# Trade Interdependence in the Modern Global Economy

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**Abstract**

Analyzing global trade interdependence requires an approach that incorporates fundamental features of the modern economy: intense trade in intermediates and the changing availability of alternative partners and substitute products. We use theoretical models of structural gravity to construct measures of dyadic dependence that directly incorporate these features. The measures describe (1) how much trade interruptions damage a country's welfare and (2) how much additional trade it would take from their existing trade partners to compensate. We then show three important findings. First, the new measures differ from traditional measures based on aggregate trade statistics. Second, they show how, contrary to much common wisdom, the world has *not* marched inexorably towards greater interdependence. Third, we use China's foreign assistance, as exemplified by the Belt and Road Initiative, to assess the consequences of one major government policy. Chinese assistance has increased partners' dependence on China, without a reciprocal increase in Chinese dependence.

# 1 Introduction

The world has experienced an unprecedented explosion in international commerce since the late 20th century. The modern global economy is characterized by historically open markets and a sprawling network of interlinked value chains. Scholarship has interpreted the skyrocketing levels of international trade as an indication of the increasing interdependence of national economies (Keohane and Nye 1973). However, broad changes in the global economy necessitate a reevaluation of this interpretation. On the one hand, trade in intermediates and in differentiated products has increased, making many trade relationships even more valuable than nominal trade values would suggest. On the other hand, states can trade with more and larger markets in the event that any single trading relationship breaks down. Therefore, even as states have plugged into an integrated global economy, they are also better positioned to endure interruptions in trade than ever before.

Taking account of these fundamental changes in the global economy has critical implications for fundamental questions in geopolitics, both new and old. Have states become more dependent on one another over time? Have trading relationships become more interdependent – i.e. symmetric in the degree of dependence between states? The question "who is dependent on whom" has become even more urgent as governments increasingly view dependence as a vulnerability to be remedied or a pressure point to exploit. Shocks like the COVID pandemic demonstrated the unforeseen consequences of dependence by revealing supply chain vulnerabilities. Inoculating against these dependencies is now a key driver of many governments' desire to become self-sufficient in critical sectors. The United States' willingness to use tariffs for geopolitical leverage is premised on the idea that other countries need the U.S. more than the U.S. needs them. Since avoiding or manipulating dependence are key drivers of state policy, modeling and measuring dependence will only become more important for understanding the causes and consequences of states' choices.

Understanding global economic dependence requires models and measurements that account for intermediates trade along value chains, the availability of alternative partners, and the substitutability of products. The most commonly used approaches describe dependence by tallying aggregate statistics of bilateral trade flows as a fraction of GDP or total trade. These approaches were more appropriate in an earlier era when it was reasonable to assume that trade flows of equal value contributed equally to the gains from trade, and were equally easy to replace with alternate suppliers. However, in an era characterized by global value chains and productive alternative trading partners, the link between the volume of trade and dependence on trade has deteriorated. New approaches are necessary to fully capture "who is dependent on whom."

We build on recent advances in the structural gravity approach to model and measure dependence while accounting for these dimensions. For almost 60 years, economists have explained bilateral trade flows using equations that resemble Newton's theory of gravitation. Arkolakis, Costinot, and Rodríguez-Clare (2012) show that, within an extremely wide class of gravity models encompassing Armington (1969), Krugman (1980), Eaton and Kortum (2002), and Melitz (2003), a handful of parameters are sufficient to create a measure of the gains from trade and market access. These parameters – trade elasticities, shares of domestic value-added in production, and the share of intermediate products in production – are the same regardless of whether the underlying model explains trade using international differences in factor endowments and technological knowledge,[1] increasing returns to scale, or heterogeneous products and firms.[2] These parameters also directly correspond to the key ways in which the global economy has evolved.

We extend this approach to create two new measures of bilateral dependence: how much welfare one state would lose if some or all of its trade with a partner were cut off. The ability of one country to harm the welfare of another is at the core of bilateral dependence and economic coercion.[3] We construct an "upper bound" measure of dependence, which describes a country's loss of welfare if market access were interrupted and no further adjustments were made. We also construct a "compensation" measure, which describes how much that country would have to scale up their trade flows with other partners to restore its welfare to *ex ante* levels. If only small adjustments would be needed, then that shows a low level of dependence, and vice versa. Our measures' major advantages over existing approaches are that they directly incorporate key features of the global economy by plac-

[1] Rogowski (1987), Hiscox (2001)

[2] Kim and Osgood (2019)

[3] Baldwin (1980).

ing greater weight on intermediates trade that has downstream effects along production chains and greater weight on flows for which there are fewer available substitute products or producers.

Additionally, our approach directly models the counterfactual nature of dependence. Baldwin (1980) defined dependence as the opportunity cost if a country were to interrupt trade with a partner. He lamented that the counterfactual nature of opportunity cost makes it hard to operationalize. Existing measures using only aggregate trade and GDP statistics make no attempt to measure the opportunity cost of interrupted trade, since they are based solely on the nominal value of observed trade. Almost 30 years later, Mansfield and Pollins (2009) noted the persistence of this problem, since "the size of the flow of trade between states … may not accurately reflect the costs [if] economic relations were disrupted" (13). Describing the consequences if trade were interrupted requires a theoretical model of the welfare consequences of lost trade and a measurement derived from that model.

Our approach answers these calls. Our theory unpacks the black box between trade and dependence. Not every dollar of trade is equally consequential for dependence. The implication of a trade flow on dependence depends on key facets of what they're trading and who else they could trade with. Existing approaches based on variations of aggregate statistics measures or individual products only partially incorporate these facets in an ad hoc fashion. It is unclear which ad hoc approach is a better proxy for the effect of trade on welfare, and therefore dependence. In contrast, our approach is directly tied to generalizable, robustly verified economic theory linking trade to welfare. We are providing a unified framework that goes from a model of the welfare effects of different types of trade to a measurement that can be used to answer consequential questions about the nature and evolution of dependence.

We describe the approach and measure construction in detail, then present three sets of substantive findings. First, our measurements diverge from commonly used existing measures and these divergences increase over time. The correlation between our measures and existing measures deteriorates over time and as we account for intermediates trade, changing availability of partners and alternative products.

Second, we show that global dependence has not changed in the ways scholars often think. For

Keohane and Nye (1973) and many others, the concept of complex interdependence refers to the depth and symmetry in dependence relationships. *Dependence* describes how state $i$'s welfare is affected when its trade with state $j$ is interrupted, either because $j$ limits its exports or $i$ raises tariffs on imports. *Interdependence* refers to whether $i$'s dependence on $j$ is similar in magnitude to $j$'s dependence on $i$. Scholarly and popular descriptions of the liberal economic order often describe a broad trend in which countries became more dependent on one another overall, to the point where it can deter conflict and encourage more cooperation among states (Friedman 2005; Keohane 1984; Keohane and Nye 1973).

We show that the data do not match these stories in several meaningful ways. Global levels of dependence have increased over time, on average. But there is intense heterogeneity in the trends. Dependence among Asian countries has broadly increased, but for many countries, dependence has decreased over time, especially among those in Europe and North America. Other countries have a U-shaped trend over time, with dependence decreasing and then increasing. We show that the common cause is skyrocketing dependence on China. Rising dependence is usually attributable to direct dependence on China. Declining dependence usually reflects how the emergence of China as an alternate trade partner has undercut dependence on countries' existing trade partners. For many countries, dependence on China has grown to the point where they have become more dependent on China than they had ever been on their previous trading partners.

Additionally, global interdependence has not increased over time. In fact, interdependence – symmetry in dependence relationships – has decreased significantly when considering each state's primary dependency (typically, the U.S. or China). Furthermore, these trends are not apparent when using aggregate trade statistics, which do tend to support the conventional wisdom about increasing dependence and symmetry. The world only looks more dependent and symmetric over time when using aggregate GDP and trade measures that assume all trade flows are equally important. Contrary to a common belief, the global distribution of dependencies has not become more egalitarian.

Third, we turn to the question of why dependence on China has grown so dramatically. Much of the rise in dependence is due to China's emergence as an economic powerhouse, but we also consider whether government policies contributed to the trend. We study one of the most ambitious projects that could increase dependence on China: the Belt and Road Initiative (BRI), which increased Chinese foreign assistance. Using a difference-in-differences specification, we find that Chinese assistance increased recipients' dependence on China. However, the reverse was not true. China has not increased its dependence on recipients, meaning that it has further increased asymmetry in dyadic dependence. Again, these effects are not apparent using aggregate trade statistics. Governments the world over are hyper-focused on whether they can use policy levers to manipulate dependencies. Our analysis of Chinese assistance is a critical case to study for assessing whether these efforts are likely to succeed.

We conclude by describing the types of questions that we hope our approach can shed additional light on.[4] Some of these questions are again "old," such as whether interdependence fosters peace? Others are "new," such as whether the effects of climate change or evolving artificial intelligence capabilities will change who is likely to be dependent on whom in a rapidly changing future. An approach that accounts for fundamental changes in the global economy will be critical for answering all of these questions. Since deep changes to the global economy will likely endure, using old approaches to understanding dependence risks leading us astray about the answers.

## 2 Dependence and Interdependence

What is dependence? In geopolitics and trade, "dependence" has been used to describe a multitude of concepts.[5] We use it here to mean the opportunity cost of lost commerce – the difference in a state's welfare when a particular trading relationship is interrupted (Baldwin 1980).[6] Dependence is a fundamentally counterfactual concept; it compares economic welfare in a status quo scenario with welfare after a trade relationship is interrupted. Neither value is observable at the same moment. Thus, dependence is a latent quantity that must be theorized and estimated.

Dependence is a critical concept in international relations because it is the "ammunition" one country has when it attempts to use economic coercion against a target. It is the relevant concept for studying the structure of global economic power and deliberate attempts to manipulate commer-

[4] Our measures will be publicly available and updated.
[5] Coate, Griffin, and Elliott-Gower (2015)
[6] See also Mansfield and Pollins (2001).

cial relations to influence another country (Hirschman 1980; Eaton and Engers 1992).[7] One state may attempt coercion by conditioning market access on compliance with a demand.[8] Beyond coercion, the structure of dependencies also affects international cooperation because states that fear economic coercion will be reluctant to embrace openness (Abdelal and Kirshner 1999; Carnegie 2014).

The term "interdependence" also has many uses, but the most influential describe a two dimensional concept. Interdependence requires depth: states $i$ and $j$ should have significant dependence on each other. Interdependence also entails symmetry: both state $i$ and state $j$ are approximately equally dependent on each other. Keohane and Nye (1973) argued that relative parity across countries in their degree of dependence on one another was a key feature of "complex interdependence."

Why should we care about dependence? Few core concepts have been linked with as many fundamental questions in international relations. Dependence plays a key role in understanding of the origins of international cooperation (Keohane 1984). Scholarship dating back to Cooper (1968) argues that increasing dependence is a core motivation for states to cooperate and coordinate economic policy. Ikenberry (2018) extends this logic, arguing that the emergent institutions supporting cooperation are a liberal international order whose purpose is to promote democracy and "reconcile the dilemmas of sovereignty and interdependence" (8). Moreover, the expectation that interdependence will increase is itself an important driver of cooperation. Increasing interdependence establishes an expectation of mutual gains from cooperation in the shadow of the future (Axelrod and Keohane 1985). Asymmetry in dependence is concerning enough that states actively manage it with the rules-based liberal international order. The construction of the liberal international order stemmed in part from a desire to limit the hegemonic power of the United States, on whom states were very dependent (Ikenberry 2001). Powerful states subject themselves to a rules based system in order to attract greater participation in the global economy from smaller states who would otherwise fear that dependence would be used against them (Carnegie 2014).

[7] Previous work distinguished between sensitivity and vulnerability. The former describes how *unintended* interruptions affecting one country affect its partners. Our approach fits most naturally with vulnerability dependence, but can also capture the consequences of unintentional interruptions.

[8] Threats to use dependence as an instrument of coercion must be credible (Mangini 2024). Obstacles to the credibility of economic coercion, including domestic politics and institutions, are outside the scope of this paper.

Levels of dependence and expectations about future dependence have also been at the core of explanations of conflict (Copeland 2014). Some think that dependence and interdependence have a pacifying effect, while others think that it invites tension or war.[9] The former camp argues that dependence increases the costs of conflict. States will be less likely to fight or coerce each other because their reciprocal dependencies deter aggression. They fight less because they have more to lose. Interdependence also affects the credibility of coercive threats. States in interdependent relationships are potentially protected from non-military economic coercion via mutually assured economic destruction – neither partner is willing to risk the gains from trade. The potential for blowback undermines the credibility of some threats. State A's dependence on State B is less useful for coercive purposes if State B is also dependent on State A. As Knorr (1975) wrote, "The world has become less coercible" (p 318).

Others argue that trade and dependence exacerbate conflict. States have more to fight over or they fight to break dependencies.[10] Here too, symmetry of dependence is important because asymmetry could moderate the pacifying effects of dependence. Increased dependence may decrease conflict in a dyad by raising the opportunity costs of conflict, but asymmetry allows the less dependent partner greater leeway to coerce the more dependent partner (Gartzke and Westerwinter 2016; Keohane and Nye 1973).

# 3 Measuring Dependence

We first review the two broad extant approaches to measuring dependence: those using aggregate trade statistics and case studies of significant products. While these both have merit under some assumptions, neither one fully incorporates all the ways that trade flows can have different consequences for welfare. We then describe our approach and its advantages.

[9] For a summary see Mansfield and Pollins (2001).

[10] Barbieri (1996) and Mearsheimer (2015)

## 3.1 Measuring Dependence with Aggregate Trade Statistics

Many studies construct measures of dependence using aggregate trade statistics. Typically, scholars follow Oneal and Russet (1997) (OR) who use the sum of bilateral imports and exports divided by GDP. The intuition is straightforward. As bilateral trade increases (the numerator), there is more at stake in a particular trade relationship and therefore more harm in cutting off trade flows. As GDP (the denominator) increases, trade is a lower fraction of the country's overall economic activity, and therefore less harm is done. Additionally, a larger GDP could indicate a greater ability to mitigate harm by increasing domestic production.

Alternative approaches within this category are generally different permutations of aggregate GDP and trade measures combined with bilateral trade flows.[11] For example, Barbieri (1996) and much subsequent work emphasizes trade shares. Country $i$'s dependence on country $j$ equals the value of trade for the dyad $ij$ divided by $i$'s overall trade across all dyads. OR and Barbieri also use extensions of these measures to capture symmetry in a dyad.[12]

With some partial exceptions described below, these approaches share an implicit assumption that every dollar of lost trade is equally harmful for welfare. There are three major ways that this assumption is violated.

First, trade flows vary in the availability of a substitute supplier of that good. Some trade flows are more easily replaced by production from another trading partner.[13] The Philippines imports $47\%$ and $19\%$ of its steel from China and Russia respectively. None of the remaining sources make up more than $8\%$ of their imports. Malaysia, on the other hand, imports $26\%$ and $19\%$ from its two largest partners, China and Japan. Two other countries make up $12\%$ of their imports, and a third makes up $8\%$. Malaysian steel imports are more evenly spread across different producers, compared to the concentrated import origins for the Philippines. Replacing a trade flow that represents a greater percentage of total imports is harder than replacing a flow that is one among many. Mansfield and Pollins

[11] Gartzke and Li (2003).

[12] OR describes trade interdependence as the minimum of bilateral dependence in a dyad and trade asymmetry as the maximum. Barbieri uses a measure of dyadic trade symmetry equal to $1 - |(\text{trade share})_i - (\text{trade share})_j|$ and a measure of trade interdependence equal to $\left(\sqrt{(\text{trade share})_i * (\text{trade share})_j}\right) * \left(1 - |(\text{trade share})_i - (\text{trade share})_j|\right)$.

[13] Kim, Liao, and Imai (2020), Gray and Potter (2012).

(2001) and Barbieri (1996) recognized that the ease of replacing a lost trade flow with an alternative partner affected dependence. Barbieri's trade share measure $\left(\frac{\text{trade}_{ij}}{\text{trade}_{i}}\right)$ was intended to capture this.[14]

Second, flows vary in the availability of a substitute good. Not all goods have readily available substitutes. It is less disruptive to substitute brown rice for white rice, compared to finding a substitute for a specialized pharmaceutical. $10M of rice imports and $10M imports of chemotherapy drugs will have both have the same impact on measures based on aggregate trade statistics, even though substitutability means they have very different implications for welfare. Some studies of dependence have incorporated the ease with which you can find substitutes.[15] They generally use static measures of import demand elasticity at the industry level.

Third, some trade flows are in final consumption goods but others are in intermediate products. Intermediates are goods that are inputs (or inputs into inputs…) of other goods. Increased fragmentation of production along global value chains was a huge driver of intermediates trade.[16] Intermediates trade has comprised a substantial portion of global trade over the last three decades.[17] Osgood (2018) calls the ability to source intermediates inputs one of the "primary drivers of producer preferences" over liberalization.

The welfare effect of interrupting trade in final goods is direct and localized. The welfare effects of interrupting intermediates trade are more complicated, since those disruptions ripple down the value chain. The degree to which imported intermediates affect downstream production varies across countries and time, but also across industries and firms within industries.[18] If imports of integrated circuits (chips) were interrupted, this has implications for firms that use chips as inputs to circuit boards, which are inputs into electronic devices, which are inputs into the production of myriad downstream goods. Again, interruptions to final goods and intermediates have identical effects on measures based on aggregate trade statistics, but the full implications of those interruptions differs drastically.

[14] F. R. Chen (2021) analyzes how alliance networks amplify the potential trade costs of disputes.
[15] Gowa (1995), Polachek (1997), Crescenzi (2003), Liu and Yang (2025)
[16] Hummels, Ishii, and Yi (2001).
[17] Miroudot, Lanz, and Ragoussis (2009).
[18] Osgood (2017).

Though some extensions of aggregate trade measures account for one of the three considerations above, none account for them all. Most applications still default to the baseline OR or Barbieri measure.

## 3.2 Measuring Dependence with Significant Products

The second existing approach studies trade in a small number of products which are known to be very difficult to substitute. Many of the products chosen, such as oil and semiconductors, are intuitively critical to the global economy. The underlying assumption is that a country's dependence on an entire trade relationship is correlated with its dependence on the chosen products. Scholars studying resource competition analyzed the relationship between oil and conflict. States which depend on oil imports might use military means to secure their supply (Westing 1986; Klare 2007). Zeng (2024) incorporates a list of significant goods into a measure of the externalities of trade. Global value chain disruption during the COVID-19 pandemic made policymakers concerned about access to semiconductors, an extremely widely used intermediate product (Farrell and Newman 2020; L. S. Chen and Evers 2023).

Unlike aggregate trade statistics measures, this approach can differentiate between types of trade flows. However, this approach also falls short of a full accounting of dependence. First, the modern global economy includes trade in many products. The strategic goods approach misses cases where a state's political leverage does not derive from a limited number of products. Small amounts of dependence in a large number of products add up. This approach also uses a binary classification of flows as strategic or not, but provides no method of weighting the importance of different strategic products. Second, the modern global economy is dynamic. The relevance of any case study of a particular product might quickly become irrelevant. Some products may become significant in unanticipated ways. For example, COVID-19 laid bare the importance of seemingly unimportant items like masks.

## 3.3 Estimating Dependence in the Modern Economy

The ideal measurement of dependence requires a full accounting of how an interruption in trade affects a country's welfare. This measurement should account for three major features of modern international trade: substitutability, intermediates trade, and the availability of alternative trading partners. It should do so for all trade flows, not just a small subset of significant ones. Ideally, it should be microfounded in trade theory. Creating an estimate of dependence with all of these features is daunting. In principle, such an estimation could be undertaken using a structural model of bilateral trade flows. Historically, the main obstacle to such an exercise was the proliferation of models of international trade, each presumably having different implications for the gains from trade. The main tool for understanding comparative advantage trade, the Ricardian model, was not amenable to studying the gains from trade between more than two partners (Helpman 2014). Multi-country generalizations of the Heckscher-Ohlin model did not enjoy robust empirical support, making it difficult to use them as the basis for calculating the gains from trade (Bowen, Leamer, and Sveikauskas 1987; Trefler 1995). Empirical models based on a gravity-like equation were good at predicting observed trade flows, but they were not initially derived from a theoretical model of trade. The challenge was not necessarily finding a model of trade which could describe dependence, but rather choosing the right model from among the many options available.

Major developments have gradually made it possible to construct a direct estimation of trade dependence. First, Eaton and Kortum (2002) developed a quantifiable multi-country generalization of the Ricardian model. This generalization was a member of the class of gravity models. Suddenly, by virtue of its newfound connection to Ricardian trade and its previously established robust empirical support, the gravity model approach took pole position in the race for the leading model of trade theory. But there was a litany of seemingly equally valid possible variations on the gravity model.

In a major paper, Arkolakis, Costinot, and Rodríguez-Clare (2012) (hereafter ACR) showed that all variations within a very wide class of trade models generate exactly the same gains from trade, tied to a gravity equation. Moreover, the gains from trade in this class depend entirely on a small number of parameters that can be estimated from standard trade data. Crucially, these parameters have natural mappings to features of the global economy that are not captured by existing measurements. The simplicity of the estimation procedure and its wide applicability greatly reduces the complexity of estimating dependence and strengthens the connection between the theory of trade and the concept of dependence.

ACR derive an expression for the welfare effect of an interruption to trade, i.e. a trade shock, as a ratio $\hat{W}_j = W_j'/W_j$ where $W_j$ is the economic welfare of country $j$ in the no-shock scenario and $W_j'$ is its welfare in the scenario with the shock. This is ideal for studying dependence because the $\hat{W}_j$ formulation of welfare explicitly models the counterfactual nature of dependence – it compares two scenarios, one with a shock and one without. We express welfare changes as:

$$\hat{W}_j = \Pi_s (\hat{\lambda}_j^s)^{\eta_j^s/\beta_j^s \varepsilon^s} \tag{1}$$

where $\beta_j^s$ is the share of intermediate products in production in sector $s$ and country $j$, $\varepsilon^s$ is a trade elasticity for sector $s$, $\eta_j^s$ is the pre-shock consumption share of sector, and $\hat{\lambda}_j^s = (\lambda_j^s)'/\lambda_j^s$ is a ratio of the share of domestic expenditure across the scenarios. Remarkably, the quantity $\hat{W}_j$ is expressible in terms of four parameters, three of which (intermediates share $\beta_j^s$, the trade elasticity $\varepsilon^s$, and the share of domestic expenditure before the shock $\lambda_j^s$) can be directly observed or estimated from data. For ease of reading, we suppress notation for years, indexed by $t$.[19]

Two of those parameters immediately incorporate things we highlighted above: product substitutability and intermediate inputs. The interpretation of $\varepsilon$ depends on the particular underlying model of trade, but the canonical interpretation suffices to build intuition here. A smaller (less negative) elasticity means that an import flow is less sensitive to trade costs. A smaller elasticity reflects how a particular trade flow is persistent even as trade costs rise, indicating its greater importance. The welfare expression places greater weight on flows in sectors with smaller elasticities.

For an affected country and a sector, $\beta_j^s$ describes the (inverse) intermediate input shares. A higher value means the sector relies less on intermediate input shares. A sector that relies more on intermediate inputs is one in which there will be greater amplification of input/output feedback in any trade

[19] Appendix A shows the derivation of this expression from Costinot and Rodríguez-Clare (2014).

disruption. As input shares increase ($\beta_j^s$ decreases), a sector is more damaged by disruptions in its inputs from intermediate goods. The expression places greater weight on such a sector.

The share of domestic expenditure without a trade shock, $\lambda_j^s$, is observable from data. The share of domestic expenditure in the scenario with the shock $(\lambda_j^s)'$ is the one remaining parameter which is unobserved and therefore cannot be estimated from data. ACR note that this quantity is known with certainty under autarky: the share of domestic value added must be $100\%$. ACR calculate the total welfare gains from trade relative to autarky by plugging in $(\lambda_j^s)' = 1$. There is no way to know with certainty what the domestic share of value added will be in other scenarios. There are two margins of adjustment that could impact the share $(\lambda_j^s)'$ in the event of an interruption in trade with one partner. First, the domestic economy could adjust to the new prices by increasing production of some goods and decreasing production of others. Second, the alternative trading partners could adjust their exports in response to the new prices. Both adjustments could blunt the negative welfare effects from interrupting trade. Our compensation measure, described below, incorporates the second margin of adjustment.

### 3.4 Upper bound dependence and compensation dependence

Our first new measure estimates dependence using the above formula. Consider the effect on the welfare of the target state $j$ if sender state $i$ were to cease exporting to $j$.[20] To reduce the costs of this trade stoppage, the state might adjust its production or its imports from alternative partners. Any adjustment is for the purpose of increasing welfare. Therefore, the maximum reduction in welfare that state $j$ could experience when state $i$ severs its trade relationship occurs when domestic production in $j$ and the exports from alternative trade partners are unchanged. Therefore, the welfare expression – assuming zero imports from country $i$ and holding all other exports and domestic production constant – represents an upper bound on the opportunity cost of interrupted trade.

This value, which we call *upper bound dependence,* is our first major new measure of dependence. It is a direct measure of the highest possible amount of dependence in a given bilateral trade relationship.

[20] This is also equivalent to considering the effects if $j$ were to cut off its imports from $i$ with tariffs or other restrictions.

Unlike measures based on aggregate statistics, upper bound dependence can be interpreted directly. Its value represents the fraction of country $j$'s initial welfare remaining after country $i$ ceases to export all goods to $j$ holding all other production values and exports constant. In other words, it is the lowest possible fraction of country $j$'s welfare remaining if country $i$ ceases exports. An alternative interpretation of upper bound dependence is that it is a short run measure of dependence before enough time has passed for the new equilibrium to be reached.[21]

Recall that the ACR approach clearly incorporated two of the three major changes to the world economy, substitutability and intermediates trade, but it did not directly incorporate the ability of alternative trade partners to compensate for lost trade. Similarly, while useful, upper bound dependence also does not directly incorporate this. Without further strong assumptions about the cross price elasticities for all possible goods and suppliers, it is not possible to directly estimate how well alternative trade partners could replace the lost trade.

However, a single assumption can enable meaningful progress toward incorporating the availability of alternative trade partners. Assuming that the composition of the export mix from unaffected partners remains constant, we can ask: how much would unaffected trade need to increase to fully replace the lost welfare if country $i$ ceased exporting to country $j$? In other words, how much would unaffected trade need to be "scaled up", either by intensifying existing trade flows or forging new ones, in order to make the target "whole" again? We call this value *compensation dependence*. It captures the idea that the existing trade network can buttress against any one state's dependence on another.[22]

Figure 1 depicts both measures graphically. The top pane shows the *status quo ex ante*, with B trading various amounts in various industries with three partners ($A$, $C$, and $D$). The thickness of each arrow shows the value of each trade flow. The dark middle bar shows $B$'s welfare in each scenario. Suppose $A$ cuts off exports to $B$, as in the bottom left. $B$'s welfare decreases to some fraction of its original value. This drop is the upper bound measure. Now, suppose that C and D increase

[21]We construct our measures based on a stoppage of trade in all sectors, but the upper bound measure can also be calculated in the same way at a sector-specific level.

[22]Specifically, we find a scalar, $\alpha > 1$, that restores $\hat{W}_j$ to be just greater 1 when unaffected flows are increased by a factor of $\alpha$. Appendix A walks through a numerical example for the calculation of both measures.

their exports to $B$ enough to raise B's welfare back to its original level.[23] The compensation measure describes how much thicker each of those export flow arrows need to become to make $B$'s welfare "whole" again.

For a tangible example, consider the Western export restrictions targeting Russia following its invasion of Ukraine. Upper bound dependence describes the harm to Russian welfare from lost access to Western goods, based on the degree to which they are intermediate inputs and the availability of substitute goods. Compensation dependence describes the degree to which Russia can find substitute suppliers, like China, for things that previously originated from sanctioning countries.[24]

To reiterate, the main advantages of the upper bound and compensation measures is that they directly estimate the opportunity cost of an interruption in trade across the entire economy and they take into account key features of the modern global economy. The upper bound measure indicates a ceiling on the total possible dependence in a bilateral relationship. It up-weights flows in sectors that are harder to substitute ($\varepsilon$) and flows in sectors that are intermediate inputs into downstream production ($\beta$). The compensation measure accounts for the third feature of the modern economy by incorporating how easily a state's trade network could compensate for an interruption from a particular partner. These two measures are directly interpretable as statements about welfare and they depend on weaker assumptions than existing measures that rely on aggregate statistics. The two measures have relative strengths. The compensation measure captures longer-term adjustments that states can make by using alternative suppliers, but it also entails additional assumptions that the upper bound measure does not require. The compensation measure may therefore be more appropriate for analyses of interactions taking place over longer timeframes. Upper bound may be appropriate for shorter-term interactions that are resolved before states can adjust with compensation, such as episodic sanctions threats.

There are some margins of adjustment that may affect welfare which are not captured in our approach. For example, we cannot account for variation across countries or time in their ability to finance consumption by borrowing. We also cannot account for variation in the ability of countries

[23] Or equivalently, a new trade tie is forged that has the same effect.

[24] For a recent example of the growing literature on the consequences of sanctions on Russia and fragmentation of trade into blocs, see Campos et al. (2023).

