Trade Interdependence in the Modern Global Economy

Appendix

March 2026

Appendix

A Appendix Items for Section 4: Measure construction A-3
- A.1 Welfare Formula Derivation . . . A-3
- A.2 Walkthrough guide and numerical example . . . A-5
  - Initial setup . . . A-5
  - Add an interruption . . . A-5
  - Calculate Upper Bound measure . . . A-6
  - Calculate Compensation measure . . . A-7
  - Upper Bound versus Compensation . . . A-8
  - Non-identical sectors: setup . . . A-9
  - Non-identical sectors: consumption shares . . . A-10
  - Non-identical sectors: elasticities . . . A-11
  - Non-identical sectors: intermediates shares . . . A-12
- A.3 Sample description . . . A-13
- A.4 Bayesian trade elasticity estimates . . . A-13

B Appendix Items for Section 5: Our measures versus other measures A-14
- B.1 Average dependencies . . . A-14
- B.2 Correlations and outliers . . . A-18
- B.3 Movement in intermediates shares over time . . . A-20
- B.4 Movement at the extensive margin of trade over time . . . A-20

C Appendix Items for Section 6: Changes Over Time A-24
- C.1 Medians versus means . . . A-24
- C.2 Time Series Clustering . . . A-24
- C.3 "Max" measure robustness . . . A-26
- C.4 Upper bound trends . . . A-26

D Appendix Items for Section 7: Chinese Foreign Assistance A-33
- D.1 Estimates Table . . . A-33
- D.2 Effect on Chinese dependence, OR measure . . . A-33
- D.3 Alternative estimators . . . A-34
- D.4 Other aid flows . . . A-38

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, δ 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, η_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 ε_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 η_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 $\hat{C}_j$,

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

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

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
	λ_{s1}	λ_{s2}
	0.1	0.1

For now, we assume the sectors are identical in terms of their consumption shares (η), elasticities (ε), or degree of intermediate inputs (β, 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 λ for each sector. λ 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
	λ_{s1}	λ_{s2}	λ'_{s1}	λ'_{s2}
	0.1	0.1	0.333	0.333

This generates a new value of λ, denoted λ'. 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
	λ_{s1}	λ_{s2}	λ'_{s1}	λ'_{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 (α) 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
	λ_{s1}	λ_{s2}	λ'_{s1}	λ'_{s2}
	0.1	0.1	0.333	0.333

Measures

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

We gradually increase α.

α	α-scaled λ'_{s1}	α-scaled λ'_{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 α value also generates a new λ' value for each sector, which is plugged into the same $\hat{W}$ formula as before.

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

Note that increasing α 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 (α). The new α 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
	λ_{s1}	λ_{s2}	λ'_{s1}	λ'_{s2}
	0.1	0.1	0.333	0.333

Measures

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

α	α-scaled λ'_{s1}	α-scaled λ'_{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
	λ_{s1}	λ_{s2}	λ'_{s1}	λ'_{s2}
	0.2	0.2	0.667	0.222

Measures

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

α	α-scaled λ'_{s1}	α-scaled λ'_{s2}	$\hat{W}$ after scaling
2.5	0.444	0.103	0.94
2.75	0.421	0.094	≈ 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
	λ_{s1}	λ_{s2}	λ'_{s1}	λ'_{s2}
	0.2	0.2	0.667	0.222

Measures

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

α	α-scaled λ'_{s1}	α-scaled λ'_{s2}	$\hat{W}$ after scaling
2.75	0.421	0.094	0.69
		...	
4.65	0.301	0.058	≈ 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
	λ_{s1}	λ_{s2}	λ'_{s1}	λ'_{s2}
	0.2	0.2	0.667	0.222

Measures

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

α	α-scaled λ'_{s1}	α-scaled λ'_{s2}	$\hat{W}$ after scaling
2.75	0.421	0.094	0.69
		...	
3.9	0.339	0.068	≈ 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
	λ_{s1}	λ_{s2}	λ'_{s1}	λ'_{s2}
	0.2	0.2	0.667	0.222

Measures

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

α	α-scaled λ'_{s1}	α-scaled λ'_{s2}	$\hat{W}$ after scaling
2.75	0.421	0.094	0.69
		...	
4.3	0.317	0.062	≈ 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	C23 — Other non-metallic mineral products
A03 — Fishing and aquaculture	C24 — Basic metals
B05_06 — Mining, quarrying, energy producing products	C25 — Fabricated metal products
B07_08 — Mining, quarrying, non-energy producing products	C26 — Computer, electronic and optical equipment
B09 — Mining support service activities	C27 — Electrical equipment
C10T12 — Food products, beverages and tobacco	C28 — Machinery and equipment, nec
C13T15 — Textiles, textile products, leather and footwear	C29 — Motor vehicles, trailers and semi-trailers
C16 — Wood and products of wood and cork	C30 — Other transport equipment
C17_18 — Paper products and printing	C31T33 — Manufacturing nec; repair and installation of machinery and equipment
C19 — Coke and refined petroleum products	D — Electricity, gas, steam and air conditioning supply
C20 — Chemical and chemical products	J58T60 — Publishing, audiovisual and broadcasting activities
C21 — Pharmaceuticals, medicinal chemical and botanical products	R — Arts, entertainment and recreation
C22 — Rubber and plastics products	S — Other service activities

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 et al. (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).

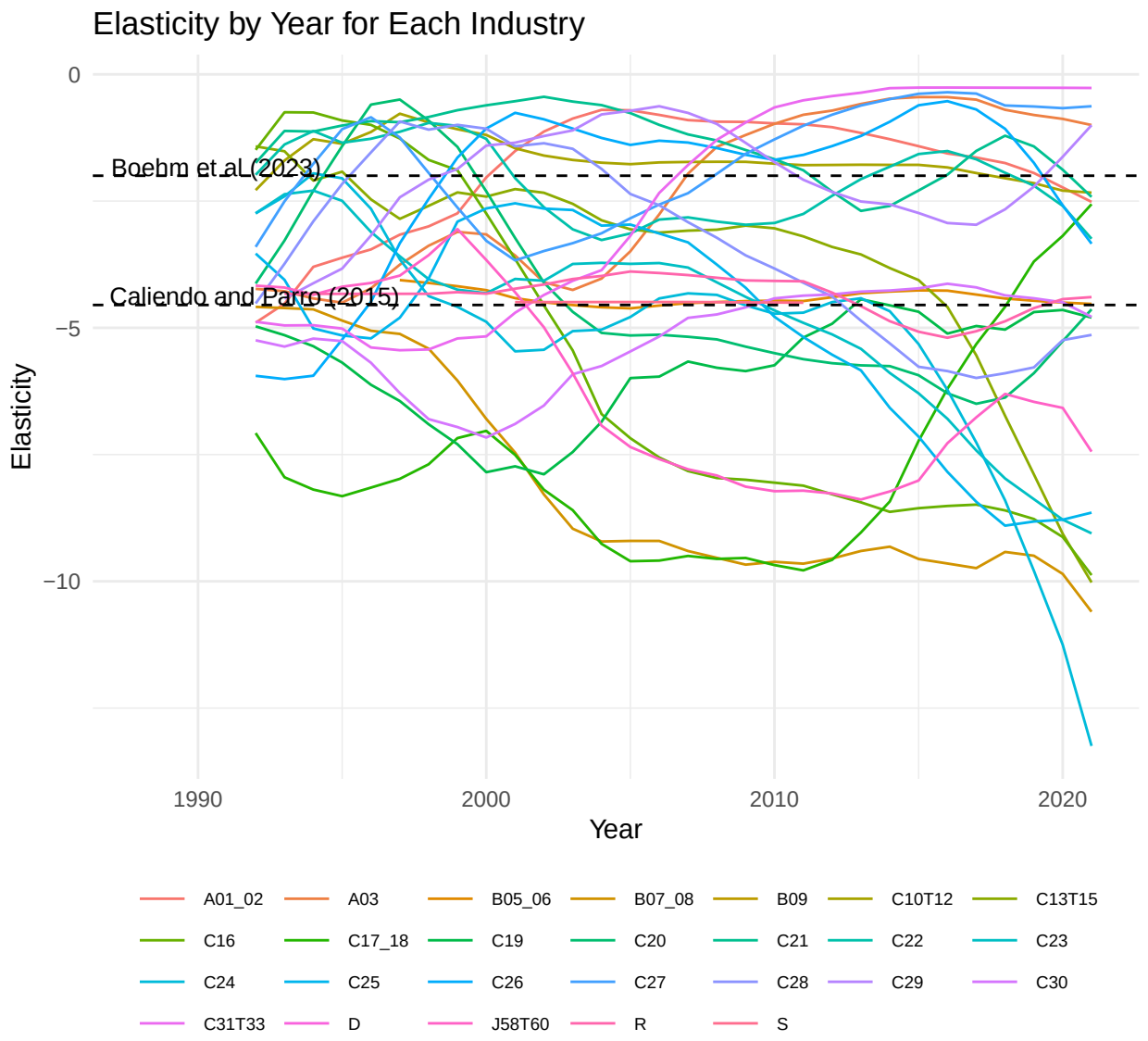


Figure A.1: Bayesian time-varying estimates of elasticities

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.

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.

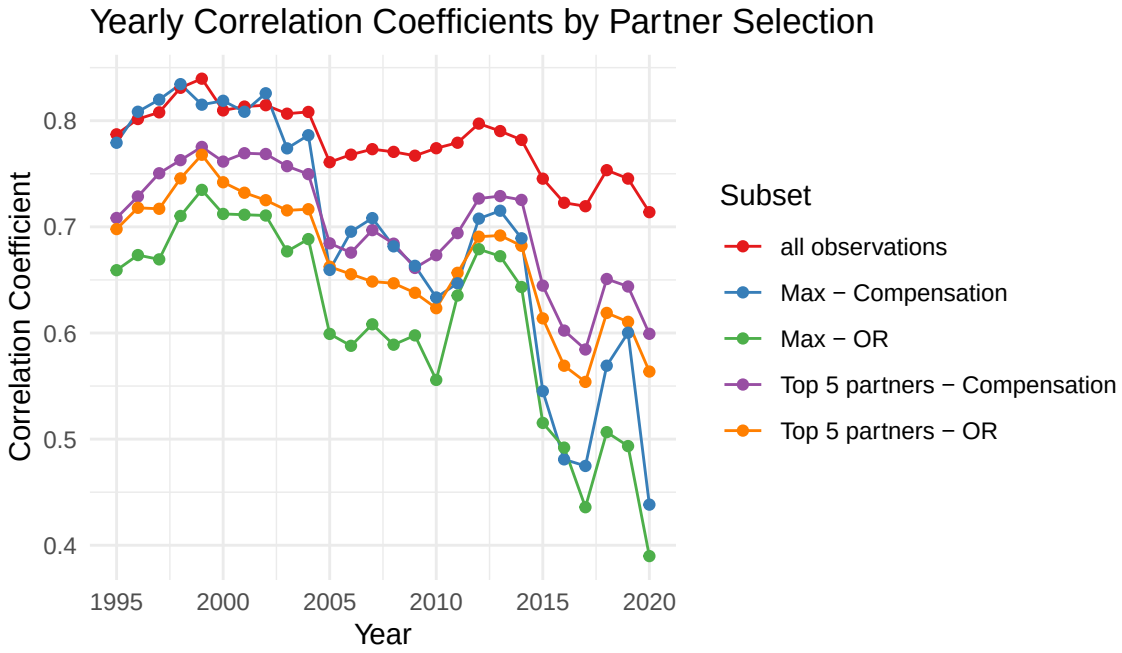


Figure A.2: Correlation coefficients between compensation dependence and Oneal-Russett measure over time.

