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Travel restrictions as border frictions: evidence from the Covid-19 pandemic

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Abstract

Using a gravity framework with internal trade flows, I find that travel restrictions translated into large and economically meaningful increases in the cost of trading goods across borders. Travel restrictions operated like a classic border friction, with a full closure reducing bilateral trade by around 19% for a typical country pair and implying a hit to global trade of approximately 23% in 2020 Q2. The effects are highly heterogeneous with respect to distance and transport mode: geographically proximate trading partners experienced larger trade losses and trade flows by road and air were significantly disrupted, while seaborne and rail trade were not. The interaction between distance and transport exposure generates substantial cross-country variation in the overall trade impact of border closures, and explains why some countries were able to close their borders at a (much) lower cost to trade flows than others. There is no evidence of long run scarring effects from restrictions, rather trade rebounded strongly with a temporary 'overshooting' once restrictions were eased.

Key words: Trade, border frictions, transportation mode, Covid-19.

JEL classification: F1, F14, F18.

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1 Introduction

The Covid-19 pandemic precipitated an abrupt tightening in international borders with governments variously imposing visa suspensions, mandatory testing, quarantines and outright border closures. At the same time the world saw one of the sharpest and largest falls ever seen in international trade on a par with the fall seen in the wake of the 2008 financial crisis (IMF, 2022; Baldwin, 2020; UNCTAD, 2021. Although travel restrictions were primarily motivated by the need to curtail the movement of people between countries, there was widespread documentation they also hindered the movement of goods between countries (OECD, 2020;U.S. International Trade Commission, 2021). With the restrictions coming at a time of a sharp contraction in many forms of economic activity, this raises the question of whether and how they affected cross-border trade flows, by increasing trade frictions - i.e. their effect above and beyond what the general decline in global output would have implied.

In this paper, I study the impact of those travel restrictions on trade flows through the lens of a gravity model. Standard empirical trade models have explored factors such as tariffs, non-tariff measures and transport costs as important determinants of bilateral trade flows. More recently, structural gravity models incorporating internal trade flows have permitted the exploration of "border frictions" - i.e. the extra cost of selling goods across borders rather than domestically- more explicitly.

To explore this novel and time-varying source of trade costs, I use a state-of-the-art specification which includes internal trade flows. By including domestic trade, and then using origin-time and destination-time fixed effects which mop up the supply-side effect of any domestic restrictions on production in the origin or demand effects on consumption in the destination, I can isolate the pure effect on border frictions, as opposed to the effects of demand or supply shocks more broadly.

I begin by estimating a model with time varying border frictions and trace out how they evolved during the course of the pandemic: documenting a sharp rise in border frictions in early 2020, which gradually eased off after 2020, and with a temporary boost to trade relative to pre-Covid levels as restrictions came off. I then relate these frictions to travel restrictions, to explore how these varied across time, space and transportation mode.

Using the Oxford Covid Tracker measure of the stringency of travel restrictions, ranging from testing at the border up to outright border closures, I show that restrictions on travel had a significant negative effect on trade, even after allowing for the contraction in output during the pandemic. Coefficient estimates imply that for a typical country pair a full border closure reduces a country's trade by 19%.

Interacting distance with travel restrictions, reveals a significant heterogeneity, with a larger effect on trade the closer the two partners are. For the closest country pair (Slovakia-Austria, 55km) a full border closure hits by around 37%, but for the most distant (Paraguay-Taiwan, 19844km) country pair at the 10th percentile the hit is 8%, around a five fold difference. Looking at other geographical features however, there were no significant effects of contiguity, or for landlocked countries or islands.

Investigating the role of mode of transport reveals that the effect of border closures was concentrated on road and air transport, rather than sea or rail trade. This provides evidence that different modes of transportation have appeared to have differing sensitivities to trade costs.

The combined effects of distance and transportation modes generates substantial variation across countries in the estimated hit to trade from border closures. At one end, countries with relative longer distance to trading partners and most trade arriving by sea (such as Australia or New Zealand) border closures are estimated to have only hit trade by around 4%. By contrast, countries with closer trading partners and greater exposure to air and road transport the hit would be close to 30%.

Exploring the dynamics of the effect with various lags of travel restrictions, I document that there was no apparent longer run "scarring" effect of earlier restrictions. On the contrary, once restrictions were lifted, trade across country pairs was temporarily boosted, largely "making up" for the flows which had been reduced by travel restrictions. Computing the overall effect of travel restrictions on global trade flows reveals a maximum hit of around 23% in 2020q2.

1.1 Related Literature

This paper relates to several strands of trade literature.

Firstly, it adds to the body of work on the effects of Covid and trade. de Lucio et al. (2022) use monthly data from for Spanish exports to explore the role containment measures in destination countries on the relative size of export flows from Spain between February and August 2020. In a similar vein Liu et al. (2022) look at Chinese exports over the 2019-2020 period, and estimate how destination country lockdown measures affected trade flows. Bas et al. (2024) use product-level difference-in-differences on monthly exports to the US, Japan, and the EU, to explore how Covid incidence (measured by destination country death rates) interacted with pre-pandemic supply-chain dependence and automation to identify which product characteristics shaped export resilience over time. Perhaps the closest paper to this one is Berthou and Stumpner (2024), which explores the effects of lockdown in a gravity model. It uses a two step approach, regressed estimates of origin-product-time and destination-product time fixed effects on importer and exporter Covid stringency measures, to estimate their effect on trade in over the period 2018-2020.

My approach has three key differences to that paper, and the rest of the literature more broadly: the inclusion of domestic trade, the use of travel restrictions and the addition of distance, transport costs and the use of interaction variables which create heterogeneity in effects across country pairs. Without domestic trade, it is not possible to distinguish between a general demand effect (i.e. restrictions reduce demand for all goods- both traded and domestically produced) and a change in the trade costs (i.e relative cost of trading externally vs domestically). The advantage of using travel restrictions is that it has a much closer correspondence to trade costs than epidemiological variables such as deaths or cases, or broader containment indices do[1].

As such this is to the best of my knowledge, the first cross-country study which quantifies the effect of border restrictions on international trade over the full course of the pandemic. In addition, by accounting for the observed heterogeneity in the effects of border restrictions in trade in terms of distance and transport medium it can explain why countries such as New Zealand and Australia were able to implement strict border closures at a much lower cost to overall trade flows than many other countries. Indeed I show that the effect on trade of a full border closure for those countries was lower than the effect of far more modest restrictions for less remote countries with greater reliance on land and air based trade, such as Slovakia or Bosnia-Herzegovina.

Second, it contributes to the literature on time varying border frictions.

[1] Liu et al. (2022) use the aggregate stringency index which is built from nine separate sub-indices, eight of which capture restrictions on domestic activities such as public transport closures, stay-at-home restrictions; and one of which is the international travel restrictions measure I use here. de Lucio et al. (2022) use similar data, and include both the aggregate index and the sub-indices, but find no significant role for travel restrictions on volumes of imports and exports

The seminal paper of Yotov (2012) introduced the idea of domestic trade as a way of capturing border frictions in a gravity model, and found evidence they had declined over time.[2] Subsequent papers in the so-called structural gravity tradition explored time-varying effects further, for example to capture the role of Economic Integration Agreements and unobserved country-pair heterogeneity (see for example, Bergstrand et al., 2015; Borchert and Yotov, 2017; Baier et al., 2018).

This literature then moved onto explore the role of other determinants of trade frictions, outside of classic trade policy variables, such as domestic institutional quality (Beverelli et al., 2024) . Typically these variables are relatively slow to change over time, and do not contain enough higher frequency variation to identify the effects of faster moving variables.

This paper contributes to that strand by providing clear evidence on the time-varying friction associated with covid travel restrictions, and shows that did not appear to have any longer term scarring effects. Indeed the evidence on the recovery phase shows that there was a degree of intertemporal substitution, where trade flows rose after the removal of travel restrictions to make up for the trade lost when they were in place.

Third, it relates to the longer-running strand of work on the geographical determinants of trade, especially the role of distance. In a key paper, Carrère and Schiff (2005) decomposed trade costs into, transport costs that vary with distance travelled distance-invariant "dwell" costs (e.g. port storage, unloading, paperwork etc).,They argued that most of the reduction in trade costs was in the latter. Because those "dwell" costs make up a higher proportion of overall trade costs the closer two partners are, reductions in dwell costs have bigger effects on trade costs for closer partners. They used this explains the seemingly paradoxical observation that globalisation has been accompanied by a decline in the average "distance-of-trade" (the average distance between importer and exporter, weighted by value, of all global trade), often dubbed the "distance puzzle" (see Disdier and Head, 2008) . Building on this, several subsequent papers explored the interaction of distance and free trade results (e.g. Freeman and Pienknagura, 2019; Freeman and Lewis, 2021; Baier et al., 2018; Vicard,

[2] A couple of decades earlier, several papers with US-state and Canadian province level data starting with McCallum (1995), used domestic trade flows alongside international trade flows to identify border frictions before Yotov introduced domestic flows into a many-country gravity framework (see for example). But because these papers only looked at two countries (and typically did not analyse variation over time) I don't discuss them further here

2011). They corroborated the original result by showing that trade agreements generate a larger boost to trade for more proximate partners. A related strand explores how distance matters in times of crisis. Mehl et al. (2024), present evidence that distance is associated with higher volatility, and larger effects on trade flows during crisis times[3] and Berman et al. (2012) show that in the 2008 financial crisis, trade was hit more between distant partners than closer ones.

These give potentially opposing predictions about how the effect of Covid-related travel restrictions should vary with distance: the dwell costs work predicts bigger hits at shorter distances, the evidence on distance and crises predicts bigger hits at longer distances. The results here are evidence of the former- that hits are bigger at shorter distances. This is consistent with the idea that travel restrictions work like a distant-invariant border friction. This suggests the role of distance in shaping how Covid shock played out in worked in the opposite way to more traditional economic and financial drivers of trade volatility in the literature - i.e. bigger hits were seen for more proximate trading partners.

Fourth, this paper relates to the study of transportation and trade. Numerous papers have documented the role of (developments) in transportation on trade. In shipping, papers by see Bernhofen et al. (2016) and Coşar and Demir (2018) found that containerisation had a large effect on boosting trade flows, Hummels (2007) found a similar result for the growth of air freight and Clark et al. (2004) found that port efficiency can have significant effects on trade.

I add to this literature by showing that border frictions created by travel restrictions had sizable negative effects on trade, over and above their general effect on economic activity. In addition I document that transport modes matter with the novel finding that there were strikingly different effects of Covid restrictions depending on mode of transport used to move goods from one country to another. Moreover, my results show that, over the time horizon of the pandemic, countries were not able to switch the "lost" trade to seaborn transport, which provides evidence that substitution between transport modes was far from perfect.

[3]The paper also presents some preliminary evidence on the very start of the covid pandemic, comparing 2019Q4 with 2020Q1 finding that trade collapsed more in the first quarter of 2020 between more distant partners

2 Travel restrictions as a barrier to trade

Central to this paper is the idea that travel restrictions may have raised the cost of selling goods in another country versus selling them domestically. There is ample evidence that measures brought in to restrict flows of people made it harder to transport goods, and they worked through different mechanisms depending on the mode of transport used.

