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Has COVID-19 led to rising trade costs and a shift towards intranational trade in the EU?

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A B S T R A C T

This paper attempts to investigate the development of trade costs in the EU during 2020 using only data on trade flows, trade cost proxies, and a constructed index of bilateral lockdown strictness. Gravity estimates point towards an abrupt but short-lived rise in trade costs during the second quarter of 2020. Evidence also suggests that lockdowns became increasingly effective at raising trade costs, the stricter they were across trading partners. However, when investigating internal relative to bilateral trade flows, it seems that trade costs rather increased gradually over the course of 2020.

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Introduction

On the 25th of March 2020, Director-General of the World Trade Organization (WTO), Roberto Azevêdo said, "Keeping trade open and investments flowing will be critical to keep shelves plentiful and prices affordable (WTO, 2020)". Indeed, international trade would prove to be critical, especially when it came to supplying countries with medical goods such as face masks, ventilators, and eventually, vaccines (Javorcik, 2020). However, on March 25th, nobody, not even the head of the WTO, had any idea how long the new global health crisis by the name of COVID-19 would last. Ultimately, global trade suffered an extraordinary collapse in 2020, even across the tightly integrated EU Customs Union (United Nations, 2021). One aspect that made COVID-19 unique from any other major crisis that was accompanied by a negative trade shock is the unprecedented level of government restrictions. Most EU countries abruptly went into lockdown in March of 2020. In April, maximum lockdown strictness was reached across the EU (Hale et al., 2020), the same month in which aggregate trade flows fell by 30% according to the UN Comtrade Database (2021).

This combination of unparalleled government restrictions along with a substantial decrease in bilateral trade flows makes COVID-19 an ideal basis for many trade-related research questions, particularly on the topic of trade costs. In theory, the record level of government restrictions seen across Europe could have substantially impacted trade costs, making trade more expensive and less attractive. To name one example, border delays in the early stages of the pandemic may well have led to rising road freight rates between EU countries, thereby contributing to the downward pressure on trade flows (Graupner, 2021).

There are several reasons why understanding the impact of COVID-19 on trade costs are of social relevance. First, it could be an indication of how quickly global trade may recover from a pandemic. This is because travel restrictions may stay in place for longer than social distancing measures due to differential levels of infections across countries and different speeds of vaccination (Bekkers and Koopman, 2020). Second, the impact of COVID-19 on trade costs could suggest to what extent highly trade dependent nations will suffer from larger economic shocks than comparatively closed economies. By definition, trade costs only have a direct effect on tradable goods, such that large exporters and importers may be particularly vulnerable to pandemic-induced restrictions (Sforza and Steininger, 2020). Finally, trade costs are linked to the productivity of countries. If COVID-19 has a significant positive effect on trade costs, the price of both imports and exports will rise, such that inputs to production may become more expensive. As such, more resources need to be allocated towards trade, that could otherwise be utilized for consumption or investment (Maliszewska et al., 2020).

From a perspective of scientific relevance, the topic at hand presents an ideal opportunity to shy away from the idea that trade costs should primarily be investigated over the long run together with globalization and technological progress (Anderson and Wincoop, 2004) (Hummels, 2007) (Jacks et al., 2008) (Novy, 2013). This paper further contributes to the existing work on gravity models by combining two methods of trade costs analysis that are not typically found in one paper. First, the theoretical gravity model devised by Anderson and Wincoop (2003) is used to estimate a relationship between trade flows and a series of trade costs proxies. Next, Novy's (2013) micro-founded trade cost measure is constructed using data on internal and bilateral trade flows. This second method is particularly interesting because it does not require observable trade cost proxies, thereby limiting this paper's exposure to biased results from a misspecified trade cost function.

The author acknowledges that unraveling the impact of COVID-19 on any trade related issue can be highly complex due to the many factors involved and, therefore, requires a well-structured approach before any credible insights can be made. As such, the paper is organized as follows. Foremost, a data-driven description of trade flow development over the course of COVID-19 will serve as an underlying motivation for this paper and mark the beginning of the literature review. Next, a general overview of what exactly defines trade costs will follow. Thereafter, the literature review will explore what actually happened across the EU as a result of COVID-19 and how these events could theoretically drive trade costs and intranational trade flows. Following the literature review, the methodology will lay the groundwork for the empirical analysis that follows.

Trade Flows and COVID-19 – A Brief Overview

There is no question that total trade between EU countries suffered an extraordinary collapse in 2020 (United Nations, 2021). Figure 1 shows the development of total exports between EU countries for each month of 2020. While the value of total monthly exports in January is nearly identical to the value in December, a steep decline is observed in April followed by a swift recovery over the remaining months of the year. In September and October, trade flows not only fully recovered from the negative shock but even exceed the level of trade recorded in January. Typically, one should refrain from making claims on cause and effect without the proper analysis; however, given the unprecedented nature of the COVID-19 pandemic, it is not unreasonable to say that this global phenomenon had some impact on the collapse of bilateral trade in the EU. Naturally, there are many channels through which COVID-19 and nation-wide lockdowns could affect trade flows. Besides a potential increase in trade costs, enforced factory closures and disrupted supply chains are thought to have had a substantial impact on trade across the EU (Javorcik, 2020).

Trade Costs – Defining Characteristics & General Determinants

In their seminal paper on trade costs, Anderson and Wincoop (2004) lay out the theoretical framework behind a method of trade costs analysis that no longer depends on the direct measurement of such costs, but rather their indirect inference. In doing so, they explain what defines trade costs in the first place. This paper will adopt their definition that trade costs "include all costs incurred in getting a good to a final user other than the marginal cost of producing the good itself" (Anderson and Wincoop, 2004, pg. 2). More specifically, this involves (i) transportation costs incurred both domestically and internationally from an exporter's point of view, (ii) costs incurred as a result of trade policy barriers, (iii) distribution costs incurred in the destination country, (iv) costs incurred from currency differences, (v) costs incurred from legal matters, (vi) costs incurred from enforcing contracts, and (vii) information costs. Importantly, trade costs are still incurred once the traded good crosses the border of the importing country and only cease to be incurred once the traded good reaches the final customer (Anderson and Wincoop, 2004).

The definition above makes it clear that trade costs have the potential to deviate considerably across countries and types of traded goods. For example, heavier goods may be more liable to high transportation costs than lighter goods and developing countries may suffer from higher trade policy barriers than advanced economies (Anderson and Wincoop, 2004). As such, understanding what contributes to high transportation costs or trade policy barriers may be crucial to understanding how and why trade costs differ between Germany and Tajikistan or between Germany and Italy. That being said, the ability to theoretically define trade costs between Germany and Tajikistan does not mean they can be measured just as easily. In fact, quite to the contrary. Obtaining reliable measurements of transportation costs, trade policy barriers, or currency barriers can be very challenging, if not impossible. While there is some literature dedicated to empirically analyzing the relationship between trade costs and bilateral trade flows through direct evidence (Anderson and Neary, 2003) (Anderson and Wincoop, 2004), most literature on this subject has adapted to the impracticalities of inaccurate data by indirectly controlling for trade costs through a series of proxies that *can* be measured.

The remaining paragraphs of this subsection are dedicated to introducing the most prominent trade cost determinants found in the literature and explaining how they are commonly proxied for.

Transportation Costs

Transportation costs are among the most well-known components of trade costs. Naturally, transporting a good from one country to another comes at a cost. In theory, this cost can include different factors such as the shipping costs invoiced by a logistics company or the cost of replacing damaged and missing goods. According to Hummels (2007), this element of trade costs is generally a substantial percentage, close to or even greater than tariff barriers. Samuelson (1954) was one of the first to model transport costs with his famous iceberg assumption, stating that a stable percentage of shipped goods are lost in transit. As such, suppliers must account for this loss by shipping the ordered amount of goods x multiplied by a factor τ, where $\tau > 1$. The costs incurred from producing the goods lost in transit are then noted as total transport costs (Bosker and Buringh, 2020). The iceberg specification of transport costs has since been widely used in the literature, where τ is treated exogenously and frequently given as a function of bilateral distance (Brancaccio et al., 2020).

Brancaccio et al. (2020) step away from the widespread assumption of exogenous transport costs by deriving equilibrium shipping prices from a spatial model on shipping patterns around the world. They show that endogenizing transport costs can have substantial implications on the way global shocks affect trade flows. This is because global shocks may change the bargaining power of major shipping companies or incentivize vessels to reallocate towards different shipping routes. As a result, there can be indirect affects running from transport costs to trade flows. Their results suggest that exogenous transport costs are a strong assumption that can limit the insights gained from models adopting it.

While it can be argued whether treating transport costs as exogenous is justified, it is relatively apparent that obtaining complete and reliable data on transport costs is extremely difficult, especially for a large sample of countries. For this reason, a sizeable portion of trade cost literature uses gravity models that proxy for transport costs with bilateral distance. The underlying motivation for this strategy is that bilateral distance is positively related to transport costs and thereby imperfectly controls for one element of trade costs without the need for any direct data on transport costs (Baldwin & Taglioni, 2006).

Trade Policy Barriers

Another prominent component of trade costs are trade policy barriers. Unsurprisingly, it is more costly to trade with a nation that levies tariffs or non-tariff barriers on its imports. The extent to which trade policy barriers contribute to trade costs can depend on the nature of the trading pair as well as the traded goods. Hoekman and Nicita (2011) show that tariff levels are negatively associated with GDP per capita whereas non-tariff barriers follow a positive relationship. Among other factors, this discrepancy in trade barriers between less developed and more advanced economies is driven by the nature of their imports. For example, many industrial economies are prime importers of agricultural products, a sector famous for being heavily protected by non-tariff measures in advanced economies. That said, tariffs are far more widespread than non-tariff measures such that trade with developing countries is often characterized by a higher overall trade restrictiveness compared to advanced economies (Hoekman and Nicita, 2011). Following this logic, trade policy barriers should contribute to a higher percentage of overall trade costs if one partner is a developing country. Indeed, Anderson and Wincoop (2004) estimate that policy barriers contribute to approximately 8% of total trade costs among industrial countries and approximately 20% for developing nations.