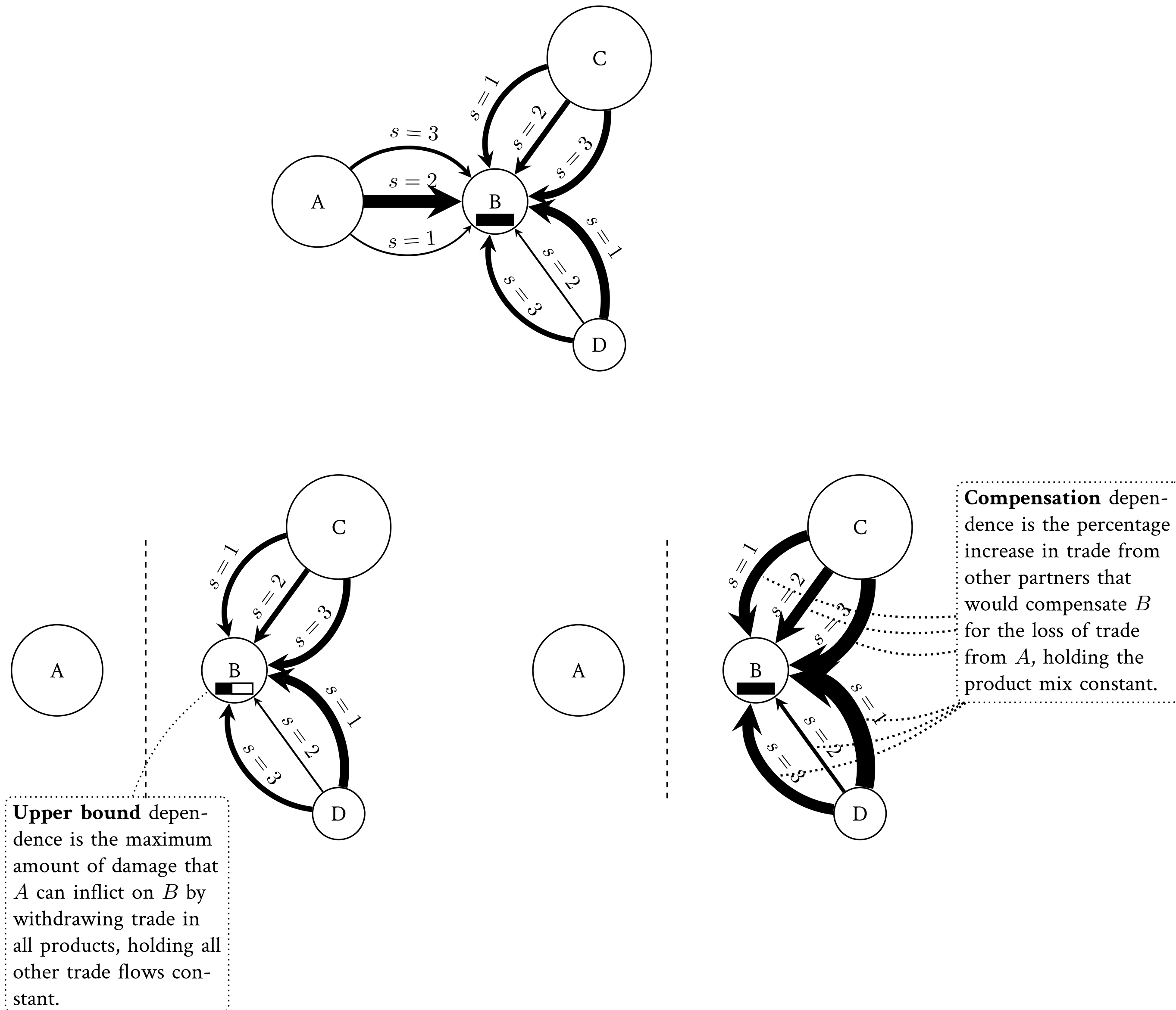



Figure 1: Upper Bound and Compensation Dependence. Four countries are depicted in each panel of the figure by circles. Trade volumes are depicted as directed edges, where the thickness of the edge is proportional to the value of country $B$'s imports. The top inset of the figure depicts an initial scenario where country $B$ imports three goods $s = \{1, 2, 3\}$ from three countries $A$, $C$, and $D$. The small rectangular bar placed inside the circle of country $B$ depicts their welfare in the initial scenario; the bar is filled completely indicating their welfare starts at $100\%$. The lower left inset shows a scenario in which country $A$ has ceased to export to country $B$. The rectangle is only partially filled indicating that country $B$'s welfare has suffered. The magnitude of the decrease in welfare is the upper bound measure. Note that in this scenario the exports from countries $C$ and $D$ are unchanged. The lower right inset shows the compensation measure. The rectangle is now fully filled once again because the exports from countries $C$ and $D$ have been increased to compensate for the welfare losses caused by $A$'s cessation of exports. The export mix, depicted by the relative thicknesses of the edges, remains unchanged in all scenarios.

to adapt using technological advances. We can partially account for variation in countries' ability to increase domestic production. If a country already has a large domestic value added in a particular sector, then our approach downweights that sector. We would note that some of these adjustments likely take a long time. For example, a country cannot rapidly advance technology to compensate for welfare losses. Ramping up domestic production also takes time and there is no guarantee that a country will reach the efficiency level of its original trade partners.

There may be unobserved factors which impede the ability of a state to "scale up" its trade with particular alternate partners in response to an interruption in trade. The compensation measure already partially accounts for these factors. Many factors which would impede scaling of a trade flow already impede trade *ex ante* – before a sender interrupts trade. Relatively low initial trade would imply a relatively large scaling factor, and therefore a relatively large compensation value. Thus, our measure already accounts for any factors which do not change when the sender chooses to interrupt trade.

Our measure also describes welfare in terms of aggregate national utility, or equivalently, the utility accrued to a representative consumer from consumption. We do not model ways in which a national leader might care more or less about specific subnational groups. For example, a democratic leader might care more about the welfare of citizens in their party or an authoritarian might have less concern for aggregate welfare.

Some related literature studies dependence and geopolitics under the heading of "geoeconomics."[25] Thoenig (2024) uses a structural gravity approach to estimate the opportunity costs of war from forgone trade and the destruction of production capacity. Clayton, Maggiori, and Schreger (2024a) model a hegemon who can coerce others by threatening to disrupt particular flows in global commerce. Clayton, Maggiori, and Schreger (2024b) derive a hegemon's power over a target country from a similar underlying economic model to ACR and incorporate manipulation of finance as a coercive lever. Another related literature describes "weaponized interdependence."[26] This literature emphasizes the coercive leverage that the United States enjoys because of its central position in finance and information

[25] For a recent summary, see Mohr and Trebesch (2025).

[26] Farrell and Newman (2019), Daniel Drezner, Farrell, and Newman (2021).

networks. Like us, they disagree with conventional wisdom about complex interdependence, but they de-emphasize trade flows as a key source of dependence. We find patterns contradicting conventional wisdom even in dyadic trade relations.

# 4 Data and Empirical Strategy

The expression for assessing welfare changes after a shock is $\hat{W}_{jt} = \Pi_s(\hat{\lambda}_j^{st})^{\eta_j^{st}/\beta_j^{st}\varepsilon^{st}}$, with year superscripts included. Here, we describe the data sources and calculations for each parameter. Our measures cover $76$ countries for the years 1995-2020. We categorize flows using the $26$ industries from the Organisation for Economic Co-operation and Development's (OECD) Trade in Value Added (TiVA) 2023 dataset.[27]

## 4.1 Trade elasticities

Trade elasticities describe the degree to which imports into country $j$ from country $i$ change as iceberg costs between the two countries, $\tau_{ij}$, change. Caliendo and Parro (2015) show that we can recover an estimate of these elasticities from any model that results in a gravity equation for trade, including the broad class of models from ACR. The procedure uses two inputs – trade flows and tariffs – to estimate $\varepsilon$. This procedure expresses trade flows between three countries as an odds ratio "triplet." This is especially useful because it simplifies an expression of $\varepsilon$ as a function of trade flows between the three countries, $i$, $j$, $k$, and a directed-dyad-specific trade cost: tariffs ($\tau$).[28]

With trade flow and tariff data, the triplets can be constructed and $\varepsilon$ can be estimated using OLS.[29] Theoretically, elasticities must be negative. An increase in iceberg costs should decrease trade. In

[27]The TiVA sectors are aggregations of the International Standard Industrial Classification (ISIC) Rev. 4 sectors. Country and industry lists are in Appendix A.

[28]The expression is $\frac{X_{ij}X_{jk}X_{ki}}{X_{ji}X_{kj}X_{ik}} = (\frac{\tau_{ij}\tau_{jk}\tau_{ki}}{\tau_{ji}\tau_{kj}\tau_{ik}})^{\varepsilon}$, and note that we have omitted time and industry subscripts for readability. This means that symmetric trade costs (e.g. distance between countries) and monadic variables (e.g. the size of their economies) will cancel out, because they appear in both the numerator and denominator. This approach also entails an orthogonality condition, which says that, if we express iceberg costs as a function of tariffs, symmetric and monadic variables, then the error term is orthogonal to tariffs.

[29]For alternate methods for estimating trade elasticities, see also Boehm, Levchenko, and Pandalai-Nayar (2023) and Bohlmann (2021) for an overview.

practice, with OLS, estimates are sometimes positive. We use a Bayesian regression to ensure that estimated elasticities are negative. We set the prior distribution for the regression coefficients to be normal, with a mean of $-4.5$ and a standard deviation of $1$.[30] We constrain the posteriors to have a maximum of $-0.25$ and an unbounded minimum. This constraint ensures that we get theoretically sensible elasticity estimates that still have meaningful variation across time and industry.

Our estimates of $\varepsilon$ are industry-specific. Elasticity estimates are global; they are not importer or exporter or dyad-specific. They vary by year and show substantial variation across time.[31] The trade flow and tariff data both come from the UNCTAD Trade Analysis and Information System (Trade and Development 2024).

## 4.2 Consumption Shares, Import Penetration, and Intermediate Products

The variable $\lambda_j^{st}$ describes the share of domestic expenditure in sector $s$ in year $t$. It is one minus the import penetration ratio, where the import penetration ratio is the share of total expenditures in an industry that are from imports. We calculate $\lambda_j^{st}$ as follows (again dropping industry and year subscripts): $1 - \frac{\text{Imports}}{\text{Production - Exports + Imports}}$. The import/export values are totals, across all partners.

Recall, $\lambda_j^{st'}$ refers to a possible counterfactual where one of $j$'s partners, $i$, cuts off exports of a certain product to country $j$, with a corresponding value of $x_{ij}$. For our upper bound measure, $\lambda_j'$ equals $1 - \frac{\text{Imports} - x_{ij}}{\text{Production} - \text{Exports} + \text{Imports} - x_{ij}}$. Data for domestic production and bilateral imports and exports come from the OECD's Trade in Value Added (TiVA) dataset. The consumption shares ($\eta_j^s$) are calculated from the same data and defined as $\frac{\text{Production} - \text{Exports} + \text{Imports}}{\text{Total Production} - \text{Total Exports} + \text{Total Imports}}$ where the term "Total" aggregates across all sectors and trade partners by state-year.

The share of domestic value added production, $\beta_j^s$, is measured at the country-year-industry level. The value of $\beta_j^s$ reflects the importance of intermediate products in that sector. These measures also come from the TiVA dataset.[32]

[30] The approximate sample average from Caliendo and Parro (2015).

[31] See Appendix A.

[32] Note that TiVA sometimes has zero or negative values for the domestic share of value added in production. For these observations, we replace the value with the global mean for the domestic value added of production for that industry-year. This is akin to assuming that those observations are not representing countries that have radically different production technologies from the rest of the world.

# 5 Comparison of measures

The upper bound and compensation measures differ meaningfully from measures based on aggregate statistics. Here, we provide further construct validity for our measures by showing that they diverge from aggregate statistics measures in ways that we would expect. Figure 2 shows how the compensation, OR, and Barbieri measures correlate over time. For each country, we calculated the maximum value of each dyadic dependence measures for each year. This monadic quantity is a good starting point because it asks "of all a country's dyadic dependencies, what is the most dependent they are on a single partner?"[33] In earlier years, our measures are more strongly correlated with aggregate statistics. These correlations deteriorate, especially in the 2001-2010 time period.

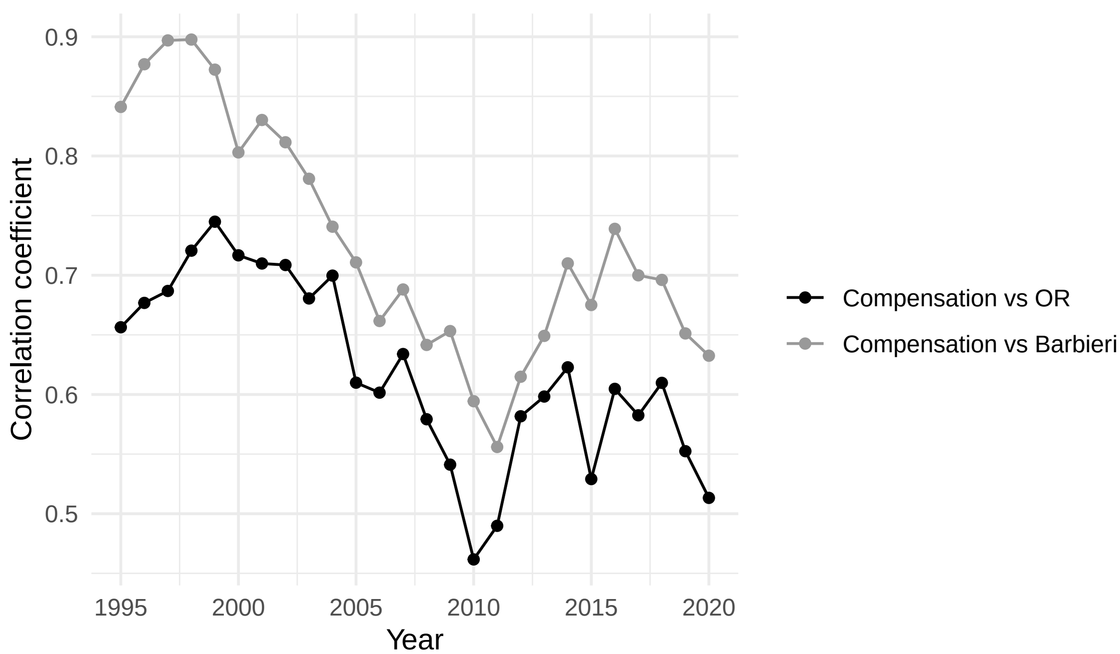



Figure 2: Correlation coefficients over time between values of compensation dependence and the Oneal–Russett and Barbieri measures. Dependence values are the maximums of each measure at the country-year level.

The increasing divergence in measures over time makes clear why our measures have substantial advantages over conventional approaches. This divergence occurs because there is much variation

[33] Appendix B shows similar results using average dependence levels. We also show similar results using our upper bound measure.

across time, industries, and countries in the three key differences between the two measures: accounting for substitutability, intermediates trade, and the availability of alternative trading partners.

Consider intermediates trade first. The United Nations classifies trade flows by Broad Economic Categories (BEC): consumption goods, intermediate goods, and capital formation.[34] BEC categorizations therefore give a broad measure of how much of a country's imports and exports fall into each use category. Countries vary greatly in the percentage of their imports consisting of intermediates, according to BEC categories. This percentage ranges from roughly $6\%$ to $25\%$, with a mean and median of roughly $15\%$. There is also a great deal of within-country variation over time, in terms of where countries fall in this distribution. To see this, we ranked each country by year in terms of the percentage of their imports made up of intermediates. From 2010-2021, 48 out of 78 countries in the BEC dataset changed their rank by 5 places or more. Thirty two countries changed their rank by 10 places or more! The import profiles of many countries, in terms of the percentage of their imports made up of intermediates, changed a great deal over that decade. Some increased this percent, while others decreased, and this movement was spread all over the distribution.[35] There were similar changes in the preceding decade, though slightly smaller in magnitude.

The tremendous amount of variation across countries, industries, and time in the concentration of trade among partners also helps drive divergence between our measures and conventional ones. Some countries import a substantial amount of value added for a particular industry from a small number of partners, while others' imports are spread over many partners. The typical country imports $80\%$ of its value added in mining and energy from only 3-4 partners. Though, for some countries, their mining and energy imports are spread over as many as 13 partners or as few as 1. For the average country, $80\%$ of their food imports are spread over 12 partners, but this too ranges from 2 to over 25, depending on the country. The dispersal of imports across partners also varies over time.[36]

Variation across industries and time in estimated elasticities of trade also contributes substantially to divergence in measures. From 1995-2021, the industry with the largest over-time variation

[34] The first two categories are self-explanatory. Capital goods are used in production but not *used up*.

[35] See Appendix B for full descriptions and plots.

[36] See Appendix B.

is "Chemical and chemical products" (C20). It has a minimum elasticity estimate of approximately $-18.3$ in 2021, compared to $-1.8$ in 1995. In contrast, the industry "Mining and quarrying, energy producing products" (B05_06) had a much tighter range over time, with the difference between its minimum and maximum being only $0.7$.

# 6 Global Dependence and Interdependence

## 6.1 Dependence over time

Has dependence increased over time? Using our compensation measure, we can show that the answer is: yes, very quickly, and overwhelmingly driven by China. With aggregate statistics, the story is less clear. To describe global dependence, we again look at the maximum value of the compensation measure for each country-year observation across its partners. The maximum value asks "how dependent is your most dependent relationship." It is a good way to summarize dependence because the maximum dependency represents a kind of worst case scenario for that state. It describes the height of potential economic coercion targeting that state, since no other trade partner can do more damage. The maximum dependency is also arguably more relevant than, for example, the mean dependence across all of a state's trading partners. A small decline in dependence on a dozen trading partners might be more than cancelled out by a large increase in dependence on a single large partner. Looking at the distribution of maximum dependencies is also theoretically grounded. Ikenberry (2001) and Keohane (1984) argued how hegemonic power profoundly shapes the logic of international cooperation. Studying maximum dependencies describes the international structure of states' dependence on hegemonic power(s).

Figure 3 plots trends in the maximum values of the compensation measure on the left side and in the maximum value of the OR measure on the right side.[37] Since there are many observations per year, we plot the average of the metric across countries for each year and include a third degree polynomial

[37] Since this section is about longer-term, global trends, we focus on the compensation measure and not the upper bound measure. Appendix C discusses when each measure might be more appropriate and trends in the upper bound measure.

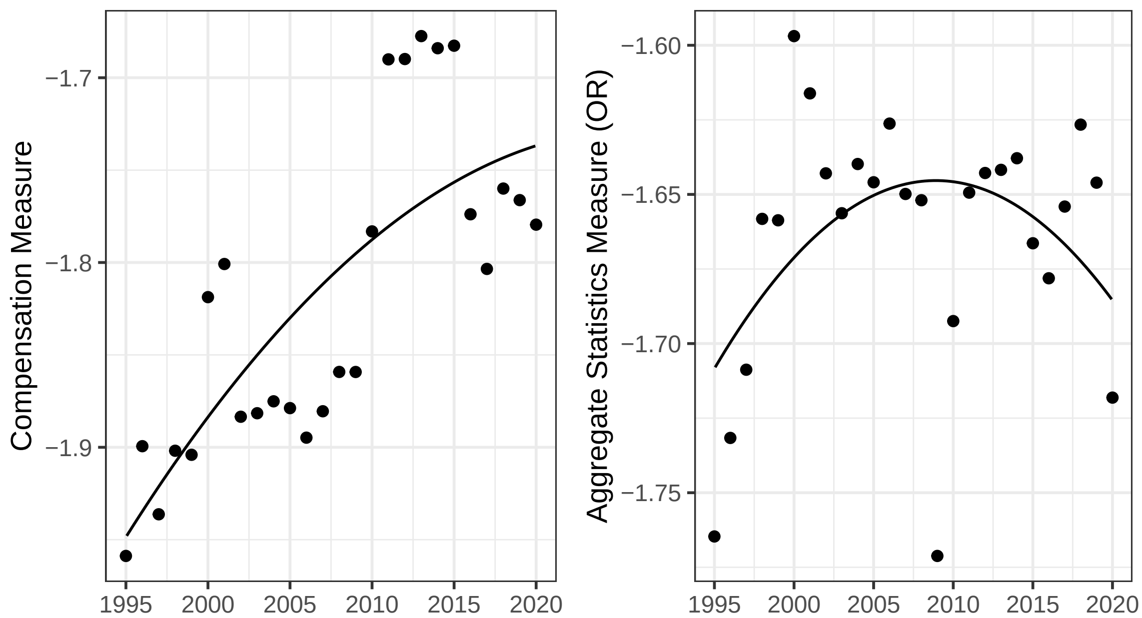



Figure 3: Bin scatter of the maximum values of the compensation and OR dependence measures, logged and normalized to the unit interval to equalize their support and facillitate comparison.

line.[38] We take logarithms due to the high skewness in the measures from a few states being highly dependent. Then, measures are normalized to the unit interval to equalize their support.[39]

The largest values of the compensation dependence measure have generally increased over time. OR dependence has also increased, but in a more non-monotonic way. In particular, the OR measure is sensitive to years in which a global crisis caused a temporary decrease in trade as a share of world GDP. OR dependence is quite low in 2008/2009 because of the financial crisis and again in 2020 as COVID decreased trade. However, lower levels of trade may indicate lower levels of dependence according to the OR measure, they do *not* necessarily mean lower levels of dependence according to our measures. Suppose a shock (like the financial crisis or COVID) interrupted nearly all trading relationships. In some ways, dependence has gone down since a country now trades less with each partner and overall. But at the same time, dependence on the remaining relationships has increased substantially, even if aggregate trade flows are lower.

[38] We follow procedures for optimal binned scatter plots from Cattaneo et al. (2019), implemented via the `R` package `binsreg`.

[39] The vertical axis is negative since it shows the natural log of a number between zero and one.

Furthermore, there is immense heterogeneity across countries in how compensation dependence has changed over time. Figure 4 shows results from a clustering algorithm designed to detect how changes over time differ across groups of countries.[40] We found three types of trends: countries whose compensation dependence monotonically increased, monotonically decreased, and whose dependence was U-shaped, decreasing and then increasing. All three trends have a common cause: increased dependence on China.

Figure 5 illustrates the role of China in explaining these patterns. The vertical axis measures each state's dependence on China while the horizontal axis measures its greatest dependence on any partner other than China. Often, this is the United States, but not always. The first column shows each country's starting point in 1995. Points above the 45 degree line are most dependent on China while points below the line are most dependent on some other state. The middle and right columns show how each country's dependence on China and the other partner has changed in that time period. Countries are grouped into the same groups as in Figure 4. This helps show why the trends differ for each cluster of countries.

[40] Our preferred clustering technique identifies three clusters using a partitional approach with centroids calculated by barycenter averaging under data time warp and distance measured via global alignment kernels. We implement the clustering using the R package `dtwclust`.

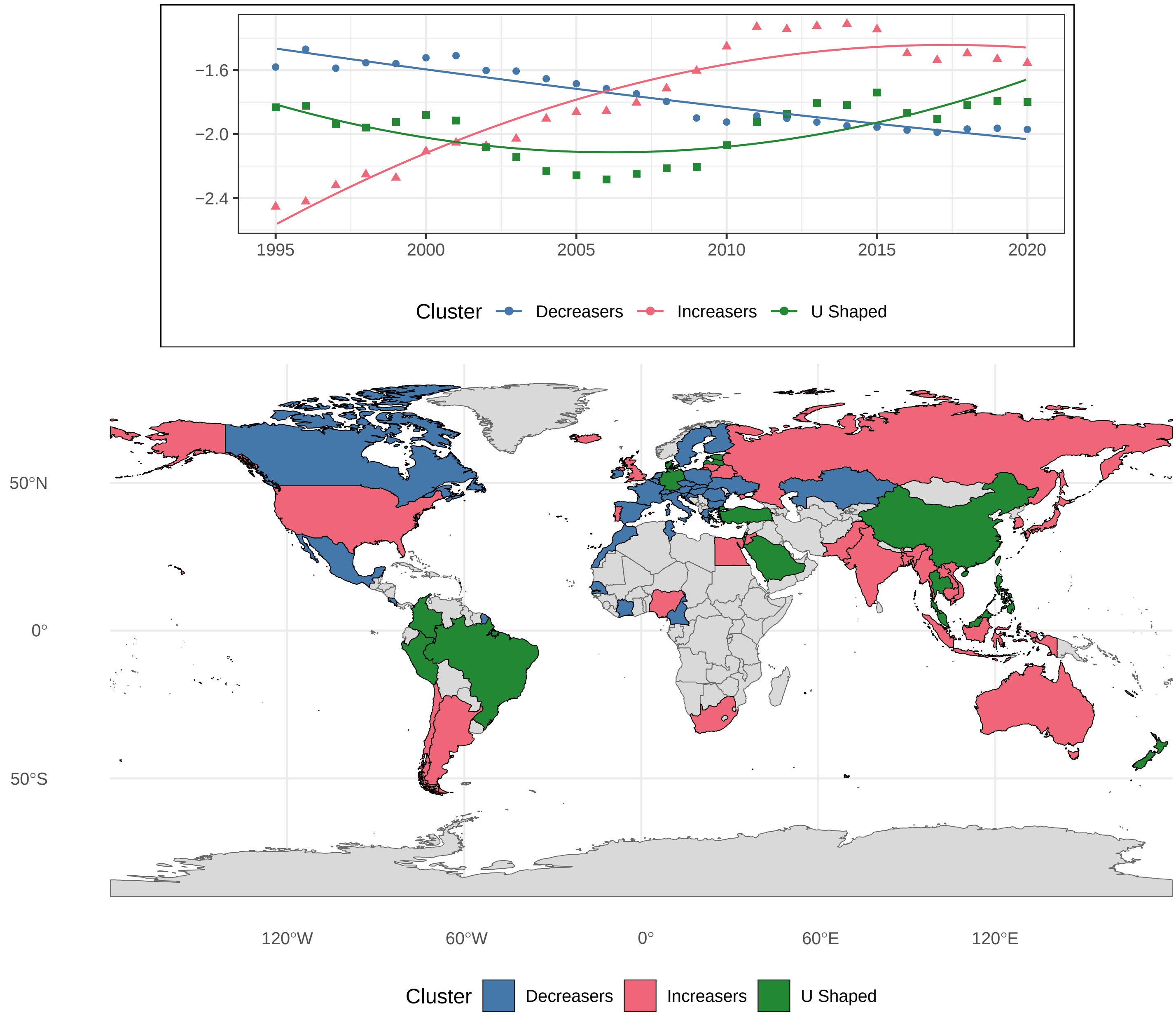



Figure 4: Clustering countries by their trends in maximum values of compensation dependence. Blue countries have decreasing dependence. Red countries have increasing dependence. Green have U-shaped trends.

Consider first the group, with decreasing dependence over time. These states (especially European states) have historically been dependent on traditional powers other than China. Their dots tend to cluster in the lower right portion during the earlier years. Yet, over time, their dependence on China increases. Dependence on their original traditional partners has fallen as China become a more productive alternative trade partner. As indicated by the vectors in the middle and right columns, these states approach, but generally do not cross, the 45 degree line from below.

Consider next the group with increasing dependence over time. States whose dependence is increasing tend to have always had relatively strong economic connections with China. Countries in this cluster cross the 45 degree line relatively early and continue moving towards the northwest corner. They, too, became more dependent on China during its economic rise.

Finally, the U shape states seem to have both patterns occurring simultaneously. Initially, China's rise reduces their dependence on traditionally powerful trade partners like the United States. But then China becomes a superior trading partner causing dependence on China to increase. These points begin relatively far below the 45 degree line, but they quickly cross it and then move northwest.

The story of global dependence between 1995 and 2020 is the story of competition between the United States and China. Dependence on China grew dramatically over time. Figure 6 shows how the measure used gives very different answers for when, how fast, and why this change occurred. The OR measure shows a weak, slow decline in dependence on the US. Since trade with most countries increases with the US over this time, the OR measure (because of how it is constructed) can only explain this by saying that trade with the US has not risen as quickly as GDP growth in its partner countries. The compensation measure tells a different story. The decline in dependence on the US starts much earlier and is much steeper. The US fell further, faster. This means that the additional changes that our measure accounts for – trade in intermediates, sector level trade elasticities, and alternative trade partners – combined to undercut other countries' dependence on the US. The decline is not simply explained by other countries' GDP growth.