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.

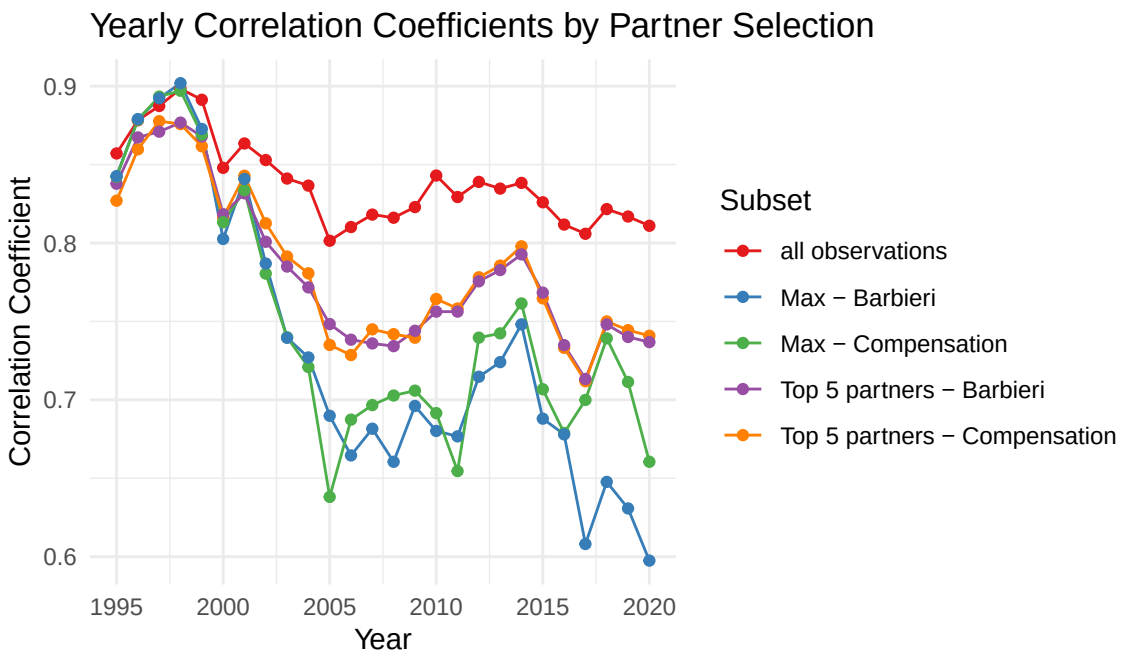


Figure A.3: Correlation coefficients between compensation dependence and Barbieri measure over time.

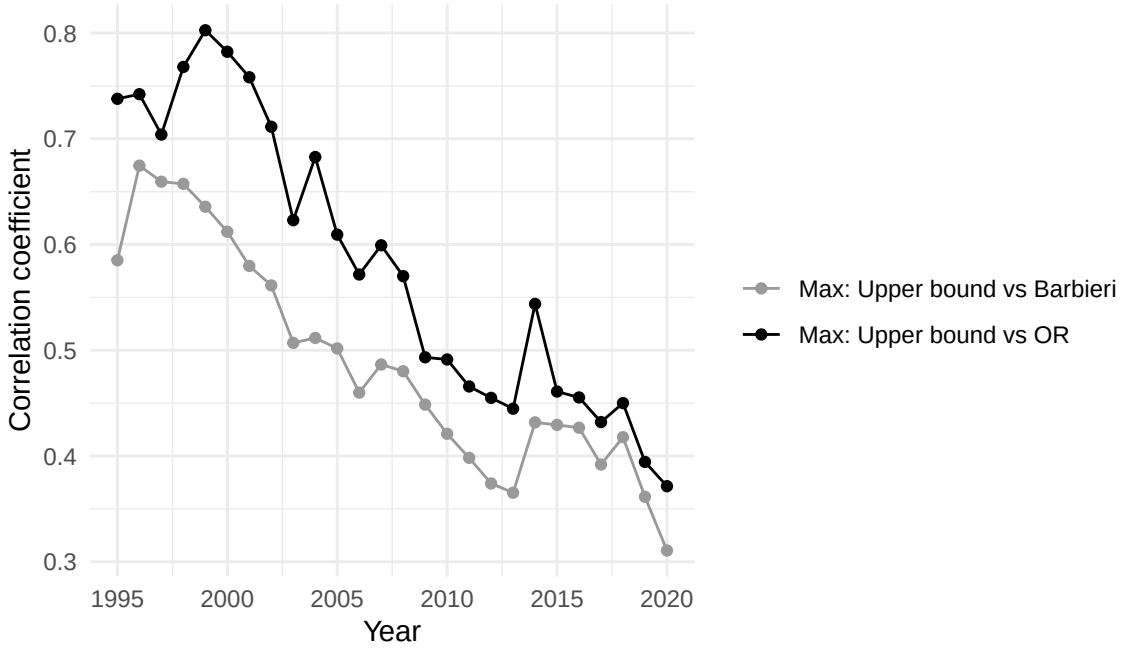


Figure A.4: Correlation coefficients over time between values of the upper-bound dependence measure and the Oneal–Russett and Barbieri measures. Dependence values are the maximums for each country-year.

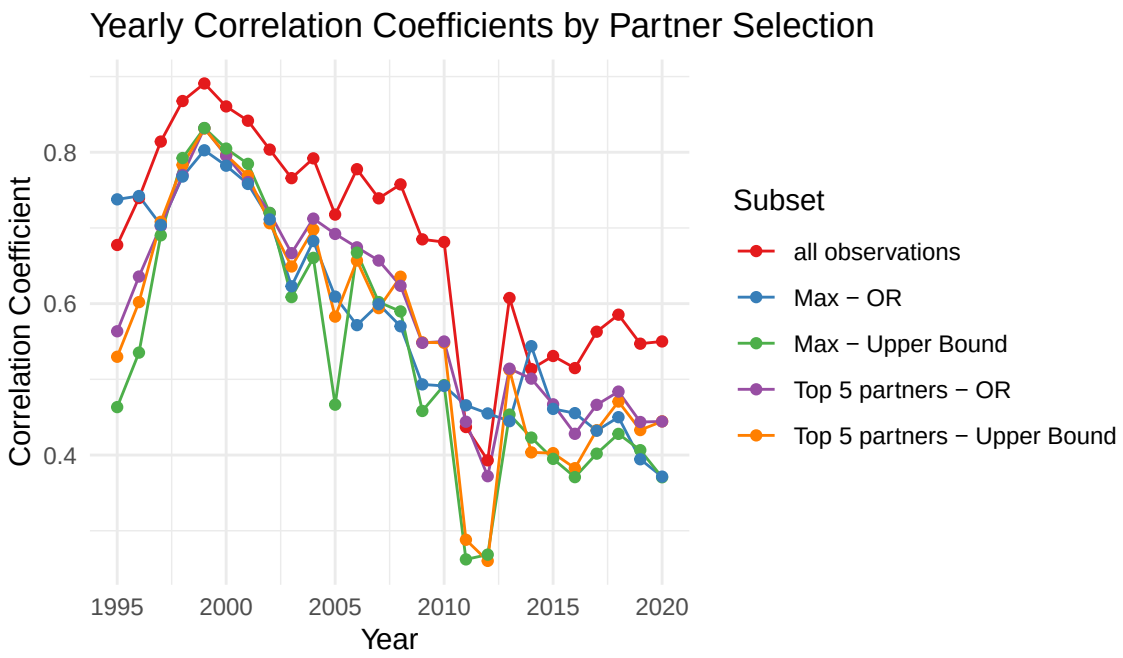


Figure A.5: Correlation coefficients between upper bound dependence and OR measure over time.

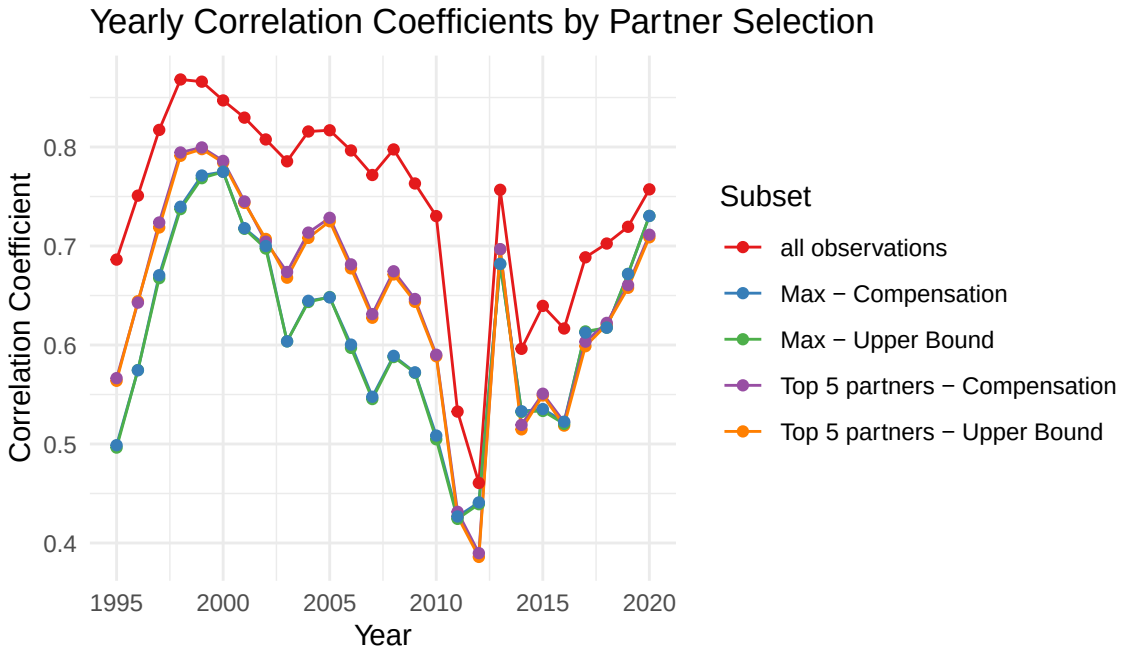


Figure A.6: Correlation coefficients between upper bound dependence and compensation dependence measure over time.