As with the other trade cost determinants, it can be challenging to obtain complete and reliable data on trade policy barriers for a large sample of trading pairs. It is therefore common practice to include regional trade agreement dummy variables when interested in the effect of barriers on trade flows (Baldwin & Taglioni, 2006). Conveniently, this paper focuses solely on EU countries which are not allowed to raise trade barriers on other member states (European Parliament, 2013). As such, the need to control for bilateral trade policy barriers falls away.

Other Border Barriers

Certainly, transport costs and policy barriers are not the only factors contributing to the cost of trade between two countries. The literature is renowned for citing common currencies, languages, and borders as key determinants of trade costs. Anderson and Wincoop (2004) estimate that currency barriers contribute to approximately 14% of tax equivalent trade costs among advanced economies. The contribution of language barriers is estimated at 7% while information costs contribute 6%. But how exactly can differences in language, currency, and information lead to higher trade costs?

Looking at currency differences, the main driver of trade costs are transaction costs. Before a good is shipped, a financial transaction typically takes place between the buyer and the seller. Such international transactions can be more costly if the buyer and seller use different currencies. As a result, the cost of trade rises (Frankel and Rose, 2002) (De Sousa, 2012). The mechanism with which language differences contribute to trade costs is less straightforward. Kónya (2006) argues that the cost of language differences is related to the cost of human capital. Typically, when two companies in different countries trade, at least one side needs to speak the language of the other. Therefore, at least one company needs to invest in the required human capital for trade to occur. Granted, this example may not entirely reflect reality when looking at trade between two advanced economies. If both parties already speak English, it may not necessarily be required to hire a foreign language speaker. Still, it can be argued that hiring English-speaking human capital to facilitate trade comes at a cost.

Information costs of trade can be related to language and cultural differences between trading partners according to Casella and Rauch (2003). They argue that cultural differences are frequently at the root of imperfect information about the other trading partner. For example, not speaking the local language can inhibit exporting firms from finding the cheapest distributor for their products in the importing country. As a result, exporters incur a higher trade cost due to cultural or language differences.

Literature interested in estimating the effect of language and currency differences on trade flows typically include dummy variables for common language and currency. Common border dummies are also frequently found in the empirical literature on trade costs. Common borders should intuitively reduce trade costs between two partners for a variety of reasons. For one, a shared border implies a certain proximity between two countries which should exert downward pressure on transport costs. Furthermore, proximity may be related to higher cultural integration and therefore lower information costs between trading partners. Felbermayr et al. (2018) show that having a common border in the unrestricted Schengen Area is associated with an increase in bilateral trade flows of 2.6%. Of course, the degree to which a shared border facilitates bilateral trade will depend on the openness of the mutual border.

Trade Costs and COVID-19 – What points to rising trade costs in the EU?

One of the central challenges of writing a paper on the impacts of COVID-19 in the year of 2021 is the lack of available data and existing literature on this topic. With limited evidence of how trade costs have developed in light of the global pandemic, a traditional literature review becomes difficult. Consequently, the following subsection aims to paint an overarching picture of how bilateral trade costs *could have* developed within the EU. This prediction will be based on a general analysis of what unfolded in Europe over the course of 2020 along with insights from established literature to gauge how COVID-19 may have affected trade costs.

Maliszewska et al. (2020) conduct a quantitative simulation of how COVID-19 could affect trade flows of developing and industrial economies using computable general equilibrium models. The authors simulate four major shocks to the global economy, one of which is an increase in global trade costs of 25%. They hypothesize that COVID-19 has exerted upward pressure on trade costs due to more border controls and rising transport costs. While it has been shown that border controls and high transport costs can inflate trade costs (Felbermayr et al., 2018) (Hummals and Schaur, 2013) (Hummels, 2007), Maliszewska et al. (2020) fail to cite any direct evidence that COVID-19 has in fact led to higher global trade costs. As such, let us investigate exactly what evidence points towards rising transport costs and border delays.

Transport Costs with Demand and Supply-side Effects

Switching from a global to a European perspective, there is mixed evidence of rising transport costs following the major lockdowns observed in March of 2020. One of the most representable measures of transport costs within the EU are road freight rates. This is down to the fact that 76.3% of inland freight was shipped by road in 2019 (Eurostat, 2021). Research center Transport Intelligence (TI) provides one of the most comprehensive quarterly reports on European freight rates called the European Road Freight Rate Benchmark. This benchmark is constructed using data on over 250 million freight prices recorded on the freight marketplace Upply. Over the course of 2020, the average European road freight rate decreased by 1.6% (Ti & Upply, 2021). That said, a simple decreasing average does not necessarily imply that the European road freight rate was solely negatively affected by COVID-19. In an effort to understand how COVID-19 may have impacted transport costs across the EU, it is worth looking into the different mechanisms through which the pandemic can drive road freight rates. Primarily, these are the tightness and timing of government restrictions as well as supply and demand-side effects. In addition, Brexit and a sharp decrease in diesel prices during the beginning of 2020 likely impacted freight rates as well.

In the early stages of the pandemic, demand shortages and over-capacity on freight routes likely exerted downward pressure on rates (TI & Upply, 2020) (TI & Upply, 2021). Many large manufacturers were forced to close their facilities as lockdowns swept across Europe, leading to fewer goods being shipped (Baldwin and Tomiura, 2020) (Maliszewska et al., 2020). This phenomenon was particularly prevalent among German automobile manufacturers in the early stages of the lockdown (ifo Institute, 2021). With fewer cars and other manufactured goods being exported from Germany to other European countries, freight rates out of Germany should theoretically fall, due to excess capacity on freight lanes. After all, Germany accounts for 10% of the world's manufactured exports (Baldwin and Tomiura, 2020).

Indeed, road freight rates between Duisburg and Madrid fell by 2.2% in the second quarter of 2020, a 9.6% decrease compared to the second quarter of 2019. Rates between Duisburg and Lille fell by 7.8% from April to May (TI & Upply, 2020). Of course, large decreases in demand for German exports likely added to these declining rates as many retailers were forced to close their stores across Europe. This combination of demand shortages and over-capacity likely contributed to the falling rates observed on other routes in the second quarter. Road freight rates from Milan to Warsaw as well as Lille to Antwerp fell by over 9% in May (TI & Upply, 2020).

In spite of falling rates on many routes in the second quarter of 2020, the average European road freight rate rose by 0.76% during this time (TI & Upply, 2021). This raises the question as to what could have caused a net increase in second quarter rates, despite low levels of consumer demand and over-capacity on freight lanes. According to Transport Intelligence and Upply (2021), delays at border crossings and Brexit exerted substantial upward pressure on freight rates during the second and third quarter.

Transport Costs & Border Delays

The German-Polish border was a prime example of how government restrictions led to considerable border delays. From March 13th to April 30th, the polish government required all drivers to undergo mandatory temperature checks when crossing into Poland from Germany, Slovakia, Lithuania, or the Czech Republic (UNECE, 2020). With each driver needing to be checked, these measures resulted in long queues and delays of up to 20 hours for trucks entering from Germany (Graupner, 2020). While there is no empirical evidence of delays at the Polish border increasing road freight rates, Hummels and Schaur (2013) estimate that an additional day of travel is associated with a 0.6 to 2.1 percent increase in ad valorem trade costs. By this logic, a 20hr delay would increase total trade costs by 0.5 to 1.75 percent[1]. According to Transport Intelligence and Upply (2021), road freight rates between Duisburg and Warsaw rose by 2.4% in the second quarter of 2020. In addition to increasing the transit time of traded goods coming into Poland, the Polish government also introduced measures that likely increased the transit time of goods passing through the country on route to other destinations. This is because all truck drivers passing through Poland were denied entry between March 13th and May 30th, forcing many haulers to reroute and potentially incur higher fuel costs (UNECE, 2020).

Of course, there are many other countries that introduced border controls or similar travel-limiting restrictions such as quarantine requirements and total border closures. For the sake of brevity, this paper will not go into a detailed analysis of how each country's restrictions may have impacted transport costs, as was done with Poland. Figure 2 shows how the Oxford COVID-19 Government Response Tracker (OxCGRT) has mapped international travel restrictions across the EU.[2] This graph provides a general overview of how EU member states adapted their border policy within the typically unrestricted Schengen Area. From the 17th of March onwards, the average travel restriction stringency remained above 2.5 for the entirety of 2020. This meant that for 290 days of 2020, the average EU country fell between (2) quarantining arrivals from some or all regions and (3) banning arrivals from some regions. Looking at this previously unprecedented level of travel restrictions within the EU, the question arises as to how this may have impacted transport costs.