On maritime transport UNCTAD (2021) document that *"Many economies have changed port protocols, ranging from port closures and crew-change restrictions to additional documentation requirements and physical examinations on vessels and of crew members originating from, or having called at, exposed economies, which disrupt shipping services."*

Regarding air freight, U.S. International Trade Commission (2021) outlined two other channels specific to airborne freight, in addition to the effects on transportation personnel *"The first and most significant impact was a sharp decrease in the capacity to transport freight in the cargo hold of passenger aircraft ("belly cargo") due to canceled flights; the second impact was a pandemic-related increase in air freight demand for certain merchandise imports, primarily for products such as personal protective equipment (PPE).These resulted in a steep increase in air freight rates compared to 2019."*

For goods transported by road, various measures increased delays at border crossings, including temperature checks, shortages of personnel, increased surveillance of cargo and other additional protocols (see Finanicial Times, 2020). World Trade Organization (2021) reports that *"These measures exacerbated existing difficulties with regard to the cost of transport and the time needed at border crossings. The bottlenecks which have formed have caused considerable reductions in trade flows."*

These frictions are present to some degree at all levels of travel restriction, not merely full border closures. For example, quarantine requirements create severe costs and risks on the logistics side. Mandatory testing takes both time at the border itself, and carries the risk that a positive rest results in denied entry, quarantine or social distancing. At the lowest end, vaccine requirements create extra paperwork and administrative burden for transport personnel moving goods across borders.

To measure these, I use data from the Oxford Covid-19 Response dataset, Hale et al. (2021), which compiles an index of "Restrictions on international travel". In its raw form, this a 5-point ordinal scale of each countries travel restriction at a daily frequency. This index is coded to 0 if no restrictions are in place, 1 if there is screening of arrivals, 2 if there is quarantining of arrivals from some or all regions, 3 if there are bans on arrivals from some regions and 4 if there is a ban on all arrivals or a total border closure.

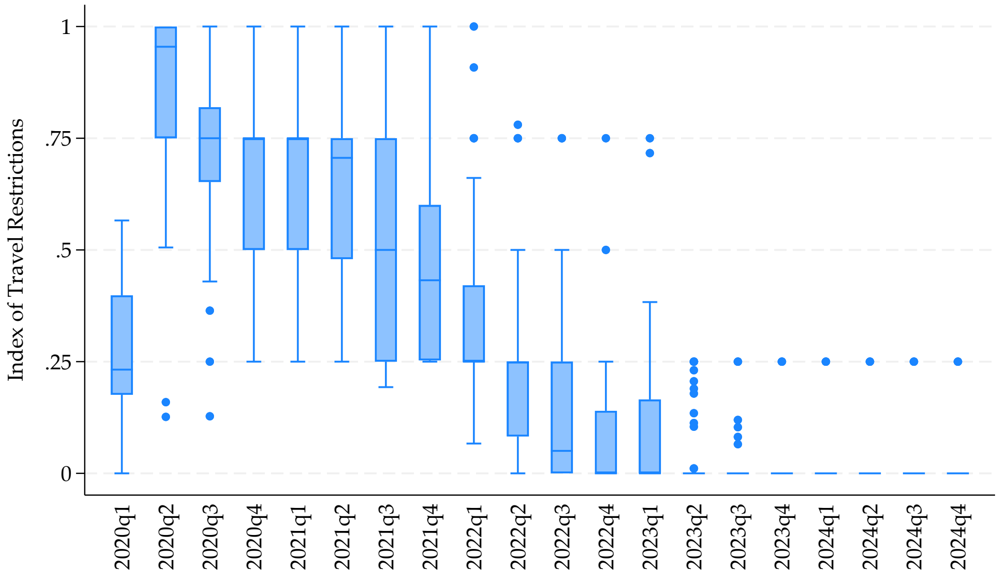
Prior to the Covid pandemic, I code the index at 0 for all countries by default. Because the Oxford dataset stops at the end of 2022, I need to extend this to cover the additional two years for which I have economic data. To do this I use AI to search for news articles, government announcements or travel information websites which imply a change in restrictions on dates in 2023 and 2024 on which the index "would have" changed. Full details of the process and prompt used are contained in the appendix.[4]

To convert this daily data to the same quarterly frequency as the economic data used in the estimations and to yield a continuous variable, I take the average value of the index in all calendar days in a given quarter; and then divide by four so that the index takes a value between 0 and 1.

The chart below shows, for each quarter since 2020Q1, a box and whisker plot of the distribution of the variable across the 98 origin countries in the estimation sample.

[4]As the chart shows, by end the end 2022 the variable is zero for most countries, there are only a handful of countries that persist with restrictions into 2023. As a robustness check to verify that the results are not driven by or sensitive to the additional years of data generated using the AI search, I run the baseline regression using only the original data, with no AI extension. This shows very similar results to the result over the full sample.

Figure 1: Travel Restrictions



This shows how fast the restrictions came in at the start of the pandemic- by 2020Q2 the median country had a value of over 0.9 (indicating partial/full border closure). Restrictions eased gradually after that, such that by 2023 only a handful of countries still had travel restrictions in place. The chart also makes plain the significant cross country dispersion in travel restrictions. In 2022Q1 for example, we observe values spanning almost the entirity of the 0 to 1 range. At the top end Japan still had full border closures; and at the other end of the scale Slovenia was at 0.06 implying almost no restrictions. This makes the point that in the empirical results which follow there is substantial cross-country variation for the estimations to use.

In an empirical trade context, travel restrictions have the appealing property that they only operate in regard to cross-border movements of people and goods. For domestic producers selling in domestic markets, these frictions do not apply because the goods do not cross a border.

Of course there were many other restrictions which may have affected domestic transportation and distribution and sale of goods. For example, the Oxford dataset compiles as indices of retail closures. But these don't have an obvious interpretation in terms of trade costs, because a shop closure would increase (or even prevent) the sale of goods regardless of whether they were domestically produced or imported. Similarly, social distancing measures which impeded the production of goods, would have the same effect on production costs whether those goods stayed in the domestic economy or were exported. And local transportation difficulties, due to extra regulations, or staff absences, would work in the similar way for moving domestically produced goods to domestic markets, versus sending them to an airport or sea port for international shipment.

Several papers in the Covid literature[5] have used the overall stringency index, a weighted average of 9 sub-indices (of which travel restrictions is one) capturing different policy responses.

Other papers have used case or death numbers as a proxy for exposure to Covid to test for its influence on trade.[6] This has several drawbacks: first, early on in the pandemic lack of testing facilities meant cases and Covid related deaths may be poorly measured; second, some countries tested more than others so the numbers may not comparable across nations (See Chen et al., 2021 on both points). Third, it's not clear how they map onto trade costs- because they do not in themselves change the marginal cost of trading internationally versus domestically. Fourth, the correlation between cases/deaths and measures to prevent Covid (including travel) is complicated: border restrictions may be imposed in response to rising cases elsewhere, and if borders are closed completely, domestic cases may be extremely low (for example in mid 2020, Jefferies et al. (2020) document that New Zealand recorded no locally transmitted cases for over 100 days), so it's not clear what sign the coefficient should take.

For these reasons I take travel restrictions as the relevant measure. Nevertheless because they are used elsewhere in the literature, I also estimate specifications using cases, deaths and the stringency index as regressors and show that these variables perform poorly.

[5]For example, de Lucio et al. (2022), Liu et al. (2022) or Berthou and Stumpner (2024)

[6]See, for example, Bas et al. (2024)

3 Empirics

I estimate a gravity model on dyadic trade data at a quarterly frequency. Data for international trade are taken from the COMTRADE database. These are downloaded at monthly frequency as exporter reported flows over the period 2016 to 2024. My sample consists of 98 origin countries to 151 destination countries, where the choice of origins is governed by the availability of domestic demand and travel restriction data. These are summed to give trade flows at quarterly frequency. For internal trade flows, I use the measure recommended by Yotov et al. (2016), GDP minus total exports[7], which is calculated from GDP and trade data taken from the IMF's WEO datbase. For geographical variables I use the CEPII database (Conte et al., 2022). For a full list of variables and sources, please see the appendix.

3.1 Border frictions over time

To explore the evolution of border frictions through the pandemic, I begin with a canonical gravity equation with international trade and set of quarter-specific border dummies

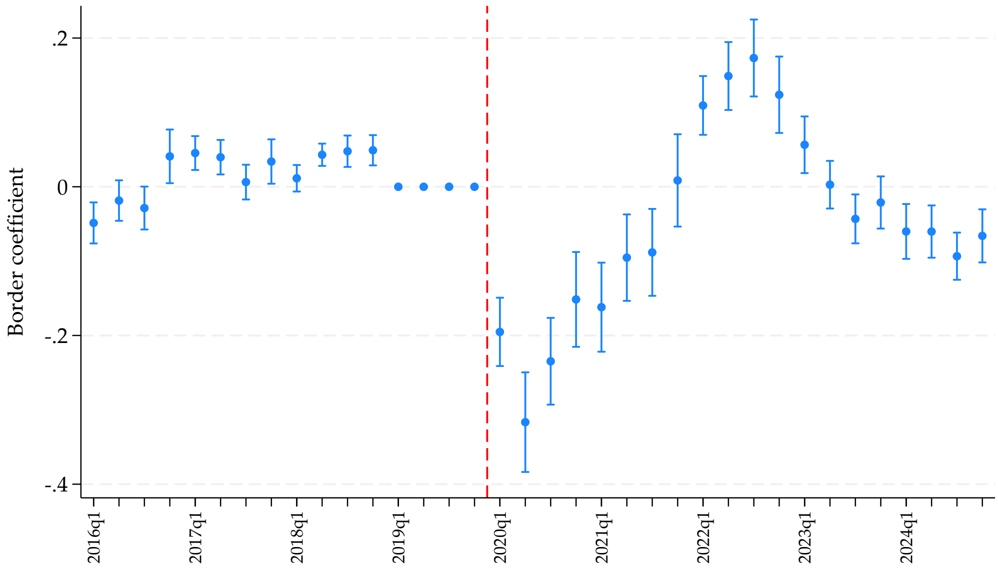
$$Trade_{odt} = \exp(\Sigma(\eta_t Border_{od}) + \delta_{od} + \gamma_{ot} + \lambda_{dt} + \mu_{bq}) \times \epsilon_{odt} \tag{1}$$

Where $Trade_{odt}$ is the value of exports from origin o to destination d at time t, *Border* is a dummy equal to one if origin and destination country are different and the term in brackets denotes the set of time-specific border coefficients. I include the trio of fixed effects: origin-time, destination-time and origin-destination; plus an border-quarter-of-the-year fixed effects, to purge the data any seasonality in border effects. The equation is estimated using the PPML estimator of Santos Silva and Tenreyro (2006). Because I include internal trade, the inclusion of origin-time fixed effects captures the effect of any domestic restrictions on the supply side of the economy (i.e. those which reduce productive capacity regardless of whether the goods are consumed domestically or exported) and the effects of any restrictions on the demand side (i.e those which reduce demand for all goods consumed in the country, regardless of whether they are made domestically or imported). As such, the coefficients on the border variable (and on any variable interacted with it) isolate the effect border frictions. The

[7]For China there is no data available on total exports, only good exports, so for China I uses GDP minus goods exports

interpretation of the η coefficients is as the marginal change in the border effect, relative to the base period. For ease of comparison I select the four quarters of 2019 as the base period. The results are shown graphically below:

Figure 2: Border frictions relative to 2019



Note: Dots show the point estimate, the lines indicate a 95% confidence interval

A negative coefficient implies a rise in border frictions and a decline in trade. The chart reveals largely stable border effects before 2019, followed by a sharp rise in border frictions in the when the pandemic starts (shown by the red line). At its nadir in 2020Q2, the coefficient was -0.32. Using the exponential function $e^{\gamma_t} - 1$, this implies a 27% decline in trade. Because the specification includes origin-time and destination-time fixed effects and internal trade, this decline is attributable to the rise and border frictions, over and above what would have been implied by the contraction in activity. This is a sizable effect- for comparison Yotov (2012) documenting the decline in border frictions finds an effect of around 0.06 per decade. In other words, the initial shock to trade costs in 2020 of the pandemic was equivalent to about 40-50 years of globalisation being unwound.