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.

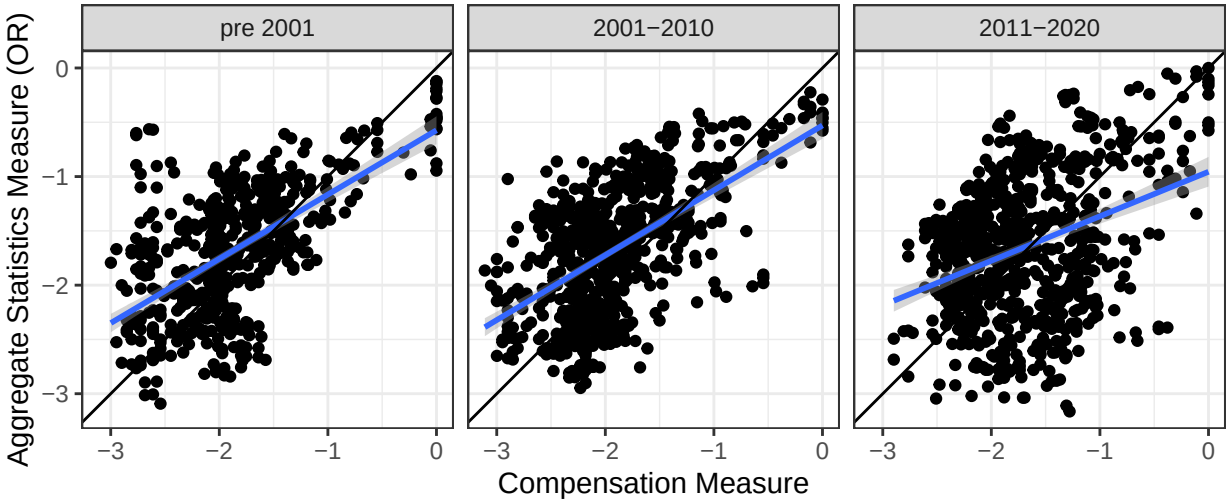


Figure A.7: Compensation dependence versus Oneal and Russett aggregate statistics measure, compared over three periods. Each dot represents a country's maximum level of dependence for a given year, across all its partners. The measures are normalized to the unit interval to ensure comparability of the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

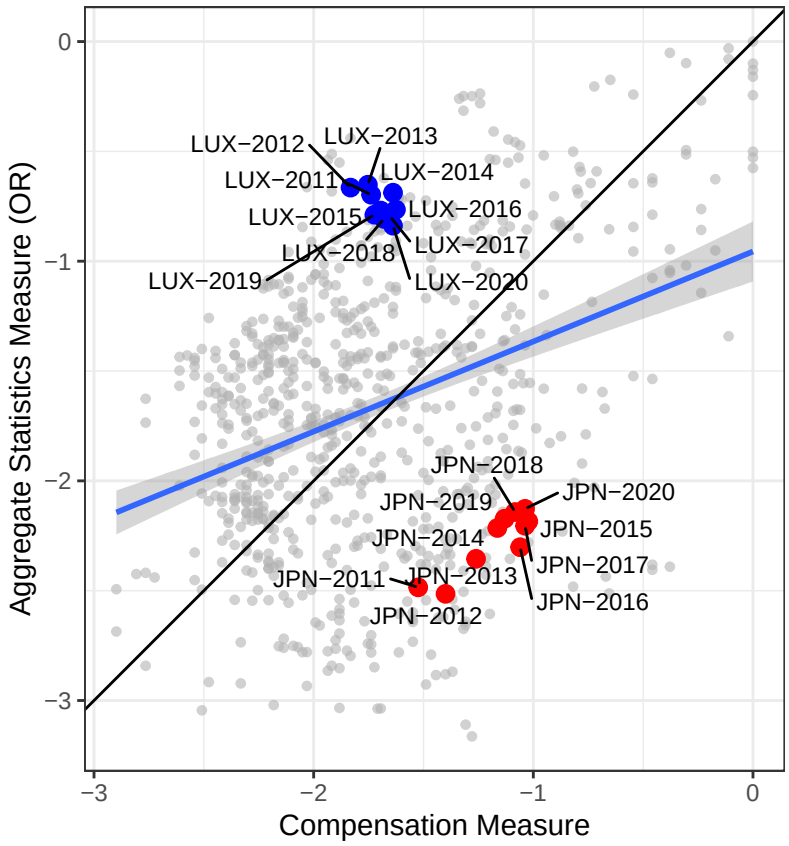


Figure A.8: Compensation dependence versus Oneal and Russett aggregate statistics measure, 2011–2020 only. Points for JPN (red) and LUX (blue) are highlighted and labeled.

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.[66] 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.

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.

[66] 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.

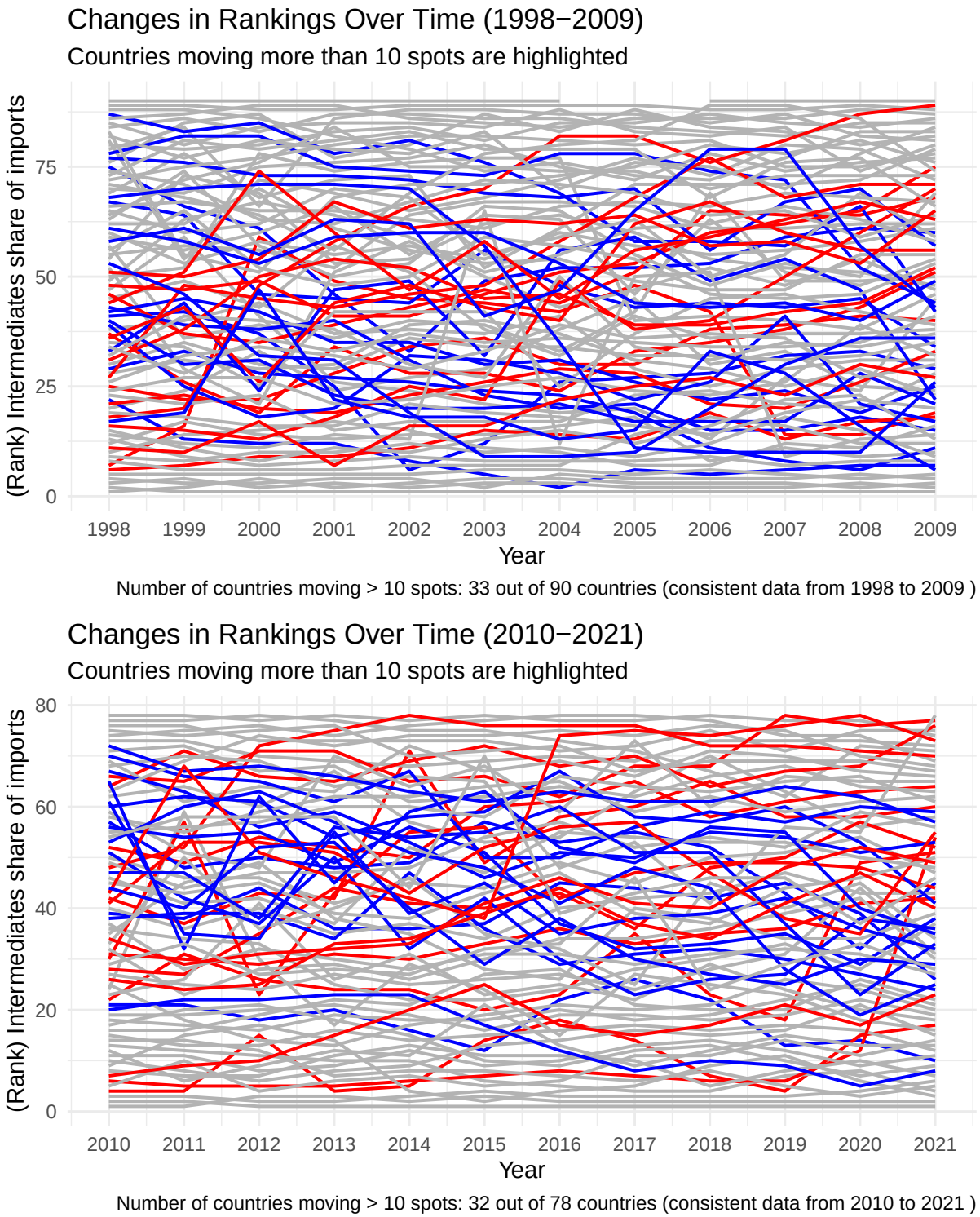


Figure A.9: Plots showing countries that changed their intermediates share of imports the most over different time periods.

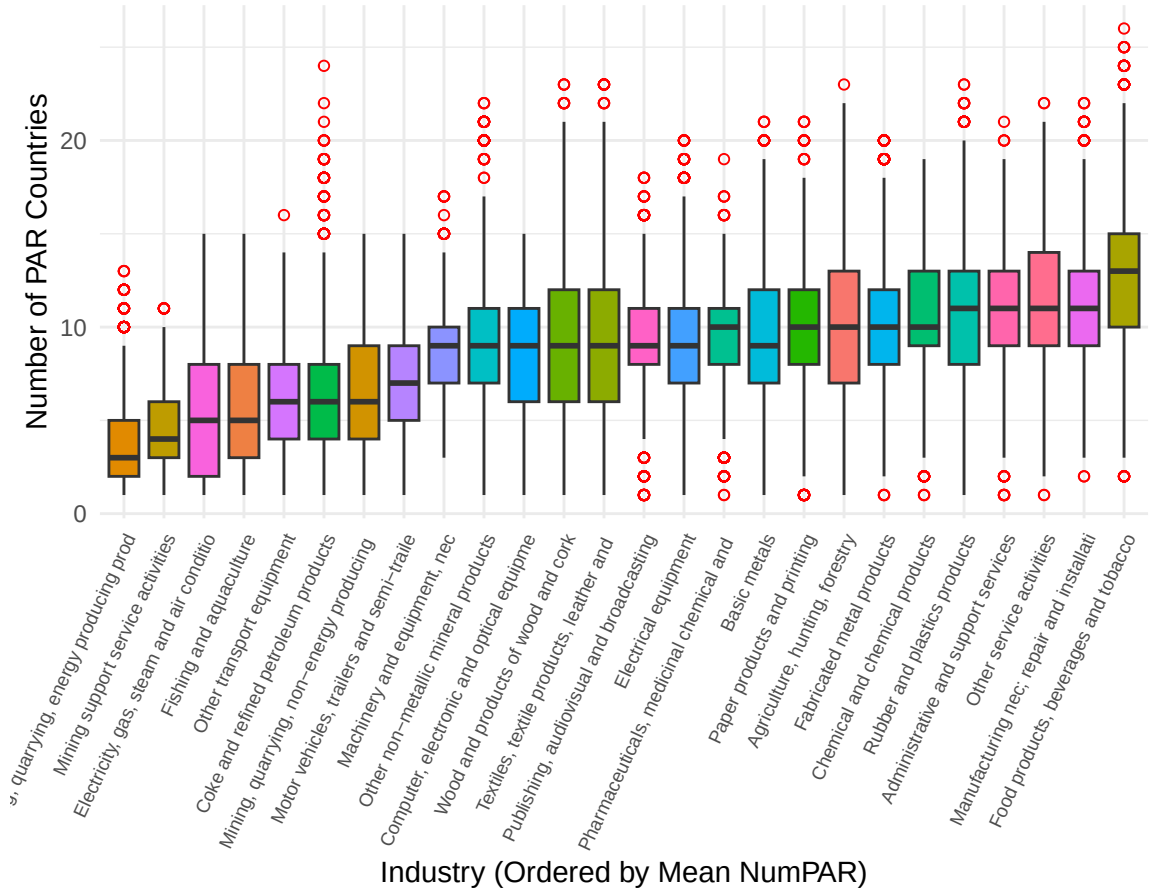


Figure A.10: Distribution of the number of partners making up 80% of imports, across industries.