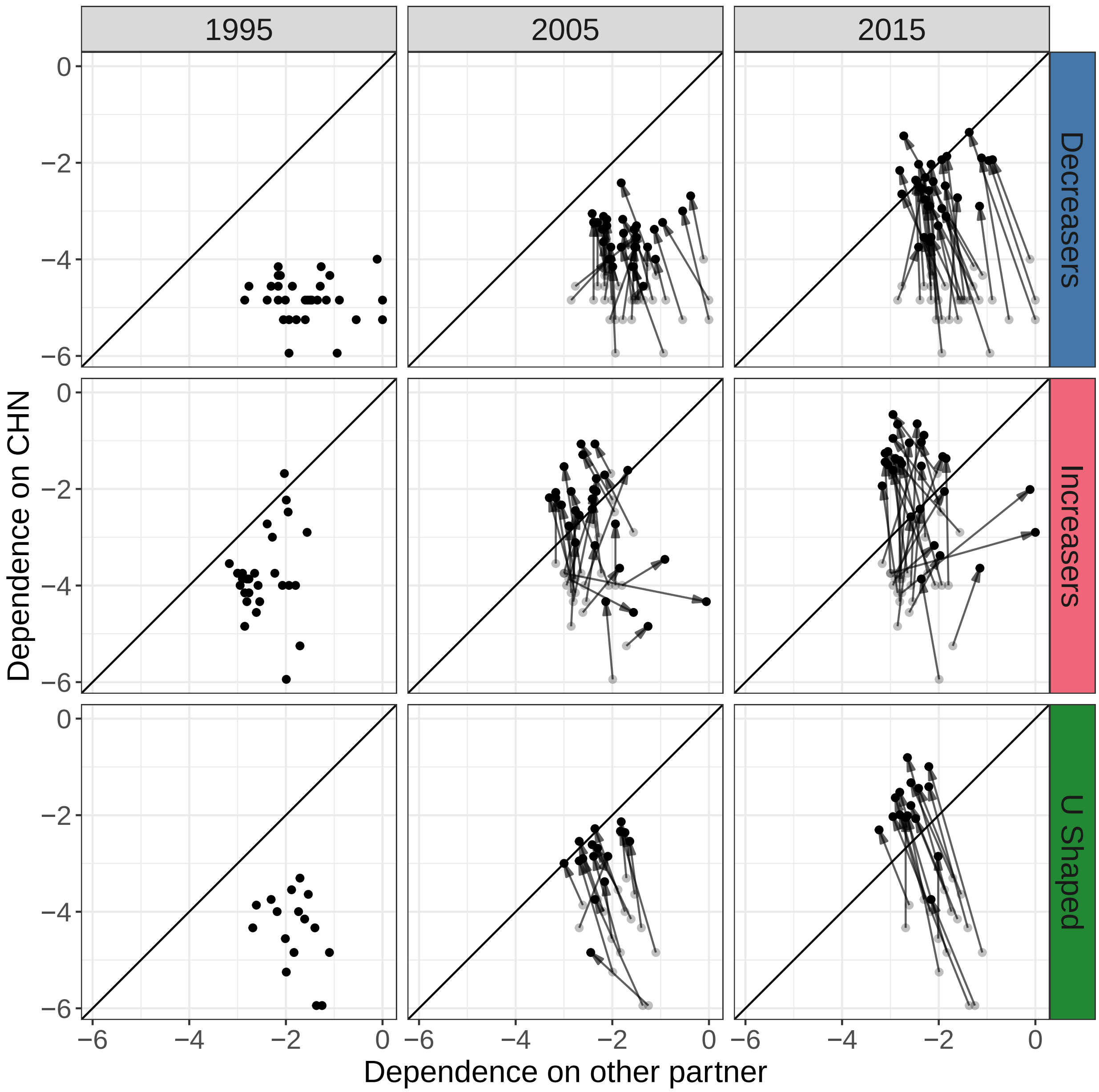



Figure 5: Vectors indicating change over time in a country's dependence on China (vertical axis) and its maximum dependence on any other (non-China) partner. Lines connect the initial values for each state in 1995 to their values in the year shown. The diagonal black line is a 45 degree line. Points above the line are most dependent on China. Dependence is plotted after normalization to the unit interval and after taking the natural log.

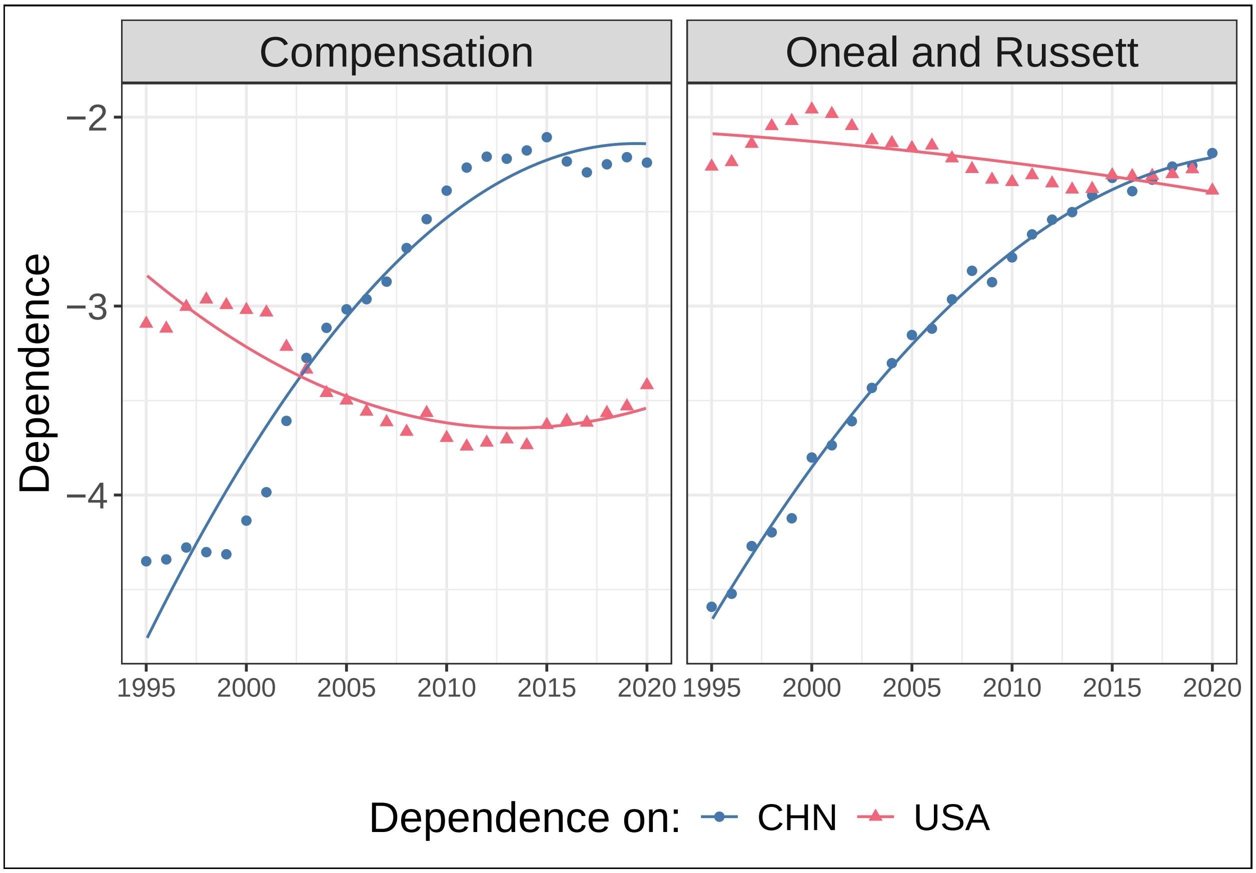


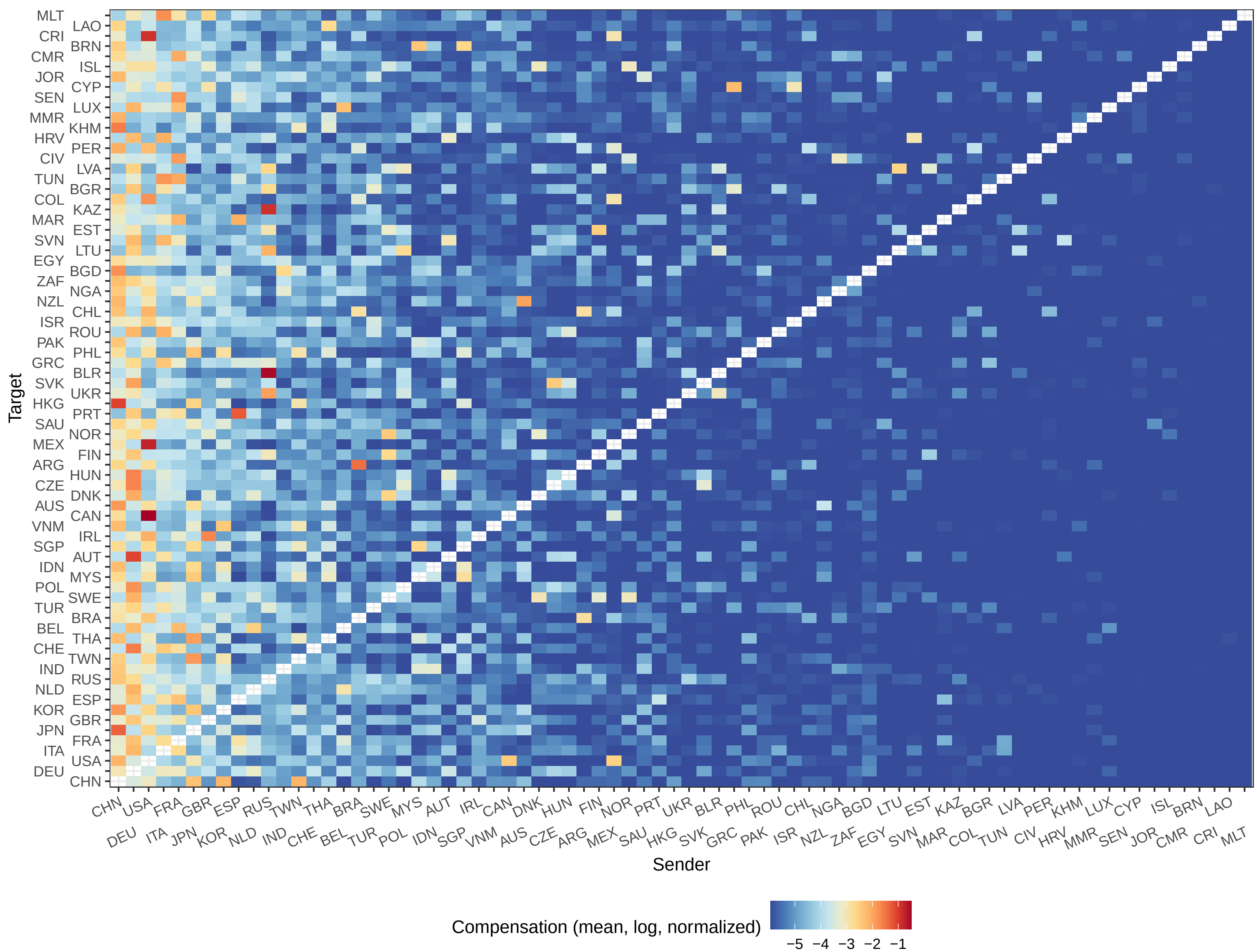

Figure 6: Global dependence on USA and CHN over time

## 6.2 Interdependence over time

How has interdependence changed over time? Using our measures, it has not increased. Dependencies have gotten more asymmetric over time – contrary to trends when using aggregate statistics. Figure 7 illustrates the entire dyadic dataset by averaging compensation dependence across years for each pair of states.[41] The horizontal axis shows "sender" states and the vertical axis shows "targets." The color of each cell represents the compensation dependence of the target state on the vertical axis on the sender state on the horizontal axis. Darker, redder squares mean that the target is more dependent on the sender. We order states by their average dependence as a sender, from left to right.

The plot highlights the extent to which dependence is dominated by a small number of great power sender states. If dependence was symmetric and interdependent then the matrix would also be symmetric. Clearly it is not – there are many brighter colors above the diagonal than below. Most states are highly dependent on China, the US, or Germany. In turn, these great powers depend on relatively few other partners. States of the former Soviet Union tend to be particularly dependent on Russia. The largest dependencies in the entire dataset are in South Asia – Japan and Cambodia are highly dependent on China. These findings are not necessarily at odds with the standard narrative about interdependence. After all, in a hegemonic world, we would expect some degree of concentrated economic power. What matters more to the standard theory is whether the global economy is becoming *more* interdependent over time.

[41] We again focus only on compensation dependence in this section.



Target
MLT LAO CRI BRN CMR ISL JOR CYP SEN LUX MMR KHM HRV PER CIV LVA TUN BGR COL KAZ MAR EST SVN LTU EGY BGD ZAF NGA NZL CHL ISR ROU PAK PHL GRC BLR SVK UKR HKG PRT SAU NOR MEX FIN ARG HUN CZE DNK AUS CAN VNM IRL SGP AUT IDN MYS POL SWE TUR BRA BEL THA CHE TWN IND RUS NLD ESP KOR GBR JPN FRA ITA USA DEU CHN
CHN DEU USA ITA FRA JPN GBR KOR ESP NLD RUS IND TWN CHE THA BEL BRA TUR SWE POL MYS IDN AUT SGP IRL VNM CAN AUS DNK CZE HUN ARG FIN MEX NOR SAU PRT HKG UKR SVK BLR GRC PHL PAK ROU ISR CHL NZL NGA ZAF BGD EGY LTU SVN EST MAR KAZ COL BGR TUN LVA CIV PER HRV KHM MMR LUX SEN CYP JOR ISL CMR BRN CRI LAO MLT
Sender
Compensation (mean, log, normalized)
−5 −4 −3 −2 −1


Figure 7

Over time, dyads have *not* trended towards greater parity in their dependencies. The top two panels of Figure 8 shows trends in interdependence across all dyads, using the compensation measure and the OR measure. For each dyad, we calculate the difference in $i$'s dependence on $j$ and $j$'s dependence on $i$. We then take the absolute value of this difference, for each measure. Smaller values reflect more interdependence. As before, both measures are normalized to the unit interval and log-transformed before taking differences.

For the OR measure, the difference in dependencies for a dyad are steeply decreasing over time, indicating that interdependence is rising quickly. The "average" dyad has trended towards greater parity. This is not the case for compensation dependence. Differences in compensation dependence are very weakly decreasing over time.

The relationship of each state to the hegemon and other great powers is distinctly important for international relations. Thus, we also investigate whether interdependence is increasing according to the maximum degree of dependency for a country. The difference in trends between compensation and OR dependence is even more stark if we focus on maximum values of each measure. The bottom two panels of Figure 8 make the same calculations for differences in dependencies, but using only the maximum value for a country. As above, we take each country and find the partner on whom they are most dependent. Then we take the difference in the dependency measure for that dyad. This asks "Who are you most dependent on, and how dependent are they on you?" It therefore describes trends in parity within a dyad, when looking only at a country's most dependent relationship.

Compensation dependence tells a very different story from the aggregate statistics. Once again, the OR series declines over time, showing that interdependence is rising even among highly dependent partners. But the compensation measure actually shows the world becoming less interdependent among maximally dependent relationships. Countries' maximum values of compensation dependence are increasing, and those partners that they greatly depend on are not becoming corresponding more dependent on them.

One interpretation of these two results is that symmetry in compensation interdependence among all dyads is rising because compensation interdependence has become greatly imbalanced when look-

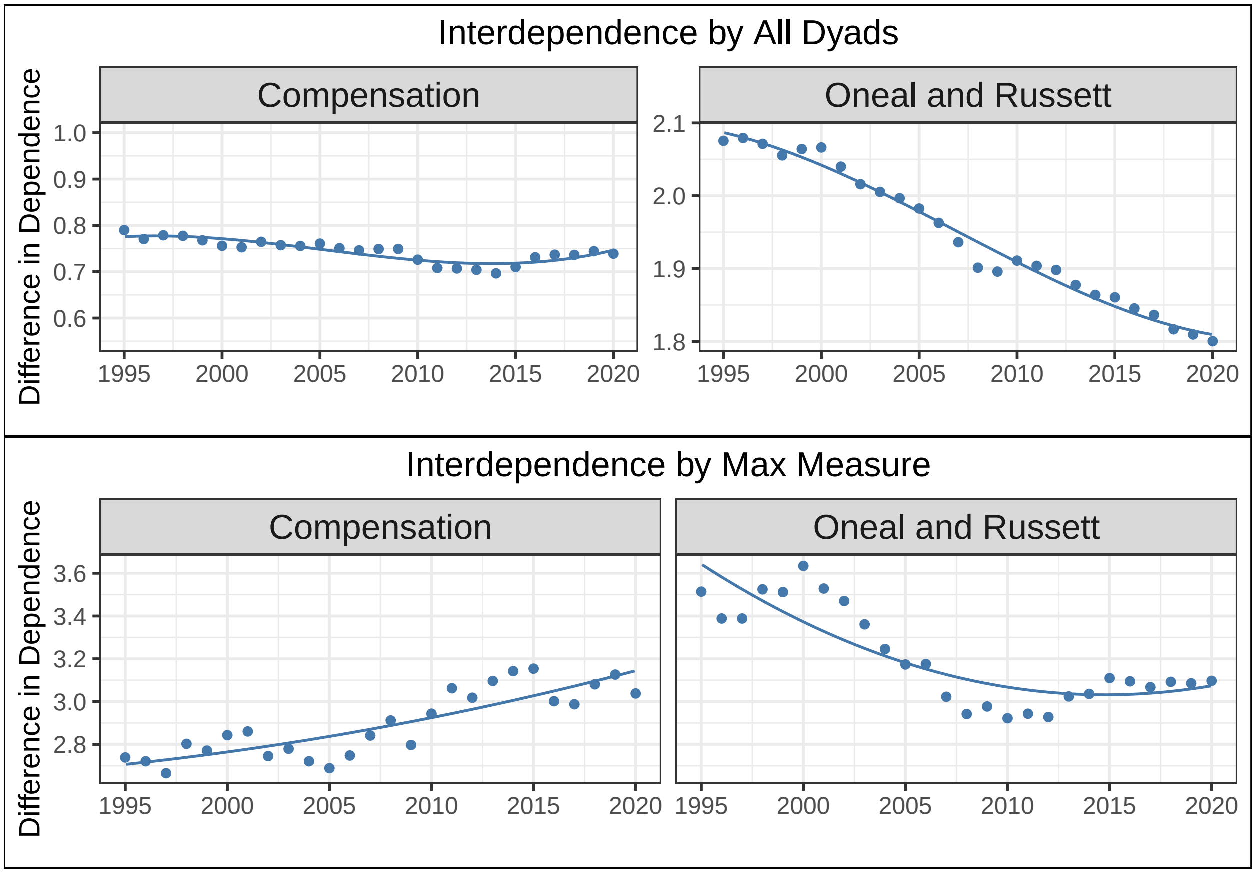



Figure 8: Interdependence over time. Points show differences in directed dyadic dependence over time, averaged across dyads. The top pane shows this difference for all dyads. The bottom pane shows this for maximally dependent dyads.

ing at maximum dependencies. Higher dependence on states like China, in general, increases the symmetry of dependence between states, by comparison. For example, consider two states, A and B. In 1995, an interruption in trade between the two might have caused more economic pain in State A than in State B according to compensation dependence. However, by 2015 both states trade extensively with China. Although they are both now more dependent on China than they ever depended on any other state, an interruption between States A and B is now a relatively minor problem that can be solved by increasing imports from China by a small percentage. It looks like A and B are closer to parity in their mutual dependence, only because they both became tremendously dependent on another partner. Figure 9 shows that this describes the experience of Japan, Korea, and the US as potential targets. This figure shows compensation dependence on China and each country's highest non-China dependencies from 1995. In each panel dependence on non-China states is displaced by dependence on China, and the dependence on China hits a higher peak than with any other state.

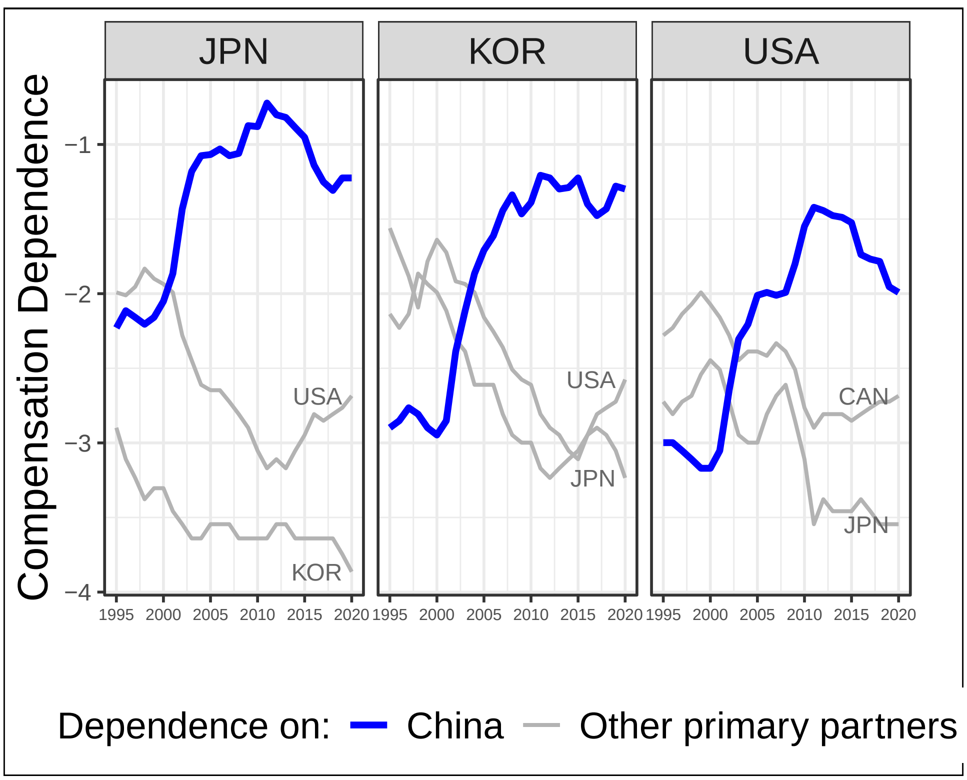



Figure 9: Dependence on China versus primary non-China partners dependencies for Japan, Korea, and the USA. For each country, the grey lines show the countries they dependended on most in 1995. These examples show how interdependence can fall among all dyads even while it rises for when looking at maximum levels of dependence.

## 7 Is Chinese Foreign Assistance a Conduit of Dependence?

Some forces that change dependencies are structural or global, such as the rise of GVC production. And these forces play a major role in changing dependencies on their primary beneficiaries, such as China.[42] To what extent can an individual state manipulate others' dependence on them and their own dependence on others? Whether states can influence dependencies has long been recognized as an important question (Waltz 1979). More recently, the COVID-19 pandemic laid bare the degree to which many supply chains had links concentrated in certain countries. The question has taken on added urgency as the backlash against globalization in many countries has made policymakers more eager to manipulate trade policy for geopolitical gains. In the opening salvos of the Trump administration's trade war, the President used high tariffs to decrease imports from targeted countries.[43] As D. Drezner et al. (2023) describes, "a bipartisan elite consensus has calcified this fear [of excessive dependence]."

China has also proved willing to manipulate trade for political purposes. For example, China retaliated against countries that hosted unsanctioned visits from the Dalai Lama.[44] The specter of economic coercion via trade dependence loomed so large that the European Union preemptively armed itself with a process designed to fast-track retaliatory tariffs against economic coercion. The Anti Coercion Instrument has been called a "bazooka" intended to deter coercion in the first place.[45]

Countries try and inoculate themselves from coercion by decreasing their dependence on others. The CCP touts "national independence" and "self-reliance" as among their key achievements and guiding aspirational goals for policymaking. The CCP's plenary session in 2021 concluded with the adoption of a landmark, overarching resolution in which these terms appear three times in the preamble alone.[46] The "Made in China 2025" initiative stress "indigenous innovation" and "self-sufficiency" as core motivations for policies designed to replace foreign-origin technology with Chinese compo-

[42] R. Baldwin (2016).

[43] Fajgelbaum et al. (2024).

[44] Fuchs and Klann (2013).

[45] Bounds, Andy. "EU prepares to hit Big Tech in retaliation for Donald Trump's tariffs." Financial Times. February 5, 2025.

[46] "Resolution of the CPC Central Committee on the Major Achievements and Historical Experience of the Party over the Past Century," November 16, 2021.

nents.[47] The U.S. CHIPS act mirrors Chinese techno-nationalism with its emphasis on using illiberal policies to decrease dependence on others for semiconductors.[48] Former U.S. Treasury Secretary Yellen touted "friendshoring" and "allyshoring" as steps to move supply chains away from adversaries.[49] There is much debate over whether such efforts can work. The depth of "de-coupling" between the United States and China remains unclear.[50]

The above examples focus on how states decrease their dependence on others. But equally important is how states try to make others dependent on them in the first place. Sometimes, states use coercive interventions to facilitate dependence.[51] More often, states use positive inducements to plant the seeds for the recipient to become more dependent on the country offering the inducement. Here, we focus on the effect of Chinese foreign assistance. China's Belt and Road Initiative (BRI) is one of the most significant examples of assistance and investment policy initiatives that could increase dependence. Announced by President Xi in 2013, it generally consists of financing and direct assistance for major infrastructure projects in partner countries.

While part of its original impetus was to provide an outlet for excess production, Chinese foreign assistance and the BRI have become understood as a broader initiative to provide an alternative to the US-led international order.[52] The goals of these policies are multifaceted and complex, but many analysts think that they are intended to increase China's influence over recipients. Initial fears focused on whether Chinese finance would lead to "debt-trap" diplomacy, where recipients became beholden to China because of unfavorable loans.[53]

There are many ways that Chinese assistance could increase dependence. The investment projects themselves could increase exports from China into recipient countries, especially via greater flows of goods directly associated with infrastructure and construction.[54] Investments in infrastructure, like

[47] Wübbeke et al. (2016).

[48] Luo and Van Assche (2023).

[49] Kollewe, Julia. "Friendshoring: what is it and can it solve our supply problems?" The Observer. Aug. 6, 2022.

[50] Hirsh, Michael. "The U.S. and China Haven't Divorced Just Yet." Foreign Policy. June 22, 2022.

[51] Berger et al. (2013).

[52] Callahan (2016), Huang (2016)

[53] Lai, Lin, and Sidaway (2020).

[54] "How Is the Belt and Road Initiative Advancing China's Interests?" Center For Strategic and International Studies, 2024.

ports, can greatly lower the costs of trade (Brancaccio, Kalouptsidi, and Papageorgiou 2024). Highway and rail networks can also improve transportation within the state, further increasing the efficiency of trade (Redding and Turner 2015). Kohl (2019) estimates the effects of reduced trade costs from BRI and free trade agreements on value added trade. They both have positive effects. Yu et al. (2020) find that BRI involvement increased the degree to which exports from China matched predictions from a gravity model. Broz, Zhang, and Wang (2020) find a positive association between trade with China and leaders' decisions to attend a prominent BRI conference.

The potential effects of Chinese assistance are also indirect, through other sectors. In canonical models of trade,[55] only the most productive firms can justify a fixed cost to export. Overcoming fixed costs is potentially "contagious" across firms or industries. Once one firm overcomes the hurdles to exporting to a destination, this can make it easier for another firm to do so. In China, where state-owned enterprises (SOEs) play a large role in exports, this contagion could be even more pronounced. In a fully competitive market, firms are loathe to share insights about export markets. In a centrally planned market, sharing information across SOEs is a good thing from the planner's perspective. Early firm-level analysis of Chinese exports to BRI recipients suggested that effects were most pronounced for SOEs.[56]

On the other hand, assistance and infrastructure projects in recipient countries could increase their domestic capacity, which might decrease dependence on China. Investments in infrastructure could lead to a general decrease in trade costs with all partners. Investments could cause a greater increase in trade between the recipient and its nearby neighbors, thereby reducing dependence on the state funding the investment. Lu et al. (2024) find that BRI investments increase the centrality of recipients in the trade and investment network, which could mean that recipients have cultivated alternative suppliers. There are also prominent examples of backlash against BRI projects, which could blunt or reverse any gains.

Ultimately, assessing the downstream effects of Chinese assistance will determine how history judges the success or failure of massive projects like BRI. The stakes are high for the liberal interna-

[55] Melitz (2003)

[56] Görg and Mao (2020).

tional order and domestic politics within China. Whether the BRI succeeds in increasing interconnectedness can affect the survival prospects of the CCP.[57]

### 7.1 Effect on Compensation Dependence

We first use the compensation dependence of country $i$ on China in year $t$ as the outcome variable. The treatment variable is a binary indicator that equals 1 in the first year in which China gave the recipient $\$1$ million or more in ODA-like funding according to the AidData project.[58] We focus on actual disbursement of money, rather than announced participation in BRI, since the former describes when economic transactions actually begin.

Our empirical approach needs to distinguish the effect of increased Chinese assistance from the effects of China's general rise in the world economy. A simple correlation of Chinese assistance with dependence on China could mean that programs like BRI have increased dependence, but it could also be an artifact of how most states increased their dependence on China regardless of whether they receive any Chinese assistance. To better isolate the effects of Chinese assistance on dependence, we leverage China's staggered assistance and investment around the world in a difference-in-differences framework. Our objective is to estimate the dependence of states having received Chinese assistance under the counterfactual where they received none. The difference-in-differences framework relies on an identification assumption: the observed trajectory of dependence for states that did not receive assistance is an estimate of what would have happened in states that did receive it. Due to the staggered nature of assistance, we use the Callaway and Sant'Anna (2021) estimator to properly weight cohorts of states that received assistance at different times. This estimator has the additional advantage of producing average treatment effects of the treated for each cohort and calendar year. We include the recipient's GDP, trade with China, and level of democracy (measured by VDEM) as controls.

Figure 10 shows the results.[59] The top panel shows our estimated treatment effects on the vertical axis, with the years since entry into treatment on the horizontal axis. Treatment has a relatively

[57] Weiss and Wallace (2021); Tan, Steinberg, and McDowell (2025)
[58] Dreher et al. (2022), Custer et al. (2023).
[59] The estimates table is in Appendix D.

quick, large and durable positive effect on compensation dependence. The treatment effect is statistically distinguishable from zero starting a few years after treatment. It remains positive and generally grows in magnitude in subsequent years. The estimates are substantively meaningful. After 5 years, a country receiving assistance would need to scale up imports from non-Chinese sources by 26% to compensate for lost trade with China, compared to 19% for a country that did not receive assistance.