This effect gradually subsides over the next two years, and the marginal coefficients go into positive territory at the end of 2021. This suggests there was a burst of trade when restrictions began to ease to "make up" for the trade lost previously and consequently there was no longer term "scarring" effect. This subsides, and the marginal coefficients stabilise at just below zero in the last period of the sample.

The results paint a striking picture how border coefficients changed over time, but by parameterising this in terms of time as opposed to economic variables, they don't directly say anything about the causes of this. In the remainder of the paper, I therefore focus on using economic variables to explain the change in border coefficients.

3.2 The Effect of Travel Restrictions

I now include the measures of travel restrictions, in the exporting country TR_{ot} to estimate equations of the form:

$$Trade_{odt} = \exp\left(\beta_1 \mathrm{TR}_{ot} + \beta_2(\mathrm{TR}_{ot} \times \ln \mathrm{Dist}_{od}) + \delta_{od} + \gamma_{ot} + \lambda_{dt} + \mu_{bq}\right) \times \epsilon_{odt} \tag{2}$$

It is not possible to include both TR_{ot} and TR_{dt} in equation because one will get automatically dropped due to collinearity. This applies for any country-specific variable one could interact with a border dummy in this framework. The econometrics of this point are discussed more fully by Beverelli et al. (2024) in the context of the effect of institutions on growth. They show that the travel restrictions term can be defined on importer or exporter side without any quantitative implications for the estimates; and that although the variable is defined on one side, the interpretation of the coefficient is of the effect on a country's international trade flows- both imports and exports.

Table 1 presents the results of the first set of regressions:

Beginning with the simplest specification (I), using travel restrictions as a single explanatory variable shows a highly significant coefficient of -0.19, this implies that when a country full border closure for a whole quarter reduces trade flows by 17%.

Interacting travel restrictions with distance (II), shows a highly significant interaction effect. The positive interaction coefficient implies that the hit to trade declines with distance.

To check the results are not driven by the inclusion of the extra data generated by AI for the years 2023 and 2024, column III reports the results

Table 1: The role of travel restrictions

	(I)	(II)	(III)
Travel Restrictions	-0.191***	-0.710***	-0.859***
	(0.0352)	(0.161)	(0.167)
Travel Restrictions		0.0636***	0.0759***
× ln(Distance)		(0.0182)	(0.0188)
Sample Period	2016-2024	2016-2024	2016-2022
Country-Pair FE	Yes	Yes	Yes
Origin-Time FE	Yes	Yes	Yes
Destination-Time FE	Yes	Yes	Yes
Border-Quarter FE	Yes	Yes	Yes
Observations	450,467	450,467	352,236

Standard errors clustered at the country pair level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

where the sample is cut off at 2022. Appendices report further robustness checks to explore whether: i) the results are not just driven by outright border closures or a few countries with very tight restrictions[8]. ii) other geographic variables beyond distance play a role[9] and iii) the declining impact of distance result is simply because the hit takes longer to show up in more distant partners where shipping lags are longer[10].

To verify that it is travel restrictions rather than other Covid-related variables driving the results, I also experiment with including cases, deaths as additional terms and on their own, these don't prove to be significant [11];

[8] I also reports the results of alternative specifications which drop: countries with border closures for 4 or more consecutive quarters, observations were TR=1, and observations where $TR > 0.75$. These yield very similar coefficient estimates indicating that the results are not driven by a handful of very strict lockdowns (see table A1).

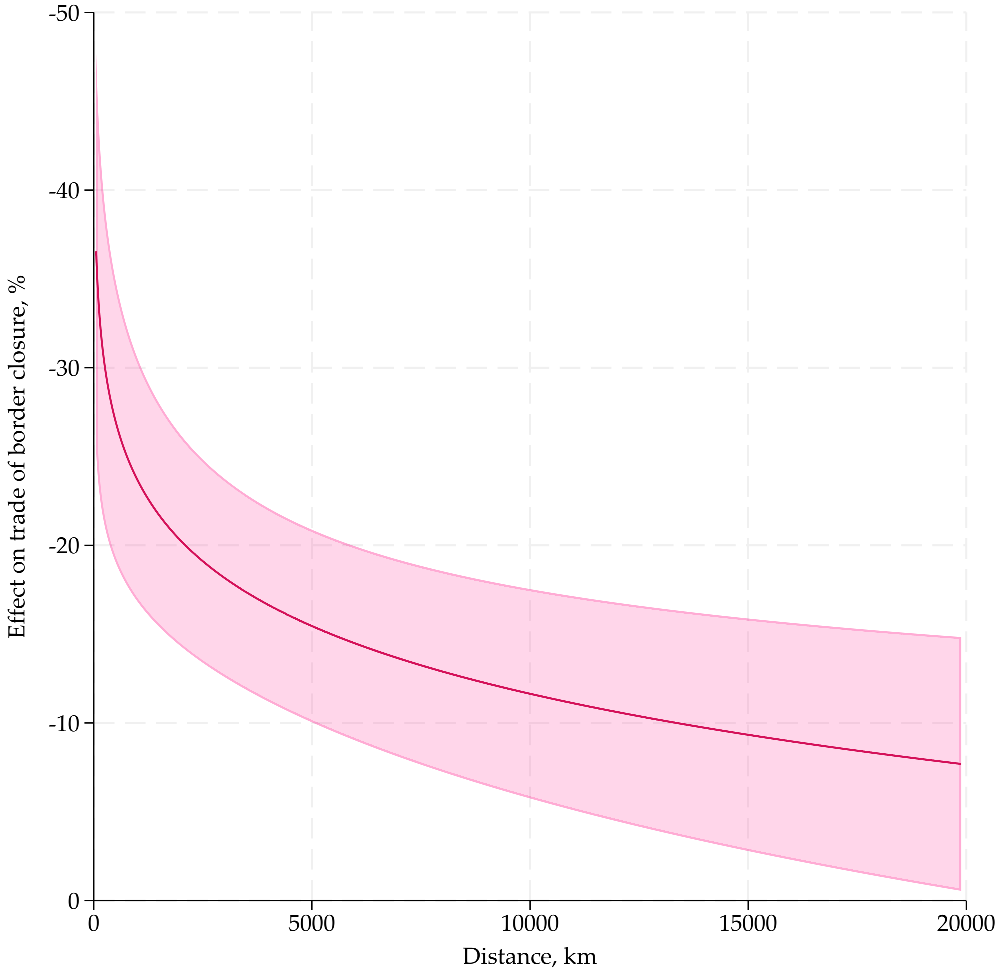
[9] One obvious candidate is contiguity (*contig*), i.e. two countries which share a common border, given the evidence of bottlenecks appearing at border crossings discussed earlier. Another is whether a country is landlocked (*landl*) or an island (*island*), since this affects port access, and may correlate with transportation mode. When included, these additional terms are highly insignificant, making clear that distance is the relevant geographic variable (see table A2).

[10] To check whether closer partners show a bigger hit merely because it takes longer to materialise for more distant partners with longer shipping times, I estimate regressions with 1 and 2 lags of the *trav* variable. Table A3 makes clear the same downward slope with respect to distance holds across all of those.

[11] Although the channel by which they should translate into trade costs is unclear, sev-

The total effect is : $exp(\hat{\beta_1} + \hat{\beta_2} \times lnDist_{od}) - 1$. For ease of interpreting the results, I present this graphically below:[12]

Figure 3: Effect of border closures



Note: The line shows the point estimate, the shaded area indicates a 95% confidence interval; the vertical lines show deciles of distance for 2019Q4 cross-border trade flows

eral papers in the literature have used them as a proxy for the effect of Covid. See table A4

[12]Note, this shows the marginal effect on trade where $TR = 1$ in one partner. If both partners close their borders, the effect would then be $exp(2 * \hat{[}\beta_1 + \hat{\beta_2} \times lnDist_{od}]) - 1$. Because the model is multiplicative, the marginal hit of a closure in one country is uniform in percentage terms, regardless of the level of TR in the other country

This chart makes plain the sizeable role of distance. At the 10th percentile of distance for international trade flows (457km), the effect is 27.3%, at the 90th percentile (11500km) the effect is 10.8%, about two and half times larger.[13]

This finding has close parallels with the literature exploring border frictions in international trade. Several papers have found that the effects of trade agreements is larger, the closer together the partners are. The intuition for this is as follows: trade costs comprise two components, a distance-invariant border friction, and distance related cost of moving the goods over the distance. The closer two partners are, the smaller is the share of those costs accounted for by transport costs. Trade agreements don't affect the marginal cost of moving goods an extra kilometre, but they do lower the distance invariant border friction. So closer partners see a larger proportionate reduction in costs than more distance ones, and hence closer partners see a larger boost to trade. The same logic applies here, for the rise in border frictions. For the closest pair of countries in our sample (Austria- Slovakia, with a distance of 55km) transport costs are very low and almost all trade costs are the border friction, and so the results predict a hit of 37% . By contrast, for the longest distance pair in the sample transport costs are a much larger share of total trade costs, so a change in border frictions has a much lower effect on trade costs: (Paraguay-Taiwan, 19844km) the effect is around 8% barely significant at the 5% level.

3.3 The role of transport mode

It's not possible to estimate an entirely separate gravity model for each transport mode because i) UNCTAD transport data is only available at an annual frequency and ii) there is no comparable data to use for the internal trade flows which are central to the approach used in this paper. Instead I develop an exposure based measure to capture the role of transport mode.

My data on transport mode are taken from UNCTAD's annual database on trade and transportation. This records, at an annual frequency, the free-on-board value of trade at the country pair level transported by: air, sea, road,

[13] To check that the declining role of distance is not simply a timing effect- where travel restrictions take longer to show up at longer distances, because of lengthier shipping times, I repeat the regressions replacing current restrictions with 1, 2 and 3 lags of restrictions respectively. Each regression shows the a clear decline in the hit over distance, albeit with a smaller overall hit. Thus I conclude the declining effect of restrictions over distances is not driven by longer shipping times at greater distances.

rail and a miscellaneous "other" category [14].