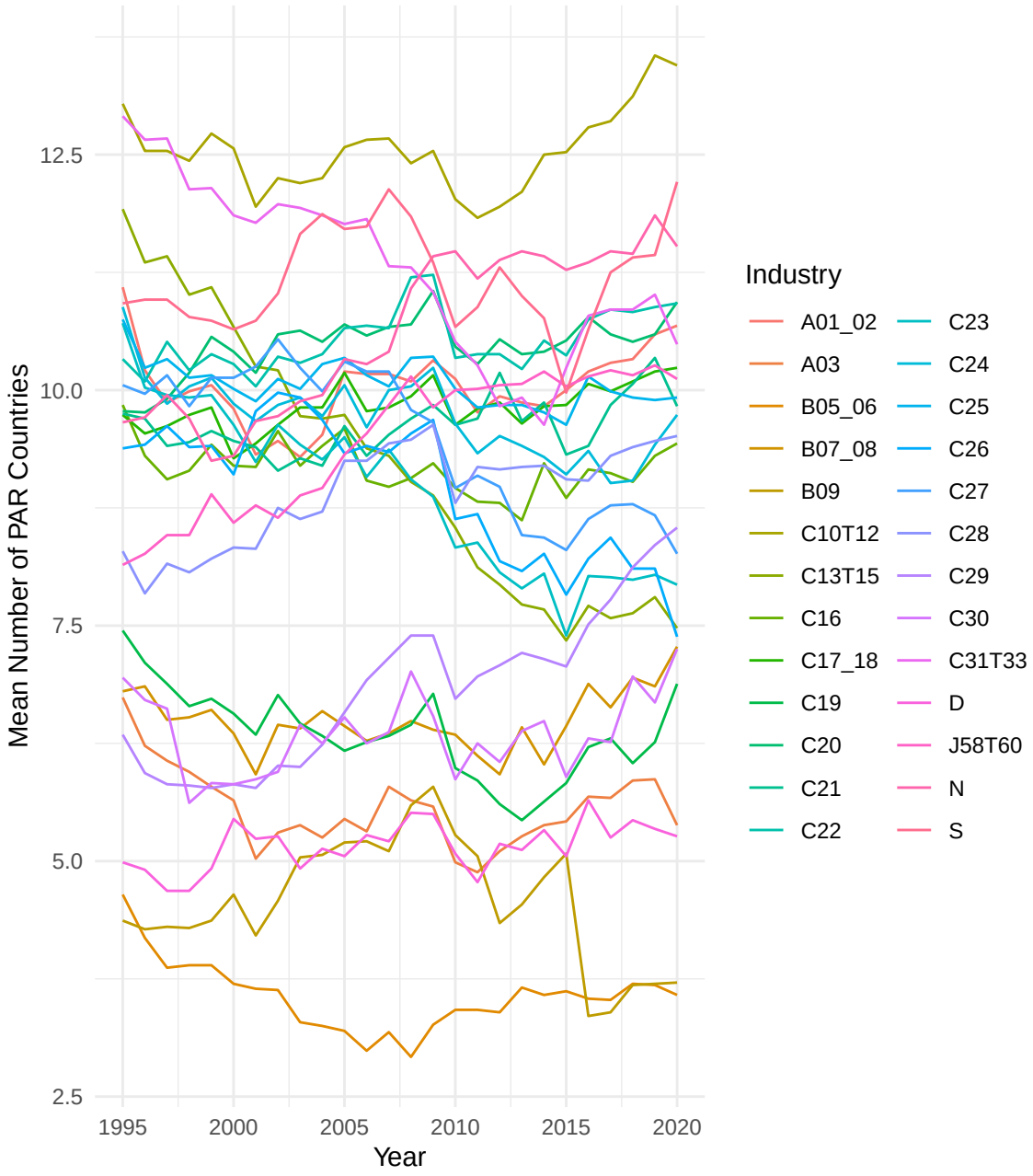


Figure A.11: Mean Number of Partner Countries making up 80% of imports, by Industry and Year.

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.

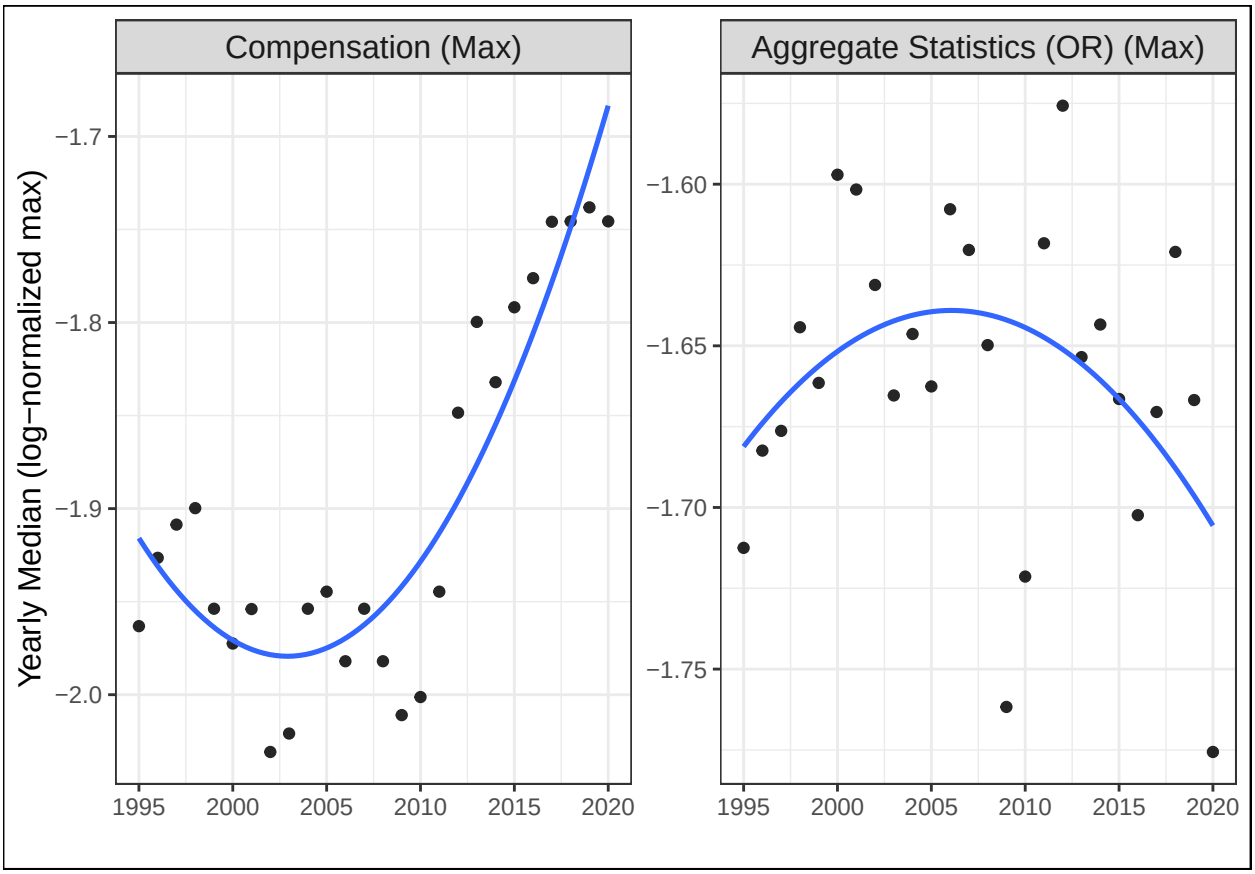


Figure A.12: Yearly medians of log-normalized max dependence for Compensation and OR.

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 two 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.