Felbermayr et al. (2018) provide evidence that unrestricted internal borders within the Schengen area have substantial trade-creating impacts. They estimate that a Schengen border between two countries increases bilateral trade in goods by 2.6 percent. According to the authors, a lack of border controls and the associated waiting time decreases bilateral trade costs and increases trade flows. Davis and Gift (2014) provide more conservative evidence that

[1] $\frac{20}{24} \times 0.6 = 0.5$ and $\frac{20}{24} \times 2.1 = 1.75$

[2] This measure of travel restrictiveness is based on the following scale. 0 = No restrictions, 1 = Screening Arrivals, 2 = Quarantine arrivals from some or all regions, 3 = Ban arrivals from some regions, 4 = Ban all arrivals or total border closure

Schengen borders are positively associated with bilateral trade flows, estimating that a Schengen border between two countries increases exports by 0.14 percent on average. Even if the real-life effects of unrestricted Schengen borders on trade are closer to the estimates of Davis and Gift (2014) than to those of Felbermayr et al. (2018), the travel restrictions introduced in the wake of COVID-19 would have substantially reduced bilateral trade within the EU via increased border costs. For context, Germany exported goods worth $74 billion to Poland in 2019. Assuming that the estimate of Schengen border effects by Davis and Gift (2014) holds and border controls were introduced for only one month, the total decrease in German exports to Poland would amount to approximately $9 million.[3] Assuming that the estimate of Schengen border effects by Felbermayr et al. (2018) holds, this decrease would amount to $160 million over the course of one month. Either way, a decrease in exports caused by travel restrictions in Schengen area would be an indicator of rising trade costs, as a result of COVID-19.

Trade Costs and COVID-19 – A Hypothesis

Before diving into any empirics, this paper aims to make a prediction as to how intra-EU trade costs developed during COVID-19. The question comes down to whether the initial downward pressure on transport costs, caused by negative supply and demand shocks, outweighs the following upward pressure caused by border delays and travel restrictions. Prior to answering this question, it is worth discussing a trend that could provide additional insight on the trade cost development in 2020.

In the first two quarters of 2020, the European diesel price fell by 27.7 percent, while the average European freight rate rose by 0.76 percent (European Commission, 2021) (TI & Upply, 2021). Typically, the diesel price accounts for 20 to 40 percent of road freight rates, such that their resulting correlation amounts to approximately 0.7 (TI & Upply, 2020). Since freight rates did not mirror the same negative trend as diesel prices, it is likely that other factors positively affected freight rates and thereby offset the negative effect of diesel prices. While upward pressure on freight rates from border delays and travel restrictions may not be the only

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[3] $\frac{\$73 billion}{12 months} = \$6.2\ billion$ -> $\$6.2\ billion * 0.0014 = \$8.6\ million$

factor compensating the negative effect of diesel prices, it is likely that they played a role. If this is the case, trade costs from border delays and travel restrictions may be higher than the freight rate data suggests.

Based on a review of road freight rates, international travel restrictions, and existing literature on trade costs, this paper predicts that trade costs in the EU have risen as a result of the COVID-19 pandemic. The main indicators of rising trade costs are (i) increasing road freight rates between the second and fourth quarter despite a large fall in diesel prices, and (ii) historically high levels of travel restrictions. While it is likely that low demand and supply exerted downward pressure on trade costs via freight rates in the early stages of the pandemic, a relatively swift recovery fueled by high demand for e-commerce and pharmaceuticals indicates that this trend was likely short-lived (TI & Upply, 2021).

Intranational Trade and COVID-19

The central aim of this section will be to explore the factors pointing towards a potential increase or decrease of *intra*national relative to international trade across the EU in light of COVID-19. At its core, internal goods trade is simply the exchange of a product for financial payment between a buyer and a seller within the same country (InforMEA, 2021). Theoretically, the case could be made that certain ramifications of the global pandemic may exert upward pressure on internal relative to international trade flows. For example, the disruption of global supply chains along with shipping and border delays may incentivize households and firms to shift their focus towards procuring goods and inputs locally. Whether this means substituting international for internal trade is, of course, open for debate.

Consumers and firms have one of two choices when it comes to buying goods. They can either buy from domestic or foreign producers, assuming the desired good is available at home and abroad. Over the past decades, globalization combined with steadily decreasing trade policy barriers has allowed firms to set up vast global value chains to keep overall costs at a minimum. As such, the question of buying local versus foreign inputs is often a matter of keeping costs and not necessarily shipping distances low. For many European and American companies, this reasoning points towards Chinese imports and supply chains that wrap around the globe. However, COVID-19 showed many firms that the most cost-efficient supply chain is perhaps no longer the best. As COVID-19 forced factories to close across the Hubei province of China, production came to a standstill in many high technology factories around the world. For example, pharmaceutical manufacturers in France, Germany, and Italy could no longer produce certain antibiotics given that approximately 40% of their antibiotic ingredients are imported from Hubei (Javorcik, 2020).

Chief economist at the European Bank for Reconstruction and Development, Beata Javorcik (2020), argues that it is worth rethinking global supply chains but not necessarily in favor of *intra*national trade. She is doubtful that multinationals will rethink value chains with the goal of localization in mind. Rather, the objective will be to avoid putting all eggs into one Chinese basket. Looking at European high-tech manufacturing, she points out that reshaping supply chains would most likely involve swapping high-tech Chinese imports for eastern European inputs. This is because many eastern European countries specialize in car parts and pharmaceuticals, the same product categories as major Chinese exports. So, even if Europe's manufacturing giants decide to scrap parts of their global value chains, it is unlikely that Chinese imports will be replaced with inputs produced domestically. The focus will simply shift to the next best alternative, which is not necessarily the home country itself.

Next to industrial intermediate goods, consumer demand is also responsible for a large proportion of imports across the EU. So, is it likely that consumer demand shifted towards internal trade? Once again, the evidence on this subject is scarce. However, trends in e-commerce may provide a few hints on this matter. In total, the share of EU GDP spent on e-commerce rose from 3.26% in 2019 to 3.62% in 2020, an increase of roughly 52 billion EUR (Lone et al., 2021). Remes et al. (2021) explain that a large part of the increasing demand for e-commerce during the pandemic was driven by high income households that engaged in so-called home nesting. As it became clear that COVID-19 would not vanish in a matter of months, wealthy consumers began to settle in, invest in their own homes, and spend parts the savings they had accumulated from not going on vacation or eating out. The question now becomes whether this increase originates primarily from inter or intranational trade. To answer this question, it is worth comparing the percentage of people making domestic versus cross-border online purchases. The percentage of people making domestic online purchases rose from 86% to 88% between 2019 and 2020. For comparison, the percentage of people making cross-border online purchases fell from 44% to 40% between 2019 and 2020 (Lone et al., 2021).[4] While these numbers do not say whether internal e-commerce increased relative to cross-border e-commerce, they do indicate that consumer engagement with domestic online retailers increased relative to their engagement with foreign online retailers.

In summary, it is difficult to rationalize whether intranational trade should have increased or decreased relative to international trade, as a result of COVID-19. The above-mentioned analysis explains that a shift towards intranational trade is unlikely amongst major industrial manufacturers in need of intermediary inputs (Javorcik, 2020). On the other hand, business to consumer e-commerce may have shifted towards domestic versus cross-border trade (Lone et al., 2021). In the end, only the data will tell. Luckily, it is relatively straightforward to construct intranational trade flows within each EU country. As such, this paper will compute the ratio of intra to international trade for every month of 2020 to see what actually happened.

Data

All data on bilateral trade flows is acquired from the UN Comtrade Database and only includes the unidirectional flow of exported goods between countries. These nominal exports are measured in U.S. dollars and are registered as soon as goods cross the exporting country's border (United Nations, 2019). All countries in the dataset belong to the EU Customs Union, legally restricting any tariff or non-tariff measures (European Parliament, 2013). In total, there are 27 countries in the dataset, forming 702 unidirectional bilateral pairs[5]. The proposed paper will perform estimates using monthly data for the year 2020. By this logic, there will be 8,424 observations[6].

[4] Note that these percentages do not refer to the share of domestic versus cross-border e-commerce but to the percentage of people that engaged in either of the two activities. Furthermore, people can order goods both internally and internationally.

[5] $27 \times 26 = 702$

[6] $702 \times 12 = 8424$

Along with trade flows, the dataset includes bilateral distance between trading partners. Bilateral distance is simply the distance between two country's capitals measured in kilometers. Additionally, the dataset includes three dummy variables. The first is equal to unity if a country pair shares a common international border. The second is equal to unity if a country pair has the same official language. The third is equal to unity if a country pair shares the Euro as a common currency. Data on bilateral distance, common language, and common border is retrieved from the CEPII database on gravity indicators.

This paper aims to control for lockdown strictness using a stringency index constructed by the Oxford COVID-19 Government Response Tracker (OxCGRT). This index derives a measure of lockdown stringency for each country based on a set of indicators that map pandemic-induced government interventions. In total, nine indicators are considered, resulting in a stringency index that increases in lockdown strictness and ranges from 0-100.[7] The OxCGRT calculates this index on a daily basis for each country in the dataset, allowing changes in lockdown strictness to be analyzed over time and across countries (Hale et al., 2020). To fit the dataset of this paper, the reported stringency index is transformed from daily to monthly data. This is done by taking a simple average of all daily indices reported over the course of a month. As such, all 27 EU countries will have an average stringency index for each month of 2020. Finally, the average monthly stringency index across each bilateral pair is constructed. This ensures that only one index variable goes into the regression analysis to avoid potential collinearity between importer and exporter stringency indices.

Data on intranational trade flows is constructed as the difference between total industrial production and total exports. This is common practice in gravity literature using intranational trade flows. Gross domestic product (GDP) is intentionally avoided since it includes services (Novy, 2010) (Shepherd, 2013) (Yotov et al., 2016). Data on monthly industrial production for each country is retrieved from the World Bank Global Economic Monitor. Total exports are retrieved from the UN Comtrade Database. After constructing intranational trade flows, the proposed panel dataset will include a total of ten variables.

[7] Standardized Indicators: (i) School closing, (ii) workplace closing, (iii) cancelation of public events, (iv) restrictions on gathering size, (v) closed public transport, (vi) stay at home requirements, (vii) restrictions on internal movement, (viii) restrictions on international travel, (ix) public information campaigns.