Data is recorded on the import side, and it records the mode of transport by which it arrived in the importing country. For some countries and trade flows, the mode of transport is unrecorded, and so this further limits the country coverage. I use this data to calculate an exposure measure for transport flows. Specifically, it records the value of (identifiable) trade flows across a country pair which have travelled by a given mode of transport in 2019. So a "sea intensity" score of 1 means that the value of seaborne freight equals 100% of the trade flow between the a country pair. A value of zero means there is no seaborne freight between the two.

Because some goods use more than more type of transport to reach their destination, the sum of the mode-specific flows can exceed total trade. The UNCTAD dataset reports a "multi-modal" adjustment figure, to reconcile with aggregate flows. For example, consider the case of "roll-on roll-off" ferries - lorries containing goods are driven on to the ferry, the ferry sails between countries, and the lorries drive off. These trade flows would be counted towards both the sea and road trade flows. Adding the the sea and road trade intensity would lead to double "double counting". At the aggregate level this means the sum of the intensities can exceed 100%. The data also records a multimodal adjustment which captures the double counting.[15]

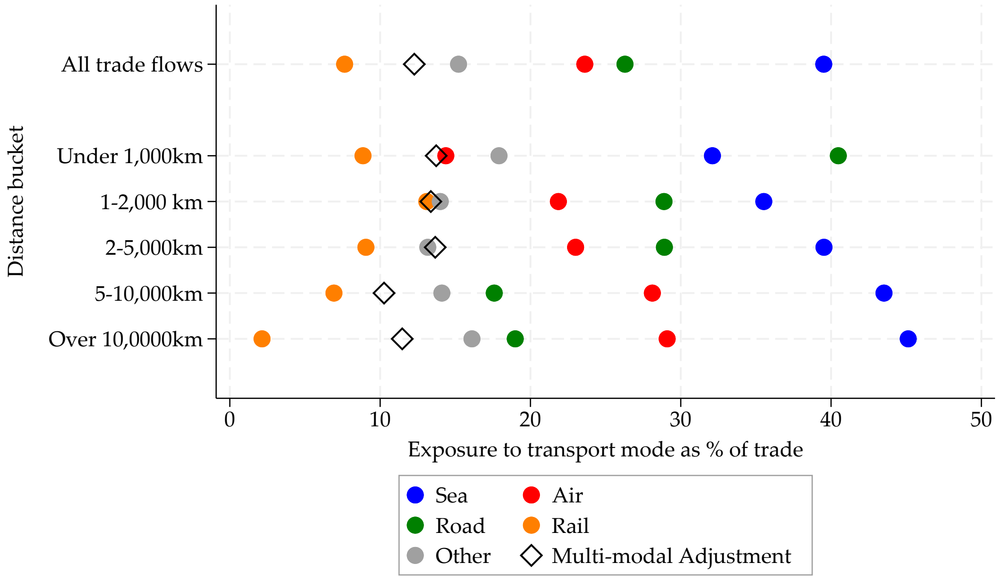
I then interact these intensity measures with the travel restriction variable (and the equivalent interaction with distance). This is shown below for all flows, and by distance buckets[16].

[14]This includes goods sent by post, self propelled vehicles, and goods transported in pipelines and other fixed infrastructure.

[15]This is an important advantage with respect to the more widely used COMTRADE data which doesn't account for multimodal trade. In COMTRADE, the sum of the modal flows adds up to the total trade flow, and so multimodal flows are either arbitrarily assigned to one mode of transport, or coded under "other".

[16]Note that the dots do not sum to 100, because of the multi-modality point. This means we cannot interpret them as the "share" of trade moving by a given transport mode, hence I use the term "exposure" here. The sum of the dots minus the black diamonds does equal 100%

Figure 4: Exposure to transport modes



The largest exposure is to sea, which is equal to nearly 40% of total trade flows. This is followed by road and air, which have exposures of around 25%.

But this masks important variation by distance. At lower distances (under 1000km), road transport is the largest single mode, accounting for over 40% of trade, over double what it accounts for at the longest distance bucket. Similarly, air transport accounts for a relatively small amount of trade flows at short distances, but about double that at the longest distances. This emphasises the importance of controlling for transport mode, to tease out whether the distance effects found a above are truly related to distance, and are not merely driven by differences in transport mode over distance.

I then include each of these mode-specific measures in a regression of the following form, where the index $m \in M = \{1, \ldots, 5\}$ represents the transport mode (e.g., road, rail, air, sea, and other) , and then test down to find the appropriate restrictions.

$$\text{Trade}_{odt} = \exp\Big[\sum_{m\in M}(\kappa_1^m \times \text{TR}_{ot} \times \text{Int}_{od}^m) + \sum_{m\in M}(\kappa_2^m \times \text{TR}_{ot} \times \ln \text{Dist}_{od} \times \text{Int}_{od}^m)$$
$$+ \delta_{od} + \gamma_{ot} + \lambda_{dt} + \mu_{bq}\Big] + \epsilon_{odt} \quad (3)$$

The regression results are presented below:

Table 2: The role of travel restrictions

	(I)	(II)	(III)	(IV)
Travel Restrictions	-1.161			
× Air Intensity	(0.997)			
Travel Restrictions × ln(Dist.)	0.130			
× Air Intensity	(0.108)			
Travel Restrictions	-1.165**			
× Road Intensity	(0.461)			
Travel Restrictions × ln(Dist.)	0.115*			
× Road Intensity	(0.0586)			
Travel Restrictions	0.289			
× Sea Intensity	(0.383)			
Travel Restrictions × ln(Dist.)	-0.0647			
× Sea Intensity	(0.0460)			
Travel Restrictions	1.877	1.720		
× Rail Intensity	(1.144)	(1.112)		
Travel Restrictions × ln(Dist.)	-0.220	-0.207		
× Rail Intensity	(0.142)	(0.138)		
Travel Restrictions	-1.853***			
× Other Intensity	(0.514)			
Travel Restrictions × ln(Dist.)	0.217***			
× Other Intensity	(0.0657)			
Travel Restrictions		-1.187***	-1.033***	-1.335***
× Air/Road/Other Intensity		(0.259)	(0.222)	(0.471)
Travel Restrictions × ln(Dist.)		0.116***	0.0980***	0.167***
× Air/Road/Other Intensity		(0.0290)	(0.0251)	(0.0561)
Travel Restrictions				0.195
				(0.341)
Travel Restrictions				-0.0488
× ln(Distance)				(0.0412)
Sample Period	2016-2024	2016-2024	2016-2024	2016-2024
Country-Pair FE	Yes	Yes	Yes	Yes
Origin-Time FE	Yes	Yes	Yes	Yes
Destination-Time FE	Yes	Yes	Yes	Yes
Border-Quarter FE	Yes	Yes	Yes	Yes
Observations	442,157	442,157	442,157	442,157

Standard errors clustered at the country pair level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Beginning with all 5 pairs of transport mode terms (I) reveals very different effects by transport type. There are similarly sized coefficients for air and road (implying a negative effect, getting smaller with distance), insignificant and close to zero coefficients for exposure to seaborne trade , and coefficients for railfreight implying a positive (albeit insignificant) boost, but declining with distance. Given the similarity of the air and road coefficients, this suggest an obviously equality restriction. [17] I construct a new variable which captures the combined share of the three (equal simply to the sum of the air, road and other modes intensities). When included (II) including this is strongly significant. Dropping those (III) gives the preferred specification with strongly significant coefficients for exposure to road and air travel. If the original travel restrictions term and distance interaction are included as extra regressors (IV), they are both insignificant. Their lack of explanatory power means that the entirity of the effect of travel restrictions can be captured by the air+road+other exposure variables.

Taken together these results also demonstrate that the declining hit with distance found in the previous section is not simply an artifact of different transport modes being used. Rather, it persists even after controlling for differences in exposure to transport modes at different distances.

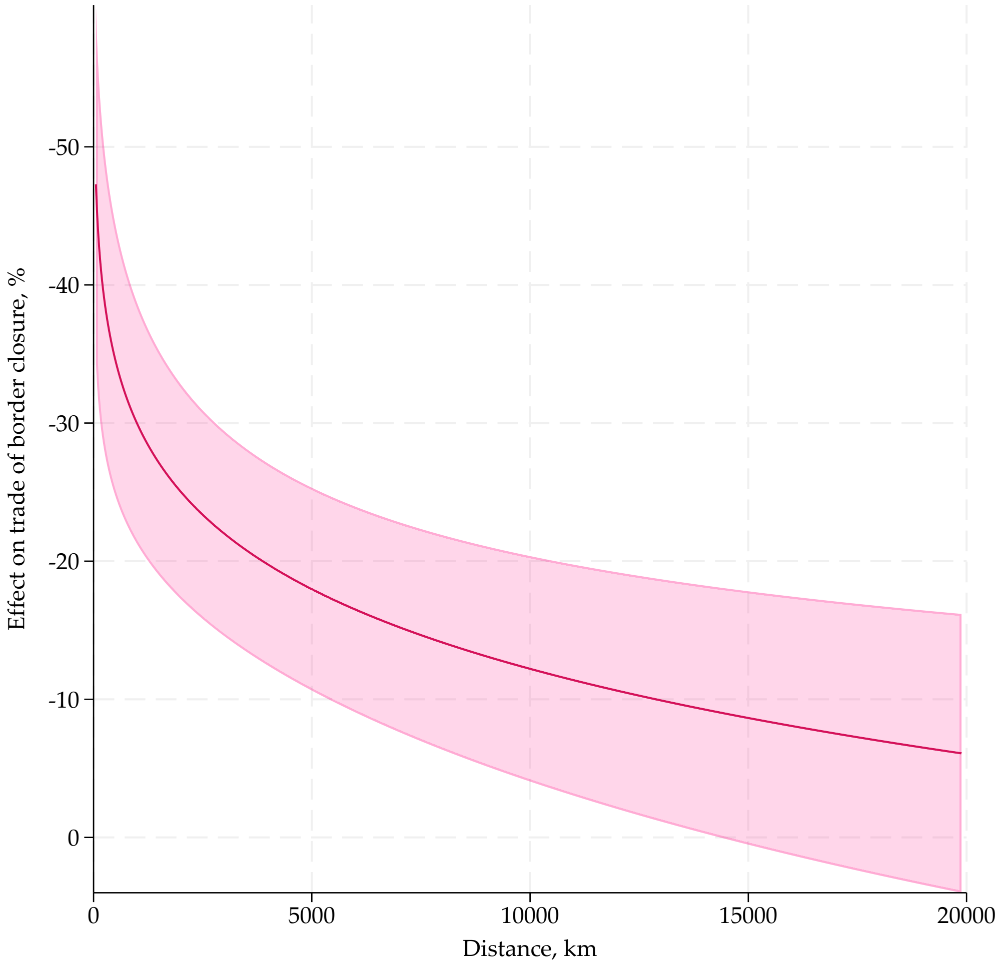
Containerised trade does not require physical contact between ships crew and port workers, nor does it require crew to disembark the ship. This meant containerised trade was less affected once appropriate measures were introduced. By contrast, freight in lorries requires a driver, and as such faces the potential frictions associated with entry to the destination country. In our measure this difference is accounted for in the data because the roll-on roll-off freight is impeded by the frictions to road travel.