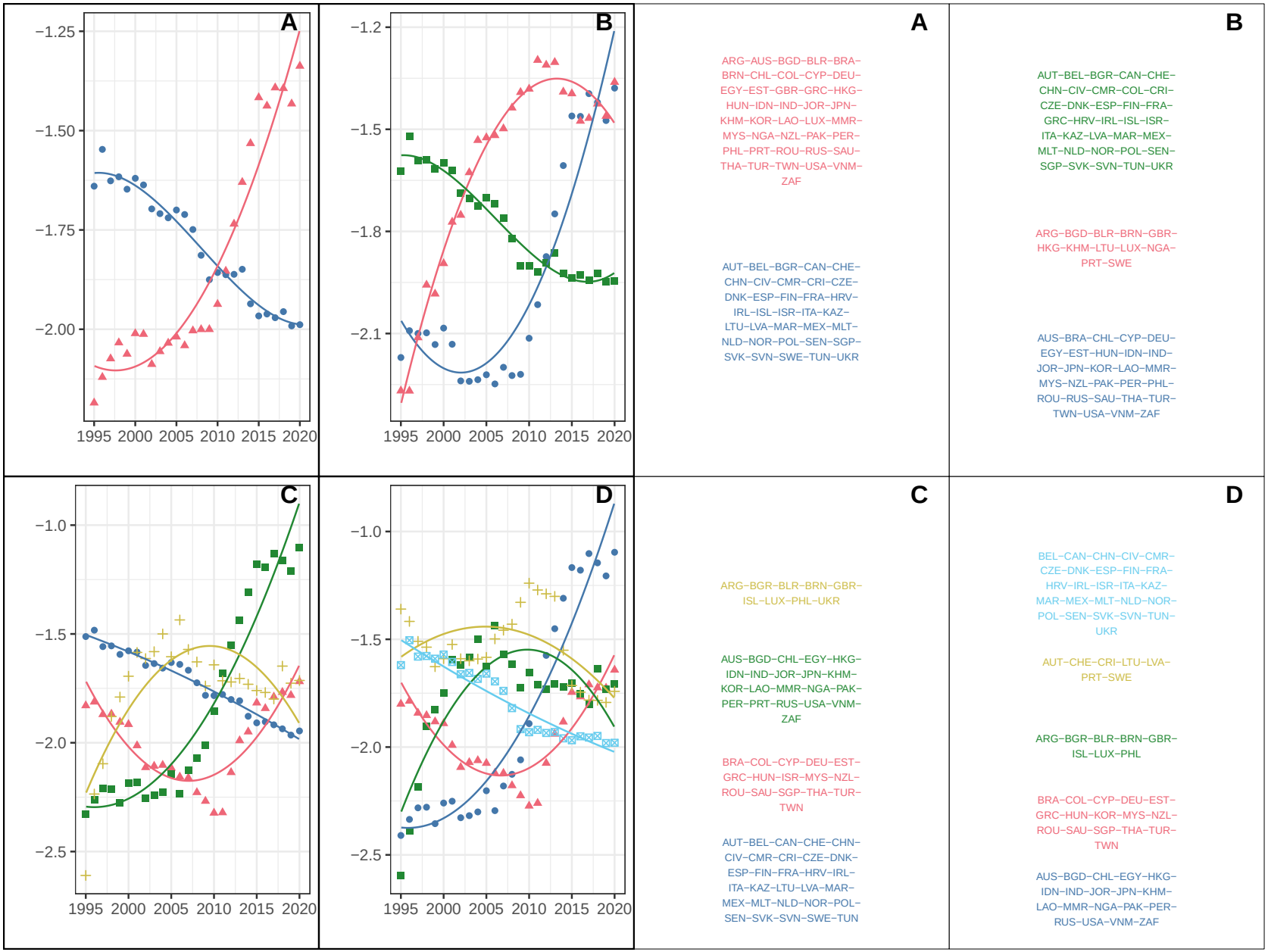


Figure A.13: Robustness of the clustering procedure to the number of clusters. The ISO codes for cluster members are produced alongside their trends. Labels in the upper right hand corner of each panel indicate the specification.

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.

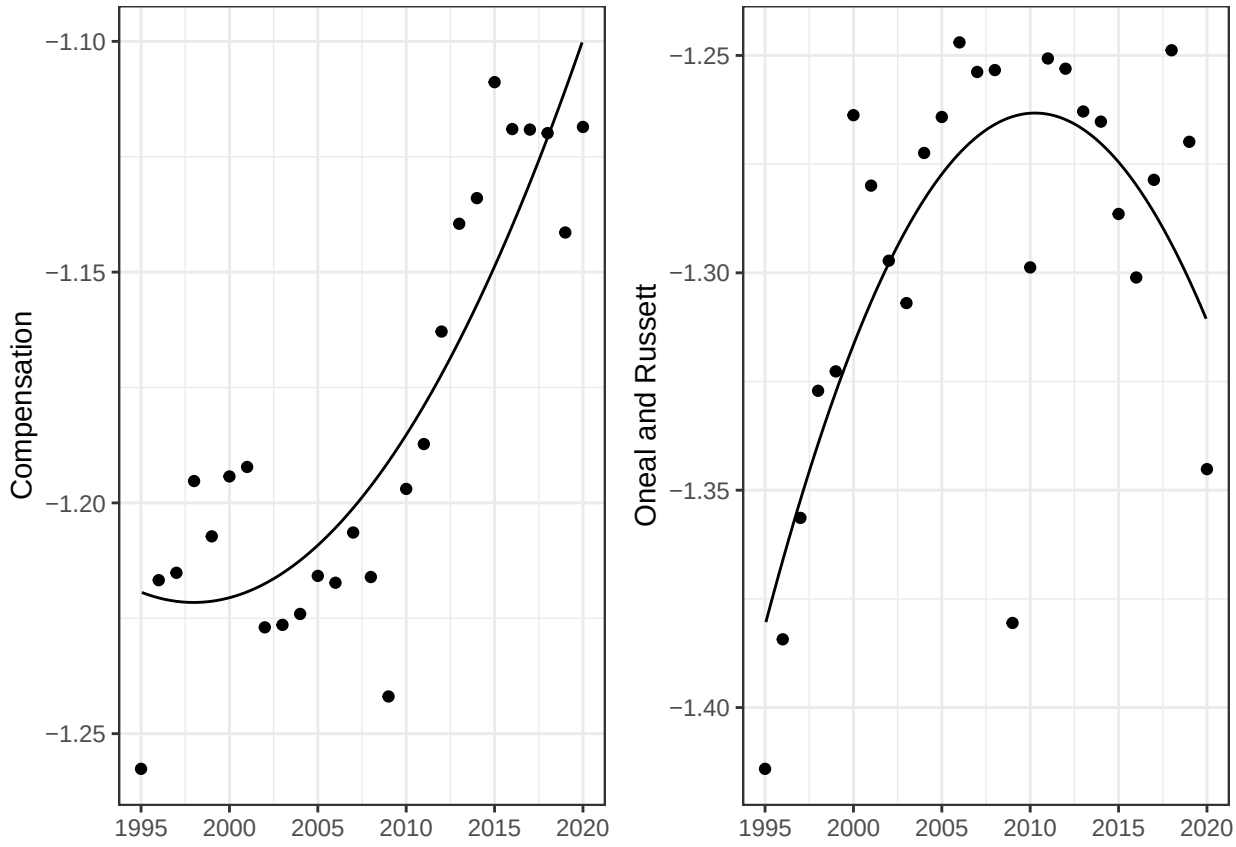


Figure A.14: Bin scatters of the top 5 of each measure after taking the natural logarithm. Both variables are normalized to the unit interval before taking logs to equalize their support and facillitate comparison.

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).

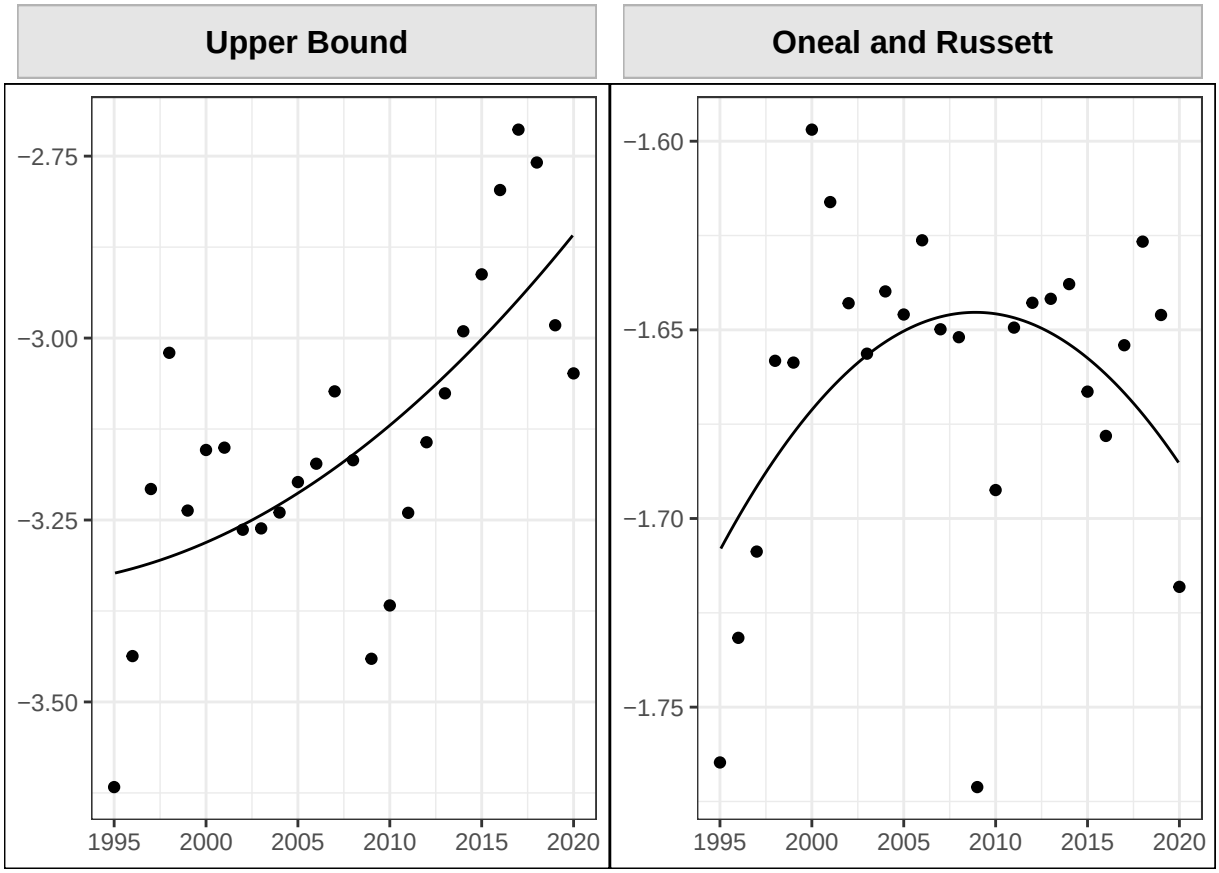
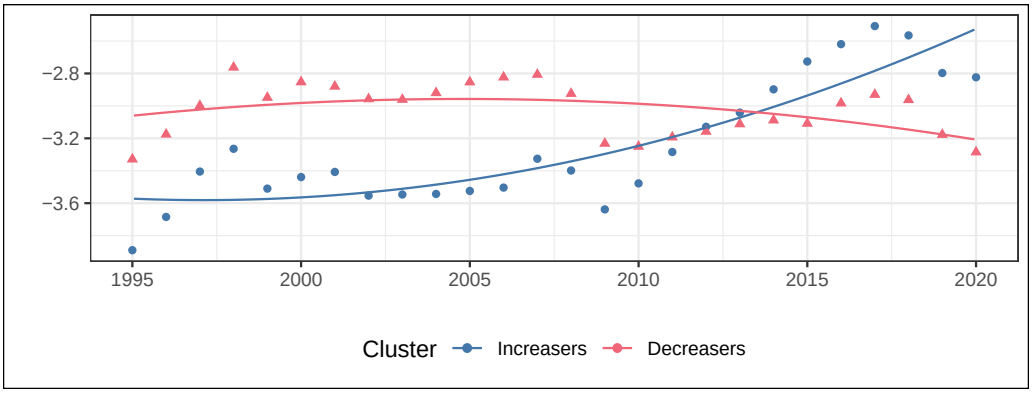


Figure A.15: Bin scatter of the maximum values of the upper bound and OR dependence measures, logged and normalized to the unit interval to equalize their support and facillitate comparison.