Table 1

List of all variables used in this paper

Variable	**Measured in**
Time Period	Monthly intervals
Exporter Country	-
Importer Country	-
Nominal Unidirectional Exports	U.S. Dollars
Nominal Intranational Trade	U.S. Dollars
Bilateral Distance	Kilometers
Common Border Indicator	-
Common Language Indicator	-
Euro Area Indicator	-
Average Monthly Bilateral Stringency Index	Scale of 0-100

Methodology

Controlling for and estimating the effects of Covid-19

Along with analyzing the development of trade costs over the course of 2020, this paper aims to investigate the extent to which this development can be attributed to COVID-19. Having established that human response to the virus has the potential to affect trade costs, it is important that these responses are controlled for adequately. Judging by scale, government restrictions are undoubtedly the human response most capable of impacting trade costs. The fixed effects estimation detailed in the next section will already capture the individual lockdown strictness of each exporter and importer in a given country pair. While this is useful from the perspective of mitigating bias, fixed effects prevent the paper from estimating a direct effect of lockdown strictness on trade costs. As such, a measure of bilateral lockdown strictness is added to the fixed effects regression. The underlying rational is that variables which differ bilaterally cannot be absorbed by fixed effects, allowing their coefficients to be estimated. The following section details the construction of this bilateral measure of lockdown strictness, which is based on the unilateral stringency index published by the Oxford COVID-19 Government Response Tracker (OxCGRT).

OxCGRT presents itself as an attractive measure of lockdown strictness for three main reasons. First, it allows for time-varying lockdown strictness within countries as well as differential levels of strictness between countries. Second, it encapsulates nine possible government measures in an effort to prevent the index from being overly sensitive to changes in one particular government response. Third, the index can account for nationwide as well as local government measures, giving the latter a lower weight to ensure they do not contribute to the same magnitude as nationwide measures (Hale et al., 2020). While these three traits contribute to a comprehensive control variable for government response to COVID-19, the OxCGRT stringency index does not come without disadvantages.

Perhaps the biggest shortcoming of the stringency index revolves around the fact that its value will heavily depend on the underlying assumptions of what factors should go into the measure in the first place. The OxCGRT does not justify the inclusion of any of the nine chosen indicators. As such, it seems somewhat arbitrary as to why the closure of nonessential stores such as fashion retailers is not included, while the closure of public transport is included. If the closure of nonessential stores happens to be systematically related to bilateral trade flows, the stringency index could lead to biased coefficients when estimating the theoretical gravity model (Hale et al., 2020).

Finally, the OxCGRT stringency index for exporters and importers must be combined into a bilateral stringency index, given that fixed effects estimation already controls for country-specific lockdown strictness. This is done by taking the geometric mean of exporter and importer lockdown strictness. The geometric mean is chosen over the more common arithmetic mean to avoid perfect collinearity with the fixed effects when estimating regression coefficients. More specifically, using a bilateral average created with the arithmetic mean would be the same as including both exporter and importer lockdown strictness in the same regression.[8] However, the geometric mean is a multiplicative index, such that perfect collinearity is no longer an issue in the regression equation.[9]

Of course, using the geometric mean to construct average bilateral lockdown strictness comes with a few caveats. First, this measure will always be equal to zero if lockdown stringency of either the exporter or importer is zero. As such, all values of lockdown strictness among exporters and importers that take on a zero are transformed into a 1. Given that lockdown strictness ranges from 0-100, this small increase does not substantially alter the original data. Second, the geometric mean puts more weight on the smaller of the two numbers. This means that the constructed index will be a more conservative approximation of lockdown strictness than the arithmetic mean. In fact, the index could be somewhat misleading if importer and exporter strictness are very far apart. For example, if exporter lockdown strictness equals 1 and importer strictness equals 100, the geometric mean would be 10. However, lockdown strictness among EU countries developed very similarly over the course of 2020, such that very large differences in strictness do not occur.

Figure 3 illustrates how lockdown stringency in separate EU countries changed throughout 2020. The maximum difference between exporter and importer strictness amounts to 45.4 and is observed in May between Portugal and Lithuania. In this specific case, Portugal has a strictness of 71.3 while that of Lithuania amounts to 25.9, resulting in a geometric mean of 43. In general, it should be noted that one cannot isolate the effect of importer and exporter lockdown strictness on trade flows through this bilateral index. It is only possible to analyze the relationship between the geometric mean of bilateral lockdown strictness and bilateral trade flows.

So then, how should the coefficient of this geometric mean be interpreted? Simply put, it is the additional effect of both the exporter and importer being very strict. The geometric mean is the interaction effect between the square root of exporter and the square root of importer lockdown strictness. Therefore, the coefficient details the responsiveness of bilateral trade flows to the square root of lockdown strictness of the other trading partner. A negative

[8] $\beta_5\ Arithmetic\ Bilateral\ Avg._{ij} = \beta_5 \times \left[\frac{(INDEX_i + INDEX_j)}{2}\right] = \beta_5 \frac{INDEX_i}{2} + \beta_5 \frac{INDEX_j}{2}$

[9] $\beta_5\ Geometric\ Bilateral\ Avg._{ij} = \beta_5\ \times \sqrt[2]{INDEX_i \times INDEX_j} = \beta_5 \left(INDEX_i \times INDEX_j\right)^{1/2}$

coefficient on the interaction term would indicate that the square root of lockdown strictness exerts a higher negative effect on trade flows if your trading partner also has a high square root of lockdown strictness.

The Theoretical Gravity Model

The theoretical gravity model suits itself to the question at hand because it not only describes the relationship between bilateral trade costs and trade flows but also considers that changes in multilateral trade costs with all other partners can affect bilateral trade. It has been shown that the theoretical gravity specification devised by Anderson and Wincoop (2003) is more realistic and less prone to bias than the basic gravity model which omits multilateral trade resistance (Baldwin & Taglioni, 2006).

Theoretical Gravity Model

$$X_{ij,t} = \frac{Y_{i,t}Y_{j,t}}{Y_{W,t}}\left(\frac{\tau_{ij,t}}{P_{i,t}P_{j,t}}\right)^{1-\sigma} \qquad \text{(i)}$$

$X_{ij,t} = bilateral\ trade\ flows\ between\ i\ and\ j\ at\ time\ t$
$Y_{i,t} = GDP\ of\ country\ i\ at\ time\ t$
$Y_{j,t} = GDP\ of\ country\ j\ at\ time\ t$
$Y_{W,t} = World\ GDP\ at\ time\ t$
$\tau_{ij,t} = bilateral\ trade\ costs\ between\ i\ and\ j\ at\ time\ t$
$P_{i,t} = Multilateral\ resistance\ of\ country\ i\ at\ time\ t$
$P_{j,t} = Multilateral\ resistance\ of\ country\ j\ at\ time\ t$
$\sigma = elasticity\ of\ substitution\ between\ goods, approx. range\ \{5, 10\}$[10]

According to this model, the ratio of bilateral relative to average multilateral trade barriers determines the trade flow between two countries, after accounting for country size. More specifically, if bilateral trade costs rise relative to average multilateral trade costs, the two countries i and j will trade less with each other given that it is now relatively cheaper to trade with other countries. Conversely, if average multilateral trade costs rise relative to bilateral

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[10] According to Hummels (1999), the average elasticity of substitution between goods falls in the range of 5-10 across industries.

trade costs, bilateral trade between i and j becomes relatively cheaper (Anderson & Wincoop, 2003) (Shepherd, 2013) (Yotov et al., 2016). Having established the theoretical model behind our estimation strategy, it must be transformed in such a way that the relationships between the variables can be empirically quantified. If we wish to do so through ordinary lest squares (OLS) regression, the first step is to log-linearize the model and extended it by adding an error term (Yotov et al., 2016). The addition of an error term is motivated by the fact that all variables in the theoretical gravity model can be specified except for the bilateral trade costs between *i* and *j*. These bilateral trade costs are inherently uncertain because we cannot be sure what factors are included in $\tau_{ij,t}$ and what factors are not. This uncertainty is modelled by the error term $\varepsilon_{ij,t}$.

Log-Linearized Theoretical Gravity Model

$$\ln X_{ij,t} = \ln Y_{i,t} + \ln Y_{j,t} - \ln Y_{W,t} + (1-\sigma)\left[\ln \tau_{ij,t} - \ln P_{i,t} - \ln P_{j,t}\right] + \varepsilon_{ij,t} \qquad \text{(ii)}$$

Next, the trade cost term must be addressed. As mentioned, not all factors affecting bilateral frictions are observed. Following a popular approach in gravity literature, bilateral trade costs will be controlled for using a trade cost function of observable cost proxies (Yotov et al., 2016). The cost function is composed of bilateral distance, a common international border dummy, a common official language dummy, a common currency dummy, and the geometric average of lockdown stringency across both trading partners in a given month. The underlying logic is that each of the five components controls for a part of the bilateral trade costs. Of course, this is an imperfect measure of trade frictions since it potentially excludes a variety of factors that both affect trade flows and are correlated with the included trade cost proxies. Often, tariffs are amongst these omitted trade cost proxies because it can be difficult to collect reliable data on the exact tariff level between trading partners (Yotov et al., 2016).

Trade Cost Function

$$\ln \tau_{ij} = \beta_1 \ln DIST_{ij} + \beta_2 CBD_{ij} + \beta_3 CLG_{ij} + \beta_4 EUR_{ij} + \beta_5 INDEX_{ij,t} \qquad \text{(iii)}$$

This paper aims to circumvent bias from omitting tariffs by only focusing on countries in the EU. Simply put, the function used to specify bilateral trade costs in this paper cannot omit tariffs as a trade cost determinant, if there are no bilateral tariffs to begin with. All countries in the dataset belong to the EU Customs Union, thereby falling under the same regional trade agreement (RTA) which does not permit any tariff or non-tariff measures within its union (European Parliament, 2013). Still, this does not ensure that all determinants of trade costs are controlled for.