Airfreight does not require any contact between ground crew and aircrew, but was hindered by two factors- the decline in passenger freight leading a reduction in "belly cargo" noted above;

Taking the coefficients from equation (III) I calculate the implied hit to air/road/other trade flows as a function of distance between country pairs: $exp(\hat{\kappa}_1^{airroadoth} + \hat{\kappa}_2^{airroadoth} \times lnDist_{od}) - 1$

[17] A joint test of the pair of restrictions $\kappa_1^{road} = \kappa_1^{air}$ and $\kappa_2^{road} = \kappa_2^{air}$ yields a p-value of 0.89

Figure 5: Effect of border closures: Road+Air trade



This again implies a sizeable effect of border closures, and an economically significant distance effect. The effect at the 10th percentile is around three times that at the 90th percentile. The difference between the closest and most distance country pairs (55km vs 1988km) is around eight-fold.

I then calculate what these coefficients imply for different pairs. Analogous to the hit Ω_{od} for the simple model of the previous section, allowing for differences in transport mode, the hit to air, road and other exposed trade trade between a pair of countries is given by:

$$\hat{\Omega}'_{odt} = \exp\left(\hat{\kappa}_1[TR_{ot}] + \hat{\kappa}_2[TR_{ot} \times \ln \mathrm{Dist}_{od}]\right) - 1 \tag{4}$$

κ denotes the estimated coefficients from model (III) above.

But the effect on overall trade flows between any pair of countries will of course also depend on the exposure to different modes of transport. To get a sense of this, at the country pair level this will be given by:

$$\hat{\Omega}''_{odt} = \exp\left(\hat{\kappa}_1[TR_{ot} \times Int_{od}^{AirRoadOth}] + \hat{\kappa}_2[TR_{ot} \times \ln \mathrm{Dist}_{od} \times Int_{od}^{AirRoadOth}]\right) - 1 \tag{5}$$

I then compute this aggregate trade-weighted effect on imports and exports for each country i, given the distances, transport exposures and trade shares of each partner j. I then take a simple average to give the estimated effect on trade.[18] These are shown below for three cases:

i) Hit to air/road/other trade flows if borders are closed ($TR_i = 1$)

ii) Hit to total trade flows for if its borders are closed ($TR_i = 1$)

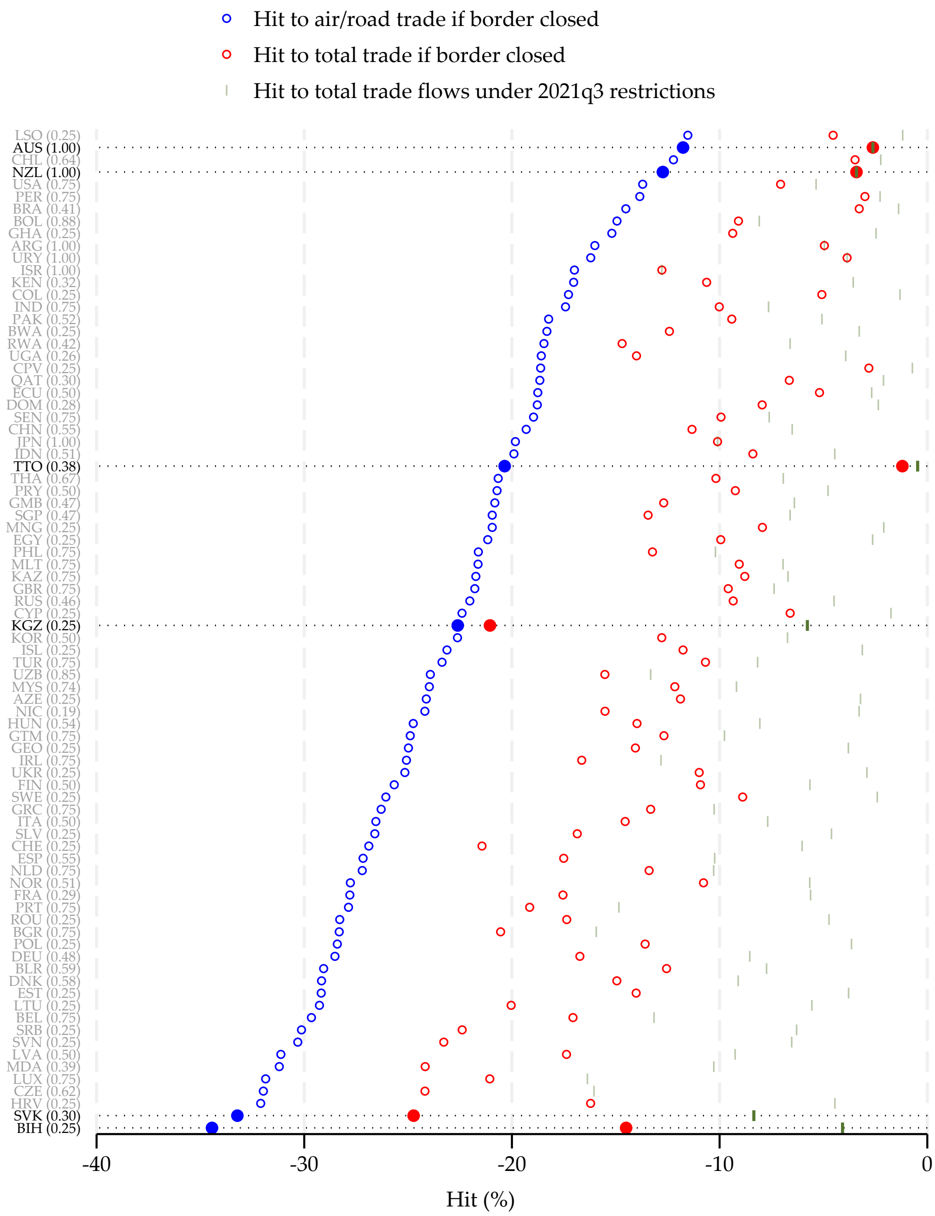
iii) Hit to total trade flows country given actual level of restrictions observed in 2021Q3 ($TR_i = TR_{i,2021Q3}$)[19]

I then take a simple average of import and export hits to give the total effect on aggregate trade of a country closing its borders. These are shown below for each of the countries in the dataset:

[18] These show the marginal effect on trade, of country i imposing travel restrictions, holding the partner restrictions constant. Again, as per the remark for figure 3, note that because underlying PPML model is multiplicative the marginal effect on country i's trade of changing border restrictions in i will be the same in percentage terms, regardless of the level of restrictions in country j.

[19] This quarter was chosen because it has the widest cross-country dispersion in TR of any quarter

Figure 6: Effect of own border closures by country



The blue dots show the effect on air and road exposed flows from a country closing its own borders. The only source of variation across the countries in these is differences in the (trade-weighted) average distance that goods travel. At the very lowest end is Australia, which has the highest distance because its main trading partners are relatively distant. This implies a hit to air and road exposed trade of 16.6%. By contrast at the upper end, the largest hit is for Bosnia, 36.6%, which has a much lower distance of its traded goods, for whom the maximum hit is around double.

The red dots then show the effect on total trade when a country closes its own borders. Relative to the previous measure this allows differences in exposure to transport modes. In the limiting case where all trade across a pair moves only by sea and rail, the effect on total trade flows is zero, because travel restrictions have a zero effect on those modes. At the other end, if exposure to road, air and "other" is 100% then the red dot would be the same as the blue dot, because 100% of trade flows are affected.

Comparing the experience of Kyrgyzstan with that of Trinidad and Tobago makes plain the importance of transport mode. For both countries, the blue dots in similarly sized (in the mid 20s) because the average distance their trade travels is very similar. Strikingly, Kyrgyzstan faces a hit of around 25% to trade from closing its borders because nearly all of its trade moves by air, road or "other" modes; whereas by contrast, Trinidad and Tobago has very low exposure, with almost all of its trade moves by sea; and hence it can can close its borders at almost no cost to trade facing a hit of only around 2%. These differences in transport modes generate a twelve fold differences in the effects of own border closure across the two countries

Lastly, the green lines indicate the estimated hit to trade based on each countries actual choice of travel restrictions in 2021Q3. These again reveal substantial heterogeneity. Australia implemented full border closure, and did so at at an estimated hit of only 4% to trade. By contrast, Bosnia and Herzegovina had one of the loosest travel restrictions in the sample, but this came at a higher cost (around 5%) to trade flows than Australia's. This makes the point that the heterogeneity potentially has relevance for explaining the differences in policy setting, because it highlights that border closures had very substantially different consequences for trade flows depending on the interaction of distance and transport mode.[20]

[20] This point is even starker at the country pair level. There are several pairs for which the exposure to road and air is zero - and hence this model posits zero marginal effect on trade from closing borders. By contrast, there are instances of very close trading partners with very high levels of exposure: fore example between Austria and Slovakia, where almost all trade moves by road

3.4 Dynamic Effects

Up to now, specifications have been based on the assumption that only current restrictions affect trade. In this section, I relax that assumption to allow for dynamic effects. One possibility is that previous travel restrictions having impeded trade, had longer lasting "scarring" effects on trade. Another possibility, is that once restrictions eased, this generated a burst of extra trade, as firms sought to make up for the trade lost during the the restricted period. At the aggregate level there is some evidence of this from time-varying border friction plotted in figure 2.

To explore the shorter run "backlog" hypothesis , I construct three measures of the earlier travel restrictions. The first is a simple moving average of previous p quarters. In what follows I use $p = 6$, based on a grid search over different values.[21]

$$PTR_{ot} = \sum_{t-1}^{t-p} TR_{ot} \tag{6}$$

The backlog effect can be pushing up on trade whilst current restrictions are pushing down. This specification assumes bounceback can occur even when borders are fully closed, counteracting the effect of contemporaneous restrictions. An alternative might be too assume that bounceback only kicks in once borders are fully re-opened. To implement this, one can define a dummy variable D^{OPEN} which is equal to 1 when TR_o is zero, and is zero for all other states, and interact this with past travel restrictions variable:

$$backlogA_{ot} = PTR_{ot} * D_{ot}^{OPEN} \tag{7}$$

Equally, the above might be too restrictive an assumption, by assuming that no bounceback happens until borders are completely open. To capture the notion that some recovery occurs at non-zero levels of current restrictions then a third and intermediate, measure is to define the backlog as the gap between current and previous restrictions:

$$backlogB_{ot} = \max(PTR_{ot} - TR_{ot}, 0) \tag{8}$$

[21] See appendix A2 for details

The table below reports the results, when each of these are included as additional regressors (alongside their counterpart interaction term):

Column (I) reports the basic equation without any backlog. Adding in the simple average of the previous restrictions (II) yields a pair of strongly significant coefficients, the with opposite signs and slightly smaller absolute magnitudes. That indicates that there was some "catchup" growth in trade to make up for the lost flows due to travel earlier restrictions, but that it was incomplete. Adding in the $BacklogA$ (III) and $BacklogB$ (IV) terms yields very similar values of the coefficients in top two rows are fairly similar for both backlog measures to the case without any backlog, suggesting that the initial results are robust to allowing for a bounceback effect in trade. In terms of the backlog coefficients they are again with significant opposite signs to the first two rows, implying catchup trade. But magnitude of these coefficients are not straightforward to interpret, so to facilitate understanding, the chart below plots the implied effect on global trade from each of the specifications.