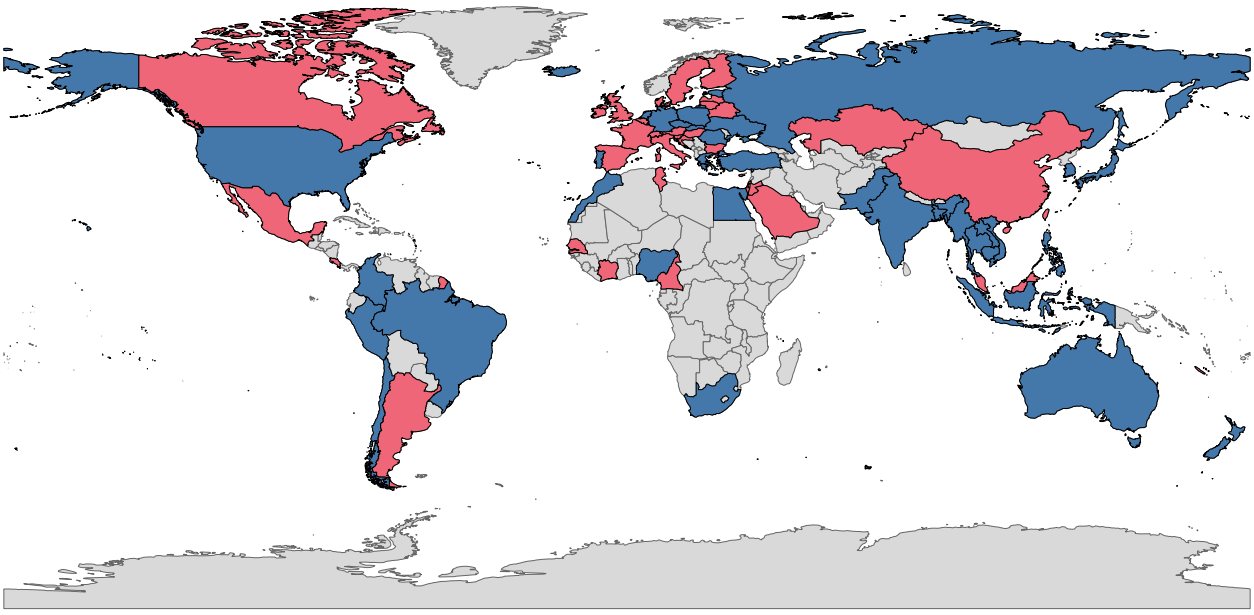


Figure A.16: Clustering countries by their trends in maximum values of upper-bound dependence.

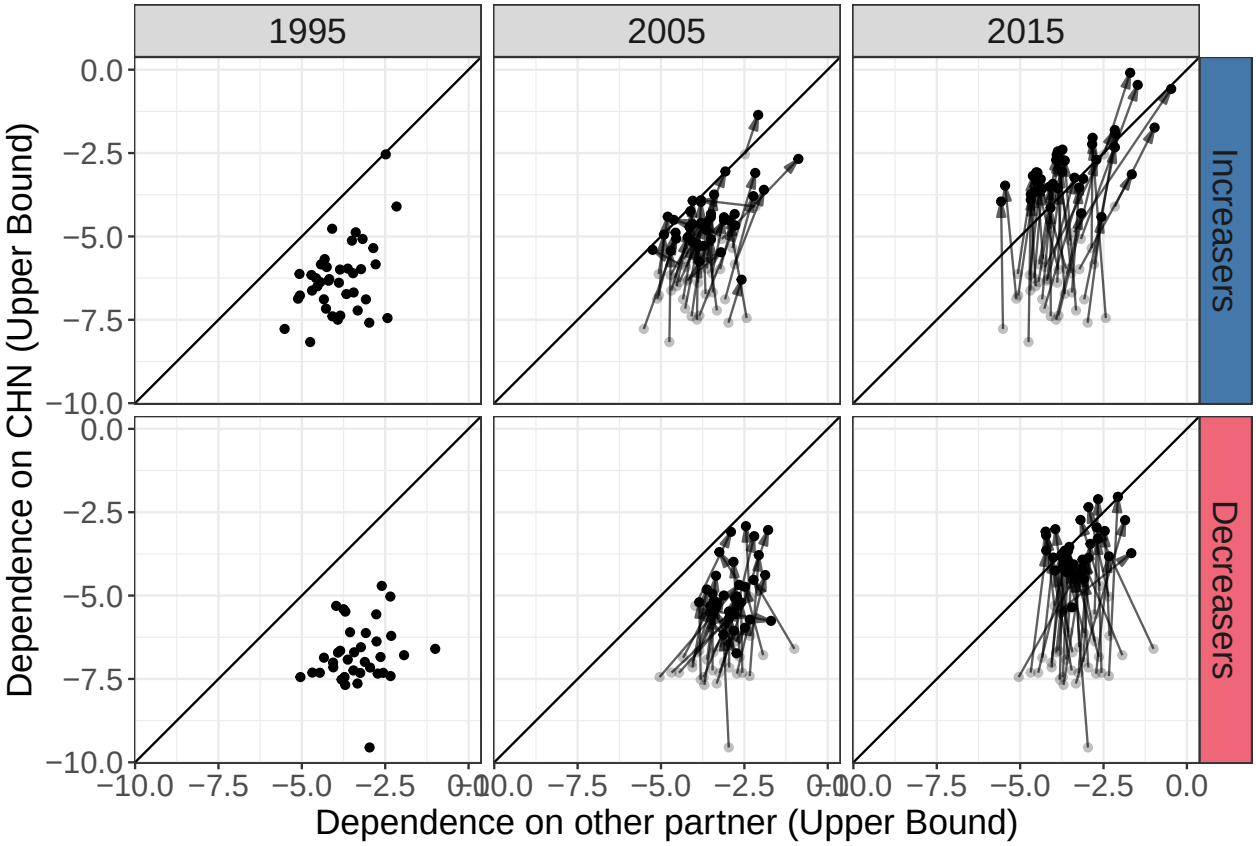


Figure A.17: Vectors indicating change over time in a country's dependence on China (vertical axis) and its maximum dependence on any other (non-China) partner, using the UPPER BOUND dependence measure. Lines connect 1995 values to the highlighted year. The diagonal black line is a 45 degree line. Dependence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

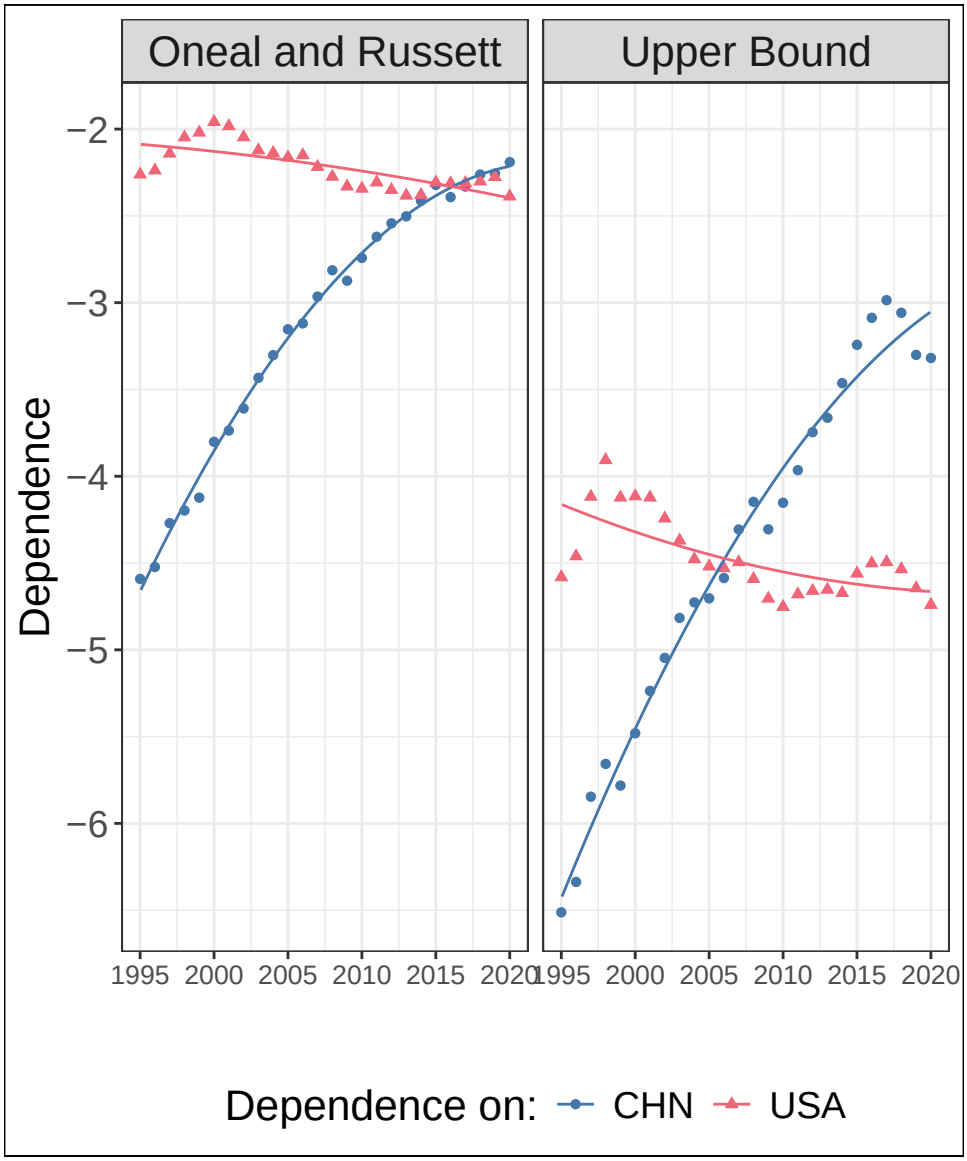


Figure A.18: Global dependence on USA and CHN over time (Upper Bound and OR measures)

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.