Importer and exporter multilateral resistance cannot be controlled for using observables. This is because the concept of average trade resistance with all other trading partners is derived from a theoretical model (Yotov et al, 2016). However, not controlling for it would lead to omitted variable bias when estimating the theoretical gravity model (Baldwin and Taglioni, 2006). It is possible control for multilateral resistances using fixed effects estimation. Dummy variables are used to specify both exporter ($\gamma_{i,t}$) and importer ($\chi_{j,t}$) fixed effects, thereby controlling for any unobservable time-invariant characteristics specific to exporters and importers. Since multilateral resistance is country-specific and does not vary between periods, fixed effects estimation will absorb these trade frictions along with exporter and importer GDP. Importantly, the trade cost proxies will not be absorbed by the fixed effects specification since they differ bilaterally i.e., between country pairs (Shepherd, 2013) (Yotov et al., 2016).

OLS Specification

OLS Equation Specification

$$\ln X_{ij,t} = \gamma_{i,t} + \chi_{j,t} + \sum_{T=Jan.2020}^{Dec.2020} \beta_1^T \ln DIST_{ij} + \sum_{T=Jan.2020}^{Dec.2020} \beta_2^T CBD_{ij} + \sum_{T=Jan.2020}^{Dec.2020} \beta_3^T CLG_{ij} + \sum_{T=Jan.2020}^{Dec.2020} \beta_4^T EUR_{ij} + \sum_{T=Jan.2020}^{Dec.2020} \beta_5^T INDEX_{ij,t} + \varepsilon_{ij,t} \quad \text{(iv)}$$

Standard errors will always be clustered by country pair, given that the error terms may be correlated within these pairs (Shepherd, 2013). The OLS equation includes time-varying effects of trade cost proxies on bilateral trade flows. It is therefore possible to estimate separate coefficients for distinct periods of time (Borchert & Yotov, 2016). For example, the equation can estimate the effect of bilateral distance on trade flows for each month from

January to December of 2020. The same can be done for the common border and common official language dummies. In total, this specification will yield 12 separate coefficients for each trade cost proxy. Consequently, the relationship between bilateral trade flows and trade costs can be traced over the course of 2020. Given that nation-wide shutdowns suddenly began in March of 2020, it will be interesting to see whether bilateral distance actually became more costly thereafter.

Heteroskedasticity and OLS

Unfortunately, log-linear gravity specifications can run into identification issues if the error term enters multiplicatively in the stochastic model of theoretical gravity. Santos Silva and Tenreyo (2006) point out that the theoretical gravity model will only hold on average, requiring that deviations from this average be modelled as well. This is achieved with a stochastic model using a multiplicative error. If a country pair deviates from the average, the error term is different from unity.

$$X_{ij,t} = \frac{Y_{i,t}Y_{j,t}}{Y_{W,t}}\left(\frac{\tau_{ij,t}}{P_{i,t}P_{j,t}}\right)^{1-\sigma}\varepsilon_{ij,t} \qquad where\ \varepsilon_{ij,t} = \frac{X_{ij,t}}{\mathbb{E}\left[X_{ij,t}|Y_{i,t},Y_{j,t},Y_{W,t},\tau_{ij,t},P_{i,t},P_{j,t}\right]}$$

$$\ln X_{ij,t} = \ln Y_{i,t} + \ln Y_{j,t} - \ln Y_{W,t} + (1-\sigma)\left[\ln \tau_{ij,t} - \ln P_{i,t} - \ln P_{j,t}\right] + \ln \varepsilon_{ij,t}$$

If the stochastic model with a multiplicative error term is log-linearized, the error term ends up being expressed in logarithms as well. Santos Silva and Tenreyo (2006) have shown that the identifying assumption of OLS $\mathbb{E}\left[\ln \varepsilon_{ij,t}|\ all\ covariates\right] = 0$ will not hold if the data exhibits heteroskedasticity and the error is in logarithms. When these two conditions are met, the expected error will depend on the explanatory variables, making OLS inconsistent. Typically, there is good reason to believe that trade data is in fact heteroskedastic (Santos Silva & Tenreyo, 2006) (Yotov, et al., 2016). From a theoretical perspective, heteroskedasticity makes sense because it would be unreasonable to assume that the variance for trading partners France and Germany is the same as the variance for Slovenia and Luxembourg. The former pair includes two of the largest economies in Europe that share a common border. The same can hardly be said about the latter pair. Therefore, it is intuitive to assume heteroskedasticity, where the error variance depends on the covariates (Santos Silva & Tenreyo, 2006).

Poisson Pseudo Maximum Likelihood Specification

The Poisson Pseudo Maximum Likelihood (PPML) estimator presents itself as an attractive alternative to OLS for a few reasons. Firstly, any observations with zero bilateral trade flows are no longer dropped from the estimation, preventing potential non-random selection of observations. Secondly, PPML has been shown to produce consistent estimates using heteroskedastic data (Santos Silva & Tenreyo, 2006). For this reason, PPML is the preferred estimation method of the gravity equation in this paper. Basically, PPML estimates a nonlinear least squares regression on the theoretical gravity equation (Shepherd, 2013). Similar to the OLS specifications, PPML estimation will be performed using fixed effects.

PPML Equation Specification

$$X_{ij,t} = exp\left[\gamma_{i,t} + \chi_{j,t} + \sum_{T=Jan.2020}^{Dec.2020} \beta_1^T \ln DIST_{ij} + \sum_{T=Jan.2020}^{Dec.2020} \beta_2^T CBD_{ij} + \sum_{T=Jan.2020}^{Dec.2020} \beta_3^T CLG_{ij} + \sum_{T=Jan.2020}^{Dec.2020} \beta_4^T EUR_{ij} + \sum_{T=Jan.2020}^{Dec.2020} \beta_5^T INDEX_{ij,t}\right] + \varepsilon_{ij,t} \quad \text{(v)}$$

Micro-Founded Measure of Trade Costs

Finally, the proposed paper will utilize the micro-founded measure of trade costs devised by Novy (2013) which does not rely on the specification of a trade cost function. This micro-founded trade cost measure increases when intranational trade increases relative to international bilateral trade. The underlying logic is that increased intranational relative to international trade indicates that the latter has become more costly, thereby prompting domestic firms to sell more of their products in their home country. This measure will be estimated for each country pair using monthly intervals such that it can be plotted over time. Ultimately, an average time series for the entire EU will be constructed and compared to the trade costs proxy coefficients estimated via PPML and OLS. As such, the paper will have two separate methods of tracking the development of trade costs over time.

Indirect Micro-Founded Measure of Trade Costs

$$\tau_{ij,t} = \{(X_{ii,t}X_{jj,t})/(X_{ij,t}X_{ji,t})\}^{1/(2(\sigma-1))} - 1 \quad \text{(vi)}$$

$X_{ii,t} = intranational\ trade\ flows\ in\ country\ i\ at\ time\ t$
$X_{jj,t} = intranational\ trade\ flows\ in\ country\ j\ at\ time\ t$
$X_{ij,t} = bilateral\ trade\ flows\ between\ i\ and\ j\ at\ time\ t$
$\tau_{ij,t} = bilateral\ trade\ costs\ between\ i\ and\ j\ at\ time\ t$
$\sigma = elasticity\ of\ substitution\ between\ goods, approx. range\ \{5, 10\}$

Unlike the conventional gravity model, this method theoretically constructs trade costs using trade flow data alone. Therefore, it does not require a trade cost function or any data on trade cost proxies. As a result, there is no risk of misspecifying the trade cost function and biasing results by omitting trade cost determinants. Novy's trade cost measure indirectly accounts for a wide range of trade cost determinants, including those commonly found in the trade cost function, without having to identify them directly. In addition to avoiding misspecification, this method has the advantage of better capturing the effect of time-varying trade cost determinants. This is because Novy's trade cost measure does not solely rely on time-invariant trade cost proxies such as common border indicators or bilateral distance that are fixed by definition. As such, changes in trade costs identified by this method can stem from time-invariant as well as time-varying determinants. Given that many factors affecting trade costs may have changed with the onslaught of the global pandemic, this indirect micro-founded measure of trade costs is well-suited to the question at hand.

Importantly, Novy's trade cost measure should be interpreted as the "geometric average of the relative bilateral trade barriers in both directions" (Novy, 2013, pg.105). This is because the resulting expression for relative trade costs is the geometric mean of all intranational trade flows within country *i* and *j* divided by the geometric mean of all international trade flows between *i* and *j*. Novy (2013) takes the geometric mean to account for the possibility of asymmetric bilateral trade costs ($\tau_{ij,t} \neq \tau_{ji,t}$) as well as distinctive domestic trade costs ($\tau_{ii,t} \neq \tau_{jj,t}$). Not imposing trade cost symmetry is another advantage of Novy's cost measure compared to the theoretical gravity model of Anderson and Wincoop (2003). The latter refrains from acknowledging the probable scenario that shipping costs from *i* to *j* may differ to those incurred from *j* to *i.* Finally, it should be noted that Novy's trade costs measure is expressed as the tariff equivalent by subtracting one from the right-hand-side.