Specifically, I compute the estimated effect on bilateral trade across each country pair. I then construct a weighted average of this hit, using 2019 trade flows as weights (omitting domestic trade). The results are shown below:

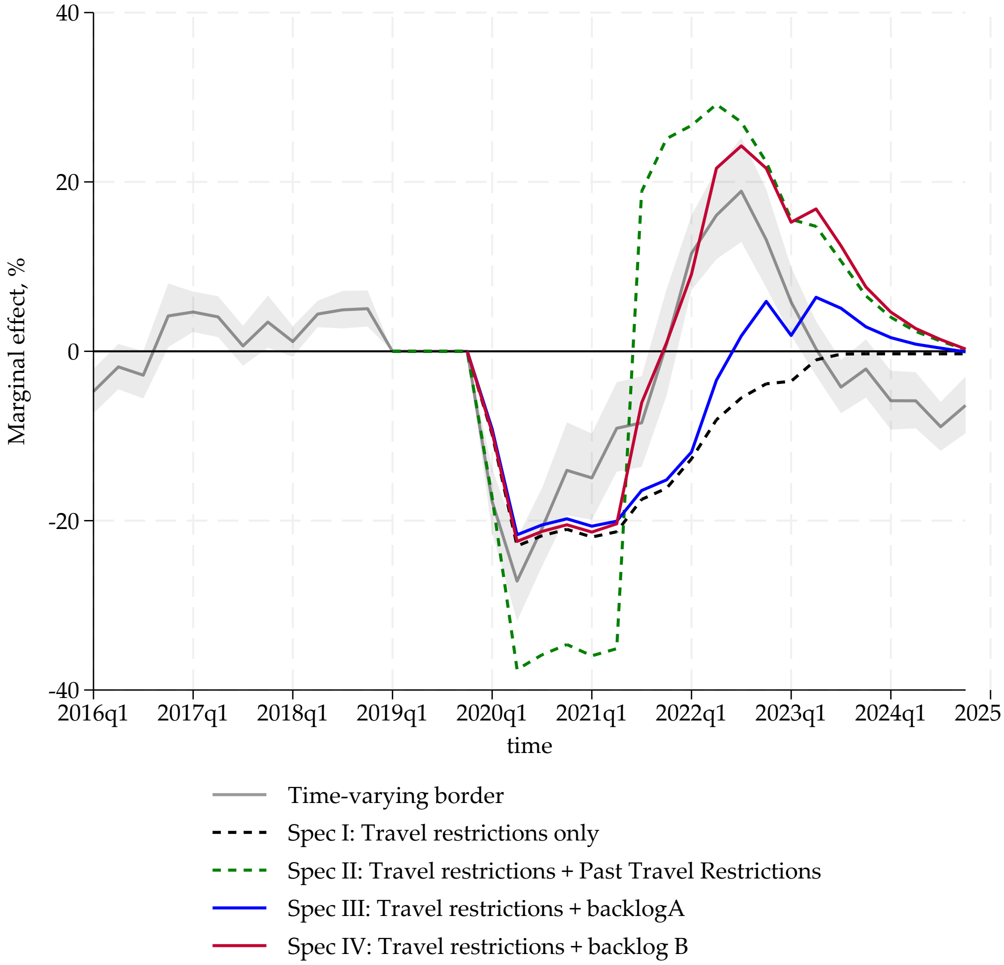
Table 3: Incorporating past travel restrictions

	(I)	(II)	(III)	(IV)
Travel Restrictions	-1.033***	-1.635***	-0.917***	-1.015***
$\times$ Air/Road/Other Intensity	(0.222)	(0.269)	(0.225)	(0.225)
Travel Restrictions $\times$ ln(Dist.)	0.0980***	0.146***	0.0856***	0.0966***
$\times$ Air/Road/Other Intensity	(0.0251)	(0.0313)	(0.0251)	(0.0252)
Past Travel Restrictions		1.215***		
$\times$ Air/Road/Other Intensity		(0.247)		
Past Travel Restrictions $\times$ ln(Dist.)		-0.101***		
$\times$ Air/Road/Other Intensity		(0.0289)		
Backlog A			1.553***	
$\times$ Air/Road/Other Intensity			(0.421)	
Backlog A $\times$ ln(Dist.)			-0.166***	
$\times$ Air/Road/Other Intensity			(0.0535)	
Backlog B				1.576***
$\times$ Air/Road/Other Intensity				(0.361)
Backlog B $\times$ ln(Dist.)				-0.137***
$\times$ Air/Road/Other Intensity				(0.0439)
Sample Period	2016-2024	2016-2024	2016-2024	2016-2024
Country-Pair FE	Yes	Yes	Yes	Yes
Origin-Time FE	Yes	Yes	Yes	Yes
Destination-Time FE	Yes	Yes	Yes	Yes
Border-Quarter FE	Yes	Yes	Yes	Yes
Observations	442,157	442,157	442,157	442,157

Standard errors clustered at the country pair level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 7: Dynamic Effects



The grey line shows the implied hit to trade the time varying border coefficients from figure 2, against which we compare the specifications in table (7). Allowing for travel restrictions only (spec I) matches the initial fall well but fails to capture the full extent of the recovery in trade over 2021-22, and by definition (since it allows for the negative effects of current travel restrictions) can't generate a marginal effect greater than zero. Simply including the PTR measure (spec II) generates too large a fall in 2020 and 2021, and too early a recovery thereafter.

Backlog A performs a little better, capturing the initial fall well and generating more of an uptick, but only a small positive effects from 2022 onwards. Intuitively, because this measure requires restrictions to go to zero before any catchup trade occurs, it places the recovery too late because it has to "wait" for restrictions to fully come off. By contrast, backlog B does a better job of fitting the path over time, and broadly captures the dynamic observed, especially in the 2021-22 upswing. For this reason it is the preferred specification of dynamic effects.[22]

[22] For a full decomposition of the effects of current restrictions vs catchup effects in this specification, please see the appendix figure A1

4 Conclusion

This paper has examined how Covid-19–related travel restrictions affected international trade flows, isolating their role as a time-varying source of border frictions over and above the general contraction in economic activity during the pandemic. Using a gravity framework that incorporates internal trade flows, I provide evidence that restrictions on cross-border movement of people translated into substantial and economically meaningful increases in the cost of trading goods internationally.

The results show that travel restrictions operate like a classic case of a "border friction" to international trade. They had a large negative effect, with a full border closure reducing bilateral trade by around 19 percent for a typical country pair. These effects represent border frictions and are over and above the effects containment measures on either the demand side (reducing consumption of goods) or supply side (impeding the productive capacity of the economy).

These effects were highly heterogeneous in two dimensions. In line with theories that emphasise the importance of distance-invariant border costs, the impact of restrictions was markedly larger for geographically proximate partners, for whom border frictions account for a greater share of total trade costs. Moreover, the effects vary strongly by transport mode: trade flows reliant on road and air transport were significantly disrupted, while seaborne trade was largely unaffected. The interaction of distance and transport exposure generates substantial cross-country variation in the overall trade impact of border closures, helping to explain why some countries were able to impose strict restrictions at relatively low cost to trade, while others faced much larger losses.

Importantly, there is no evidence of long-run scarring effects. While travel restrictions sharply reduced trade at their peak —implying a maximum global hit of around 23 percent in 2020Q2— trade flows rebounded once restrictions were eased, with a temporary overshooting to a temporarily higher level of trade (lower border frictions) than before Covid that largely offset earlier losses. This pattern suggests a degree of intertemporal substitution rather than a permanent reorganisation of trade relationships.

Taken together, these findings contribute to several strands of the trade literature by documenting a novel, high-frequency source of border frictions; by clarifying how distance and transport mode shape the trade response to non-tariff barriers; and by showing that pandemic-era travel restrictions operated differently from more conventional economic shocks.

More broadly, the results highlight that policies aimed at restricting the movement of people can have sizable and uneven consequences for goods trade, and that transportation mode can be an important variable in determining how trade flows are reshaped following shocks.

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Appendix: Supplementary Results

Table A1: Dropping severest travel restrictions

Panel A: Simple model

	(I)	(II)	(III)	(IV)
Travel Restrictions	-0.710***	-0.723***	-0.753***	-0.748***
	(0.161)	(0.177)	(0.173)	(0.193)
Travel Restrictions	0.0636***	0.0632***	0.0673***	0.0666***
× ln(Distance)	(0.0182)	(0.0209)	(0.0201)	(0.0224)
Sample	Full	Drop 4Q closed	TR <1	TR <0.75
Country-Pair FE	Yes	Yes	Yes	Yes
Origin-Time FE	Yes	Yes	Yes	Yes
Destination-Time FE	Yes	Yes	Yes	Yes
Border-Quarter FE	Yes	Yes	Yes	Yes
Observations	450,467	386,947	437,572	427,572

Standard errors clustered at the country pair level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B: with transport mode

	(I)	(II)	(III)	(IV)
Travel Restrictions	-1.033***	-1.078***	-1.098***	-1.103***
× Air/Road/Other Intensity	(0.222)	(0.235)	(0.232)	(0.260)
Travel Restrictions × ln(Distance)	0.0980***	0.0992***	0.103***	0.103***
× Air/Road/Other Intensity	(0.0251)	(0.0279)	(0.0270)	(0.0300)
Sample	Full	Drop 4Q closed	TR <1	TR <0.75
Country-Pair FE	Yes	Yes	Yes	Yes
Origin-Time FE	Yes	Yes	Yes	Yes
Destination-Time FE	Yes	Yes	Yes	Yes
Border-Quarter FE	Yes	Yes	Yes	Yes
Observations	442,157	379,308	429,481	419,654

Standard errors clustered at the country pair level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Other geographic variables

Panel A: Simple model

	(I)	(II)	(III)	(IV)
Travel Restrictions	-0.710***	-0.817***	-0.734***	-0.759***
	(0.161)	(0.217)	(0.183)	(0.167)
Travel Restrictions × ln(Distance)	0.0636***	0.0756***	0.0661***	0.0691***
	(0.0182)	(0.0243)	(0.0203)	(0.0193)
Travel Restrictions × Contiguity		0.0530		
		(0.315)		
Travel Restrictions × ln(Dist.) × Contiguity		0.00130		
		(0.0442)		
Travel Restrictions × Landlocked			0.111	
			(0.392)	
Travel Restrictions × ln(Dist.) × Landlocked			-0.00341	
			(0.0540)	
Travel Restrictions × Island				0.569
				(0.622)
Travel Restrictions × ln(Dist.) × Island				-0.0646
				(0.0703)
Sample Period	2016-2024	2016-2024	2016-2024	2016-2024
Country-Pair FE	Yes	Yes	Yes	Yes
Origin-Time FE	Yes	Yes	Yes	Yes
Destination-Time FE	Yes	Yes	Yes	Yes
Border-Quarter FE	Yes	Yes	Yes	Yes
Observations	450,467	450,467	450,467	450,467