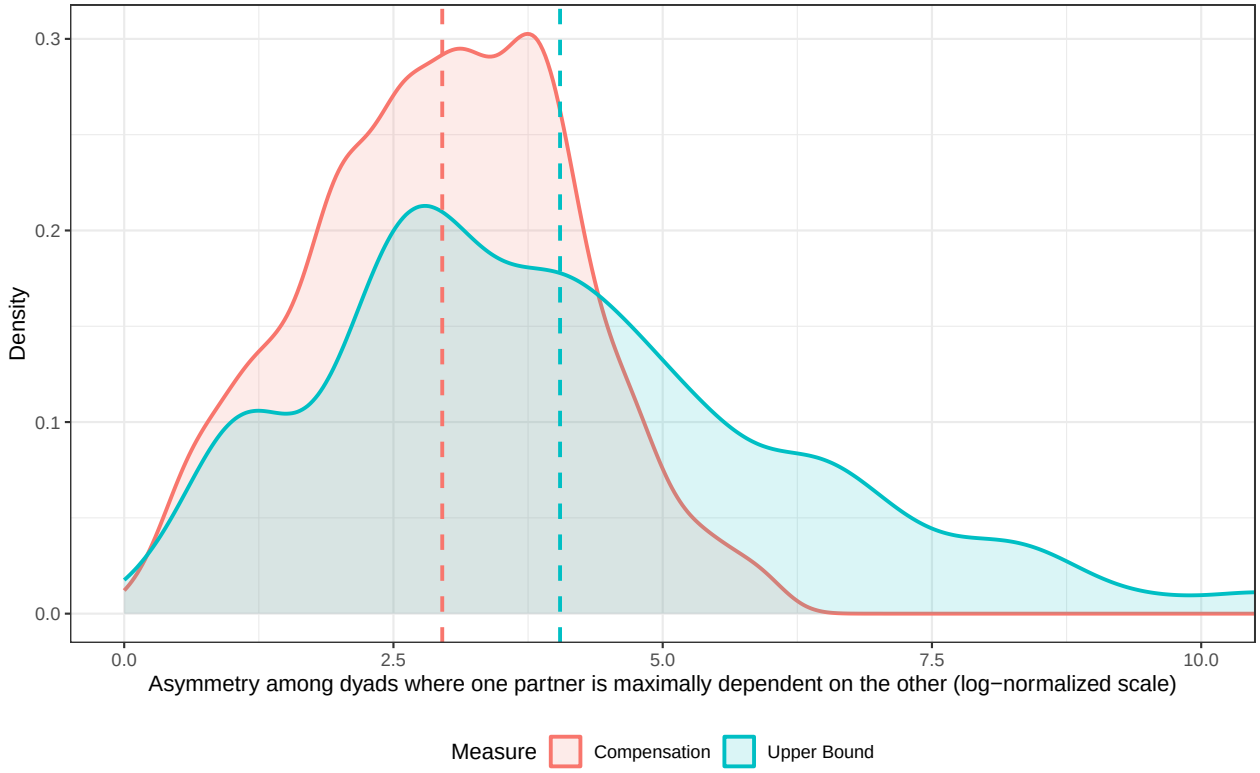


Figure A.19: Distributions of interdependence for maximally dependent relationships.

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.

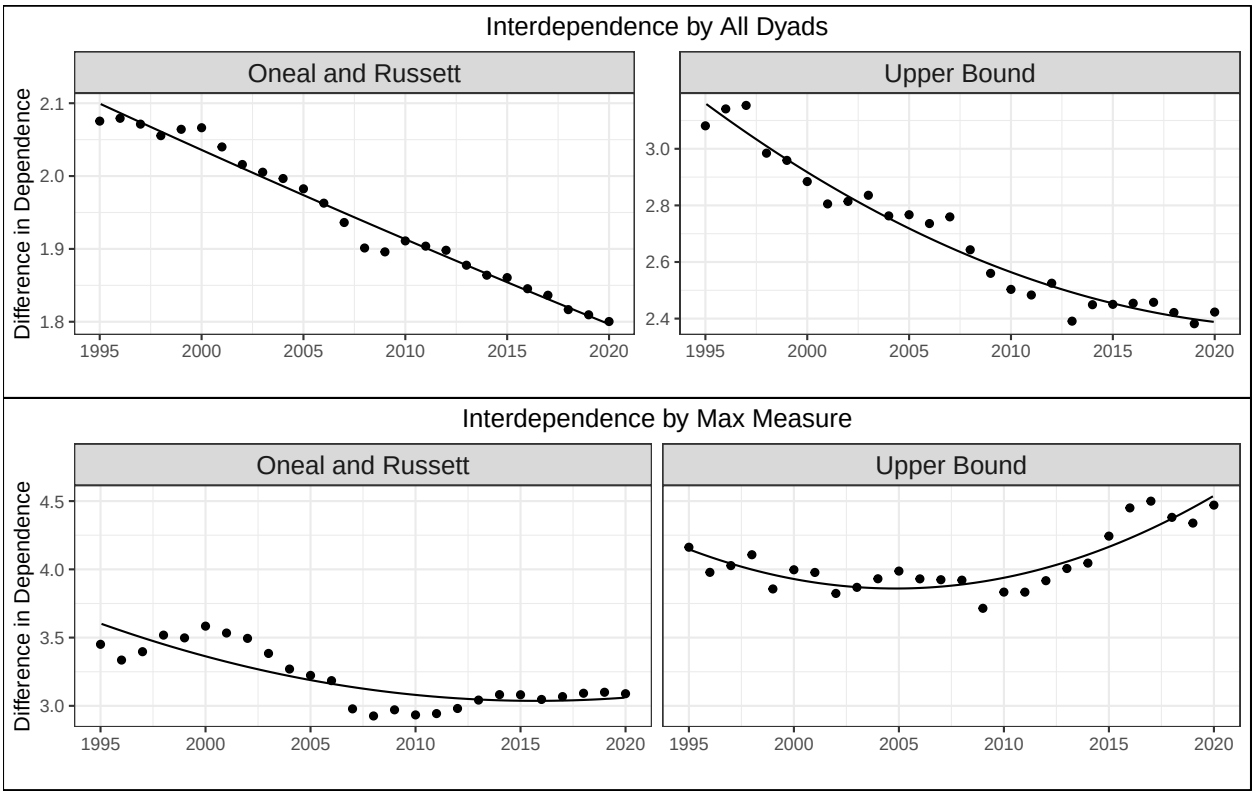


Figure A.20: Interdependence over time (Upper Bound vs OR). Points show differences in directed dyadic dependence over time, averaged across dyads. The top pane shows this difference for all dyads. The bottom pane shows this for maximally dependent dyads.

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	0.010	0.008	-0.005	0.024	0.201
18	-4	0.001	0.008	-0.013	0.016	0.865
19	-3	0.006	0.004	-0.003	0.014	0.174
20	-2	0.016	0.011	-0.006	0.038	0.163
21	-1	0.003	0.005	-0.007	0.013	0.544
22	0	0.004	0.010	-0.015	0.023	0.653
23	1	0.014*	0.007	0.000	0.028	0.052
24	2	0.014	0.010	-0.006	0.034	0.164
25	3	0.032***	0.011	0.010	0.053	0.004
26	4	0.036***	0.011	0.015	0.057	0.001
27	5	0.057***	0.013	0.030	0.083	0.000
28	6	0.070***	0.020	0.030	0.110	0.001
29	7	0.081***	0.027	0.027	0.135	0.003
30	8	0.092***	0.027	0.040	0.145	0.001
31	9	0.097***	0.031	0.037	0.157	0.002
32	10	0.135***	0.034	0.068	0.202	0.000
33	11	0.153***	0.040	0.074	0.231	0.000
34	12	0.159***	0.045	0.070	0.248	0.000
35	13	0.175***	0.045	0.087	0.263	0.000
36	14	0.205***	0.064	0.081	0.330	0.001
37	15	0.217***	0.072	0.075	0.359	0.003

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.

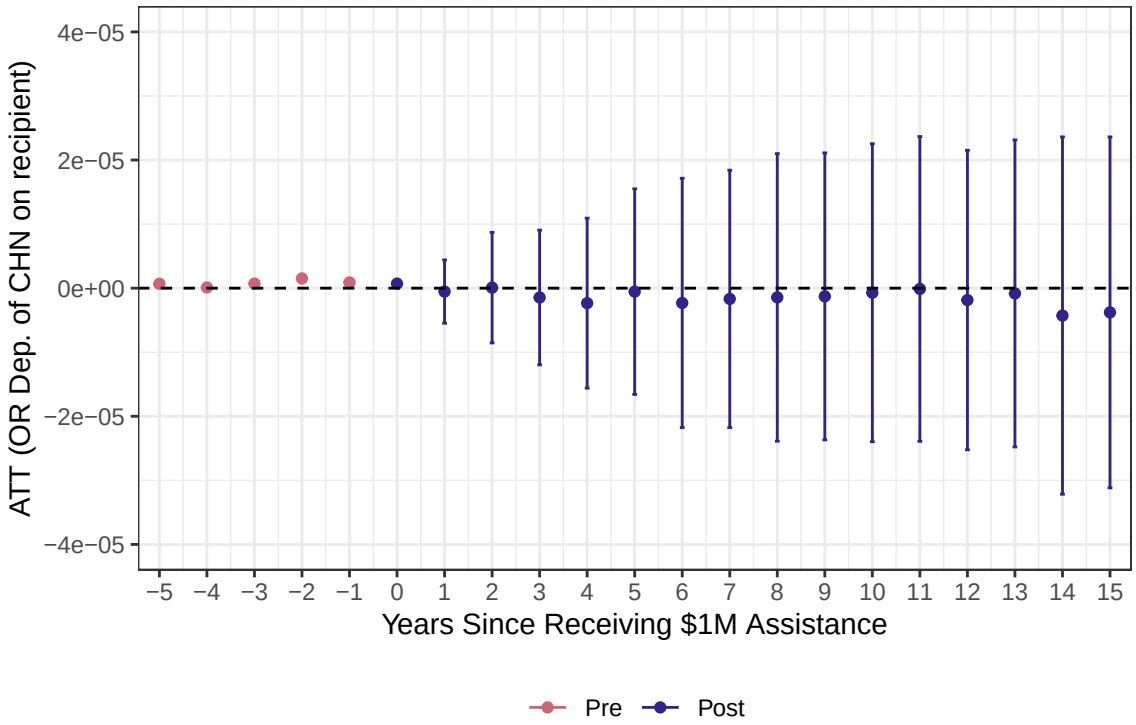


Figure A.21: Effect of Chinese assistance on China's dependence on the recipient. The OR dependence measure is the outcome variable.

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
0.1061	0.0345	0.0021	CS	~1	nevertreated	First Year Amt>$1M
0.1026	0.0324	0.0015	CS	~1	notyettreated	First Year Amt>$1M
0.1263	0.0313	0.0001	CS	~TotalTrade_log	nevertreated	First Year Amt>$1M
0.1323	0.0324	0.0000	CS	~gdp_COU_log	nevertreated	First Year Amt>$1M
0.0803	0.0368	0.0292	CS	~vdem_electCOU	nevertreated	First Year Amt>$1M
0.1007	0.0312	0.0012	CS	~TotalTrade_log + gdp_COU_log + vdem_electCOU	nevertreated	First Year Amt>$1M
0.0974	0.0328	0.0030	CS	~TotalTrade_log + gdp_COU_log + vdem_libdemCOU	nevertreated	First Year Amt>$1M
0.0858	0.0309	0.0054	CS	~TotalTrade_log + gdp_COU_log + vdem_libdemCOU	nevertreated	First Year Amt>$0
0.0904	0.0303	0.0029	CS	~TotalTrade_log + gdp_COU_log + vdem_libdemCOU	nevertreated	First Year Amt>$0.5M
0.1207	0.0402	0.0027	CS	~TotalTrade_log + gdp_COU_log + vdem_libdemCOU	nevertreated	First Year Amt>$5M
0.0760	0.0253	0.0061	Two Way FE	+ TotalTrade_log + gdp_COU_log + vdem_electCOU		First Year Amt>$1M
0.0674	0.0360	0.0650	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 2016. Its effect stays relatively stable after that.