Of course, this indirect trade cost measure comes with a few caveats. Primarily, its estimated value will heavily depend on the elasticity of substitution between different goods, σ. Anderson and Wincoop (2004) review the literature dedicated to empirically estimating σ and conclude that 5-10 is a plausible scope for the elasticity of substitution between goods. Novy (2013) sets σ equal to the middle of this plausible range found by Anderson and Wincoop (2004), such that $\sigma = 8$. This paper will make the same assumption. That being said, this paper is primarily interested in any changes in the trade cost measure, not the exact magnitude at a given time. Therefore, the value of σ is not of the utmost importance, as long as it falls within the plausible range and remains constant. Still, any changes in the indirect trade cost measure observed when $\sigma = 8$ will be compared to the changes observed when $\sigma = 5$ and $\sigma = 10$. This robustness check also follows from Novy (2013).

Whether σ remains constant is a different question altogether. On the grounds that Broda and Weinstein (2006) only found σ to decrease by 0.5 between the two periods of 1972-1988 and 1990-2001, Novy (2013) assumes constant elasticity of substitution (CES). It can be argued that the assumption of CES is reasonable for this paper as well, given that the timeframe in question only amounts to 12 months. Of course, adopting a popular assumption in gravity literature does not eliminate the possibility that the model fails to account for changes in the elasticity of substitution. For example, if the average elasticity of substitution decreased over the course of 2020 but the parameter in our model remains constant, a positive change in trade costs would be underreported, while a negative change would be overreported. This is because σ enters $\tau_{ij,t}$ negatively (Novy, 2013). Theoretically, σ could have decreased over the course of 2020 if many firms were forced to exit the market from pandemic-related complications. In such a case, the trade cost measure would fail to capture the true change in trade costs. Therefore, the inability to test whether CES holds in the year of 2020 within the EU is an obvious threat to the accuracy of Novy's indirect trade cost measure.

The final caveat concerning Novy's trade cost measure relates to what the literature calls "home bias". More specifically, this refers to a preference for domestic over foreign goods for reasons other than trade barriers. In the case of such preferences, $\tau_{ij,t}$ will suffer from upward bias given that intranational relative to international trade rises from consumers buying domestic goods over foreign imports out of personal preference rather than higher bilateral trade costs. As such, a high indirect trade cost measure between two countries may be interpreted as high trade costs when, in fact, this is only part of the story. However, with the primary focus of this paper set on investigating changes in trade costs, home bias is less of an issue, provided it remains constant over time (Novy, 2013). As with the CES assumption, there is no credible way of testing whether home biased preferences remained constant over 2020. Theoretically, it is plausible that some consumers began substituting foreign imports with domestic goods purely out of support for struggling local businesses during the pandemic. Such a phenomenon would then incorrectly show up as an increase in the trade cost measure.

Results – Estimating the Theoretical Gravity Model

The results obtained from estimating the theoretical gravity model are presented in the following section. As discussed in the methodology, this paper utilizes standard OLS regression along with PPML estimates, the latter being the preferred empirical strategy. Santos Silva and Tenreyo (2006) show that OLS estimates of the theoretical gravity model can be inconsistent if the data is exhibits heteroskedasticity. A Breusch-Pagan test reveals that we can reject the null hypothesis of constant error variance at a 1% significance level for the data in question, suggesting that heteroskedasticity may be a major concern (Breusch and Pagan, 1979). Additionally, plotting the OLS residuals versus the fitted values of the natural logarithm of trade flows shows that the distribution of residuals is substantially larger for lower values of trade flows. See figure 10. For these reasons, only PPML estimates will be interpreted in the results section below. Nevertheless, the OLS coefficients for all gravity estimates can be found in the appendix.

The empirical strategy involves estimating separate coefficients for each month of 2020, such that the effect of trade cost proxies on bilateral trade flows can be tracked over time.

Signs that bilateral trade has become more costly are (i) an increasing negative effect of bilateral distance on trade flows (ii) an increasing negative effect of bilateral lockdown strictness on trade flows, (iii) a decreasing positive effect of common borders on trade flows, (iv) a decreasing positive effect of common languages on trade flows, and (v) a decreasing positive effect of currency unions on trade flows.

Before moving on, it should be clarified why an *increasing* negative effect of bilateral lockdown strictness on trade flows is considered an indication of increasing trade costs. Here, the underlying rationale is that an additional point of lockdown strictness becomes more costly to bilateral trade as the stringency index rises. For example, an increase in lockdown strictness from 10 to 20 will not impact trade flows in the same way as an increase from 60 to 70. This is because trade costs are only slightly affected at very low levels of strictness such as advising people to stay home or introducing a mask mandate. Trade costs will largely start to rise as the government intervenes on a larger scale, such as through travel restrictions. Therefore, a one-point increase in lockdown stringency is less costly to trade at lower levels of strictness. If the government has already introduced border controls and subsequently introduces restrictions on internal movement, this additional increase in strictness will be far more costly to trade flows. Following this logic, an increasing negative coefficient of bilateral lockdown strictness on trade flows is a sign that restrictions have reached a high enough threshold that trade costs are beginning to be increasingly affected.

Coefficients will be interpreted in the following manner. Out of the twelve monthly coefficients for each trade cost proxy, the significant estimates will be examined for any visible trends throughout 2020. An F-test will then be used to check whether coefficient variation between months is significantly different from zero. Monthly changes will only be interpreted if it is possible to reject the null hypothesis that the shifting coefficients are the same. Finally, when it comes to interpreting changes in the monthly coefficients of trade cost proxies, caution should be advised for two main reasons. First, it can be difficult to convincingly argue that coefficients have changed due to a change in trade costs. Second, it is even more difficult to argue that trade costs have changed due to COVID-19. As such, the possible drivers of the identified trend will be explored to gauge whether a change in trade costs is a plausible explanation. If so, the prospect that COVID-19 played a role in shifting trade costs will be evaluated.

Estimating the Gravity Equation – Poisson Pseudo Maximum Likelihood Specification

Before attempting to analyze the monthly development of trade costs over the course of 2020, it is worth looking at regression results for the year as a whole. Table 3 shows the relationship between bilateral trade flows and all five trade cost proxies using PPML estimation. Only bilateral distance, the common border indicator, and bilateral lockdown stringency exhibit significant coefficients. All three coefficients have the expected sign. On average, a 1% change in bilateral distance is associated with -0.55% change in trade flows. A common border is associated with an average increase in bilateral trade flows of 58% within a country pair. [11] Finally, a one-point increase in bilateral lockdown strictness is associated with a -4.1% change in bilateral trade flows.

Bilateral Distance and Trade Costs – Monthly Coefficients

All coefficients of bilateral distance are significant at a 1% level, as can be seen in table 4. Figure 4 illustrates the relationship between bilateral distance and trade flows for each month of 2020. The vertical axis denotes the percentage change in bilateral trade flows in response to a 1% change in bilateral distance. The negative relationship between distance and bilateral trade flows stays constant between January and March. Interestingly, the estimates do not suggest a rising cost of bilateral distance in the same month as lockdowns were first implemented, namely March of 2020. A rising cost of distance is only observed in the subsequent months of April and May. Over the entire year, distance is the costliest to trade in May.

The decrease in trade flows associated with a 1% increase in bilateral distance changes from -0.49% in March to -0.52% in May. An F-test of the coefficients for March, April, and May yields a test statistic of 83.32. Therefore, the null hypothesis that all three coefficients are the same can be rejected at a 1% significance level. This step is important because there are not

[11] $[e^{0.46} - 1] \times 100 = 58.4\%$

that many observations in a single month. As such, there could be a risk of losing statistical power. These results suggest that distance became more costly to bilateral trade flows in the first two months after which lockdowns were introduced.

Arguably, the -0.03% change in coefficients between March and May seems rather small. However, when there is a sizeable distance between trading partners, such a change in elasticity can have a considerable impact. For example, consider the trading partners Germany and Greece with a bilateral distance of 1,991 km. In March, the bilateral distance between Germany and Greece is estimated to have changed trade flows by -3.72%.[12] Looking at April and May, this figure changes to -3.87% and -3.95% respectively.[13] Hence, bilateral trade flows are estimated to have decreased by 0.15% in April and 0.08% in May. Given that the average monthly trade flow between Germany and Greece amounted to approximately 800 million USD in 2020, the total loss would amount to 1.84 million EUR between March and May.[14] While such a decrease in bilateral trade may seem comparatively small, it should be noted that 116 out of the 702 unidirectional pairs have a bilateral distance greater than that of Germany and Greece. As such, even this slight increase in the cost of bilateral distance should not be underestimated. Of course, trading partners with comparatively low bilateral distance will suffer lower absolute costs on bilateral trade flows.

Given that there is evidence of bilateral distance becoming more costly to trade flows, the question arises as to what this means for the development of trade costs across the EU in 2020. Firstly, it should be noted that bilateral distance is not a direct measurement of trade costs. Rather, distance between trading partners attempts to indirectly control for one component of trade costs, namely transport costs. Secondly, other factors besides trade costs can make bilateral distance more costly to trade flows. For example, restrictions imposed to limit the spread of COVID-19. If the negative relationship between bilateral distance and trade flows becomes stronger because government restrictions physically hinder companies from exporting goods to more distant countries, this does not automatically imply that trade costs

[12] $\ln 1991km \times (-0.49) = -3.72\%$ in March

[13] $\ln 1991km \times (-0.51) = -3.87\%$ in April $\quad$ $\ln 1991km \times (-0.52) = -3.95\%$ in May

[14] $(800million \times 0.0015) + (800million \times 0.0008) = 1.84\ million\ EUR$

have increased. This could happen if a very distant trading partner has a much higher infection rate than a comparatively closer partner, such that the domestic government puts more restrictions on travel between their home country and the more distant partner. However, if government restrictions make exporting more expensive by raising transport costs, this would be a sign that trade costs have in fact become larger. Unfortunately, it is difficult to credibly distinguish in what instances government restrictions physically hindered exports to more distant countries versus when they made exporting more expensive.

