease in global demand. Once we have identified a shock, we look at trade linkages and flows that are subject to this shock and observe how their persistence (as measured by Ci for linkages and by WPi for flows) performed during the shock period. The trade linkages and flows that maintained Cis and WPis, respectively, at values that are high and similar to the period before the shock can be characterized as resistant. Those who experience a substantial change are less resistant, and those who break linkages and flows and experience a sudden drop in their indices are non-resistant. Note that proper attribution of the changes in network configuration to the identified shocks requires applying appropriate causal inference approaches that we did not do here (Figure 7).

Recovery and Reconfiguration

Which actors and locations have trade linkages and flows that recover and reconfigure a stable situation over time? For this question, we look at linkages and flows that are affected by a shock, i.e., show decreasing Cis and WPis during the shock period, but which afterward reconfigured their connections and flows in a way that they returned to a similar trade configuration as before the shock. Here, we make two subdivisions. The first entails the recovery toward the same previous stable configuration, i.e., after breaking linkages and flows, they recover to the same old partners and stabilize. The second entails linkages and flows that recover, but in a new configuration, i.e., they create new linkages with new partners and then maintain this stable new configuration. Here, we did not analyze causal explanations of this dimension, only observed it empirically (Figure 7).

These three dimensions can be illustrated by first identifying a shock and how the Cis and WPis drop in the period after the shock. If it recovers during subsequent snapshots, it means the linkages and flows were re-established in a more stable configuration. If we increase the analyzed time frame, for example, instead of 2007–2008 we look at Cis and WPis for 2007–2012 and see unchanged high Cis and WPis, it means that not only were the supply chain actors able to re-establish stable relations but these relations were similar to those prior to the shock; i.e., that the network restored to its previous configuration. In contrast, if Cis and WPis for 2007–2012 are low, it means that over this longer period, they changed the configuration significantly, so the network has reconfigured.

It is essential to highlight that here we do not define numeric boundaries or thresholds to determine when the stickiness of a trade linkage or flow is resistant or recovering, or not. So far, this is done simply in terms of comparison with previous patterns. In other words, if the stickiness index of a specific node varies between, e.g., 0.7 and 0.9 for a period, then it drops to 0.1 in a biannual timestamp, to go up again back to the 0.7 and 0.9 range, we can point out its recovery. More empirical analyses and stickiness observations are needed so that we can start considering the establishment of numeric boundaries and thresholds for each dimension.

SUPPLEMENTAL INFORMATION

Supplemental Information can be found online at https://doi.org/10.1016/j.oneear.2020.06.012.

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AUTHOR CONTRIBUTIONS

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DECLARATION OF INTERESTS

The authors declare no competing interests.

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