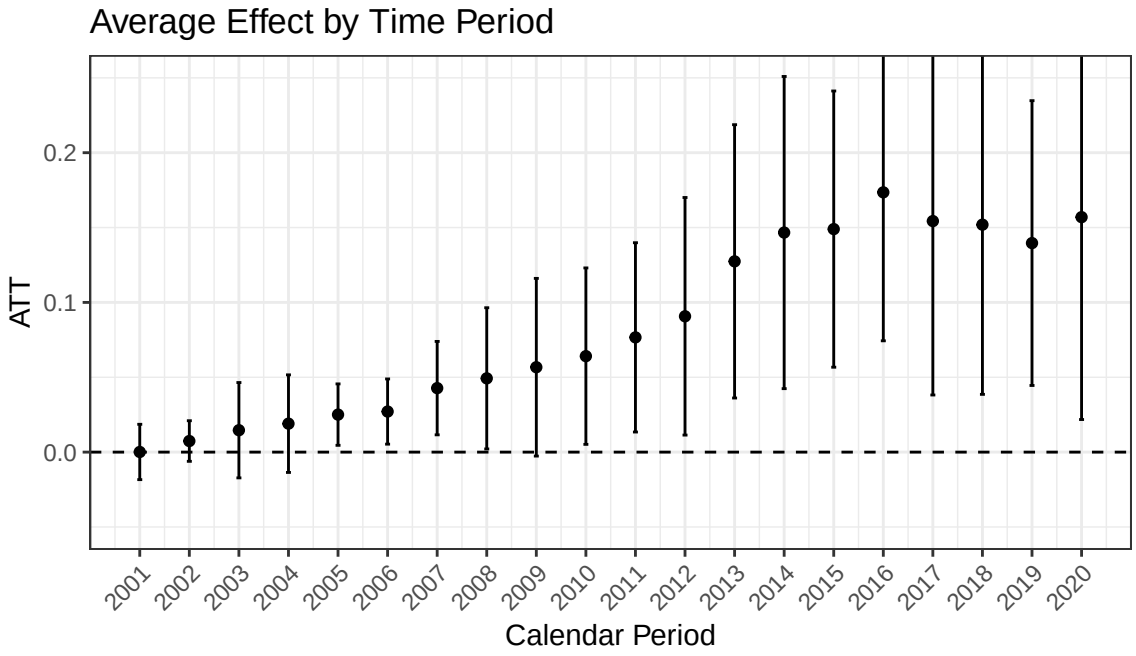


Figure A.22: Estimates of Chinese assistance effect by calendar year.

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	0.1041	Treated vs Untreated
2005		0.1003	0.0196	Treated vs Untreated
2002		0.0746	0.1720	Treated vs Untreated
2007		0.0698	0.1112	Treated vs Untreated
2004		0.0598	0.0684	Treated vs Untreated
2015		0.0507	0.1414	Treated vs Untreated
2001		0.0489	0.0943	Treated vs Untreated
2009		0.0370	0.2044	Treated vs Untreated
2011		0.0347	0.0256	Treated vs Untreated
2006		0.0335	0.0178	Treated vs Untreated
2010		0.0323	0.3062	Treated vs Untreated
2003		0.0279	0.0220	Treated vs Untreated
2017		0.0179	0.2332	Treated vs Untreated
2000	2005	0.0171	-0.1185	Both Treated
2000	2015	0.0170	-0.0354	Both Treated
2000	2007	0.0151	-0.0464	Both Treated
2000	2011	0.0098	-0.1085	Both Treated
2000	2009	0.0097	-0.0053	Both Treated
2000	2004	0.0094	-0.0766	Both Treated
2000	2010	0.0088	0.0681	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 0.077 and the estimate after excluding the highest weighted comparison is 0.07.

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	0.1007	0.0320	0.0379	0.1635	0.0017
Exclude years with TIME ≤ 1996	0.1007	0.0324	0.0372	0.1642	0.0019
Exclude years with TIME ≤ 1997	0.1007	0.0320	0.0380	0.1633	0.0016
Exclude years with TIME ≤ 1998	0.1007	0.0318	0.0383	0.1631	0.0016
Exclude years with TIME ≤ 1999	0.1007	0.0316	0.0388	0.1626	0.0014
Exclude years with TIME ≤ 2000	0.0965	0.0380	0.0220	0.1710	0.0111
Exclude years with TIME ≤ 2001	0.0626	0.0191	0.0251	0.1000	0.0011
Exclude years with TIME ≤ 2002	0.0626	0.0171	0.0290	0.0961	0.0003
Exclude years with TIME ≤ 2003	0.0623	0.0220	0.0193	0.1054	0.0046
Exclude years with TIME ≤ 2004	0.0775	0.0252	0.0281	0.1268	0.0021
Exclude years with TIME ≤ 2005	0.0775	0.0249	0.0287	0.1263	0.0019

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	0.1007	0.0334	0.0353	0.1661	0.0025
Exclude years with TIME ≥ 2010	0.0320	0.0140	0.0046	0.0594	0.0222
Exclude years with TIME ≥ 2011	0.0367	0.0157	0.0059	0.0675	0.0197
Exclude years with TIME ≥ 2012	0.0419	0.0173	0.0080	0.0758	0.0154
Exclude years with TIME ≥ 2013	0.0468	0.0195	0.0086	0.0850	0.0162
Exclude years with TIME ≥ 2014	0.0541	0.0220	0.0111	0.0972	0.0138
Exclude years with TIME ≥ 2015	0.0618	0.0220	0.0186	0.1049	0.0050
Exclude years with TIME ≥ 2016	0.0691	0.0242	0.0217	0.1165	0.0043
Exclude years with TIME ≥ 2017	0.0773	0.0252	0.0278	0.1267	0.0022
Exclude years with TIME ≥ 2018	0.0882	0.0270	0.0352	0.1412	0.0011
Exclude years with TIME ≥ 2019	0.0932	0.0305	0.0335	0.1529	0.0022

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.

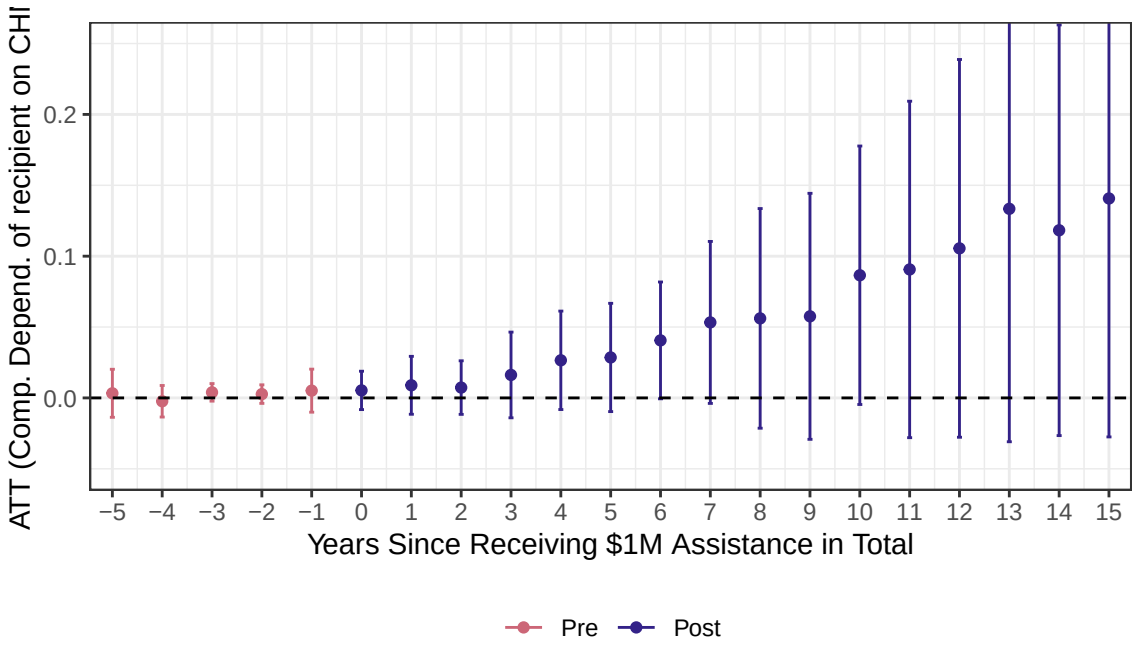


Figure A.23: Effect of Chinese assistance (total assistance, not just ODA-like) on recipient's dependence on China. The compensation dependence measure is the outcome variable.

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

estimate	se	p.value	type	controls	control_group	indepvar
0.092	0.029	0.002	CS	~1	nevertreated	First Year Amt>$1M (Tot.)
0.092	0.029	0.001	CS	~1	notyettreated	First Year Amt>$1M (Tot.)
0.111	0.026	0.000	CS	~TotalTrade_log	nevertreated	First Year Amt>$1M (Tot.)
0.119	0.030	0.000	CS	~gdp_COU_log	nevertreated	First Year Amt>$1M (Tot.)
0.078	0.033	0.017	CS	~vdem_electCOU	nevertreated	First Year Amt>$1M (Tot.)
0.079	0.030	0.008	CS	~TotalTrade_log + gdp_COU_log + vdem_electCOU	nevertreated	First Year Amt>$1M (Tot.)
0.076	0.026	0.003	CS	~TotalTrade_log + gdp_COU_log + vdem_libdemCOU	nevertreated	First Year Amt>$1M (Tot.)
0.084	0.026	0.001	CS	~TotalTrade_log + gdp_COU_log + vdem_libdemCOU	nevertreated	First Year Amt>$0 (Tot.)
0.085	0.027	0.002	CS	~TotalTrade_log + gdp_COU_log + vdem_libdemCOU	nevertreated	First Year Amt>$0.5M (Tot.)
0.067	0.023	0.004	CS	~TotalTrade_log + gdp_COU_log + vdem_libdemCOU	nevertreated	First Year Amt>$5M (Tot.)
0.060	0.022	0.013	Two Way FE	+ TotalTrade_log + gdp_COU_log + vdem_electCOU		First Year Amt>$1M (Tot.)
0.007	0.006	0.248	Two Way FE	+ TotalTrade_log + gdp_COU_log + vdem_electCOU		Amt (TOTAL, rescaled)