While it is likely that some restrictions such as border closures prevented firms from exporting to more distant countries, the EU quickly enforced legislation in support of free-flowing essential goods (European Commission, 2020). After all, it is in the EU's best interest to keep economic activity as high as possible. Therefore, it is more likely that government restrictions simply made exporting more expensive, rather than preventing it altogether. For this reason, it is plausible that the increased cost of bilateral distance observed between March and May was partly driven by government restrictions.

Finally, figure 4 reveals that average EU lockdown strictness and the effect of bilateral distance on trade follow an inverse relationship. As average lockdown strictness rose throughout March and April, the negative effect of distance on trade flows increased as well. Later in the year, this negative effect became weaker as average lockdown strictness declined.

Shared International Borders and Trade Costs – Monthly Coefficients

Bilateral distance is a useful trade costs proxy because it can partly capture the transport costs which arise between two trading nations. However, distance as a trade cost proxy may not be able to fully capture the drivers of trade costs between very close countries. Two country pairs separated by 500km may have very different levels of bilateral trade costs if one pair happens to share a border, while the other does not. As such, changes in the common border coefficient may unravel information about trade costs that bilateral distance cannot capture.

Estimating the gravity equation with OLS regression did not yield any significant coefficients for the common border indicator. The PPML estimates, on the other hand, are significant for each month of 2020. It should be noted that these coefficients must be transformed in the following manner, $[e^{coefficient} - 1] \times 100$. This is down to the PPML specification as presented in equation (v). After this transformation, the coefficient can be interpreted as the percentage increase in bilateral trade flows when a country pair shares a common border. Figure 5 shows how this percentage change in trade flows develops over 2020.

Similar to the PPML coefficients on bilateral distance, the common border coefficients decrease in April and May. Decreasing common border coefficients suggest that the positive effect of a shared border on trade flows has fallen. An F-test reveals that this shift in coefficients between March and May is significantly different from zero at a 1% level. The estimated negative change is substantial. In March, sharing a common border was associated with an average increase in trade flows of 64% in the EU. In May, the increase in trade flows associated with a shared border fell by 11.4% to 52.6%. Of course, the question arises as to whether this change is related to an increase in trade costs. If government restrictions made it more costly to transport goods across international borders by causing long queues and delays at border crossings, the decreasing coefficient mentioned above would point towards rising trade costs. Naturally, it is difficult to prove that this is actually the case. Still, the common border coefficients and average EU lockdown strictness seem to follow an inverse relationship when looking at figure 5, suggesting that stricter regulations may be accompanied by a lower positive effect of shared borders on trade flows.

Average Bilateral Lockdown Stringency and Trade Costs – Monthly Coefficients

The last of the three significant monthly coefficients is average bilateral lockdown strictness. This coefficient describes the relationship between the geometric average of importer and exporter lockdown strictness and bilateral trade flows. Table 4 summarizes the monthly coefficients of bilateral lockdown strictness. Notably, these coefficients must be transformed via $[e^{coefficient} - 1] \times 100$ to obtain the percentage change in trade flows when bilateral lockdown strictness increases by 1 point. Figure 6 illustrates how these transformed coefficients change over the course of 2020.

Only six months yield significant coefficients, namely March, April, May, September, November, and December. Once again, an F-test reveals that variation in these monthly coefficients is significantly different from zero at a 1% level. In the same month that lockdowns were first implemented, a one-point increase in bilateral lockdown strictness was associated with a 15% decrease in bilateral trade flows. In the following month of April, a one-point increase in bilateral lockdown strictness was associated with a 61% decrease in bilateral trade flows. In May, this percentage decrease in trade flows decreased in magnitude to 27%. Notably, average EU lockdown strictness reached its maximum in April, the same month in which the highest negative effect of bilateral strictness on trade flows was estimated. While we cannot credibly claim that a one-point increase in bilateral lockdown strictness is associated with a 61% decrease in bilateral trade flows[15], it is still interesting to see that the negative effect of additional strictness on trade flows rises as lockdown strictness rises. This evidence supports our hypothesis that once restrictions reach a high enough threshold, trade costs begin to be increasingly affected. Indeed, figure 7 shows that the coefficient of bilateral lockdown strictness follows an inverse relationship with average EU lockdown strictness. The significant coefficients are denoted in pink. Again, this suggests that the negative relationship between lockdown strictness and trade flows may become stronger as lockdown strictness rises across the EU.

In terms of absolute effects of bilateral lockdown strictness on trade flows, it is perhaps more realistic to look at the coefficient estimated across the entirety of 2020, rather than the monthly coefficients of bilateral lockdown strictness. The yearly coefficient for 2020 suggests that a one-point increase in bilateral lockdown strictness is associated with an average decrease in trade flows of 4.1%. Looking at Germany and France, this estimate is not totally unreasonable. Total trade flows between these two European superpowers fell by 6.1 billion USD in April of 2020. Utilizing the estimate that a one-point increase in bilateral lockdown strictness is associated with an average decrease in trade flows of 4.1%, trade flows should have fallen by 9.3 billion USD during April of 2020.[16] As such, our estimated decrease is off from

[15] The largest monthly decrease in average trade flows across the EU amounted to 53% and was observed in April.

[16]

$$4.1\%\ decline\ in\ trade\ flows\ in\ April\ = -364\ million\ USD$$
$$Change\ in\ bilateral\ lockdown\ strictness\ in\ April\ = +25.5\ points$$
$$Estimated\ fall\ in\ trade\ flows\ in\ April\ = -364 \times 25.5 = -9.28\ billion\ USD$$

reality by approximately 3.2 billion USD. While this difference is certainly a substantial amount of money, it is interesting to see that our estimation technique can be used to predict a figure that is roughly in the same ballpark as reality.

Results – The Micro-founded Measure of Trade Costs

The following section details how Novy's relative trade cost measure develops over the course of 2020 within the EU. Next to an empirical and graphical analysis of how relative trade costs relate to lockdown strictness, a series of regressions are run to gauge whether relative trade costs have an intuitive relationship with the other trade cost proxies. Novy's trade cost measure is presented for each country individually and as an EU-wide average. Due a lack of data on industrial production for Malta, Ireland, France, and Austria, intranational trade could not be computed for these four countries. As a result, the sample for relative trade cost analysis includes 23 countries, unlike the sample for traditional gravity analysis which includes all 27 countries. For each month, 253 bilateral pairs[17] are formed to calculate $\tau_{ij,t}$, culminating in 3036 bilateral pairs for the whole of 2020.

To get an idea of how $\tau_{ij,t}$ developed over the course of 2020, the average $\tau_{ij,t}$ for each country is computed across all trading partners. This country-specific average is calculated for each month and summarized in table 5. Figure 8 illustrates how the monthly trade cost measure performed when averaging across the entire sample. On average, Novy's micro-founded trade cost measure follows a large dip in February of 2020, before gradually increasing over the remaining months of the year. This indicates that the ratio of intranational to international trade saw a substantial decline in February of 2020, before starting to rise again as the year carried on. Consequently, interpreting Novy's micro-founded trade cost measure will attempt to make sense of (i) the sharp decline in relative trade costs in February and (ii) the gradual increase in relative trade costs that followed.

Before diving into these specifics, it is worth touching on the development of intranational trade in the EU in 2020. Afterall, internal trade is an essential component of

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[17] $(23 \times 22) \div 2 = 253$

Novy's measure. Figure 1 depicts the development of inter and intranational trade throughout 2020. While the data does not show a clear-cut increase in intranational trade flows, there are some signs of an upward trend. After a spike in February, intranational trade flows remained steady through March, declined in April, and followed a largely positive trend for the remaining year. This trend is very similar to that of bilateral trade, suggesting that internal trade also suffered from pandemic-related consequences. Still, intranational trade ended up being 625 billion USD higher in December of 2020 than in January. Of course, this graphical analysis is rather rudimentary and does not suffice to claim that lockdowns increased the level of internal goods trade throughout the year.

The Micro-founded Trade Cost Measure & Lockdown Strictness

As opposed to estimating the gravity equation, the relative trade cost measure proposed by Novy (2013) attempts to derive an actual measure of trade costs from trade data instead of estimating the relationship between a series of cost proxies with trade flows. Figure 8 shows the development of average relative trade costs and average lockdown stringency across the EU in 2020. In February, the average relative trade cost measure fell from 45.3% to 40.8%. Compared to the rest of 2020, this decrease stands out as the largest monthly change. It is difficult to argue that this change be traced back to pandemic-related complications and restrictions, given that Europe was largely unaffected by COVID-19 during this time (Hale et al., 2020). Indeed, figure 8 also shows that the average EU lockdown stringency in February only amounted to 6.6 out of the maximum 100 points. For this reason, it is highly likely that lockdown stringency did not play a part in this steep fall in relative trade costs.

After February of 2020, relative trade costs across the EU begin to paint a different picture. Most countries saw a steady increase in relative trade costs between March and December. All countries in the sample besides Sweden and Latvia finish 2020 with a higher relative trade cost than in February of the same year. See figure 9. From a purely graphical perspective, relative trade costs and lockdown stringency both follow upward trends after February. That said, the relative trade cost measure approaches its highest point towards the end of the year, while maximum lockdown strictness is already reached in April. So, if there happens to be an effect running from lockdown strictness to relative trade costs, it appears to have a time lag.