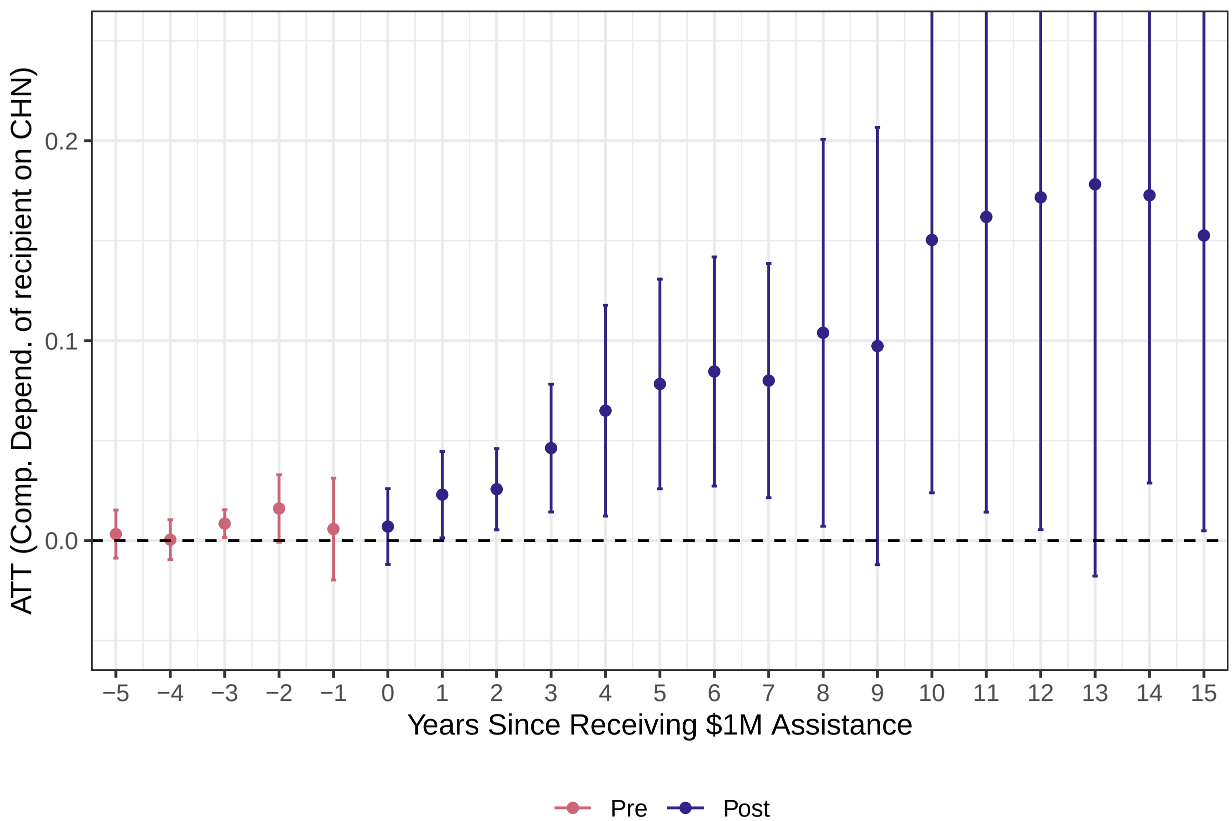



Figure 10: Effect of Chinese assistance on recipient's dependence on China. The compensation dependence measure is the outcome variable.

This positive finding is very robust.[60] We show results adding one covariate at a time to demonstrate that the results are not sensitive to the inclusion of control variables. We also include a specification where the control group includes only "not yet treated" units. We produce a two way fixed effects specification to show that our results do not depend on the use of the Callaway and Sant'Anna estimator or on binary treatment cutoffs. We also include specifications for different definitions of

[60] All robustness checks are in Appendix D.

treatment. The statistical and substantive significance of the results is unchanged whether we define treatment as the first year in which a state received greater than zero, $\$0.5$ million, $\$1$ million, or $\$5$ million in financing from China. Across all specifications, the coefficients on treatment are always between $0.089$ and $0.124$. Furthermore, we use the Goodman-Bacon decomposition to ascertain whether whether our results are driven by a small group of treated units (Goodman-Bacon 2021). If the effects are driven by an event in a single year – for example, if the results were a consequence of confounding due to China's entry into the WTO in 2001 – this decomposition would identify outlier treatment cohort. The results indicate that units treated in 2000 receive a weight of $0.2$ in the estimate, more than twice that of the next highest cohort of treated units. Yet, excluding these units does not substatially change the estimate. We also exclude years from the analysis on a rolling basis and demonstrate a high degree of robustness. We also show how results are similar using a broader definition of foreign assistance.

Figure 11 shows identical analysis, only it uses China's dependence on the recipient as the outcome measure. The treatment effects are all near zero. This suggests that Chinese assistance facilitated dependence on China but did not increase interdependence. We do not see evidence of a corresponding increase in China's dependence on the recipient.

Figure 12 shows results from an identical estimation, except using the OR measure of dependence as the outcome measure. The results are very different. The effects of aid on the OR measure are generally *negative* and indistinguishable from zero. Using this measure, we would reach the opposite conclusion of the above analysis – that Chinese aid has, if anything, decreased recipients' dependence on China.[61] We contend that the former analysis is more accurate, since it captures the myriad ways that trade patterns could subtly change. Those changes could affect bilateral dependence, even if they had minimal (or even positive or negative) effects on aggregate trade statistics.

[61] When Chinese dependence on the recipient using the OR measure is the outcome variable, the results are near-zero and insignificant, as well. See Appendix D.

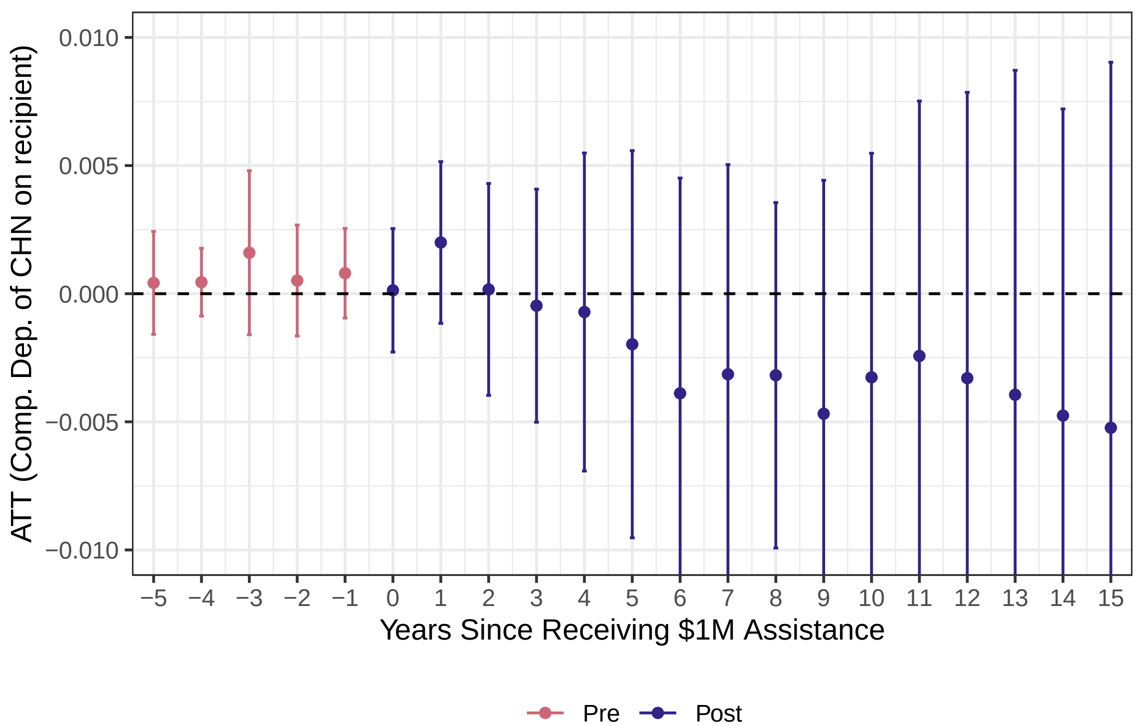



Figure 11: Effect of Chinese assistance on China's dependence on the recipient. The compensation dependence measure is the outcome variable.

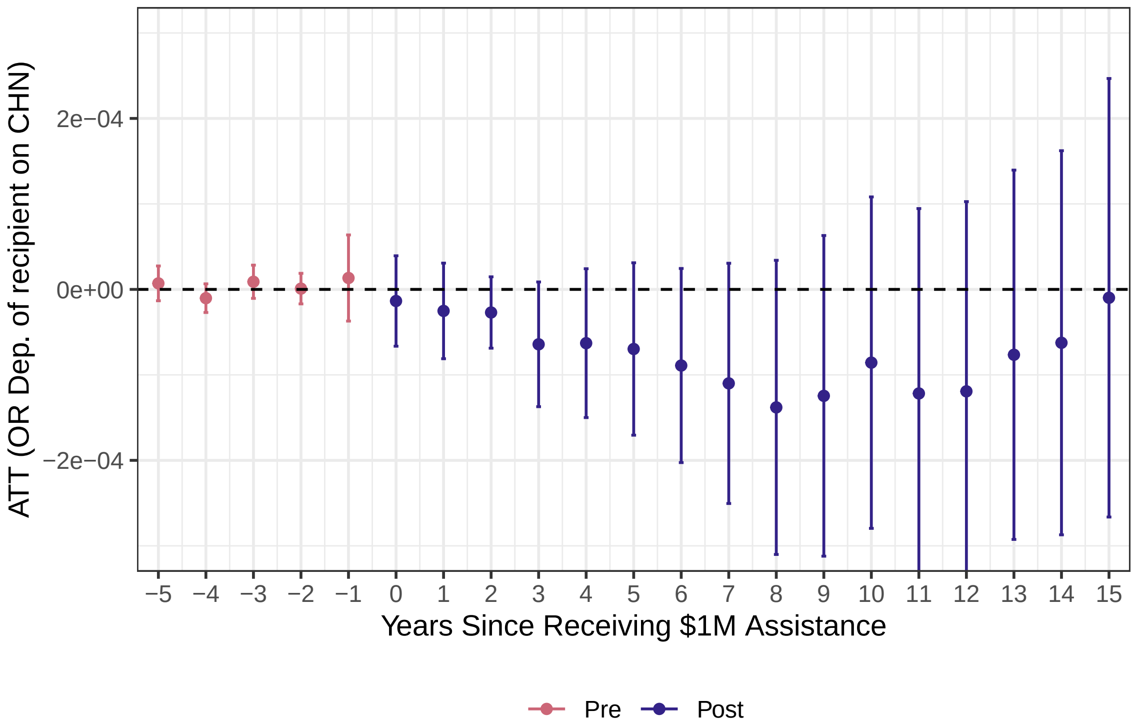



Figure 12: Effect of Chinese assistance on recipient's dependence on China. The OR aggregate statistic dependence measure is the outcome variable.

# 8 Conclusions

Who is dependent upon whom? This fundamental question in international politics speaks directly to the structure of power, polarity, and leverage in the international system. Answering this question requires measures of the welfare effects on a country if trade is interrupted. As the global economy has evolved in the composition of trade, the prevalence of intermediate products, and the availability of alternate sources, it is important for us as researchers to keep up. Our measures incorporate these key changes in the global economy in a theoretically grounded way.

Our global analysis of trends over time uncovered how dependence and interdependence have evolved in ways that depart significantly from standard intuition. Global dependence on China reached similar levels to dependence on the United States much earlier than aggregate statistics would suggest. The world has only become more interdependent in a very narrow sense. Imbalance in the most important relationships has increased. Dependence on one partner, often the US or China, has increased to such a degree that it makes most dyads look balanced by comparison. Our analysis of Chinese assistance, exemplified by the BRI, also uncovered its success in cultivating recipients' dependence on China, without a reciprocal increase in Chinese dependence. Both the global and program-specific findings would have yielded very different conclusions using aggregate trade statistics. The different results using our measures versus traditional measures suggests that existing studies relying on aggregate statistics could yield different conclusions with nuanced measures of dependence.[62]

There are myriad additional questions that our approach could answer. For example, as countries think about how to manipulate others' dependence on them and inoculate themselves from foreign influence, which products and partnerships should they target? What flows have the greatest effect on dependence? Some intermediate inputs are undoubtedly strategically valuable, like semiconductors. What other products are flying under that radar, perhaps not as flashy as computer chips, but which may also have outsized influence on the welfare of other countries?

President Trump's second-term trade war has included broadsides against traditional partners like

[62] We have efforts underway on these replications.

Canada and Mexico. His efforts to coerce partners into granting concessions and decoupling from China is premised on the idea that those countries are more dependent on the U.S. than on China. Nuanced measures of dependence are critical to predicting the outcome of this gamble. Our measures suggest that the U.S. has potentially overplayed its hand. If the U.S. changes course and instead attempts to build a cooperative coalition to influence China (Cha 2023), then which partners and which trade flows will contribute most coercive economic firepower?

The United States' recent aggressive deployment of economic coercion also puts the international system in a state of flux. Countries that had generally followed or fell in line with US demands may find themselves tempted to follow other leaders. This could manifest inside existing international institutions or in the creation of new ones or in influence campaigns wholly outside of the liberal international order. As Tan (2021) writes, "China is now well positioned to influence the development of international institutions" (22). Our analysis agrees and further shows that China's influence in the domain of international trade grew more quickly, more broadly, and earlier than previously thought.

The world is also facing large, potentially structural changes like climate change and increased automation. These tectonic changes will affect patterns of dependence in ways that go beyond simple, aggregate trade statistics. Climate change can affect production locations, endowments, and demand for goods, with effects that vary across region and industry. Scholars have begun to model potential effects on trade flows.[63] Our approach gives researchers a way to generate insights into and predictions for which countries will rise and fall with climate change from a geopolitical perspective, in the degree to which their partners depend on them.

Automation and AI could bring similarly large structural changes. Like climate change, automation can change the location of production or demand. Links in supply chains that were previously outsourced might be reshored and performed by newly automated processes.[64] Some effects on demands are already obvious, as competition over semiconductors has reached fever pitch. Automation's recent manifestations with artificial intelligence could also have huge effects on services trade, which

[63] Dellink et al. (2017), Martínez-Martínez et al. (2023)
[64] Stapleton (2019).

we have so far excluded from the above analysis.[65] Services trade flows and potential disruptions from technological changes could be incorporated into our approach with more detailed input-output tables. There is a growing awareness of how dependence on automation could affect the demand and supply of policies designed to manipulate foreign reliance, which could place automation squarely in the crosshairs previously occupied by trade.[66] If we use "old" tools for modeling and measuring dependence that do not account for key changes to the global economy, then we risk erroneous conclusions. Our approach allows analysis of the dependence implications of these changes and many more.

# 9 References


Abdelal, Rawi, and Jonathan Kirshner. 1999. "Strategy, Economic Relations, and the Definition of National Interests." *Security Studies* 9 (1-2): 119–56.

Arkolakis, Costas, Arnaud Costinot, and Andrés Rodríguez-Clare. 2012. "New Trade Models, Same Old Gains?" *American Economic Review* 102 (1): 94–130.

Armington, Paul S. 1969. "A Theory of Demand for Products Distinguished by Place of Production." *IMF Staff Papers* 16 (1): 159.

Axelrod, Robert, and Robert O Keohane. 1985. "Achieving Cooperation Under Anarchy: Strategies and Institutions." *World Politics* 38 (1): 226–54.

Baldwin. 1980. "Interdependence and Power: A Conceptual Analysis." *International Organization* 34 (4): 471–506.

Baldwin, Richard. 2016. *The Great Convergence: Information Technology and the New Globalization.* Harvard University Press.

———. 2022. "Globotics and Macroeconomics: Globalisation and Automation of the Service Sector." National Bureau of Economic Research.

Barbieri, Katherine. 1996. "Economic Interdependence: A Path to Peace or a Source of Interstate Conflict?" *Journal of Peace Research* 33 (1): 29–49.

Berger, Daniel, William Easterly, Nathan Nunn, and Shanker Satyanath. 2013. "Commercial Imperialism? Political Influence and Trade During the Cold War." *American Economic Review* 103 (2): 863–96.

Boehm, Christoph E, Andrei A Levchenko, and Nitya Pandalai-Nayar. 2023. "The Long and Short (Run) of Trade Elasticities." *American Economic Review* 113 (4): 861–905.

Bohlmann, Adrienne Margarete. 2021. "Triplets, Quads and Quints: Estimating Disaggregate Trade Elasticities with Different Odds Ratios." *German Economic Review* 22 (3): 359–81.

Bowen, Harry P, Edward E Leamer, and Leo Sveikauskas. 1987. "Multicountry, Multifactor Tests of the Factor Abundance Theory." *The American Economic Review*, 791–809.


[65] R. Baldwin (2022).

[66] Chaudoin and Mangini (2024).

Brancaccio, Giulia, Myrto Kalouptsidi, and Theodore Papageorgiou. 2024. "Investment in Infrastructure and Trade: The Case of Ports." National Bureau of Economic Research.

Broz, J Lawrence, Zhiwen Zhang, and Gaoyang Wang. 2020. "Explaining Foreign Support for China's Global Economic Leadership." *International Organization* 74 (3): 417–52.

Caliendo, Lorenzo, and Fernando Parro. 2015. "Estimates of the Trade and Welfare Effects of NAFTA." *The Review of Economic Studies* 82 (1): 1–44.

Callahan, William A. 2016. "China's 'Asia Dream' the Belt Road Initiative and the New Regional Order." *Asian Journal of Comparative Politics* 1 (3): 226–43.

Callaway, Brantly, and Pedro HC Sant'Anna. 2021. "Difference-in-Differences with Multiple Time Periods." *Journal of Econometrics* 225 (2): 200–230.

Campos, Rodolfo G, Julia Estefania-Flores, Davide Furceri, and Jacopo Timini. 2023. "Geopolitical Fragmentation and Trade." *Journal of Comparative Economics* 51 (4): 1289–1315.

Carnegie, Allison. 2014. "States Held Hostage: Political Hold-up Problems and the Effects of International Institutions." *American Political Science Review* 108 (1): 54–70.

Cattaneo, Matias D, Richard K Crump, Max H Farrell, and Yingjie Feng. 2019. "On Binscatter." *arXiv Preprint arXiv:1902.09608*.

Cha, Victor D. 2023. "Collective Resilience: Deterring China's Weaponization of Economic Interdependence." *International Security* 48 (1): 91–124.

Chaudoin, Stephen, and Michael-David Mangini. 2024. "Robots, Foreigners, and Foreign Robots: Policy Responses to Automation and Trade." Harvard University.

Chen, Frederick R. 2021. "Extended Dependence: Trade, Alliances, and Peace." *The Journal of Politics* 83 (1): 246–59.

Chen, Ling S, and Miles M Evers. 2023. "'Wars Without Gun Smoke': Global Supply Chains, Power Transitions, and Economic Statecraft." *International Security* 48 (2): 164–204.

Clayton, Christopher, Matteo Maggiori, and Jesse Schreger. 2024a. "A Framework for Geoeconomics." National Bureau of Economic Research.

———. 2024b. *A Theory of Economic Coercion and Fragmentation*. Bank for International Settlements, Monetary; Economic Department.

Coate, Roger A, Jeffrey A Griffin, and Steven Elliott-Gower. 2015. "Interdependence in International Organization and Global Governance." In *Oxford Research Encyclopedia of International Studies*.

Cooper, Richard N. 1968. *The Economics of Interdependence:. Economic Policy in the Atlantic Community*. Columbia University Press.

Copeland, Dale C. 2014. *Economic Interdependence and War*. Princeton University Press.

Costinot, Arnaud, and Andrés Rodríguez-Clare. 2014. "Trade Theory with Numbers: Quantifying the Consequences of Globalization." In *Handbook of International Economics*, 4:197–261. Elsevier.

Crescenzi, Mark JC. 2003. "Economic Exit, Interdependence, and Conflict." *The Journal of Politics* 65 (3): 809–32.

Custer, Samantha, Axel Dreher, Thai-Binh Elston, A Fuchs, S Ghose, J Lin, A Malik, et al. 2023. "Tracking Chinese Development Finance: An Application of AidData's TUFF 3.0 Methodology." *Williamsburg, VA: AidData at William & Mary*.

Dellink, Rob, Hyunjeong Hwang, Elisa Lanzi, and Jean Chateau. 2017. "International Trade Consequences of Climate Change."

Dreher, Axel, Andreas Fuchs, Bradley Parks, Austin Strange, and Michael J Tierney. 2022. *Banking on Beijing: The Aims and Impacts of China's Overseas Development Program*. Cambridge University Press.

Dreher, Axel, Andreas Fuchs, Brad Parks, Austin M Strange, and Michael J Tierney. 2018. "Apples and Dragon Fruits: The Determinants of Aid and Other Forms of State Financing from China to Africa." *International Studies Quarterly* 62 (1): 182–94. https://doi.org/10.1093/isq/sqx052.

Drezner, Daniel, Henry Farrell, and Abraham L Newman. 2021. *The Uses and Abuses of Weaponized Interdependence*. Brookings Institution Press.

Drezner, D, Clark Packard, James A Dorn, Alfredo Carrillo Obregon, and Anna Maria Mayda. 2023. "The Dangers of Misunderstanding Economic Interdependence." *Cato Institute* 12.

Eaton, Jonathan, and Maxim Engers. 1992. "Sanctions." *Journal of Political Economy* 100 (5): 899–928.

Eaton, Jonathan, and Samuel Kortum. 2002. "Technology, Geography, and Trade." *Econometrica* 70 (5): 1741–79.

Fajgelbaum, Pablo, Pinelopi Goldberg, Patrick Kennedy, Amit Khandelwal, and Daria Taglioni. 2024. "The US-China Trade War and Global Reallocations." *American Economic Review: Insights* 6 (2): 295–312.

Farrell, Henry, and Abraham Newman. 2020. "The Folly of Decoupling from China." *Foreign Affairs* 3.

Farrell, Henry, and Abraham L Newman. 2019. "Weaponized Interdependence: How Global Economic Networks Shape State Coercion." *International Security* 44 (1): 42–79.

Friedman, Thomas L. 2005. *The World Is Flat: A Brief History of the Twenty-First Century*. Macmillan.

Fuchs, Andreas, and Nils-Hendrik Klann. 2013. "Paying a Visit: The Dalai Lama Effect on International Trade." *Journal of International Economics* 91 (1): 164–77.

Gartzke, Erik, and Quan Li. 2003. "Measure for Measure: Concept Operationalization and the Trade Interdependence-Conflict Debate." *Journal of Peace Research* 40 (5): 553–71.

Gartzke, Erik, and Oliver Westerwinter. 2016. "The Complex Structure of Commercial Peace Contrasting Trade Interdependence, Asymmetry, and Multipolarity." *Journal of Peace Research* 53 (3): 325–43.

Gawande, Kishore, and Usree Bandyopadhyay. 2000. "Is Protection for Sale? Evidence on the Grossman-Helpman Theory of Endogenous Protection." *Review of Economics and Statistics* 82 (1): 139–52.

Goodman-Bacon, Andrew. 2021. "Difference-in-Differences with Variation in Treatment Timing." *Journal of Econometrics* 225 (2): 254–77.

Görg, Holger, and Haiou Mao. 2020. "Does the Belt and Road Initiative Stimulate Chinese Exports? The Role of State-Owned Enterprises." KCG Working Paper.

Gowa, Joanne. 1995. *Allies, Adversaries, and International Trade*. Princeton University Press.

Gray, Julia, and Philip BK Potter. 2012. "Trade and Volatility at the Core and Periphery of the Global Economy." *International Studies Quarterly* 56 (4): 793–800.

Helpman, Elhanan. 2014. "Foreign Trade and Investment: Firm-Level Perspectives." *Economica* 81 (321): 1–14.

Hirschman, Albert O. 1980. *National Power and the Structure of Foreign Trade*. Vol. 105. Univ of California Press.

Hiscox, Michael J. 2001. "Class Versus Industry Cleavages: Inter-Industry Factor Mobility and the Politics of Trade." *International Organization* 55 (1): 1–46.

Huang, Yiping. 2016. "Understanding China's Belt & Road Initiative: Motivation, Framework and Assessment." *China Economic Review* 40: 314–21.

Hummels, David, Jun Ishii, and Kei-Mu Yi. 2001. "The Nature and Growth of Vertical Specialization in World Trade." *Journal of International Economics* 54 (1): 75–96.

Ikenberry, G. John. 2001. *After Victory: Institutions, Strategic Restraint, and the Rebuilding of Order After Major Wars, New Edition-New Edition*. Princeton University Press.

———. 2018. "The End of Liberal International Order?" *International Affairs* 94 (1): 7–23.

Keohane, Robert O. 1984. *After Hegemony: Cooperation and Discord in the World Political Economy*. Princeton university press.

Keohane, Robert O, and Joseph S Nye. 1973. "Power and Interdependence." *Survival* 15 (4): 158–65.

Kim, In Song, Steven Liao, and Kosuke Imai. 2020. "Measuring Trade Profile with Granular Product-Level Data." *American Journal of Political Science* 64 (1): 102–17.

Kim, In Song, and Iain Osgood. 2019. "Firms in Trade and Trade Politics." *Annual Review of Political Science* 22 (1): 399–417.

Klare, Michael T. 2007. *Blood and Oil: The Dangers and Consequences of America's Growing Dependency on Imported Petroleum*. Metropolitan Books.

Knorr, Klaus. 1975. *The Power of Nations: The Political Economy of International Relations*. Vol. 91. 3. Basic Books New York.

Kohl, Tristan. 2019. "The Belt and Road Initiative's Effect on Supply-Chain Trade: Evidence from Structural Gravity Equations." *Cambridge Journal of Regions, Economy and Society* 12 (1): 77–104.

Krugman, Paul. 1980. "Scale Economies, Product Differentiation, and the Pattern of Trade." *The American Economic Review* 70 (5): 950–59.

Lai, Karen PY, Shaun Lin, and James D Sidaway. 2020. "Financing the Belt and Road Initiative (BRI): Research Agendas Beyond the 'Debt-Trap' Discourse." *Eurasian Geography and Economics* 61 (2): 109–24.

Liu, Ernest, and David Yang. 2025. "International Power." Working Paper.

Lu, Shuai, Ning Chen, Wei Zhou, and Shouwei Li. 2024. "Impact of the Belt and Road Initiative on Trade Status and FDI Attraction: A Local and Global Network Perspective." *International Review of Economics & Finance* 89: 1468–95.

Luo, Yadong, and Ari Van Assche. 2023. "The Rise of Techno-Geopolitical Uncertainty: Implications of the United States CHIPS and Science Act." *Journal of International Business Studies*, 1.

Mangini, Michael-David. 2024. "The Economic Coercion Trilemma." *Journal of Conflict Resolution* 68 (6): 1226–51.

Mansfield, Edward D, Helen V Milner, and B Peter Rosendorff. 2002. "Why Democracies Cooperate More: Electoral Control and International Trade Agreements." *International Organization*, 477–513.

Mansfield, Edward D, and Brian M Pollins. 2001. "The Study of Interdependence and Conflict: Recent Advances, Open Questions, and Directions for Future Research." *Journal of Conflict Resolution* 45 (6): 834–59.

———. 2009. *Economic Interdependence and International Conflict: New Perspectives on an Enduring Debate*. University of Michigan Press.

Martínez-Martínez, Alejandra, Silviano Esteve-Pérez, Salvador Gil-Pareja, and Rafael Llorca-Vivero. 2023. "The Impact of Climate Change on International Trade: A Gravity Model Estimation." *The World Economy* 46 (9): 2624–53.

Mearsheimer, John J. 2015. "Why We Will Soon Miss the Cold War." In *Conflict After the Cold War*, 28–44. Routledge.

Melitz, Marc J. 2003. "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity." *Econometrica* 71 (6): 1695–725.

Milner, Helen V, and Keiko Kubota. 2005. "Why the Move to Free Trade? Democracy and Trade

Policy in the Developing Countries." *International Organization* 59 (1): 107–43.

Miroudot, Sébastien, Rainer Lanz, and Alexandros Ragoussis. 2009. "Trade in Intermediate Goods and Services."

Mohr, Cathrin, and Christoph Trebesch. 2025. "Geoeconomics." Kiel Working Paper.

Oneal, John R, and Bruce M Russet. 1997. "The Classical Liberals Were Right: Democracy, Interdependence, and Conflict, 1950–1985." *International Studies Quarterly* 41 (2): 267–93.

Osgood, Iain. 2017. "Industrial Fragmentation over Trade: The Role of Variation in Global Engagement." *International Studies Quarterly* 61 (3): 642–59.

———. 2018. "Globalizing the Supply Chain: Firm and Industrial Support for US Trade Agreements." *International Organization* 72 (2): 455–84.

Polachek, Solomon W. 1997. "Why Democracies Cooperate More and Fight Less: The Relationship Between International Trade and Cooperation." *Review of International Economics* 5 (3): 295–309.

Redding, Stephen J, and Matthew A Turner. 2015. "Transportation Costs and the Spatial Organization of Economic Activity." *Handbook of Regional and Urban Economics* 5: 1339–98.

Rogowski, Ronald. 1987. "Political Cleavages and Changing Exposure to Trade." *American Political Science Review* 81 (4): 1121–37.

Stapleton, Katherine. 2019. "Automation, Global Value Chains and Development: What Do We Know so Far?" *Pathways for Prosperity Commission Background Paper Series* 26: 1–23.

Tan, Yeling. 2021. *Disaggregating China, Inc.: State Strategies in the Liberal Economic Order.* Cornell University Press.

Tan, Yeling, David Steinberg, and Daniel McDowell. 2025. "Global Economic Influence and Domestic Regime Support: Evidence from China." *Review of International Political Economy* 32 (1): 202–25.

Thoenig, Mathias. 2024. "Trade in the Shadow of War: A Quantitative Toolkit for Geoeconomics." In *Handbook of the Economics of Conflict*, 1:325–80. Elsevier.

Trade, United Nations Conference on, and Development. 2024. "Trade Analysis and Information System (TRAINS)." United Nations.

Trefler, Daniel. 1995. "The Case of the Missing Trade and Other Mysteries." *The American Economic Review*, 1029–46.

Waltz, Kenneth N. 1979. *Theory of International Politics.* Waveland Press.

Weiss, Jessica Chen, and Jeremy L Wallace. 2021. "Domestic Politics, China's Rise, and the Future of the Liberal International Order." *International Organization* 75 (2): 635–64.

Westing, Arthur H. 1986. *Global Resources and International Conflict: Environmental Factors in Strategic Policy and Action.* Sipri Monograph.