Standard errors clustered at the country pair level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B: with transport mode

	(I)	(II)	(III)	(IV)
Travel Restrictions	-1.033***	-1.043***	-1.118***	-1.134***
× Air/Road/Other Intensity	(0.222)	(0.285)	(0.259)	(0.227)
Travel Restrictions × ln(Dist.)	0.0980***	0.0992***	0.106***	0.108***
× Air/Road/Other Intensity	(0.0251)	(0.0320)	(0.0287)	(0.0262)
Travel Restrictions × Contiguity		0.0428		
× Air/Road/Other Intensity		(0.438)		
Restr. × ln(Dist.) × Contig.		-0.00591		
× Air/Road/Other Intensity		(0.0634)		
Travel Restrictions × Landlocked			0.0215	
× Air/Road/Other Intensity			(0.458)	
Restr. × ln(Dist.) × Landl.			0.0371	
× Air/Road/Other Intensity			(0.0623)	
Travel Restrictions × Island				1.269
× Air/Road/Other Intensity				(0.809)
Restr. × ln(Dist.) × Island				-0.139
× Air/Road/Other Intensity				(0.0935)
Sample Period	2016-2024	2016-2024	2016-2024	2016-2024
Country-Pair FE	Yes	Yes	Yes	Yes
Origin-Time FE	Yes	Yes	Yes	Yes
Destination-Time FE	Yes	Yes	Yes	Yes
Border-Quarter FE	Yes	Yes	Yes	Yes
Observations	442,157	442,157	442,157	442,157

Standard errors clustered at the country pair level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Lags of Travel restrictions

Panel A: Simple model

	(I)	(II)	(III)
Travel Restrictions	-0.710***		
	(0.161)		
Travel Restrictions × ln(Distance)	0.0636***		
	(0.0182)		
L1. Travel Restrictions		-0.436***	
		(0.149)	
L1. Travel Restrictions × ln(Distance)		0.0393**	
		(0.0167)	
L2. Travel Restrictions			-0.168
			(0.142)
L2. Travel Restrictions × ln(Distance)			0.0165
			(0.0157)
Sample Period	2016-2024	2016-2024	2016-2024
Country-Pair FE	Yes	Yes	Yes
Origin-Time FE	Yes	Yes	Yes
Destination-Time FE	Yes	Yes	Yes
Border-Quarter FE	Yes	Yes	Yes
Observations	450,467	450,467	450,467

Standard errors clustered at the country pair level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B: With Transport Mode

	(I)	(II)	(III)
Travel Restrictions			
$\times$ Air/Road/Other Intensity	-1.033***		
	(0.222)		
Travel Restrictions $\times$ ln(Distance)	0.0980***		
$\times$ Air/Road/Other Intensity	(0.0251)		
L1. Travel Restrictions		-0.671***	
$\times$ Air/Road/Other Intensity		(0.197)	
L1. Travel Restrictions $\times$ ln(Distance)		0.0654***	
$\times$ Air/Road/Other Intensity		(0.0222)	
L2. Travel Restrictions			-0.309*
$\times$ Air/Road/Other Intensity			(0.182)
L2. Travel Restrictions $\times$ ln(Distance)			0.0332
$\times$ Air/Road/Other Intensity			(0.0203)
Sample Period	2016-2024	2016-2024	2016-2024
Country-Pair FE	Yes	Yes	Yes
Origin-Time FE	Yes	Yes	Yes
Destination-Time FE	Yes	Yes	Yes
Border-Quarter FE	Yes	Yes	Yes
Observations	442,157	442,157	442,157

Standard errors clustered at the country pair level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Other covid variables

Panel A: Epidemiological factors

	(I)	(II)	(III)	(IV)
COVID-19 Deaths	-0.00115*	-0.00184		
	(0.000591)	(0.00251)		
COVID-19 Deaths		0.0000907		
$\times$ ln(Distance)		(0.000315)		
Excess Mortality			-0.0000848	0.000365
			(0.0000664)	(0.000238)
Excess Mortality				-0.0000593*
$\times$ ln(Distance)				(0.0000307)
Sample Period	2016-2024	2016-2024	2016-2024	2016-2024
Country-Pair FE	Yes	Yes	Yes	Yes
Origin-Time FE	Yes	Yes	Yes	Yes
Destination-Time FE	Yes	Yes	Yes	Yes
Border-Quarter FE	Yes	Yes	Yes	Yes
Observations	455,397	455,397	373,300	373,300

Standard errors clustered at the country pair level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Using index of overall Government Response

	(I)	(II)	(III)	(IV)
Travel Restrictions	-0.859***		-1.402***	
	(0.167)		(0.295)	
Travel Restrictions × ln(Distance)	0.0759***		0.0873**	
	(0.0188)		(0.0347)	
Overall Govt. Response		-0.840***	0.654**	
		(0.185)	(0.326)	
Overall Govt. Response × ln(Distance)		0.0781***	-0.0154	
		(0.0211)	(0.0393)	
Travel Restr. (Orthog.)				-0.404***
				(0.0534)
Travel Restr. (Orthog.) × ln(Distance)				0.0313***
				(0.00631)
Overall Govt. Response (Orthog.)				-0.0456
				(0.0702)
Overall Govt. Response (Orthog.) × ln(Distance)				0.0107
				(0.00835)
Sample Period	2016-2024	2016-2024	2016-2024	2016-2024
Country-Pair FE	Yes	Yes	Yes	Yes
Origin-Time FE	Yes	Yes	Yes	Yes
Destination-Time FE	Yes	Yes	Yes	Yes
Border-Quarter FE	Yes	Yes	Yes	Yes
Observations	352,236	352,236	352,236	352,236

Standard errors clustered at the country pair level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column I reports the baseline specification over the period where the index of all measures is available (up to 2022). Using the index of all measures (column II) yields very similar coefficient results, but a lower log-likelihood, suggesting it lower explanatory power. Including ait alongside the measure of travel restrictions (column III), it changes sign and is only weakly significant, consistent with the high degree of multicollinearity between the the two variables (0.777). To address this, I use orthogonalised measures of the two, implemented using the “orthog” package in stata. Column IV shows that the coefficients on orthogonalised overall response variable and its associated distance interaction are both insignificant.

Table A5: Role of product characteristics

Panel A: Simple model

	(I)	(II)	(III)
Travel Restrictions	-0.710***	-0.865*	-0.718
	(0.161)	(0.478)	(0.518)
Travel Restrictions × ln(Distance)	0.0636***	0.0778	0.0704
	(0.0182)	(0.0538)	(0.0587)
Travel Restrictions × Capital share		0.866	
		(1.560)	
Travel Restrictions × ln(Distance) × Capital share		-0.0796	
		(0.176)	
Travel Restrictions × Consumer share		0.100	
		(1.310)	
Travel Restrictions × ln(Distance) × Consumer share		-0.00971	
		(0.147)	
Travel Restrictions × Average trade elasticity			0.00108
			(0.0590)
Travel Restrictions × ln(Distance) × Average trade elasticity			0.000684
			(0.00678)
Sample Period	2016-2024	2016-2024	2016-2024
Country-Pair FE	Yes	Yes	Yes
Origin-Time FE	Yes	Yes	Yes
Destination-Time FE	Yes	Yes	Yes
Border-Quarter FE	Yes	Yes	Yes
Observations	450,467	414,601	394,617

Standard errors clustered at the country pair level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel B: With Transport Mode

	(I)	(II)	(III)
Travel Restrictions × Air/Road/Other Intensity	-1.033***	-1.071	-0.912
	(0.222)	(0.697)	(0.722)
Travel Restrictions × ln(Distance) × Air/Road/Other Intensity	0.0980***	0.0948	0.0895
	(0.0251)	(0.0782)	(0.0816)
Travel Restrictions × Capital share		1.135	
		(2.099)	
Travel Restrictions × ln(Distance) × Air/Road/Other Intensity × Capital share		-0.0955	
		(0.237)	
Travel Restrictions × Consumer share		-0.535	
		(1.806)	
Travel Restrictions × ln(Distance) × Air/Road/Other Intensity × Consumer share		0.0678	
		(0.205)	
Travel Restrictions × Air/Road/Other Intensity × Average trade elasticity			0.0187
			(0.0850)
Travel Restrictions × ln(Distance) × Air/Road/Other Intensity × Average trade elasticity			-0.00126
			(0.00978)
Sample Period	2016-2024	2016-2024	2016-2024
Country-Pair FE	Yes	Yes	Yes
Origin-Time FE	Yes	Yes	Yes
Destination-Time FE	Yes	Yes	Yes
Border-Quarter FE	Yes	Yes	Yes
Observations	442,157	407,433	387,825

Standard errors clustered at the country pair level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A1: Dynamic Effects: Decomposition