Wübbeke, Jost, Mirjam Meissner, Max J Zenglein, Jaqueline Ives, and Björn Conrad. 2016. "Made in China 2025." *Mercator Institute for China Studies. Papers on China* 2 (74): 4.

Yu, Linhui, Dan Zhao, Haixia Niu, and Futao Lu. 2020. "Does the Belt and Road Initiative Expand China's Export Potential to Countries Along the Belt and Road?" *China Economic Review* 60: 101419.

Zeng, Yuleng. 2024. "Microchips and Sneakers: Bilateral Trade, Shifting Power, and Interstate Conflict." *Journal of Peace Research* 61 (4): 659–72.

# Trade Interdependence in the Modern Global Economy

## Appendix

February 2026

# Appendix

# A Appendix Items for Section 4: Measure construction

## A.1 Welfare Formula Derivation

Our welfare formula found in Equation 1 is a simplification of a generalized version of the ACR formula found in Costinot and Rodríguez-Clare (2014). Equation 28 of the chapter is

$$\hat{C}_j = \prod_{s,k=1}^{S} \left( \hat{\lambda}_{jj,k} \left( \left( \frac{\hat{e}_{j,k}}{\hat{v}_j} \right)^{\eta_k} \left( \frac{\hat{r}_{j,k}}{\hat{v}_j} \right) \right)^{-\delta_k} \right)^{\frac{-\beta_{j,k}\tilde{a}_{j,sk}}{\varepsilon_k}}$$

where all variables with "hats" represent the ratio of that variable across a counterfactual, e.g. $\hat{h} = h'/h$ is the proportional change in any variable $h$ between the initial and counterfactual equilibria. Using the notation of Costinot and Rodríguez-Clare (2014), the variable $\hat{C}_j = C'_j/C_j$ is the change in welfare across the trade shock, $\hat{\lambda}_{jj} = \lambda'_{jj}/\lambda_{jj}$ is the change in the share of expenditure on domestic goods, $\hat{e}_{j,k}$ is the change in the share of expenditure in country $j$ allocated to sector $k$, $\hat{r}_{j,k}$ is the change in the share of total revenues in country $j$ generated from sector $k$, $\delta$ is an indicator which is zero when the model represents perfect competition and one for monopolistic competition, $\hat{v}_j$ is the change in the ratio of total income to total revenues in country $j$, $\eta_k$ captures selection effects due to the extent of firm heterogeneity in the sector, $\beta_{j,s}$ are the share of expenditure on sector $s$ in country $j$, $\tilde{a}_{j,sk}$ are the elements of a modified Leontief inverse adjusted to account for monopolistic competition, and $\varepsilon_k$ is the trade elasticity.
We derive our equation in two steps. First, we choose $\delta = 0$ to reflect our assumption of perfect competition. We believe the assumption of perfect competition is justified by a balancing of the benefits of realism against the added computational complexity and additional data requirements. In particular, we note that many of the calculations performed by Costinot and Rodríguez-Clare (2014) are similar under both assumptions. Our assumption of perfect competition immediately removes any need to add assumptions about the counterfactual quantities $\hat{e}_{jk}$, $\hat{v}_j$, and $\hat{r}_{j,k}$. It also removes any need for further assumptions about the value of $\eta_k$. Note that this assumption also allows us to set $\tilde{a}_{j,sk} = a_{j,sk}$ because no adjustments to the Leontief inverse are necessary under perfect competition, further simplifying the theory.
Our data are not detailed enough to calculate the coefficients of the Leontief inverse $a_{j,sk}$. We make a second assumption to simplify the production structure: we assume that the input-output matrix $A_j$ is diagonal (meaning that all sectors use intermediate products from their own sector). We believe that this assumption is well justified since the data are aggregated to the sectoral level. Under this assumption, the Leontief inverse $(I - A_j)^{-1}$ will also be diagonal with elements $1/(1 - \alpha_{j,k})$ where $\alpha_{j,k}$ is a diagonal element of $A_j$. Then we can write $a_{j,sk} = 1/(1 - \alpha_{j,k})$ for $s = k$ and $a_{j,sk} = 0$ otherwise. Note that $1 - \alpha_{j,k}$ is the share of domestic value added in sector $k$. Then, plugging in these values, we have

$$\hat{C}_j = \prod_{k=1}^{S} \left( \hat{\lambda}_{jj,k} \right)^{\frac{\beta_{j,k}}{-(1-\alpha_{j,k})\varepsilon_k}}$$

which is exactly our welfare formula in Equation 1 but expressed using the notation of Costinot and Rodríguez-Clare (2014). The only differences are in choice of notation. Our notation uses $\hat{W}_j$ for

$\widehat{C}_j$, and $s$ as the index for for sectors instead of $k$. We also use $\widehat{\lambda}_j^s$ instead of $\widehat{\lambda}_{jj,k}$, $\eta_j^s$ for sector shares instead of $\beta_{j,k}$, and $\beta_j^s$ for $-(1-\alpha_{j,k})$. After making these substitutions we have:

$$\hat{W}_j = \prod_s \left(\widehat{\lambda}_j^s\right)^{\eta_j^s/\beta_j^s\varepsilon^s}$$

## A.2 Walkthrough guide and numerical example

### Initial setup

Suppose we start with three Countries: A, B, and C. There are two sectors, Sector 1 and Sector 2. Country B imports certain amounts of each sector from A and C. Country B also produces some of each sector domestically.

$\eta_{s1} = 0.5$
$\eta_{s2} = 0.5$
$\varepsilon_{s1} = -1$
$\varepsilon_{s2} = -1$
$\beta_{s1} = 1$
$\beta_{s2} = 1$

**Initial Flows**

| | **Sector 1** | **Sector 2** |
|---|---|---|
| Imports from A | 7 | 7 |
| Imports from C | 2 | 2 |
| Domestic production | 1 | 1 |
| | $\lambda_{s1}$ | $\lambda_{s2}$ |
| | 0.1 | 0.1 |

For now, we assume the sectors are identical in terms of their consumption shares ($\eta$), elasticities ($\varepsilon$), or degree of intermediate inputs ($\beta$, recall that these are inverse intermediate shares, so 1 indicates that none of the domestic value added production is reliant on imported intermediates.). In other words, we are turning "off" any differential weighting placed on each sector.

These numbers generate $\lambda$ for each sector. $\lambda$ is one minus the import penetration ratio. Here, it is $1 - \frac{7+2}{7+2+1} = 0.1$, for both sectors.

### Add an interruption

Now, suppose that Country A cuts off all its exports to Country B. Country B now imports 0 of each sector from Country A.

$\eta_{s1} = 0.5$
$\eta_{s2} = 0.5$
$\varepsilon_{s1} = -1$
$\varepsilon_{s2} = -1$
$\beta_{s1} = 1$
$\beta_{s2} = 1$

| | **Initial Flows** | | **Post-shock Flows** | |
|---|---|---|---|---|
| | **Sector 1** | **Sector 2** | **Sector 1** | **Sector 2** |
| Imp. from A | 7 | 7 | 0 | 0 |
| Imp. from C | 2 | 2 | 2 | 2 |
| Dom. Prod. | 1 | 1 | 1 | 1 |
| | $\lambda_{s1}$ | $\lambda_{s2}$ | $\lambda'_{s1}$ | $\lambda'_{s2}$ |
| | 0.1 | 0.1 | 0.333 | 0.333 |

This generates a new value of $\lambda$, denoted $\lambda'$. It is one minus the new import penetration ratio, $1 - \frac{2}{2+1} = 0.333$.

### Calculate Upper Bound measure

We can plug in the correct values to the formula to calculate $\hat{W}$. In this example, it equals 0.3. In words, the ratio of Country B's welfare after the shock compared to before the shock is 0.3. This makes intuitive sense in our simple example. Country A cut off the source of 70% of Country B's consumption, so Country B's welfare is 30% of what it was before. (And recall that we have made the sectors identical and chose -1 and 1 as the values for elasticity and degree of intermediate inputs.)

The Upper Bound measure is $1 - \hat{W} = 0.7$. In words, if Country A cut off all exports to Country B, this would remove 70% of Country B's welfare.

$\eta_{s1} = 0.5$
$\eta_{s2} = 0.5$
$\varepsilon_{s1} = -1$
$\varepsilon_{s2} = -1$
$\beta_{s1} = 1$
$\beta_{s2} = 1$

| | **Initial Flows** | | **Post-shock Flows** | |
|---|---|---|---|---|
| | **Sector 1** | **Sector 2** | **Sector 1** | **Sector 2** |
| Imp. from A | 7 | 7 | 0 | 0 |
| Imp. from C | 2 | 2 | 2 | 2 |
| Dom. Prod. | 1 | 1 | 1 | 1 |
| | $\lambda_{s1}$ | $\lambda_{s2}$ | $\lambda'_{s1}$ | $\lambda'_{s2}$ |
| | 0.1 | 0.1 | 0.333 | 0.333 |

**Measures**

$\hat{W} = 0.3$
UB $= 0.7$

$$\hat{W} = \Pi_s \left(\hat{\lambda}_s\right)^{\eta^s/(\beta^s \varepsilon^s)}$$

$$\hat{W} = \underbrace{\left(\frac{0.333}{0.1}\right)^{(0.5 \cdot \frac{1}{-1} \cdot \frac{1}{1})}}_{\text{Sector 1}} \underbrace{\left(\frac{0.333}{0.1}\right)^{(0.5 \cdot \frac{1}{-1} \cdot \frac{1}{1})}}_{\text{Sector 2}}$$

$$\hat{W} = 0.3$$

Upper Bound $= 1$ - $\hat{W}$ = 0.7

## Calculate Compensation measure

To calculate alpha, recall that we're looking for a scaling factor to apply to the unaffected trade flows that will restore Country B back to its original welfare. In this case, our compensation measure ($\alpha$) equals 4.5. We would need to scale up imports from Country C by a factor of 4.5 to restore Country B's welfare back to its full value, after the interruption in imports from Country A.

$\eta_{s1} = 0.5$
$\eta_{s2} = 0.5$
$\varepsilon_{s1} = -1$
$\varepsilon_{s2} = -1$
$\beta_{s1} = 1$
$\beta_{s2} = 1$

| | **Initial Flows** | | **Post-shock Flows** | |
|---|---|---|---|---|
| | **Sector 1** | **Sector 2** | **Sector 1** | **Sector 2** |
| Imp. from A | 7 | 7 | 0 | 0 |
| Imp. from C | 2 | 2 | 2 | 2 |
| Dom. Prod. | 1 | 1 | 1 | 1 |
| | $\lambda_{s1}$ | $\lambda_{s2}$ | $\lambda'_{s1}$ | $\lambda'_{s2}$ |
| | 0.1 | 0.1 | 0.333 | 0.333 |

**Measures**

$\hat{W} = 0.3$
$\text{UB} = 0.7$
$\alpha = 4.5$

We gradually increase $\alpha$.

| $\alpha$ | $\alpha$-scaled $\lambda'_{s1}$ | $\alpha$-scaled $\lambda'_{s2}$ | $\hat{W}$ after scaling |
|---|---|---|---|
| 3 | 0.143 | 0.143 | 0.7 |
| 3.5 | 0.125 | 0.125 | 0.8 |
| 4 | 0.111 | 0.111 | 0.9 |
| 4.5 | 0.1 | 0.1 | 1.0 |

Each $\alpha$ value also generates a new $\lambda'$ value for each sector, which is plugged into the same $\hat{W}$ formula as before.

We increase $\alpha$ until $\hat{W}$ equals 1, i.e., welfare is restored to its pre-shock level.

Note that increasing $\alpha$ and scaling up unaffected trade does not mean "each unaffected trade flow is scaled up in the exact same way." Affected trade could be replaced by forming new trade relationships. We have written this example with one affected trade partner (A) and one unaffected partner (C). In reality, there are many unaffected partners (C, D, E, F, ...). Affected trade could also be replaced by scaling up unaffected partner $i$ in a different way than unaffected partner $j$, so long as A's mix of imports from unaffected partners stays the same.

Note too that in the data set, the compensation measure is $\alpha - 1$. In other words, when compensation equals 0.25, this corresponds to $\alpha = 1.25$. We did this just because $\alpha - 1$ gives intuitive values interpreted as percent increases.

## Upper Bound versus Compensation

To see how Upper Bound and Compensation are different, we'll change the amount of domestic production relative to unaffected imports. In this new example, Country B produces 2 units of each sector (previously 1) and imports 1 unit from Country C (previously 2). We hold everything else fixed from the preceding example.

We the make the same calculation for the upper bound measure $\hat{W}$. It is again 0.3.

We then follow the same steps to find the compensation measure ($\alpha$). The new $\alpha$ value is 8 (previously 4.5). We have to scale up imports from Country C by a larger factor, compared to the previous example, to restore Country B's welfare to its pre-interruption level.

$\eta_{s1} = 0.5$
$\eta_{s2} = 0.5$
$\varepsilon_{s1} = -1$
$\varepsilon_{s2} = -1$
$\beta_{s1} = 1$
$\beta_{s2} = 1$

| | **Initial Flows** | | **Post-shock Flows** | |
|---|---|---|---|---|
| | **Sector 1** | **Sector 2** | **Sector 1** | **Sector 2** |
| Imp. from A | 7 | 7 | 0 | 0 |
| Imp. from C | 1 | 1 | 1 | 1 |
| Dom. Prod. | 2 | 2 | 2 | 2 |
| | $\lambda_{s1}$ | $\lambda_{s2}$ | $\lambda_{s1}^{'}$ | $\lambda_{s2}^{'}$ |
| | 0.1 | 0.1 | 0.333 | 0.333 |

**Measures**

$\hat{W} = 0.3$
UB $= 0.7$
$\alpha = 8$

| $\alpha$ | $\alpha$-scaled $\lambda'_{s1}$ | $\alpha$-scaled $\lambda'_{s2}$ | $\hat{W}$ after scaling |
|---|---|---|---|
| 6.5 | 0.235 | 0.235 | 0.85 |
| 7 | 0.222 | 0.222 | 0.9 |
| 7.5 | 0.211 | 0.211 | 0.95 |
| 8 | 0.2 | 0.2 | 1.0 |

## Non-identical sectors: setup

We have so far had identical sectors and identical trade flows across sectors. Now, we will relax that and show how the Upper Bound and Compensation measures can be thought of as incorporating theoretically informed weighting on each sector.

We'll start by making Country B's imports from Country A more heavily concentrated in Sector 1. When Country A cuts off its exports, the effect on Country B's welfare is more heavily influenced through Sector 1, relative to Sector 2.

The Upper Bound measure is now 0.48 (previously 0.7). This makes intuitive sense, because Country A is cutting off a relatively smaller proportion of Country B's sourcing. The welfare effects are not as stark.

The Compensation measure is approximately 2.75 (previously 8). This also makes intuitive sense for the same reason. It takes less to scale up imports from Country C to restore Country B's welfare.

$\eta_{s1} = 0.5$
$\eta_{s2} = 0.5$
$\varepsilon_{s1} = -1$
$\varepsilon_{s2} = -1$
$\beta_{s1} = 1$
$\beta_{s2} = 1$

| | Initial Flows | | Post-shock Flows | |
|---|---|---|---|---|
| | **Sector 1** | **Sector 2** | **Sector 1** | **Sector 2** |
| Imp. from A | 7 | 1 | 0 | 0 |
| Imp. from C | 1 | 7 | 1 | 7 |
| Dom. Prod. | 2 | 2 | 2 | 2 |
| | $\lambda_{s1}$ | $\lambda_{s2}$ | $\lambda'_{s1}$ | $\lambda'_{s2}$ |
| | 0.2 | 0.2 | 0.667 | 0.222 |

**Measures**

$\hat{W} = 0.52$
UB $= 0.48$
$\alpha = 2.75$

| $\alpha$ | $\alpha$-scaled $\lambda'_{s1}$ | $\alpha$-scaled $\lambda'_{s2}$ | $\hat{W}$ after scaling |
|---|---|---|---|
| 2.5 | 0.444 | 0.103 | 0.94 |
| 2.75 | 0.421 | 0.094 | $\approx 1.00$ |

### Non-identical sectors: consumption shares

Now, we will change the characteristics of each sector and show how that up-weights the effect of Country A's interruption to trade. This, in turn, increases the Upper Bound and Compensation measures.

First, we will increase Sector 1's consumption share for Country B. In other words, Sector 1 constitutes a larger share of what Country B consumes.

This increases the Upper Bound measure. Interruptions to trade with Country A have greater consequences for Country B's welfare. And it increases the Compensation measure. We must scale up imports from Country C by a larger factor to restore Country B's welfare.

$\eta_{s1} = 0.75$
$\eta_{s2} = 0.25$
$\varepsilon_{s1} = -1$
$\varepsilon_{s2} = -1$
$\beta_{s1} = 1$
$\beta_{s2} = 1$

| | **Initial Flows** | | **Post-shock Flows** | |
|---|---|---|---|---|
| | **Sector 1** | **Sector 2** | **Sector 1** | **Sector 2** |
| Imp. from A | 7 | 1 | 0 | 0 |
| Imp. from C | 1 | 7 | 1 | 7 |
| Dom. Prod. | 2 | 2 | 2 | 2 |
| | $\lambda_{s1}$ | $\lambda_{s2}$ | $\lambda'_{s1}$ | $\lambda'_{s2}$ |
| | 0.2 | 0.2 | 0.667 | 0.222 |

**Measures**

$\hat{W} = 0.39$
UB $= 0.61$
$\alpha = 4.65$

| $\alpha$ | $\alpha$-scaled $\lambda'_{s1}$ | $\alpha$-scaled $\lambda'_{s2}$ | $\hat{W}$ after scaling |
|---|---|---|---|
| 2.75 | 0.421 | 0.094 | 0.69 |
| | | ... | |
| 4.65 | 0.301 | 0.058 | $\approx 1.00$ |

## Non-identical sectors: elasticities

The same intuition applies if we make Sector 1 the more inelastic sector. For example, if there were fewer substitute products, then prices changes would have less of an effect on trade flows. The formula up-weights the impact of interruptions to trade in inelastic sectors. Again, the Upper Bound measure and Compensation measures reflect this. They are both higher than their initial values when the parameters were identical across sectors.

$\eta_{s1} = 0.75$
$\eta_{s2} = 0.25$

$\varepsilon_{s1} = -0.5$
$\varepsilon_{s2} = -1$

$\beta_{s1} = 1$
$\beta_{s2} = 1$

| | **Initial Flows** | | **Post-shock Flows** | |
|---|---|---|---|---|
| | **Sector 1** | **Sector 2** | **Sector 1** | **Sector 2** |
| Imp. from A | 7 | 1 | 0 | 0 |
| Imp. from C | 1 | 7 | 1 | 7 |
| Dom. Prod. | 2 | 2 | 2 | 2 |
| | $\lambda_{s1}$ | $\lambda_{s2}$ | $\lambda_{s1}^{'}$ | $\lambda_{s2}^{'}$ |
| | 0.2 | 0.2 | 0.667 | 0.222 |

**Measures**

$\hat{W} = 0.28$
$\text{UB} = 0.72$
$\alpha = 3.9$

| $\alpha$ | $\alpha$-scaled $\lambda'_{s1}$ | $\alpha$-scaled $\lambda'_{s2}$ | $\hat{W}$ after scaling |
|---|---|---|---|
| 2.75 | 0.421 | 0.094 | 0.69 |
| | | ... | |
| 3.9 | 0.339 | 0.068 | $\approx 1.00$ |

### Non-identical sectors: intermediates shares

The same intuition applies if we make Sector 1 a sector that relies more heavily on imported intermediates. Recall that these are inverse intermediates shares. So a lower value indicates more reliance on intermediates. We are decreasing the domestically produced valued added share (*prodvash* in trade in value added terms)

Again, the Upper Bound measure and Compensation measures reflect this. They are both higher than their initial values when the parameters were identical across sectors.

$\eta_{s1} = 0.75$
$\eta_{s2} = 0.25$
$\varepsilon_{s1} = -0.5$
$\varepsilon_{s2} = -1$
$\beta_{s1} = 0.4$
$\beta_{s2} = 1$

| | **Initial Flows** | | **Post-shock Flows** | |
|---|---|---|---|---|
| | **Sector 1** | **Sector 2** | **Sector 1** | **Sector 2** |
| Imp. from A | 7 | 1 | 0 | 0 |
| Imp. from C | 1 | 7 | 1 | 7 |
| Dom. Prod. | 2 | 2 | 2 | 2 |
| | $\lambda_{s1}$ | $\lambda_{s2}$ | $\lambda_{s1}^{'}$ | $\lambda_{s2}^{'}$ |
| | 0.2 | 0.2 | 0.667 | 0.222 |

**Measures**

$\hat{W} = 0.21$
UB $= 0.79$
$\alpha = 4.3$

| $\alpha$ | $\alpha$-scaled $\lambda'_{s1}$ | $\alpha$-scaled $\lambda'_{s2}$ | $\hat{W}$ after scaling |
|---|---|---|---|
| 2.75 | 0.421 | 0.094 | 0.69 |
| | | ... | |
| 4.3 | 0.317 | 0.062 | $\approx 1.00$ |

## A.3 Sample description

Our data cover the following countries, from 1995-2020.

Table A.1: Countries Included in the Data

| Countries | | |
|---|---|---|
| ARG — Argentina | GBR — United Kingdom | NLD — Netherlands |
| AUS — Australia | GRC — Greece | NOR — Norway |
| AUT — Austria | HKG — Hong Kong SAR China | NZL — New Zealand |
| BEL — Belgium | HRV — Croatia | PAK — Pakistan |
| BGD — Bangladesh | HUN — Hungary | PER — Peru |
| BGR — Bulgaria | IDN — Indonesia | PHL — Philippines |
| BLR — Belarus | IND — India | POL — Poland |
| BRA — Brazil | IRL — Ireland | PRT — Portugal |
| BRN — Brunei | ISL — Iceland | ROU — Romania |
| CAN — Canada | ISR — Israel | RUS — Russia |
| CHE — Switzerland | ITA — Italy | SAU — Saudi Arabia |
| CHL — Chile | JOR — Jordan | SEN — Senegal |
| CHN — China | JPN — Japan | SGP — Singapore |
| CIV — Côte d'Ivoire | KAZ — Kazakhstan | SVK — Slovakia |
| CMR — Cameroon | KHM — Cambodia | SVN — Slovenia |
| COL — Colombia | KOR — South Korea | SWE — Sweden |
| CRI — Costa Rica | LAO — Laos | THA — Thailand |
| CYP — Cyprus | LTU — Lithuania | TUN — Tunisia |
| CZE — Czechia | LUX — Luxembourg | TUR — Turkey |
| DEU — Germany | LVA — Latvia | TWN — Taiwan |
| DNK — Denmark | MAR — Morocco | UKR — Ukraine |
| EGY — Egypt | MEX — Mexico | USA — United States |
| ESP — Spain | MLT — Malta | VNM — Vietnam |
| EST — Estonia | MMR — Myanmar (Burma) | ZAF — South Africa |
| FIN — Finland | MYS — Malaysia | |
| FRA — France | NGA — Nigeria | |

The data include the following industries.

Table A.2: Industries Used in the Bayesian Elasticity Estimates

| Industries | |
|---|---|
| A01_02 — Agriculture, hunting, forestry | C24 — Basic metals |
| A03 — Fishing and aquaculture | C25 — Fabricated metal products |
| B05_06 — Mining, quarrying, energy producing products | C26 — Computer, electronic and optical equipment |
| B07_08 — Mining, quarrying, non-energy producing products | C27 — Electrical equipment |
| B09 — Mining support service activities | C28 — Machinery and equipment, nec |
| C10T12 — Food products, beverages and tobacco | C29 — Motor vehicles, trailers and semi-trailers |
| C13T15 — Textiles, textile products, leather and footwear | C30 — Other transport equipment |
| C16 — Wood and products of wood and cork | C31T33 — Manufacturing nec; repair and installation of machinery and equipment |
| C17_18 — Paper products and printing | D — Electricity, gas, steam and air conditioning supply |
| C19 — Coke and refined petroleum products | J58T60 — Publishing, audiovisual and broadcasting activities |
| C20 — Chemical and chemical products | N — Administrative and support services |
| C21 — Pharmaceuticals, medicinal chemical and botanical products | S — Other service activities |
| C22 — Rubber and plastics products | |
| C23 — Other non-metallic mineral products | |

## A.4 Bayesian trade elasticity estimates

Figure A.1 shows our time varying estimates of trade elasticities by industry. Most of the estimated values fall in the 0 to -5 interval. These are larger in magnitude than the short run estimates in Boehm, Levchenko, and Pandalai-Nayar (2023), though closer to their long run estimate of -2. Their appendix (B3) also has a good comparison of estimates and samples across numerous papers.

Caliendo and Parro (2015) originally constructed estimates at the industry level that were time-invariant. They ranged from $-0.37$ to $51.08$, with an average of $-4.55$ (Table 1).

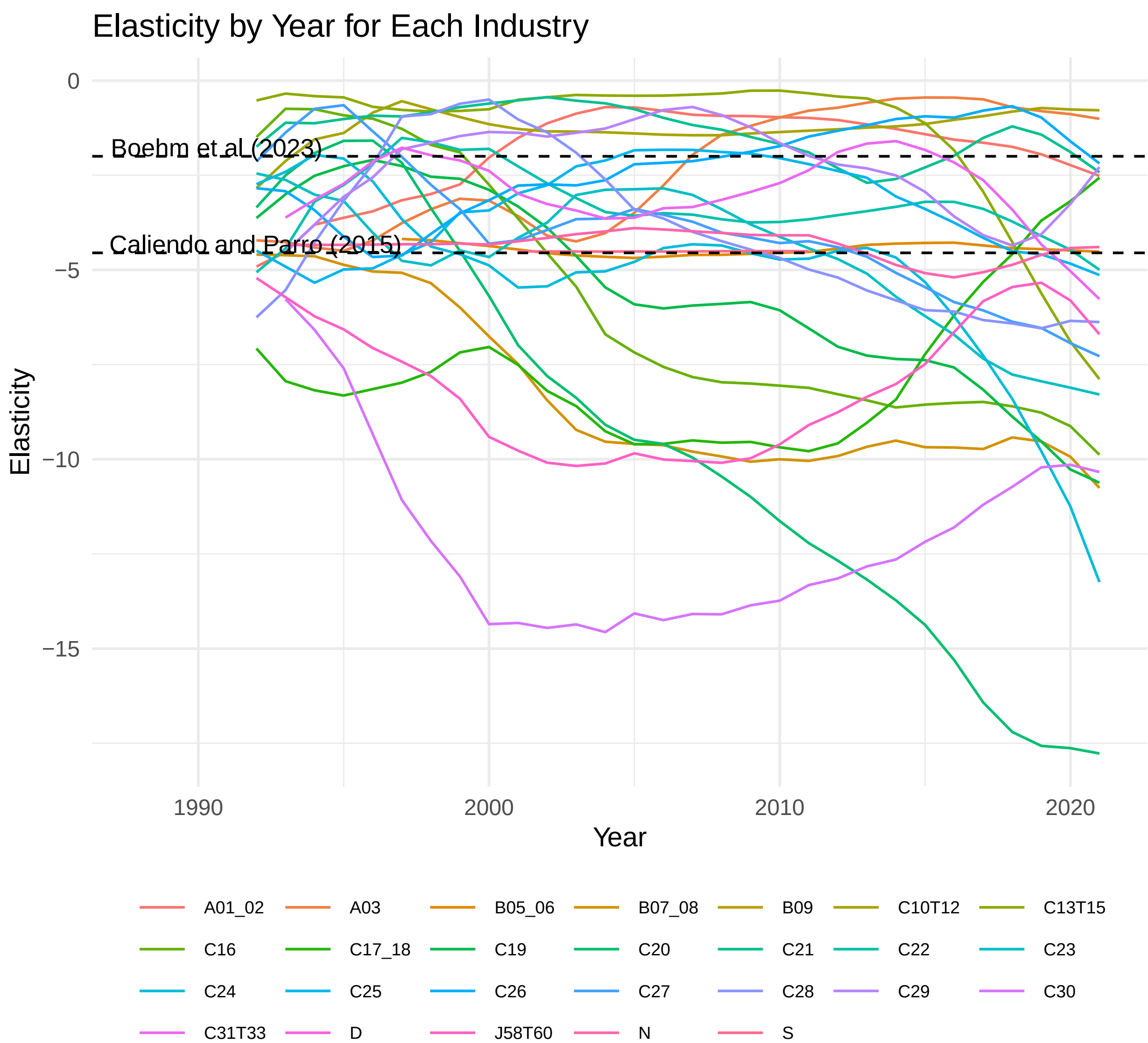



Figure A.1: Bayesian time-varying estimates of elasticities

# B Appendix Items for Section 5: Our measures versus other measures

## B.1 Average dependencies

Figure 2 compared the maximum of the log-standardized compensation dependence measure with the Oneal and Russett measure over time. It showed how there was increasing divergence between the two measures over time. Here, we show that this divergence is not just present when we use the

maximum of the log-standardized measure. Figure A.2 shows correlation coefficient between the compensation measure and the OR measure over time. The different lines show this correlation coefficient for different subsamples of the data. The red line shows the trend for the entire sample, not just looking at maximum dependencies. Two additional lines limit the sample only to a country's 5 partners that have the highest value for compensation or OR for that particular year. In other words, we have calculated the correlation coefficient only for the 5 partners upon whom you are most dependent according to that measure. Two additional lines limit the sample to only the partner upon whom you are maximally dependent in that year. In other words, it is similar to the data in Figure 2, but without any log-standardization, and looks at a country's maximum values for each year, according to either our measure or the aggregate statistics measure.
The trends over time are apparent and consistent across subsamples. All lines are downward sloping. The correlation between our measure and the OR measure deteriorates over time. Divergences are especially pronounced during the aftermath of the financial crisis.
Figure A.3 shows the same correlation coefficients, only using the Barbieri measure instead of OR. The trends are very similar. They show the same deterioration over time and large dip around 2010.

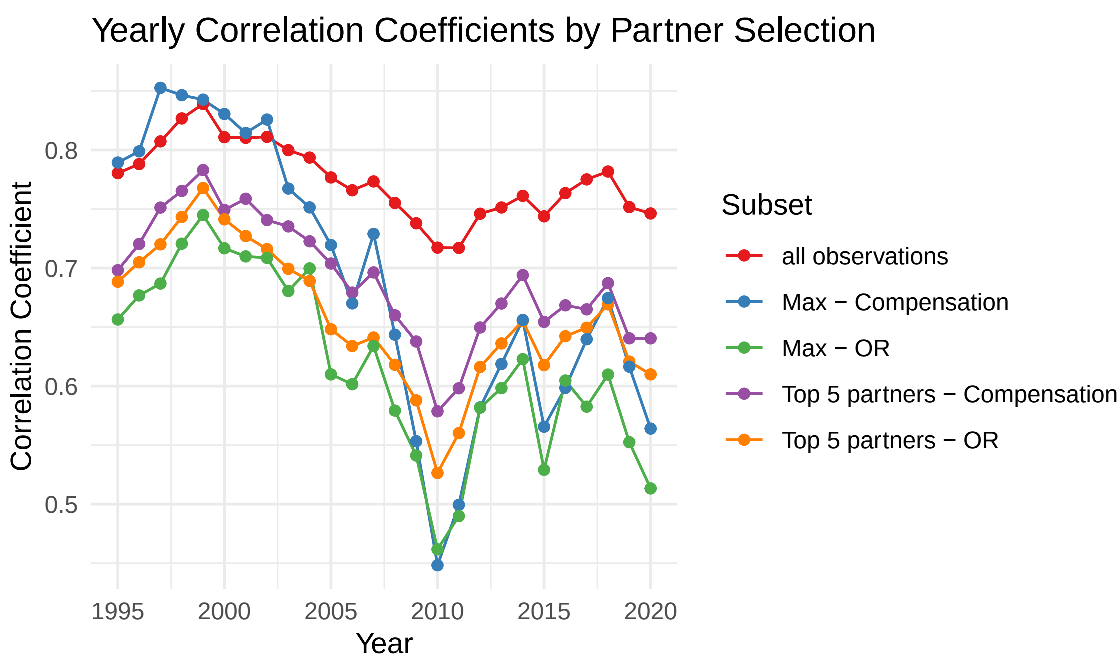



Figure A.2: Correlation coefficients between compensation dependence and Oneal-Russett measure over time.

The deteriorating correlation coefficients are also apparent when using the upper bound measure instead of compensation. Figure A.4 reproduces the figure in the main manuscript using the upper bound measure. Figure A.5 and Figure A.6 then reproduce the appendix figures above using the upper bound measure instead of compensation.

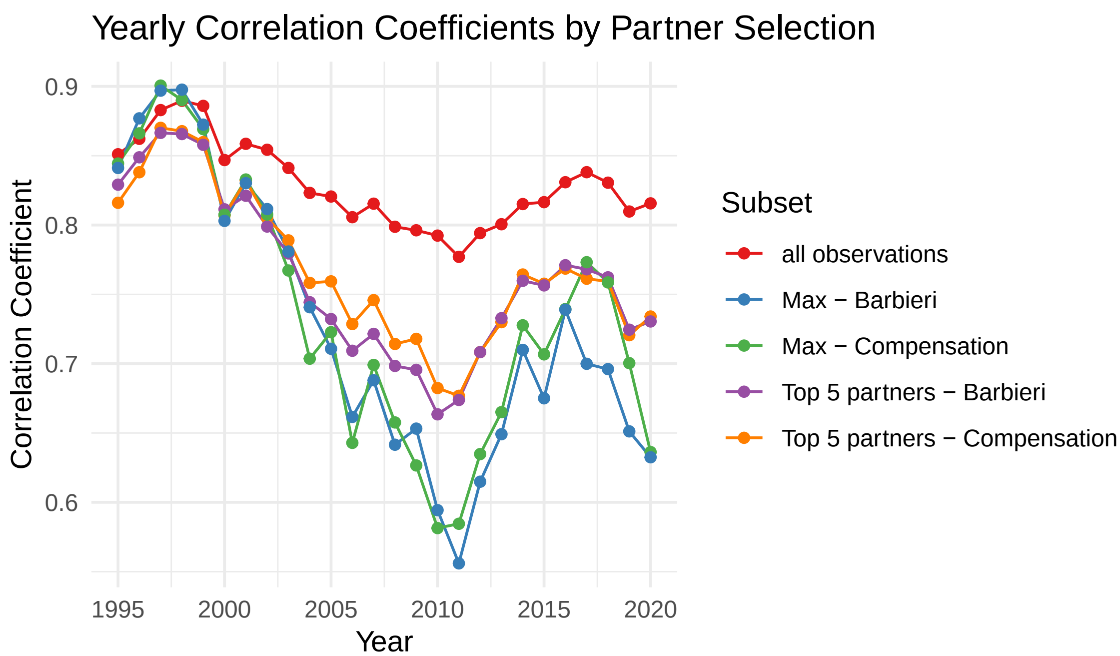



Figure A.3: Correlation coefficients between compensation dependence and Barbieri measure over time.

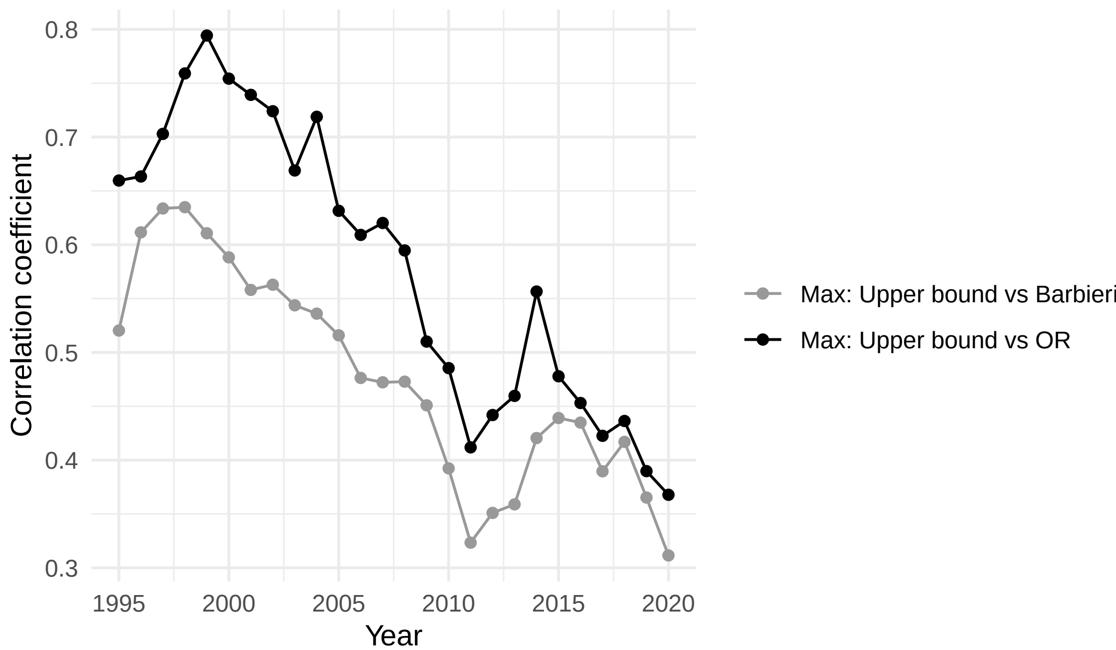



Figure A.4: Correlation coefficients over time between values of the upper-bound dependence measure and the Oneal–Russett and Barbieri measures. Dependence values are the maximums for each country-year.

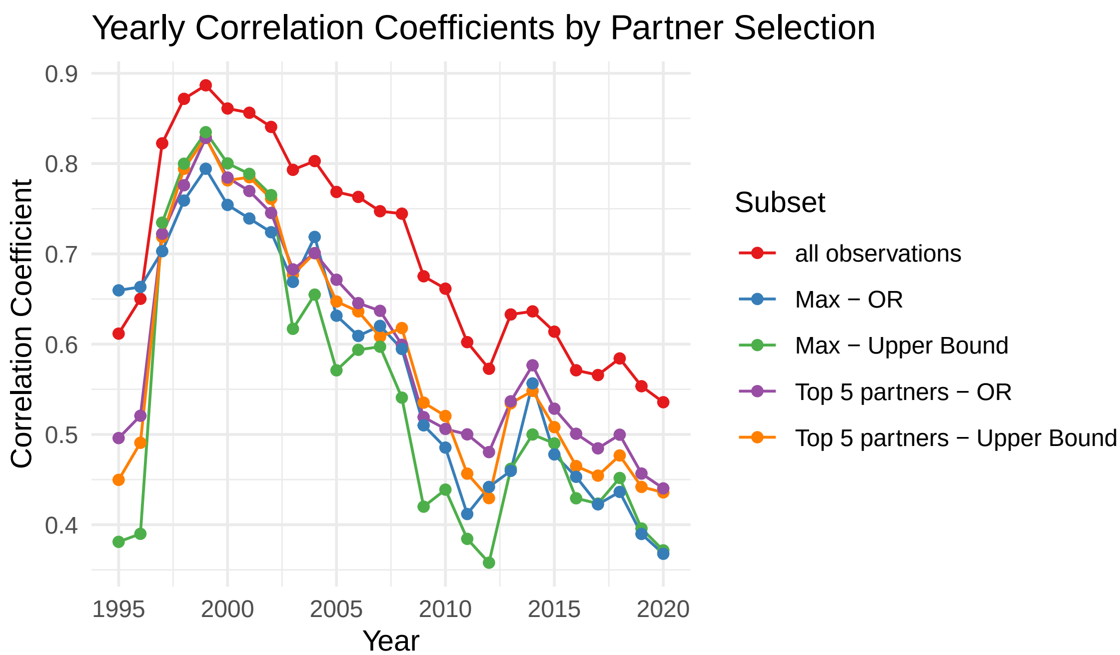



Figure A.5: Correlation coefficients between upper bound dependence and OR measure over time.

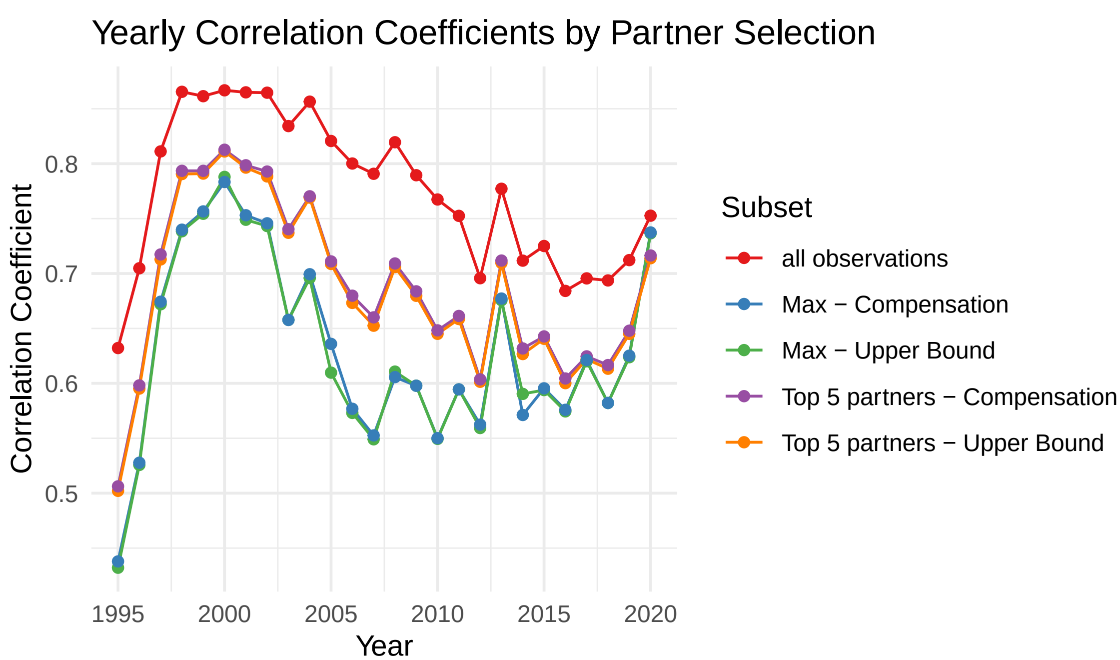



Figure A.6: Correlation coefficients between upper bound dependence and compensation dependence measure over time.

## B.2 Correlations and outliers

Figure A.7 shows another visualization of how the compensation and OR measures relate and how they have changed over time. Since our measures and the OR measure have difference scales, we normalized them to the unit interval. Each pane shows approximately one decade in our sample. As before, the two measures start fairly well-correlated. Many observations – and the line of best fit for the points – are close to the 45-degree line. In the 2001-2010 period, this begins to change. Clusters of observations move away from the 45-degree line, in both directions. This trend gets even more stark from 2011-2020. Divergence between the two measures increases.
Figure A.8 zooms in on the final pane of Figure A.7 and highlights two outlier countries: Japan and Luxumbourg. Japan's aggregate trade flows grew greatly over time, but their trade became more and more concentrated with China, in intermediates, and inelastic goods. So the aggregate trade statistics approach under-states their dependence. Luxembourg's imports, on the other hand, tend to be less comprised of intermediates, and they have a variety of partners, especially among EU countries. So the aggregate trade statistics approach over-states their dependence, relative to our measures.

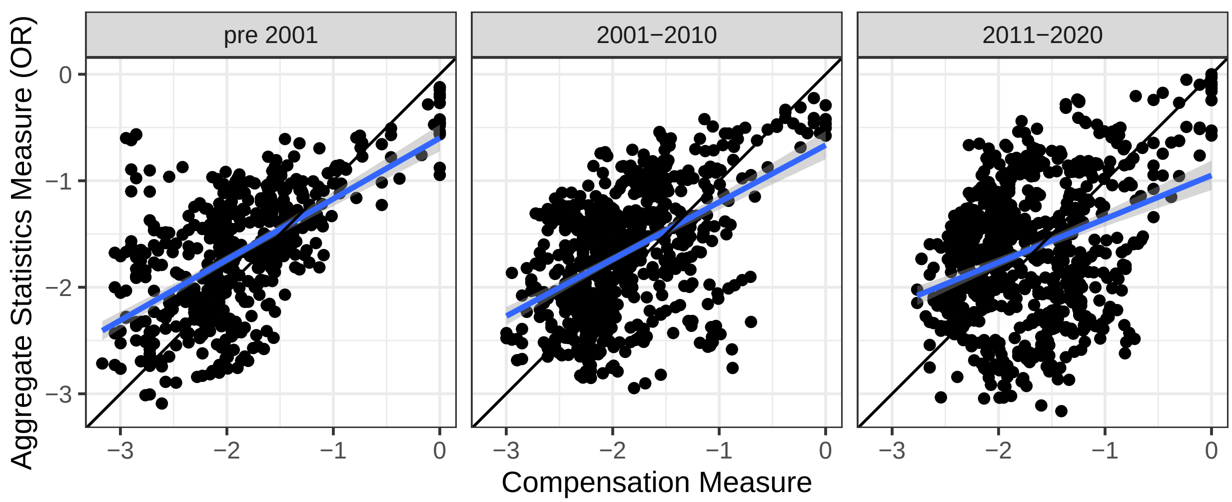



Figure A.7: Compensation dependence versus Oneal and Russett aggregate statistics measure, compared over three periods. Each dot represents a country's maximum level of dependence for a given year, across all its partners. The measures are normalized to the unit interval to ensure comparability of the scales across measures. Each point represents, for every state, its maximum dependence across all trade partners in a given year, logged.

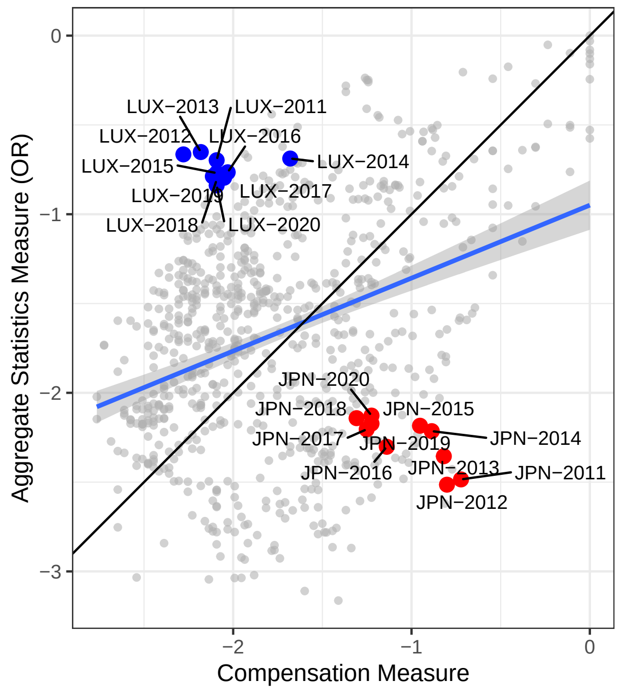



Figure A.8: Compensation dependence versus Oneal and Russett aggregate statistics measure, 2011–2020 only. Points for JPN (red) and LUX (blue) are highlighted and labeled.

## B.3 Movement in intermediates shares over time

In the main manuscript, we described how countries change the share of their imports that are made up of intermediates over time. Here, we show this in greater detail. BEC data are divided into a hierarchy of commodity codes. For reasons that are not immediately apparent to us, the number of observations in the BEC data increases substantially in 2010. It nearly doubles. So for the descriptive plots below, we show data from before and after this jump.

For Figure A.9, we calculated each country's share of total imports that were made up of intermediates for each year. We then calculated the country's rank in that distribution, i.e. a lower rank means the country-year observation has a higher intermediates share of total imports. The top pane shows these as line plots for 1998-2009 and the bottom pane for 2010-2021. If a country's rank went up by 10 or more slots, comparing the start of that time period to the end, then its line is colored red If its rank went down, it is colored blue.

There is a lot of movement within-country across-time in where they stand in the distribution of intermediates shares. In the first time period, almost 36% of countries had a rank-difference of at least 10. In the second period, almost 33% had a similarly large shift.[67] Movement was also not concentrated in any part of the distribution. Some high-rank countries went up, while others went down, and vice versa for countries that started lower in the rankings.

[67]Note that we limited the plots to only countries with complete data for a particular time period, so the denominator for this calculation changes slightly.

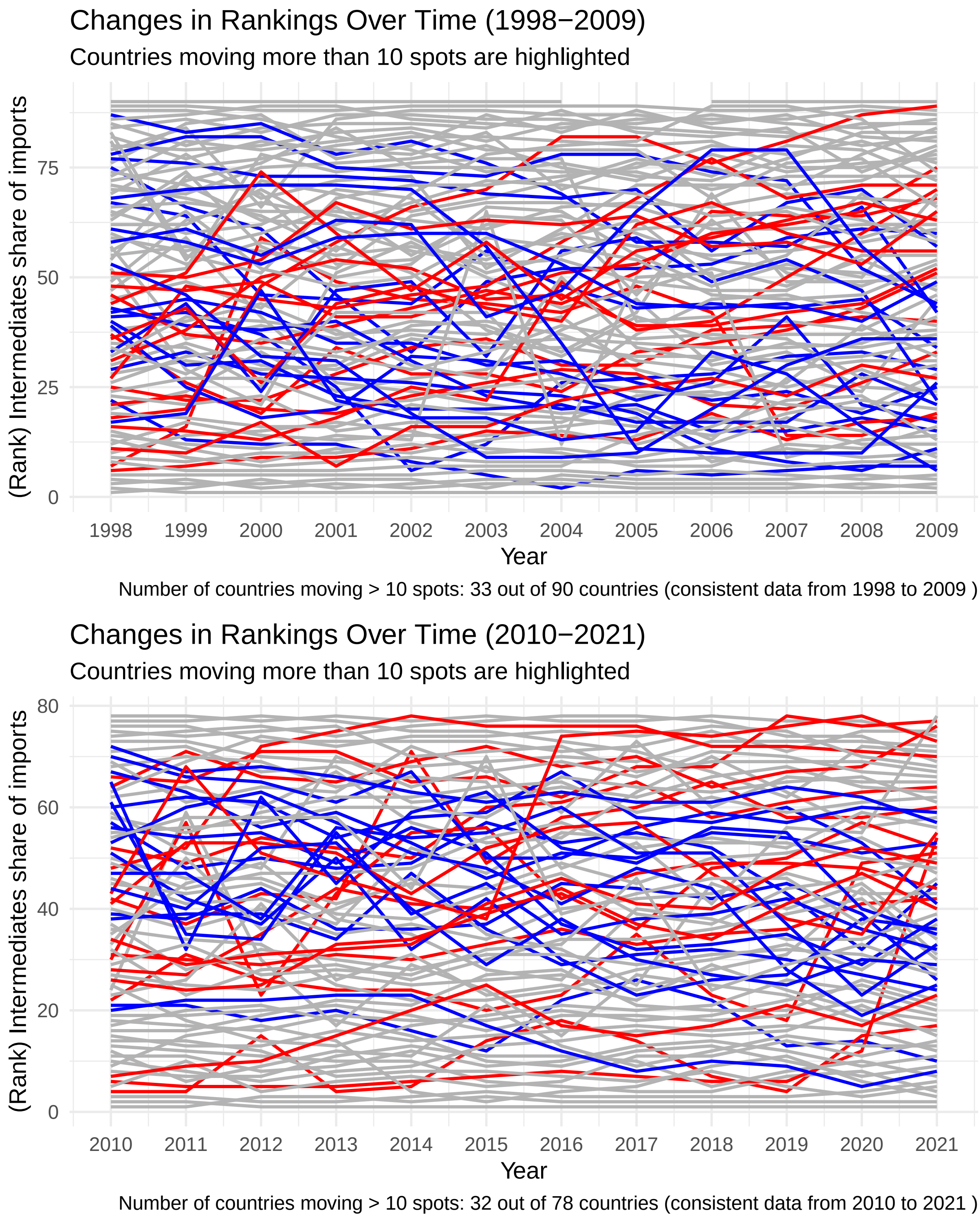



Figure A.9: Plots showing countries that changed their intermediates share of imports the most over different time periods.

## B.4 Movement at the extensive margin of trade over time

One potential driver of differences between our measures and others is the degree to which a country trades at the extensive margin. More trade spread across more partners could decrease compensation dependence. Figures A.10 and A.11 shows one way of conceptualizing variation at the extensive margin. For each country and industry, we calculated the number of partner countries that it takes to make up at least 80% of that country's imported value added. For example, if a country's imports of a particular industry were spread equally over 100 partners, this measure would equal 80. If a country imported all of that good from one partner, the measure would equal 1.

Figures A.10 shows box and whiskers describing the distribution of this value across countries and industries, for all years. The middle line for each industry shows the mean across countries. The boxes show the interquartile range and the whiskers show 1.5x the interquartile range. Red dots mark outliers.

There is substantial variation in the degree to which certain industries are concentrated or spread out across different trading partners. For the average country, approximately 3-4 partners make up 80% of their imports for energy and mining imports. Yet, the average country has 80% of its food imports spread over more than 12 partners. These values can also vary over time.

There is also substantial variation across countries, even within a particular industry. Across nearly all industries, there are countries that import at least 80% from a single partner in at least one of the sample years. Across all industries, the distributions of these values are spread out across countries. Figure A.11 shows the mean of this value across countries for each industry-year. The degree of partner-concentration can increase or decrease for different industries over time.

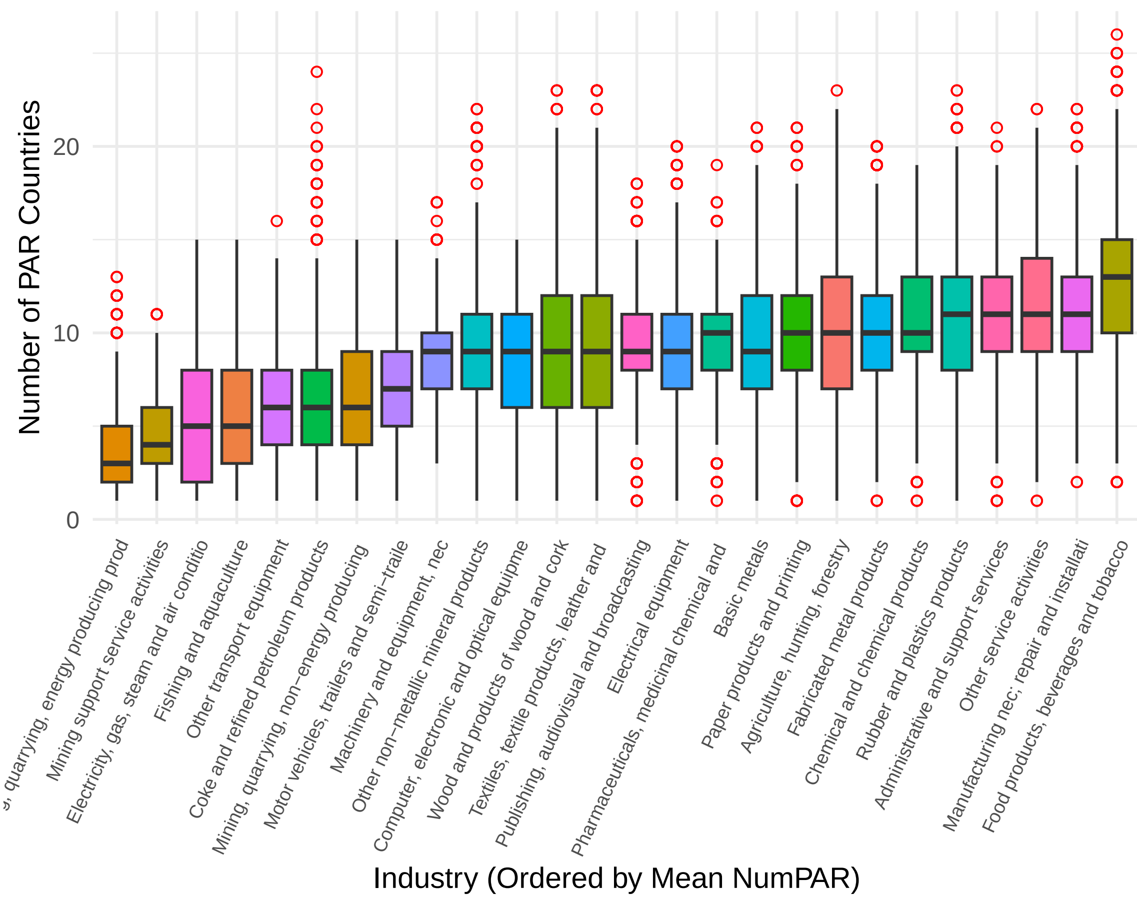



Figure A.10: Distribution of the number of partners making up 80% of imports, across industries.

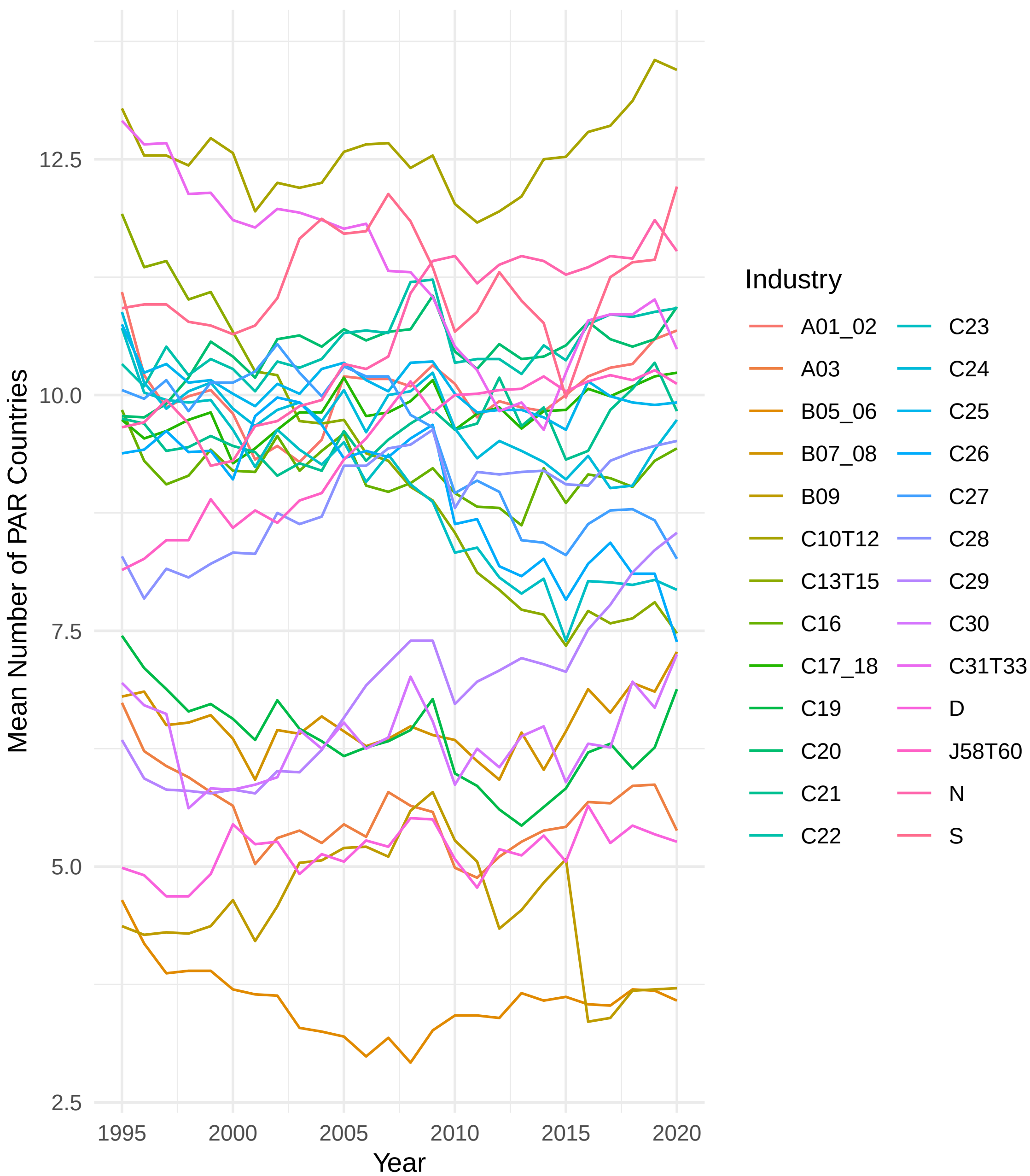



Figure A.11: Mean Number of Partner Countries making up 80% of imports, by Industry and Year.