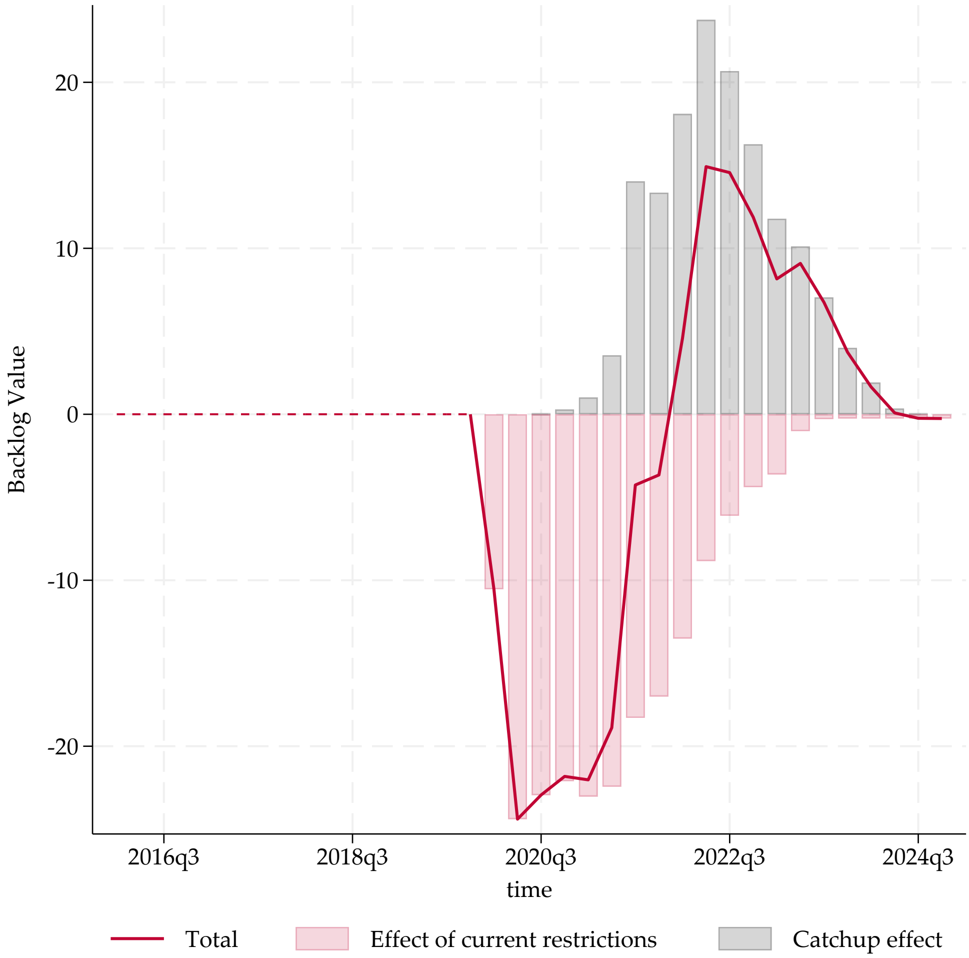
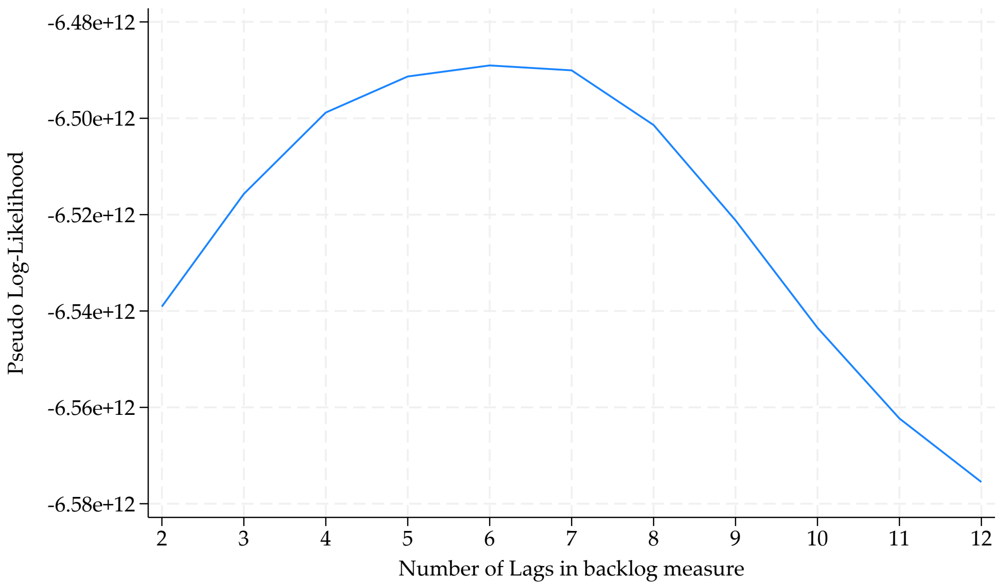


Figure A2: Testing for optimal lags of backlog B measure



Appendix: Extending dataset using AI

Prompt used in Chat GPT

The following prompt was used to identify changes in travel restrictions in 2023 and 2024, using the last published values of the index (i.e. those on 31st December 2022).

```
You are tasked with extending the Oxford COVID-19 Government
Response Tracker (OxCGRT) dataset for the C8 indicator
(\International travel controls") beyond its final official
date of 31 December 2022, covering all countries for the years
2023 and 2024.

You will be given:
1.  The OxCGRT dataset file ending on 2022-12-31.
2.  The C8 values for all countries on 2022-12-31, either
directly or derivable from the dataset.
```

Your objective is to estimate the evolution of C8 values during 2023{2024 by conducting deep internet research into COVID-related border restrictions and international travel controls.

===========================
BACKGROUND: OXCGRT C8 INDEX
===========================

The OxCGRT C8 \International travel controls" index takes these values: // 0 = No measures
1 = Screening arrivals
2 = Quarantine arrivals from some or all regions
3 = Ban arrivals from some regions
4 = Ban on all regions or total border closure

Assume that the value for each country on 2022-12-31 is the starting value entering 2023.

==================
RESEARCH OBJECTIVE
==================

For every country in the OxCGRT dataset:

1. Determine whether COVID-related international travel restrictions changed during 2023 or 2024.
2. Identify the effective date of each change.
3. Estimate the new C8 value after the change.
4. Produce a sparse-format dataset that records ONLY dates on which the C8 value changed.

You must search deeply and systematically for every country using:
- Government announcements
- Ministries of Health / Foreign Affairs
- Airport / immigration authorities
- Official tourism boards
- IATA / travel advisories
- Reuters, AP, BBC, Bloomberg, major newspapers

- Embassy advisories
- Trusted travel restriction databases

For every country, search for phrases such as:
- "COVID travel restrictions lifted"
- "COVID travel restrictions removed"
- "COVID travel restrictions abolished"
- "entry requirements removed"
- "PCR test no longer required"
- "vaccination proof no longer required"
- "health declaration no longer required"
- "border restrictions abolished"
- "travel rules relaxed"
- "international arrivals restrictions removed"
- "quarantine requirement ended"
- "state of emergency lifted"
- "border reopening"
- "COVID entry rules scrapped"

==============================
IMPORTANT INTERPRETATION RULES
===============================

1. ONLY COVID-related international travel controls count.

Ignore: - Security closures - War-related closures - Visa rules - Political sanctions - Migration restrictions unrelated to COVID

2. If a country removes all COVID entry requirements: Set C8 → 0.

3. If a country merely removes testing but still requires: - health forms, - vaccination proof, - screening, then estimate accordingly, usually C8=1.

4. If a country temporarily introduces restrictions targeted at travelers from a specific region, for example China-specific testing in early 2023: - Estimate an appropriate temporary C8 increase. - Record both: - the tightening date - the later relaxation/removal date

5. Use best judgment where exact OxCGRT coding is unclear.

6. Prefer official sources over media reports.

7. Use media reports only when official sources are unavailable.

8. If multiple changes occur during 2023{2024: Record all changes in chronological order.

=================
RESEARCH STRATEGY
=================

You MUST derive ALL changes independently through research.

DO NOT assume any pre-existing list of "known verified changes."

Instead:
1. Start from the baseline C8 value on 2022-12-31.
2. Research every country systematically and thoroughly.
3. For every country, search for:
- relaxation/removal of restrictions,
- tightening/reintroduction of restrictions,
- changes in testing requirements,
- changes in vaccination requirements,
- changes in quarantine requirements,
- changes in health declaration/screening requirements,
- regional or origin-specific restrictions.
4. Infer all changes from publicly available evidence.
5. Verify dates carefully.
6. Build the sparse dataset entirely from scratch.

=============
OUTPUT FORMAT
=============

Produce TWO CSV files:
1. 2023_2024_sparse.csv
2. 2023_2024_full.csv

================== SPARSE FILE FORMAT ==================

The sparse-format CSV must contain these columns EXACTLY:

Countryname iso3 date from to link1 link2 link3

Definitions:

Countryname: - Country name exactly as used in OxCGRT

iso3: - ISO-3 country code

date: - Date the new rule TOOK EFFECT - Format YYYY-MM-DD

If no change occurred: put: N/A

from: - Previous C8 value

If no change occurred: put: no change

to: - New C8 value

If no change occurred: put: 0 throughout 1 throughout 2 throughout 3 throughout etc.

link1/link2/link3: - Up to 3 supporting URLs - Prefer official sources - Leave blank if unavailable

==========================
SPARSE FORMAT REQUIREMENTS
==========================

IMPORTANT: - DO NOT output daily rows in the sparse file. - ONLY output rows when a country's C8 value changes. - Countries with NO changes should have ONE row only.

===================
DATA CLEANING RULES
===================

If a country was initially classified as: - ‘‘1 throughout" - ‘‘2 throughout" - ‘‘3 throughout"

BUT later research discovers evidence of a change:

1. DELETE the obsolete \throughout" row. 2. INSERT the dated change row(s).

The final sparse dataset must NOT contain contradictory rows for the same country.

========================
FULL DAILY PANEL DATASET

========================

After creating the sparse dataset:

1. Expand it into a FULL DAILY PANEL dataset covering every day from: 2023-01-01 to: 2024-12-31

2. Use forward-filling of sparse C8 changes.

3. For each country create ONE ROW PER DAY containing: - country - time - c8

4. Rules for expansion: - Start each country from its baseline C8 value on 2022-12-31. - Apply each sparse change from its effective date onward. - Forward-fill values until the next change occurs. - Countries with "throughout" rows should retain the same value for all days in 2023{2024.

5. Save the expanded daily panel as: 2023_2024_full.csv

==================
FINAL INSTRUCTIONS
==================

1. Search systematically and thoroughly across ALL countries in the OxCGRT dataset.

2. Verify changes carefully.

3. Remove obsolete "throughout" rows when changes are discovered.

4. Produce a single clean sparse-format CSV file.

5. Sort sparse output by: - Countryname - date

6. Ensure no duplicate contradictory entries exist.

7. Save sparse-format output as: 2023_2024_sparse.csv

8. Expand sparse data into a complete daily panel.

9. Ensure: - no missing dates - no overlapping contradictory values - internal consistency between sparse and full datasets

10. Preserve UTF-8 encoding and standard CSV formatting for both files.

Identified changes in travel restrictions after 2022

Table A6: Changes in Travel Restrictions, 2023–2024

Country	Date	From	To	Source 1	Source 2	Source 3
Azerbaijan	28-03-2023	3	0	link 1	link 2	link 3
Bolivia	31-07-2023	1	0	link 1	link 2	link 3
Brazil	05-06-2023	1	0	link 1	link 2	link 3
Canada	05-01-2023	0	1	link 1	link 2	link 3
Canada	17-03-2023	1	0	link 1	link 2	link 3
Chile	09-05-2023	1	0	link 1	link 2	link 3
China	08-01-2023	2	0	link 1	link 2	link 3
Colombia	05-04-2023	1	0	link 1	link 2	link 3
France	05-01-2023	0	1	link 1	link 2	link 3
France	16-02-2023	1	0	link 1	link 2	link 3
Ghana	20-05-2023	1	0	link 1	link 2	link 3
Indonesia	09-06-2023	1	0	link 1	link 2	link 3
Italy	01-03-2023	1	0	link 1	link 2	link 3
Japan	29-04-2023	1	0	link 1	link 2	link 3
Kenya	09-05-2023	1	0	link 1	link 2	link 3
Nicaragua	25-07-2023	1	0	link 1	link 2	link 3
Pakistan	15-06-2023	1	0	link 1	link 2	link 3
Philippines	14-08-2023	1	0	link 1	link 2	link 3
Senegal	08-08-2023	1	0	link 1	link 2	link 3
Singapore	13-02-2023	1	0	link 1	link 2	link 3
South Korea	05-01-2023	0	3	link 1	link 2	link 3
South Korea	11-02-2023	3	1	link 1	link 2	link 3
South Korea	10-03-2023	1	0	link 1	link 2	link 3
Spain	03-01-2023	0	1	link 1	link 2	link 3
Spain	16-02-2023	1	0	link 1	link 2	link 3
Uganda	07-03-2023	1	0	link 1	link 2	link 3
Ukraine	01-07-2023	1	0	link 1	link 2	link 3
United Kingdom	05-01-2023	0	1	link 1	link 2	link 3
United Kingdom	05-04-2023	1	0	link 1	link 2	link 3
United States	12-05-2023	1	0	link 1	link 2	link 3
Venezuela	04-05-2023	1	0	link 1	link 2	link 3