# C Appendix Items for Section 6: Changes Over Time

## C.1 Medians versus means

In the main manuscript, we described trends in average levels of dependence over time. Figure A.12 shows the same thing as Figure 3, using medians instead of means. The trends are very similar, for both the compensation and OR measures.

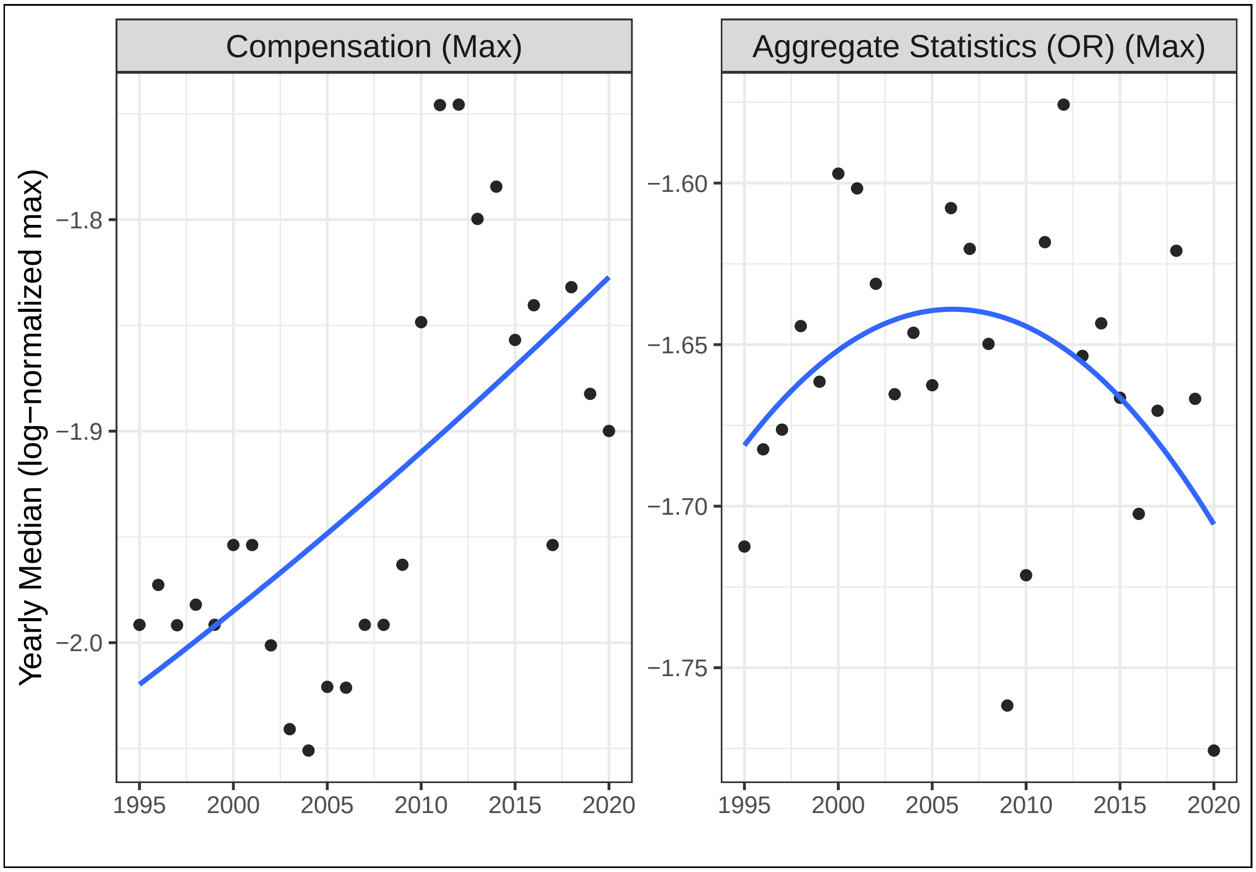



Figure A.12: Yearly medians of log-normalized max dependence for Compensation and OR.

## C.2 Time Series Clustering

Our preferred clustering algorithm does not endogenously determine the number of clusters. The specification shown in the main text uses three clusters. To demonstrate some robustness to the number of clusters requested, we produce in Figure A.13 the bin scattered graphs for a range of numbers of clusters. In addition, we also produce a list of states which are associated with each cluster, to help readers assess the stability of cluster membership across specifications. Across all panels with three or more clusters, we can identify at least one cluster whose dependence is increasing, one whose dependence is decreasing, and one which follows the U shaped pattern.

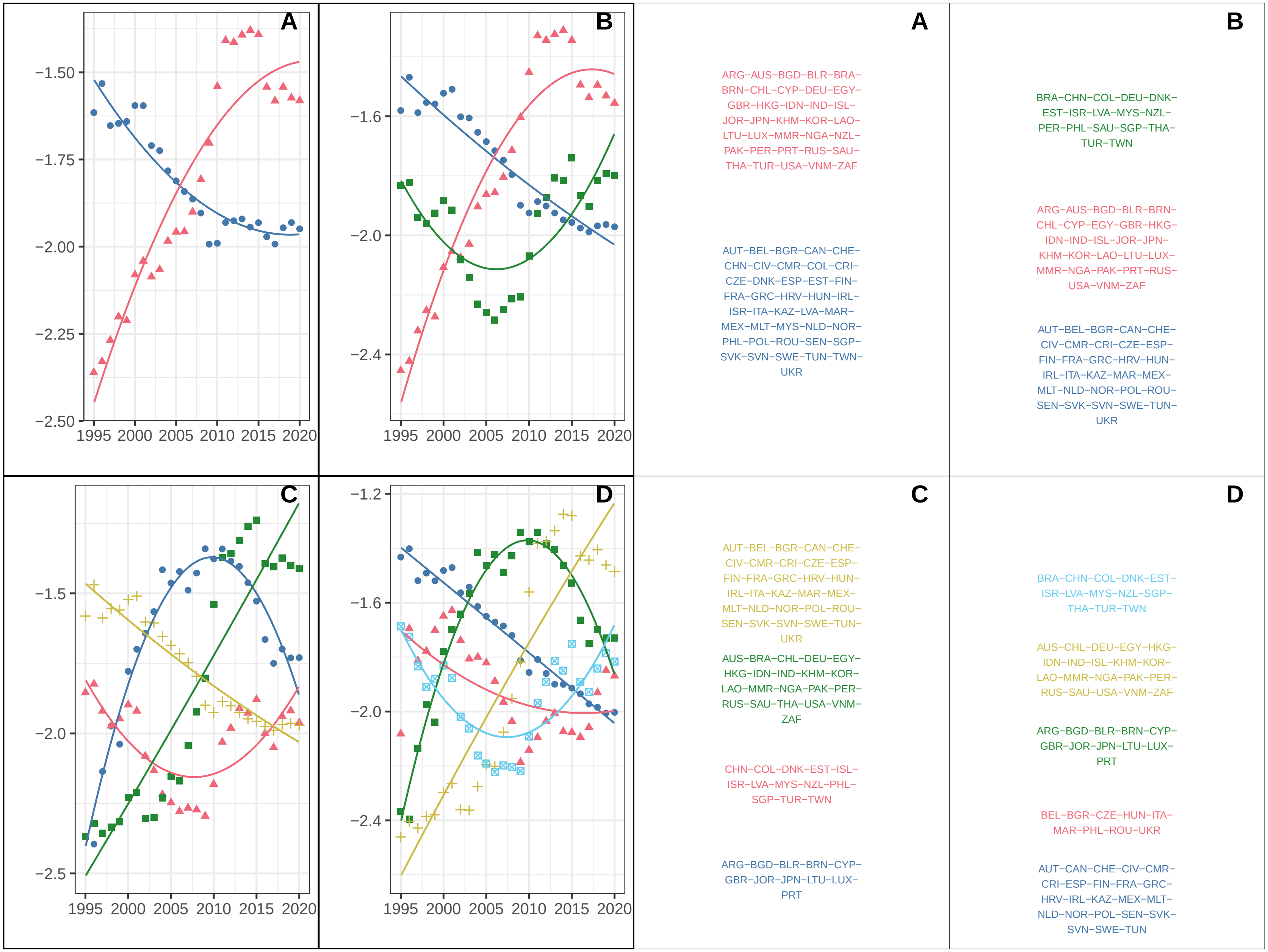



Figure A.13: Robustness of the clustering procedure to the number of clusters. The ISO codes for cluster members are produced alongside their trends. Labels in the upper right hand corner of each panel indicate the specification.

## C.3 "Max" measure robustness

In the main manuscript, Figure 3 showed trends in our measure over time. It showed each country's maximum value of a particular measure. Figure A.14 shows the same thing, only it is based on each country's 5 most dependent relationships, instead of the maximally dependent relationship.

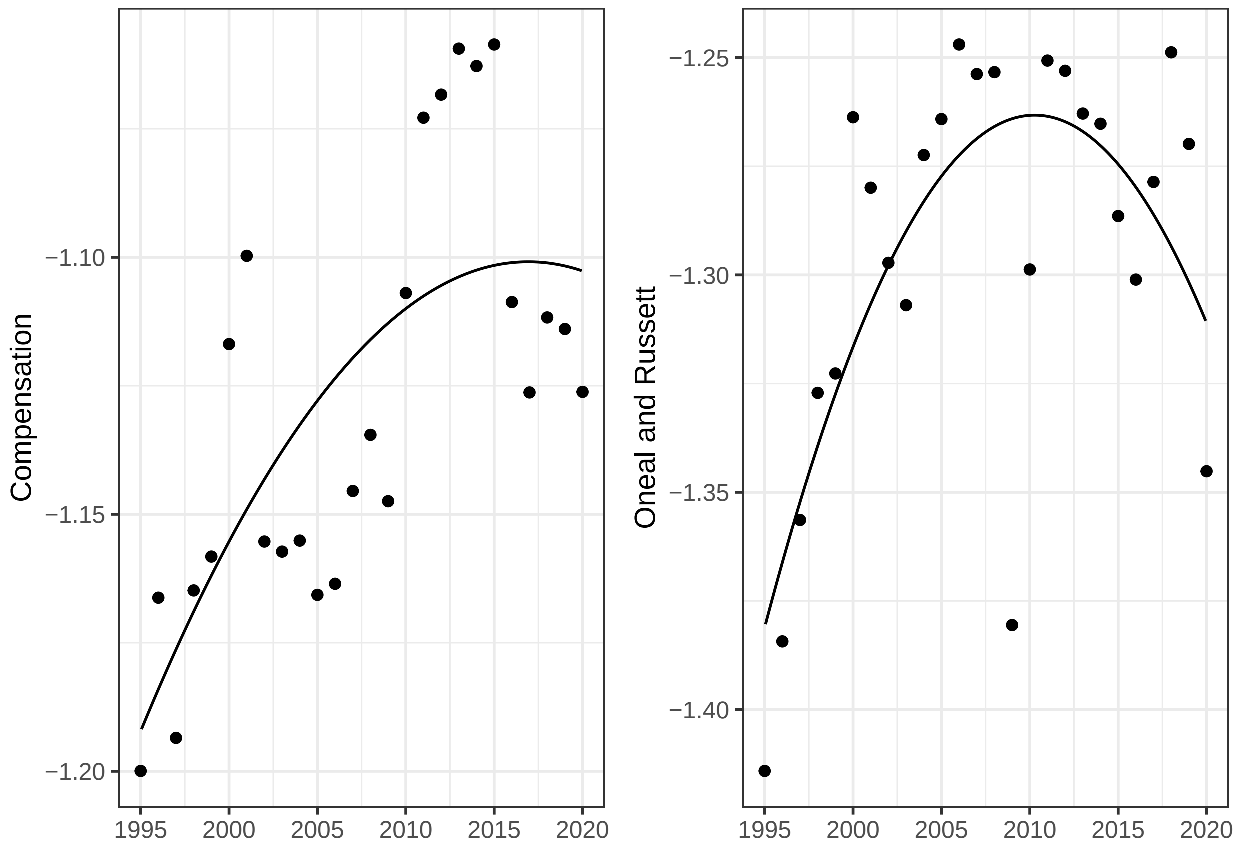



Figure A.14: Bin scatters of the top 5 of each measure after taking the natural logarithm. Both variables are normalized to the unit interval before taking logs to equalize their support and facillitate comparison.

## C.4 Upper bound trends

In the main manuscript, for Section 6, we used the compensation measure and not the upper bound measure. The UB measure describes the maximum damage to welfare from an interruption in trade, and the compensation measure incorporates the idea that the target could compensate by increasing supply from other partners. Whether and when to use which measure depends on a researcher's specific question. In one sense, the compensation measure takes a longer-term view. If trade is interrupted, then the target incurs the pain described by the UB measure. And then gradually, over time, they can compensate. But it takes time to shift suppliers.

If the theoretical scope of a researcher's analysis was of a shorter timeframe, then the UB measure potentially is more appropriate. If the scope is for a longer timeframe, then compensation is potentially more appropriate. For example, suppose a researcher wanted to ask "As tensions rise between blocs of countries, how does their dependence change over time?" The compensation measure might be more appropriate, since the researcher might theorize about longer term adjustments like friend-shoring. Another researcher might want to ask "What's the effect of dependence on the probability of success of episodic compellent threats?" They might theorize that upper bound dependence is more appropriate, if they thought that the ability to inflict shorter-term damage to the target's welfare was most important. Since Section 6 describes longer-term, macro trends, we used the compensation measure.

The figures below reproduce the analysis from the main manuscript, using the upper bound measure instead of the compensation measure. There are important similarities and differences. The maximum levels of upper bound dependence have, like the OR aggregate statistics measure, decreased over time (Figure A.15). There are more countries in the "decreasers" cluster and fewer in the "increasers" cluster (Figure A.16). As with the compensation measure, other countries dependence on China began to exceed dependence on the United States at a much earlier year than the OR measure would suggest (Figure A.17).

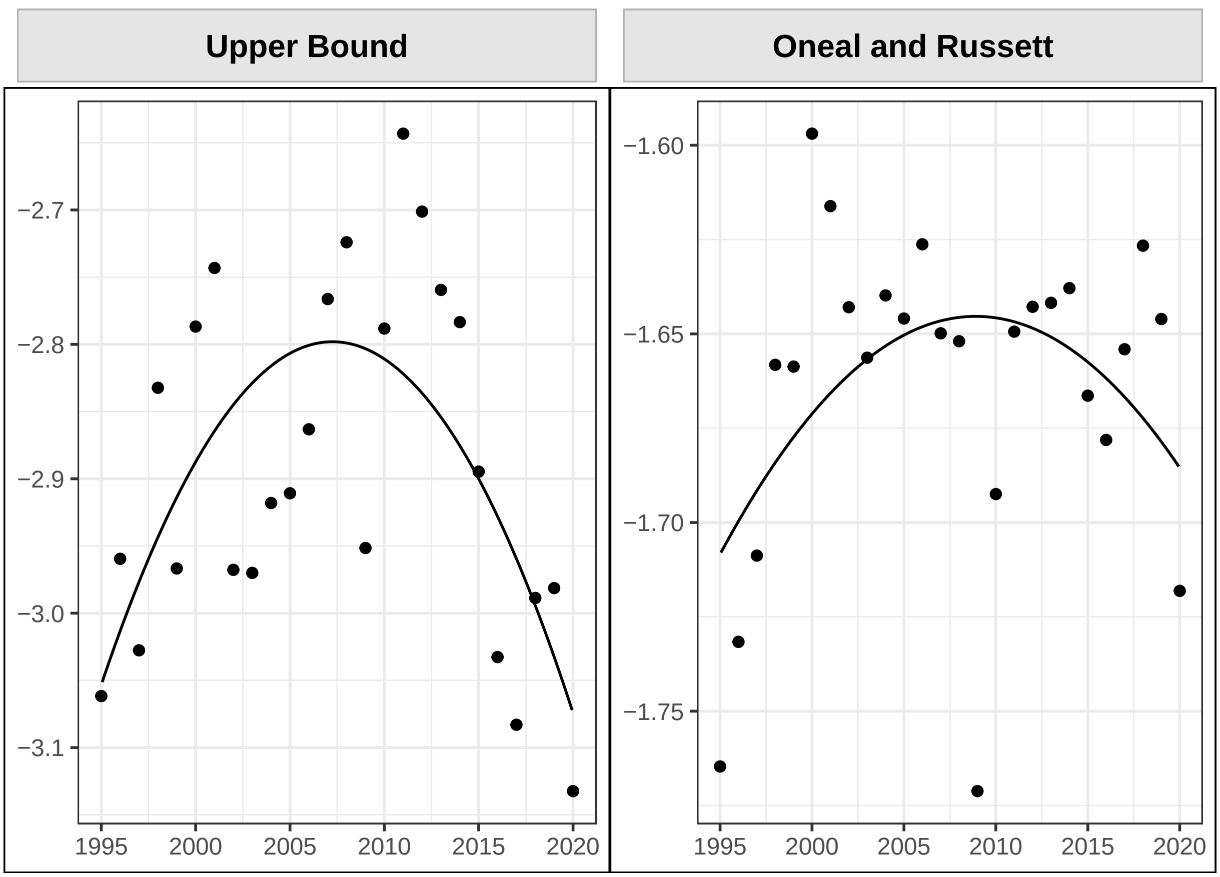



Figure A.15: Bin scatter of the maximum values of the upper bound and OR dependence measures, logged and normalized to the unit interval to equalize their support and facillitate comparison.

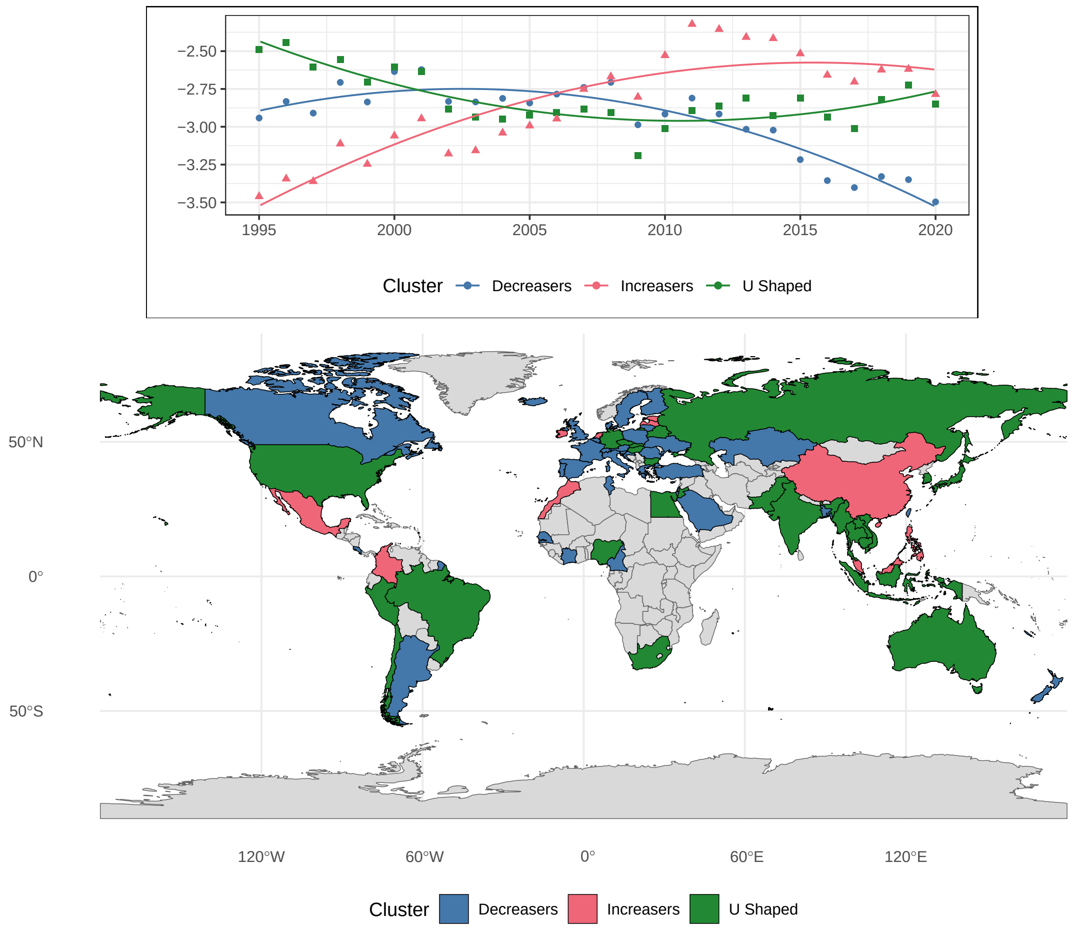



Figure A.16: Clustering countries by their trends in maximum values of upper-bound dependence. Blue countries have decreasing dependence. Red countries have increasing dependence. Green have U-shaped trends.

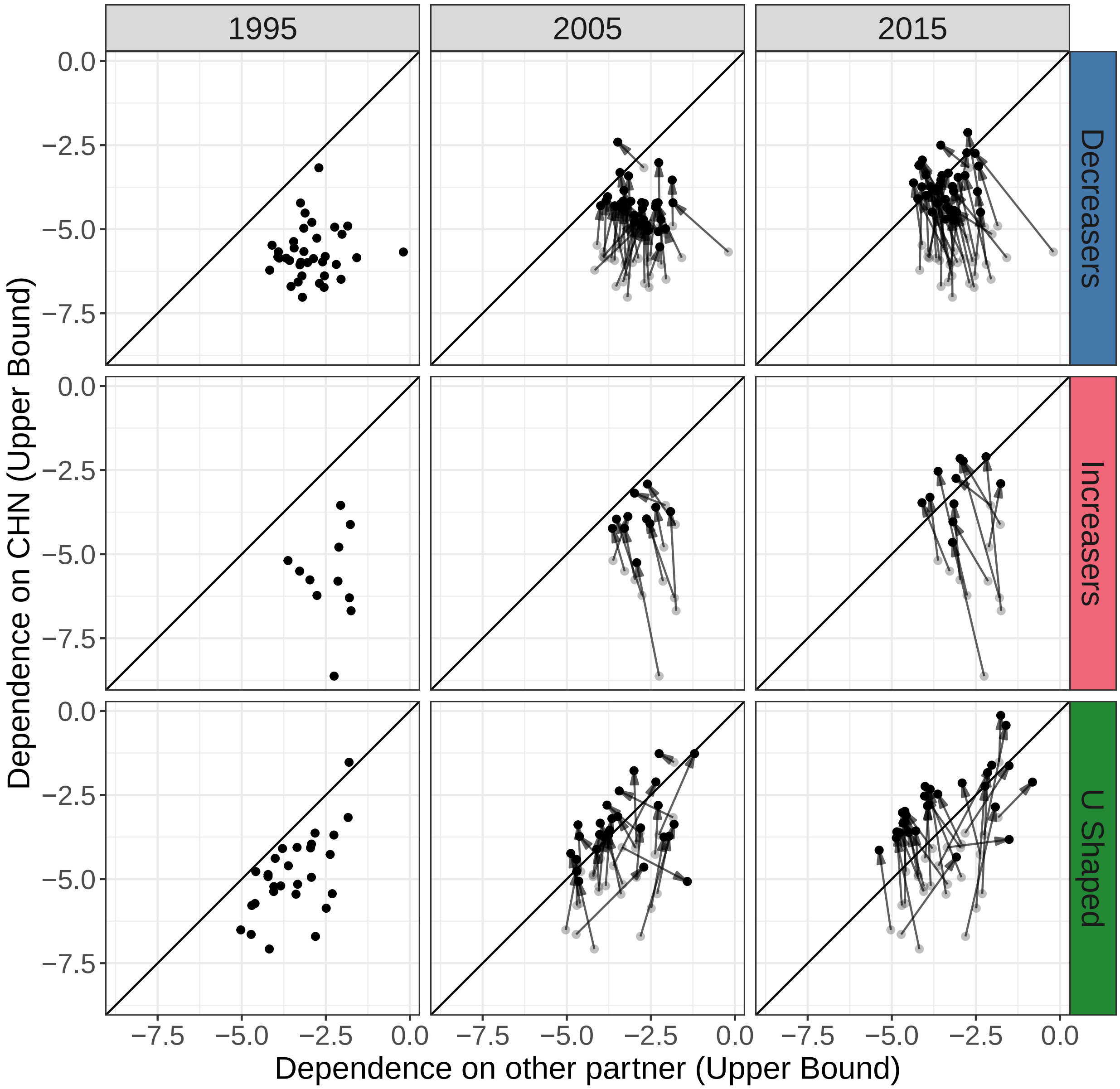



Figure A.17: Vectors indicating change over time in a country's dependence on China (vertical axis) and its maximum dependence on any other (non-China) partner, using the UPPER BOUND dependence measure. Lines connect 1995 values to the highlighted year. The diagonal black line is a 45 degree line. Dependence is plotted after normalization to the unit interval and after taking the natural log.

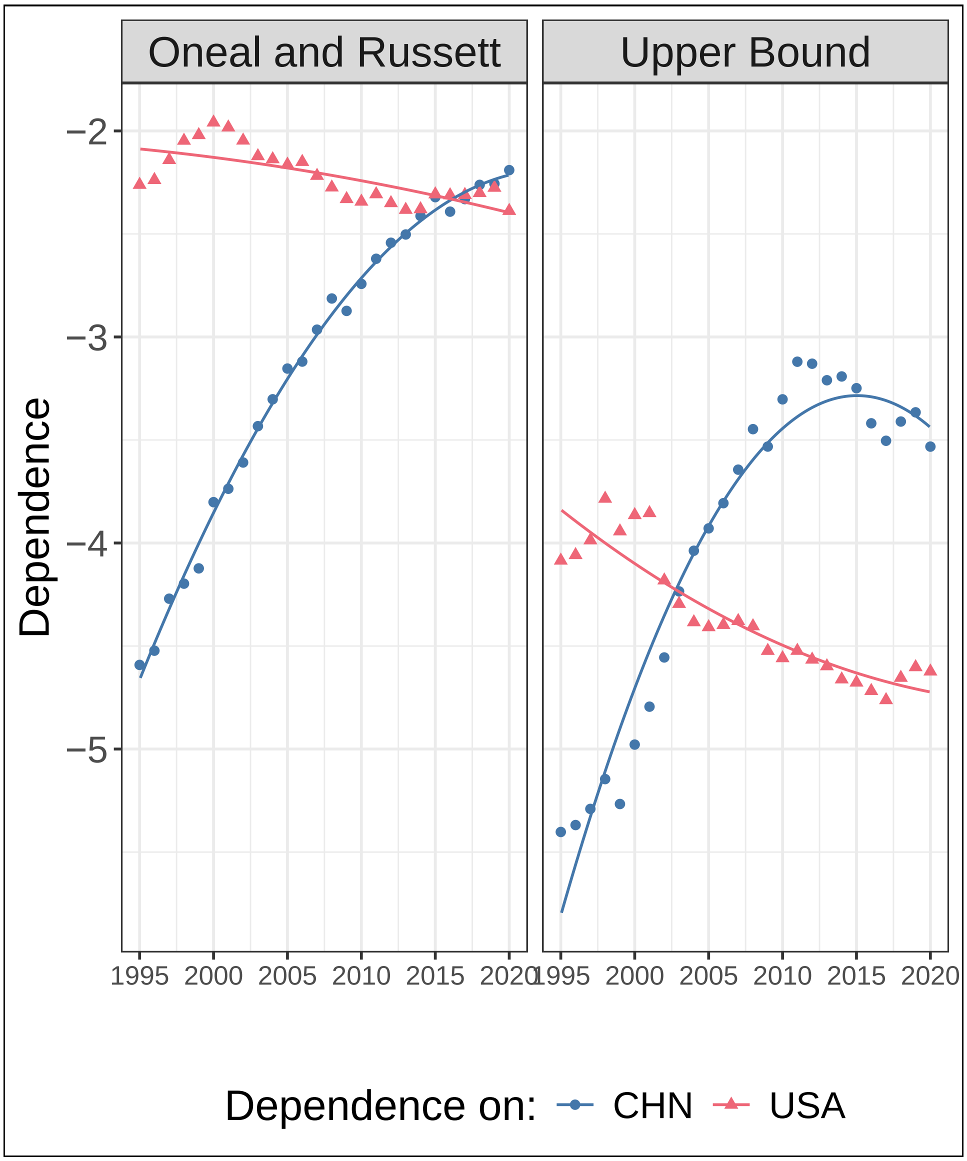



Figure A.18: Global dependence on USA and CHN over time (Upper Bound and OR measures)

The distribution of dyadic upper bound dependencies are also asymmetric, as with the compensation measure. Figure A.19 shows these distributions in a similar way to the main manuscript's mosaic plot. Here, we took each country and found its maximum dependence relationship for each year. Then, we calculated the difference between $i$'s dependence on $j$ and $j$'s dependence on $i$. In other words, for each country-year observation, we found the maximum of their dependency. Then, we calculated the asymmetry in dependence for that dyad-year. Figure A.19 shows the distributions of those differences. The differences tend to be larger for the upper bound measure, compared to the compensation measure. The same is true using all observations, not just looking at maximally dependent dyads.

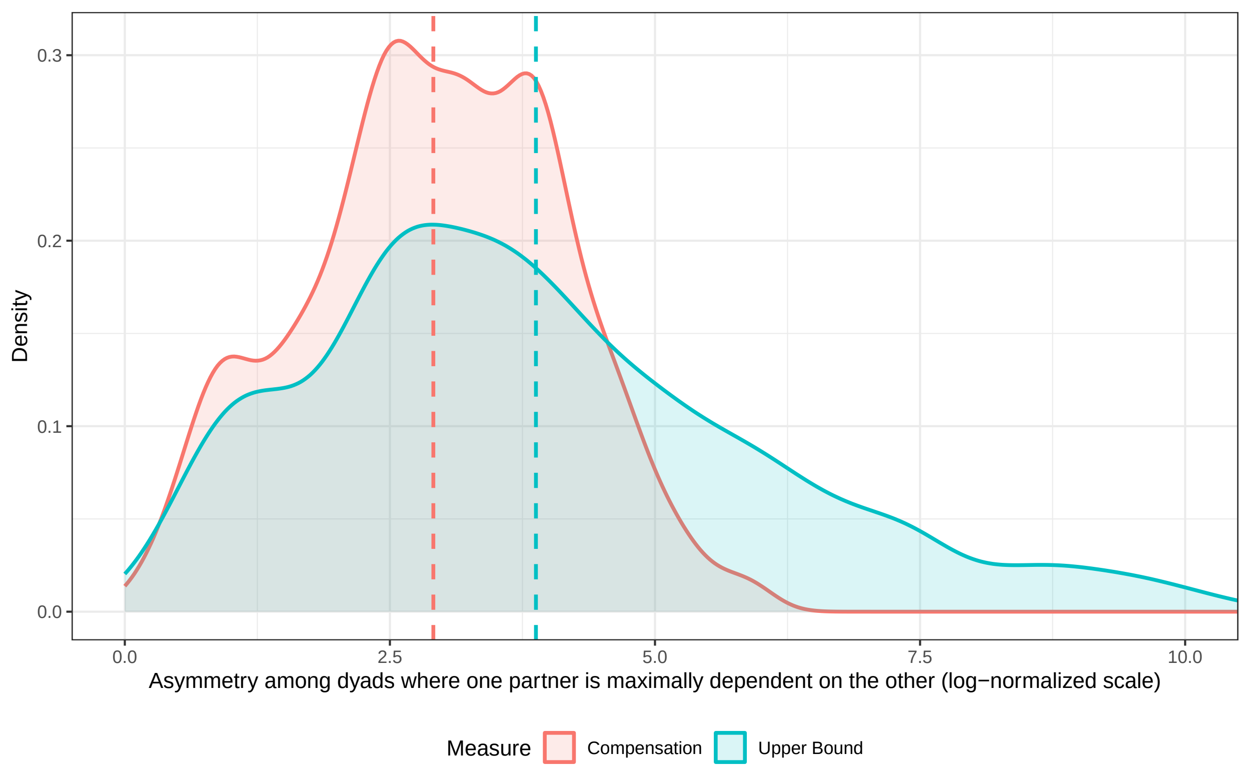



Figure A.19: Distributions of interdependence for maximally dependent relationships.

Figure A.20 shows trends in asymmetry. Interestingly, asymmetry among all dyads has trended downwards according to the upper bound measure, as with the OR measure. Though it still increases when looking at maximum dependencies. Most dyads have gotten more symmetrical in their dependencies over time, according to the upper bound measure. For the compensation measure, this trend was flat. But as with the compensation measure, when looking at countries' most dependent relationships, asymmetry has increased.

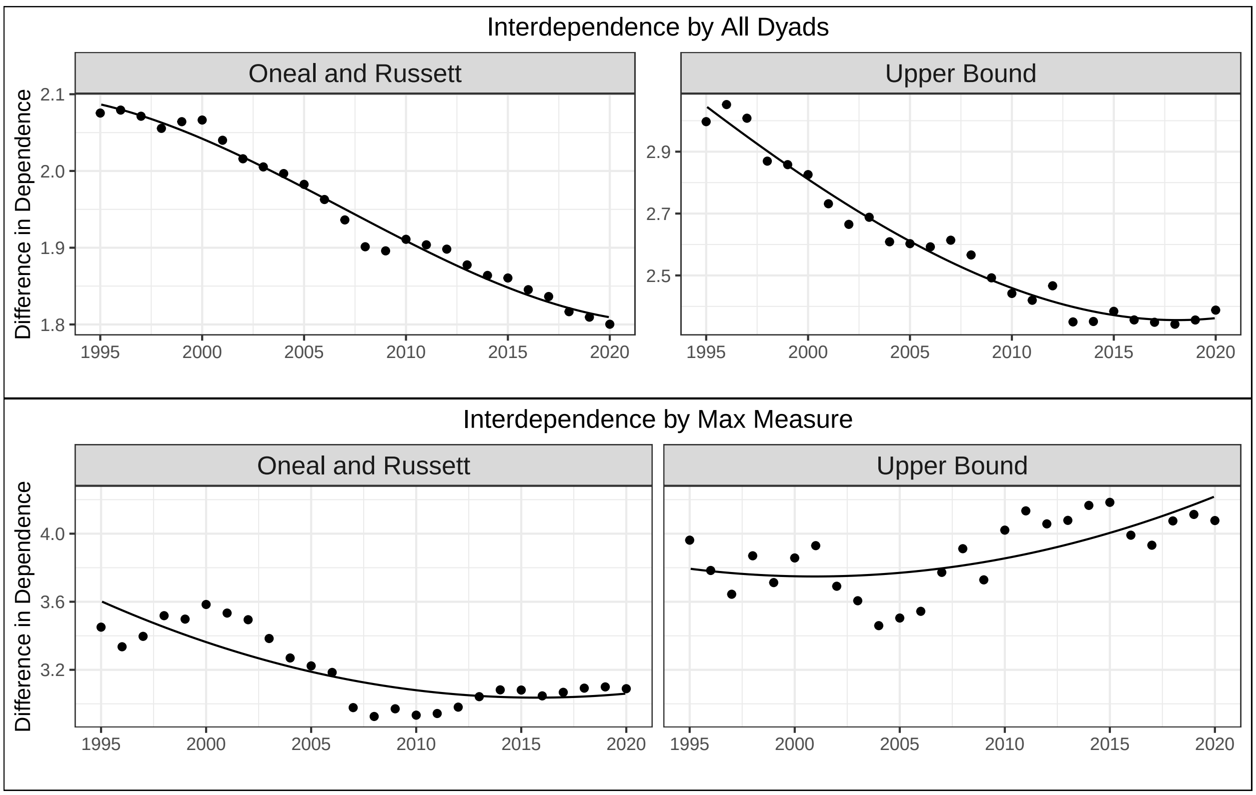



Figure A.20: Interdependence over time (Upper Bound vs OR). Points show differences in directed dyadic dependence over time, averaged across dyads. The top pane shows this difference for all dyads. The bottom pane shows this for maximally dependent dyads.

# D Appendix Items for Section 7: Chinese Foreign Assistance

## D.1 Estimates Table

Below is the estimates table for the results shown in Figure 10.

Table A.3: Dynamic ATT Estimates with Significance Stars (–5 to 15)

| | Event Time | Estimate | Std. Error | CI Lower | CI Upper | P-value |
|---|---|---|---|---|---|---|
| 17 | -5 | 0.003 | 0.005 | -0.006 | 0.012 | 0.482 |
| 18 | -4 | 0.000 | 0.004 | -0.008 | 0.009 | 0.914 |
| 19 | -3 | 0.008*** | 0.003 | 0.003 | 0.014 | 0.002 |
| 20 | -2 | 0.016** | 0.007 | 0.003 | 0.029 | 0.014 |
| 21 | -1 | 0.006 | 0.009 | -0.012 | 0.023 | 0.518 |
| 22 | 0 | 0.007 | 0.007 | -0.007 | 0.021 | 0.326 |
| 23 | 1 | 0.023** | 0.009 | 0.005 | 0.041 | 0.012 |
| 24 | 2 | 0.026*** | 0.008 | 0.010 | 0.041 | 0.001 |
| 25 | 3 | 0.046*** | 0.013 | 0.022 | 0.071 | 0.000 |
| 26 | 4 | 0.065*** | 0.020 | 0.025 | 0.105 | 0.001 |
| 27 | 5 | 0.078*** | 0.021 | 0.037 | 0.120 | 0.000 |
| 28 | 6 | 0.085*** | 0.022 | 0.042 | 0.127 | 0.000 |
| 29 | 7 | 0.080*** | 0.021 | 0.039 | 0.121 | 0.000 |
| 30 | 8 | 0.104*** | 0.039 | 0.027 | 0.181 | 0.008 |
| 31 | 9 | 0.097** | 0.043 | 0.014 | 0.181 | 0.023 |
| 32 | 10 | 0.150*** | 0.049 | 0.054 | 0.247 | 0.002 |
| 33 | 11 | 0.162*** | 0.059 | 0.046 | 0.278 | 0.006 |
| 34 | 12 | 0.172*** | 0.064 | 0.047 | 0.296 | 0.007 |
| 35 | 13 | 0.178** | 0.075 | 0.031 | 0.325 | 0.017 |
| 36 | 14 | 0.173*** | 0.058 | 0.059 | 0.286 | 0.003 |
| 37 | 15 | 0.153*** | 0.057 | 0.040 | 0.265 | 0.008 |

## D.2 Effect on Chinese dependence, OR measure

Figure A.21 shows the effect of Chinese foreign assistance on China's dependence on the recipient, using the OR measure.

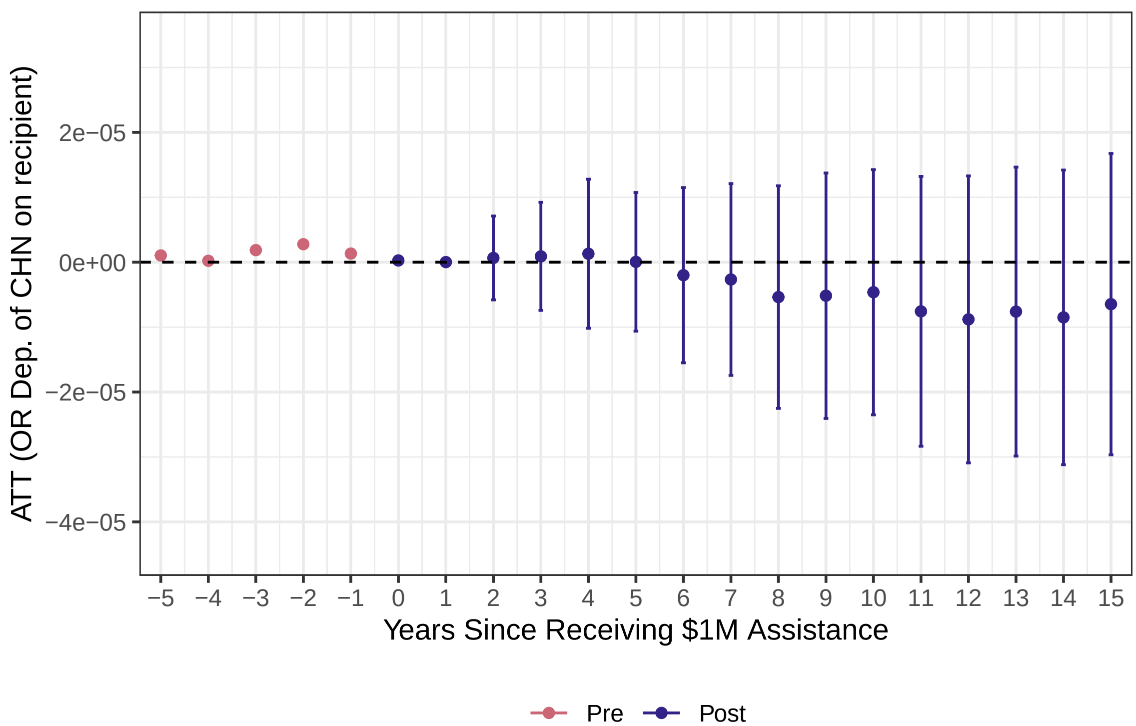



Figure A.21: Effect of Chinese assistance on China's dependence on the recipient. The OR dependence measure is the outcome variable.

## D.3 Alternative estimators

In the main manuscript, we showed treatment effects estimated from Callaway and Sant'Anna (2021) with a particular set of control variables and definition of the control group. Table A.4 below shows the aggregate treatment effects for a wide array of variations on assumptions about control variables and control group. It also shows estimates from a two-way fixed effects model. The estimates for the effect of assistance on dependence are very consistent in size and significance.

Table A.4: Robustness of Chinese Assistance/BRI Effect Estimates

| estimate | se | p.value | type | controls | control_group | indepvar |
|---|---|---|---|---|---|---|
| 0.1164 | 0.0397 | 0.0034 | CS | ~1 | nevertreated | First Year Amt>$1M |
| 0.1123 | 0.0366 | 0.0022 | CS | ~1 | notyettreated | First Year Amt>$1M |
| 0.1374 | 0.0372 | 0.0002 | CS | ~TotalTrade_log | nevertreated | First Year Amt>$1M |
| 0.1447 | 0.0407 | 0.0004 | CS | ~gdp_COU_log | nevertreated | First Year Amt>$1M |
| 0.0805 | 0.0365 | 0.0276 | CS | ~vdem_electCOU | nevertreated | First Year Amt>$1M |
| 0.1064 | 0.0362 | 0.0033 | CS | ~TotalTrade_log + gdp_COU_log + vdem_electCOU | nevertreated | First Year Amt>$1M |
| 0.1079 | 0.0361 | 0.0028 | CS | ~TotalTrade_log + gdp_COU_log + vdem_libdemCOU | nevertreated | First Year Amt>$1M |
| 0.1093 | 0.0321 | 0.0007 | CS | ~TotalTrade_log + gdp_COU_log + vdem_libdemCOU | nevertreated | First Year Amt>$0 |
| 0.1144 | 0.0349 | 0.0010 | CS | ~TotalTrade_log + gdp_COU_log + vdem_libdemCOU | nevertreated | First Year Amt>$0.5M |
| 0.1074 | 0.0402 | 0.0076 | CS | ~TotalTrade_log + gdp_COU_log + vdem_libdemCOU | nevertreated | First Year Amt>$5M |
| 0.0981 | 0.0260 | 0.0009 | Two Way FE | + TotalTrade_log + gdp_COU_log + vdem_electCOU | | First Year Amt>$1M |
| 0.0763 | 0.0346 | 0.0307 | Two Way FE | + TotalTrade_log + gdp_COU_log + vdem_electCOU | | Amt (rescaled) |

Figure A.22 shows the estimated effects of Chinese assistance using the original specification, but broken down by calendar year instead of year of treatment. The effect of assistance tends to grow and reach its height around 2013. Its effect stays relatively stable after that.

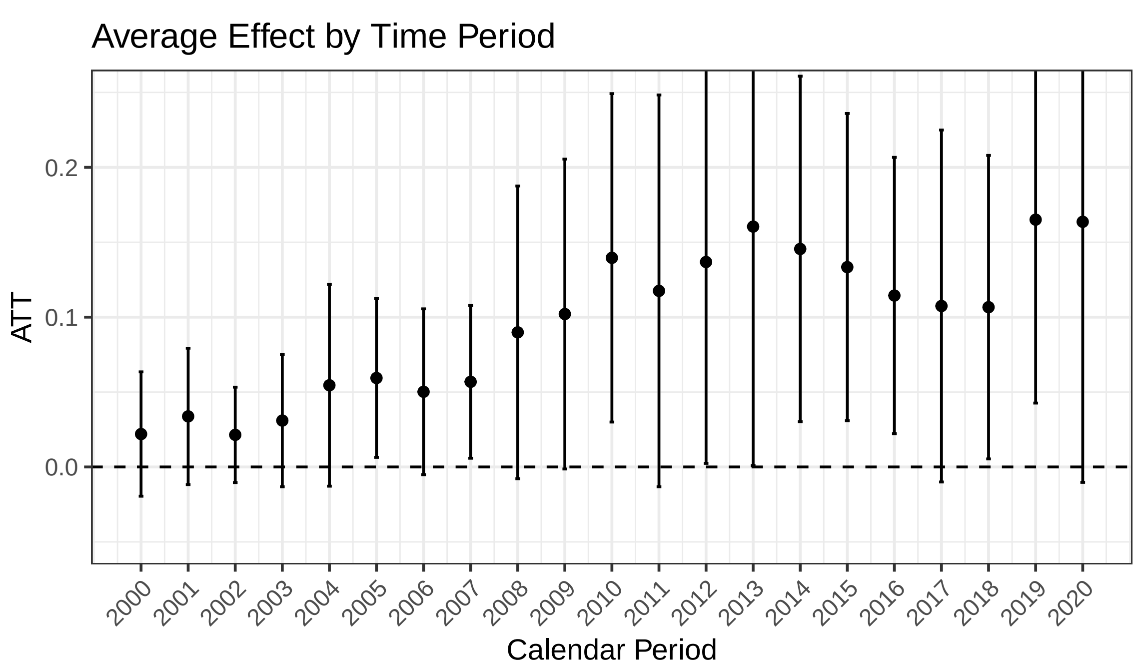



Figure A.22: Estimates of Chinese assistance effect by calendar year.

Table A.5 shows information from the Goodman-Bacon decomposition of the overall effect we estimated (Goodman-Bacon 2021). It decomposes the aggregate estimate into a weighted average of different comparisons. The table shows the comparisons that make up our aggregate effect that have the highest weights in this decomposition. They are generally comparisons of treated versus untreated units. The highest is a comparison from the year 2000. Even when we drop that comparison, the estimated effect is still very similar to the aggregate effect.

| treated | untreated | weight | estimate | type |
|---|---|---|---|---|
| 2000 | | 0.2064 | 0.1325 | Treated vs Untreated |
| 2005 | | 0.1003 | 0.0230 | Treated vs Untreated |
| 2002 | | 0.0746 | 0.1804 | Treated vs Untreated |
| 2007 | | 0.0698 | 0.1177 | Treated vs Untreated |
| 2004 | | 0.0598 | 0.0767 | Treated vs Untreated |
| 2015 | | 0.0507 | 0.1464 | Treated vs Untreated |
| 2001 | | 0.0489 | 0.0937 | Treated vs Untreated |
| 2009 | | 0.0370 | 0.2260 | Treated vs Untreated |
| 2011 | | 0.0347 | 0.0218 | Treated vs Untreated |
| 2006 | | 0.0335 | 0.0239 | Treated vs Untreated |
| 2010 | | 0.0323 | 0.4159 | Treated vs Untreated |
| 2003 | | 0.0279 | 0.1592 | Treated vs Untreated |
| 2017 | | 0.0179 | 0.2157 | Treated vs Untreated |
| 2000 | 2005 | 0.0171 | -0.0864 | Both Treated |
| 2000 | 2015 | 0.0170 | 0.0609 | Both Treated |
| 2000 | 2007 | 0.0151 | -0.0269 | Both Treated |
| 2000 | 2011 | 0.0098 | -0.0544 | Both Treated |
| 2000 | 2009 | 0.0097 | 0.0599 | Both Treated |
| 2000 | 2004 | 0.0094 | -0.0559 | Both Treated |
| 2000 | 2010 | 0.0088 | 0.1569 | Both Treated |

Table A.5: Top 20 weights produced by the Goodman-Bacon decomposition. The weights indicate each comparison's influence on a two way fixed effects estimate of a difference-in-differences model. The overall estimate is 0.1 and the estimate after excluding the highest weighted comparison is 0.092.

Table A.6 shows summary information about the sample. Most of our specifications use a binary indicator variable for years after a country has received a particular level of Chinese assistance. This table shows that year for each country.

| Country | Treatment Year | Country | Treatment Year |
|---|---|---|---|
| BGD | 2000 | JOR | 2003 |
| CIV | 2000 | IDN | 2004 |
| KAZ | 2000 | TUN | 2004 |
| KHM | 2000 | BLR | 2005 |
| LAO | 2000 | SEN | 2005 |
| MAR | 2000 | THA | 2005 |
| MMR | 2000 | UKR | 2006 |
| PAK | 2000 | CRI | 2007 |
| PHL | 2000 | ZAF | 2007 |
| VNM | 2000 | MEX | 2009 |
| CMR | 2001 | CHL | 2010 |
| IND | 2001 | TUR | 2011 |
| EGY | 2002 | ARG | 2015 |
| NGA | 2002 | MYS | 2015 |
| PER | 2002 | COL | 2017 |

Table A.6: All treated units by treatment year.

Table A.7 and Table A.8 show how estimates change as we exclude earlier or later years from the sample. A potentialy worry would be that only early periods or late periods drove estimates. In each table, we re-estimate the effect of assistance on dependence, but we gradually truncate the sample. Even excluding the first ten years or the last ten years, the estimated effects are still positive and significant.

| sample_label | estimate | se | conf.lower | conf.upper | p.value |
|---|---|---|---|---|---|
| Full sample | 0.1064 | 0.0365 | 0.0348 | 0.1779 | 0.0036 |
| Exclude years with TIME ≤ 1996 | 0.1064 | 0.0357 | 0.0364 | 0.1763 | 0.0029 |
| Exclude years with TIME ≤ 1997 | 0.1064 | 0.0355 | 0.0367 | 0.1760 | 0.0028 |
| Exclude years with TIME ≤ 1998 | 0.1064 | 0.0351 | 0.0375 | 0.1753 | 0.0025 |
| Exclude years with TIME ≤ 1999 | 0.0847 | 0.0301 | 0.0257 | 0.1436 | 0.0049 |
| Exclude years with TIME ≤ 2000 | 0.0816 | 0.0365 | 0.0100 | 0.1532 | 0.0255 |
| Exclude years with TIME ≤ 2001 | 0.0554 | 0.0173 | 0.0215 | 0.0893 | 0.0014 |
| Exclude years with TIME ≤ 2002 | 0.0643 | 0.0152 | 0.0346 | 0.0940 | 0.0000 |
| Exclude years with TIME ≤ 2003 | 0.0634 | 0.0170 | 0.0300 | 0.0968 | 0.0002 |
| Exclude years with TIME ≤ 2004 | 0.0664 | 0.0191 | 0.0289 | 0.1038 | 0.0005 |
| Exclude years with TIME ≤ 2005 | 0.0609 | 0.0249 | 0.0120 | 0.1098 | 0.0147 |

Table A.7: Effect of Chinese Assistance/BRI with All Controls, Excluding Early Years (up to 2005)

| sample_label | estimate | se | conf.lower | conf.upper | p.value |
|---|---|---|---|---|---|
| Full sample | 0.1064 | 0.0347 | 0.0383 | 0.1744 | 0.0022 |
| Exclude years with TIME ≥ 2010 | 0.0612 | 0.0221 | 0.0179 | 0.1044 | 0.0056 |
| Exclude years with TIME ≥ 2011 | 0.0725 | 0.0242 | 0.0251 | 0.1198 | 0.0027 |
| Exclude years with TIME ≥ 2012 | 0.0786 | 0.0265 | 0.0266 | 0.1306 | 0.0031 |
| Exclude years with TIME ≥ 2013 | 0.0850 | 0.0283 | 0.0295 | 0.1405 | 0.0027 |
| Exclude years with TIME ≥ 2014 | 0.0923 | 0.0323 | 0.0289 | 0.1556 | 0.0043 |
| Exclude years with TIME ≥ 2015 | 0.0969 | 0.0323 | 0.0336 | 0.1603 | 0.0027 |
| Exclude years with TIME ≥ 2016 | 0.0939 | 0.0325 | 0.0302 | 0.1576 | 0.0038 |
| Exclude years with TIME ≥ 2017 | 0.0952 | 0.0328 | 0.0309 | 0.1594 | 0.0037 |
| Exclude years with TIME ≥ 2018 | 0.0978 | 0.0354 | 0.0284 | 0.1673 | 0.0057 |
| Exclude years with TIME ≥ 2019 | 0.0984 | 0.0360 | 0.0280 | 0.1689 | 0.0062 |

Table A.8: Effect of Chinese Assistance/BRI with All Controls, Excluding Late Years (down to 2005)

## D.4 Other aid flows

The main text emphasizes ODA-like flows as the main independent variable. We focus on this form of financing because Dreher et al. (2018) found that ODA-like flows are primarily explained by political determinants while OOF-like flows are better explained by economic factors. As robustness, we also recoded our independent variables using total flows (the sum of ODA-like flows, OOF-like flows, and all uncategorized flows). The results of this analysis, which are very similar to our main results, are shown in Figure A.23. Table A.9 shows the same robustness table as above, but using total flows. The results are very similar with positive and significant estimates in all but the continuous amount two-way fixed effect specification.

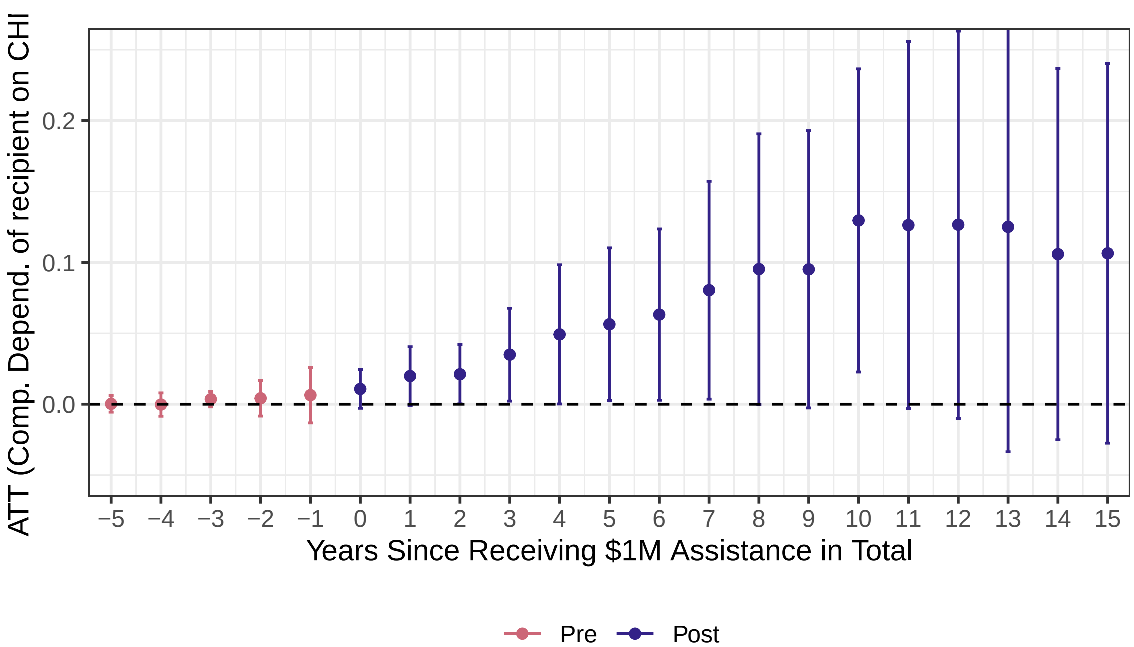



Figure A.23: Effect of Chinese assistance (total assistance, not just ODA-like) on recipient's dependence on China. The compensation dependence measure is the outcome variable.

Table A.9: Robustness of Chinese Assistance/BRI Effect Estimates (Total Flows)

| estimate | se | p.value | type | controls | control_group | indepvar |
|---|---|---|---|---|---|---|
| 0.107 | 0.035 | 0.002 | CS | ~1 | nevertreated | First Year Amt>$1M (Tot.) |
| 0.107 | 0.031 | 0.001 | CS | ~1 | notyettreated | First Year Amt>$1M (Tot.) |
| 0.125 | 0.030 | 0.000 | CS | ~TotalTrade_log | nevertreated | First Year Amt>$1M (Tot.) |
| 0.132 | 0.033 | 0.000 | CS | ~gdp_COU_log | nevertreated | First Year Amt>$1M (Tot.) |
| 0.078 | 0.032 | 0.015 | CS | ~vdem_electCOU | nevertreated | First Year Amt>$1M (Tot.) |
| 0.085 | 0.031 | 0.006 | CS | ~TotalTrade_log + gdp_COU_log + vdem_electCOU | nevertreated | First Year Amt>$1M (Tot.) |
| 0.084 | 0.030 | 0.004 | CS | ~TotalTrade_log + gdp_COU_log + vdem_libdemCOU | nevertreated | First Year Amt>$1M (Tot.) |
| 0.090 | 0.027 | 0.001 | CS | ~TotalTrade_log + gdp_COU_log + vdem_libdemCOU | nevertreated | First Year Amt>$0 (Tot.) |
| 0.091 | 0.031 | 0.004 | CS | ~TotalTrade_log + gdp_COU_log + vdem_libdemCOU | nevertreated | First Year Amt>$0.5M (Tot.) |
| 0.093 | 0.031 | 0.002 | CS | ~TotalTrade_log + gdp_COU_log + vdem_libdemCOU | nevertreated | First Year Amt>$5M (Tot.) |
| 0.083 | 0.023 | 0.001 | Two Way FE | + TotalTrade_log + gdp_COU_log + vdem_electCOU | | First Year Amt>$1M (Tot.) |
| 0.004 | 0.003 | 0.242 | Two Way FE | + TotalTrade_log + gdp_COU_log + vdem_electCOU | | Amt (TOTAL, rescaled) |