Switching to an empirical analysis, it is possible to regress all trade cost proxies on the relative trade cost measure for each individual month of 2020. The obtained coefficients of average bilateral lockdown strictness are positive and significant for the months of May to December. These results are found in table 6. In a nutshell, the regression results suggest that an increase in bilateral lockdown strictness is associated with an increase in intranational relative to international trade for a given country pair between May and December of 2020. According to Novy (2013) an increase in the ratio of intranational to international trade indicates that the latter has become more expensive, suggesting that bilateral trade costs have increased. While there is no credible way of verifying that this assumption holds with certainty for the dataset in question, the results partially support the hypothesis of rising trade costs in light of stricter lockdowns.

The largest coefficient of bilateral lockdown strictness on relative trade costs is observed in September and amounts to 0.013. Since the dependent variable is in the form of a natural logarithm, the exponentiated value of this coefficient must be taken as follows $(e^{0.013} - 1) \times 100\%$. Consequently, an increase in average bilateral lockdown stringency of 1 point is associated with a 1.3% increase in the relative trade cost measure $\tau_{ij,t}$. For the eight significant months, this effect falls in a range of 0.3% to 1.3%. At first glance, these coefficients may seem rather small; however, their effect quickly adds up once lockdown stringency rises by multiple points. Interestingly, the estimated coefficients are insignificant for the months that saw the largest spike in lockdown strictness, namely March and April.

The Micro-founded Trade Cost Measure – Credibility Checks

Novy's relative trade cost measure inherently depends on the trade data substituted into its formula. Given that intranational trade data is not freely available and had to be manually constructed for this analysis, it makes sense to question whether the theoretically constructed measure exhibits realistic characteristics and whether the results resemble the measure found in the literature. Compared to Novy (2013), the trade cost measure calculated in this paper tends to be considerably smaller in magnitude. For example, Novy (2013) reports an average tariff equivalent trade cost of 85% for Germany between 1970-2000. This paper reports an average tariff equivalent of 52% for Germany in 2020. For Finland, this difference is even larger, resulting in a delta of approximately 90% between Novy (2013) and this paper's calculation. That said, these differences do not automatically imply that the calculations of this paper are flawed.

Evidence that trade costs have fallen over time pose as a possible explanation for this difference in magnitude. Novy (2013) investigates the development of trade costs for 13 OECD countries between 1970 and 2000. He shows that the average tariff equivalent trade cost across all 13 countries fell by 50% over these 30 years. If one were to extrapolate this decreasing trend for all EU countries found in Novy's dataset until the year of 2020, the resulting trade cost measures would be very similar to that found by this paper. Table 7 compares the predicted trade cost measures for 2020 to the measures calculated in this paper. The similarity of these figures provides confidence that no major calculation mistakes occurred when computing the micro-founded trade cost measure in this paper.

In addition to checking whether the calculated measure resembles the results found in the literature, the underlying characteristics of the trade cost measure will be investigated. This can be done by regressing the trade cost proxies used in the traditional gravity analysis on the constructed relative trade cost measure (Novy, 2013). The aim of these regressions is to establish whether the relationship between trade cost proxies and the relative trade cost measure makes intuitive sense. For example, one would expect a positive relationship between bilateral distance and Novy's trade cost measure. On the other hand, common language and border indicators should be negatively related to trade costs, as should the common currency indicator (Novy, 2013). Furthermore, the evidence presented on border delays and rising freight rates in the literature review could suggest that the relationship between lockdown stringency and relative trade costs could be positive. If the estimated coefficients exhibit these expected signs, this could be another indication that the constructed measure has credibility. Unlike the more traditional gravity analysis found in the section prior, these regressions do not require importer and exporter fixed effects to control for multilateral resistances. This is because the multilateral resistance terms cancel out in the construction of equation (vi) (Novy, 2013).

The corresponding regression results are found in table 6. Regressions are run separately for each month and for the entire year of 2020. Columns 1-12 report monthly coefficients while column 13 shows a pooled regression for the entire year of 2020. The significant coefficients for bilateral distance, common currency, and lockdown stringency have the anticipated signs. This means that the ratio of intranational to international trade rises as (i) the distance between two countries increases and (ii) the average bilateral lockdown stringency between two countries increases. Alternatively, this ratio decreases if two countries share the Euro as a common currency. An increase (decrease) in the ratio of intranational to international trade indicates that bilateral trade may have become relatively more (less) expensive compared to trade within a country's borders.

The common border and common language indicators do not exhibit the anticipated relationship with Novy's trade cost measure. As such, sharing a common language or border is associated with higher intranational trade or lower bilateral trade, causing the trade cost measure to rise. Intuitively, one would expect both factors to be associated with lower bilateral trade costs. Naturally, the question arises as to whether these regression results limit the credibility of the constructed trade cost measure and any interpretations that stem from it. To answer this question, it is worth considering how the common border and common language indicators enter Novy's trade cost measure $\tau_{ij,t}$. According to Novy (2013), the equation which constructs $\tau_{ij,t}$ can be rewritten in terms of its separate trade cost functions $t_{ii,t}, t_{jj,t}, t_{ij,t}, t_{ji,t}$ instead of trade flows $X_{ii,t}, X_{jj,t}, X_{ji,t}, X_{ij,t}$. This is possible because trade flows are a function of the trade cost function.

$$\tau_{ij,t} = \{(X_{ii,t}X_{jj,t})/(X_{ij,t}X_{ji,t})\}^{1/(2(\sigma-1))} - 1 \qquad \text{(vi)}$$

$$\tau_{ij,t} = \{(t_{ij,t}t_{ji,t})/(t_{ii,t}t_{jj,t})\}^{1/2} - 1 \qquad \text{(vii)}$$

$$\ln t_{ii,t} = \beta_1 \ln DIST_{ii} + \beta_2 CBD_{ii} + \beta_3 CLG_{ii} + \beta_4 EUR_{ii} + \beta_5 INDEX_{ii,t} \qquad \text{(viii)}$$

$$\ln t_{jj,t} = \beta_1 \ln DIST_{jj} + \beta_2 CBD_{jj} + \beta_3 CLG_{jj} + \beta_4 EUR_{jj} + \beta_5 INDEX_{jj,t} \qquad \text{(ix)}$$

Each of the four trade cost functions that make up equation (vii) contain common border and common language dummies. However, for $t_{ii,t}$ and $t_{jj,t}$ these two dummies will always be equal to unity. This is down to the fact that $t_{ii,t}$ and $t_{jj,t}$ are intranational trade cost functions and a country always shares a common border with itself. After substituting the trade cost functions $t_{ii,t}, t_{jj,t}, t_{ij,t}, t_{ji,t}$ into equation (vii) and rearranging, we end up with an expression for $\tau_{ij,t}$ given by equation (x). This expression includes inverse common border and common language indicators as seen in equation (xi) and (xii). Since CBD_{ii} and CBD_{jj} are always equal to unity, CBD_{ij} and CBD_{ji} will cancel out whenever a country pair actually shares a common border. As a result, the calculated $\tau_{ij,t}$ for two countries will always be higher if this trading pair shares a common border compared to when it does not. The same goes for the common language indicator. The detailed calculations to derive equation (x) can be found in the appendix.

$$\tau_{ij,t} = \left(\frac{DIST_{ij}DIST_{ji}}{DIST_{ii}DIST_{jj}}\right)^{\beta_1} exp\{\beta_2(CBD_{ij} - CBD_{ii} + CBD_{ji} - CBD_{jj}) + \beta_3(CLG_{ij} - CLG_{ii} + CLG_{ji} - CLG_{jj}) + \beta_4(EUR_{ij} - EUR_{ii} + EUR_{ji} - EUR_{jj}) + \beta_5(INDEX_{ij} - INDEX_{ii} + INDEX_{ji} - INDEX_{jj})\} \qquad \text{(x)}$$

$Given\ that\ CBD_{ii}, CBD_{jj}, CLG_{ii}, CLG_{jj}\ are\ all\ equal\ to\ 1$

$$\beta_2[CBD_{ij} - CBD_{ii} + CBD_{ji} - CBD_{jj}] = \beta_2[CBD_{ij} - 1 + CBD_{ji} - 1] \qquad \text{(xi)}$$

$If\ CBD_{ij} = 1\ \&\ CBD_{ji} = 1, then\ \beta_2(0) = 0$

$If\ CBD_{ij} = 0\ \&\ CBD_{ji} = 0, then\ \beta_2(-2)$

$\beta_2(0) > \beta_2(-2)$

$$\beta_3[CLG_{ij} - CLG_{ii} + CLG_{ji} - CLG_{jj}] = \beta_3[CLG_{ij} - 1 + CLG_{ji} - 1] \qquad \text{(xii)}$$

$If\ CLG_{ij} = 1\ \&\ CLG_{ji} = 1, then\ \beta_3(0) = 0$

$If\ CLG_{ij} = 0 \ \& \ CLG_{ji} = 0, then\ \beta_3(-2)$

$\beta_3(0) > \beta_3(-2)$

For this reason, sharing a border or language is systematically related to a higher relative trade cost measure $\tau_{ij,t}$. Consequently, the positive coefficients of common border and language dummies can be explained by the construction of Novy's relative trade cost measure and do not undermine the credibility of the measure itself.

Discussion & Conclusion

The question this paper strives to answer is inherently challenging due to the unavailability of complete and reliable trade cost data. Nevertheless, it attempts to investigate the development of trade costs during COVID-19 by utilizing the most suitable data that is freely available, namely bilateral trade flows between all EU countries as published by the UN Comtrade Database. Together with trade flows, a series of trade cost proxies, and a constructed index on bilateral lockdown strictness, two empirical strategies examine trade costs without the need for any data on shipping rates or distribution costs. Of course, this analysis rests on the shoulders of several assumptions, without which this paper would not be possible.

The Trade Cost Function

Estimating the theoretical gravity model requires the specification of a trade cost function, $\tau_{ij,t}$. Exactly which functional form $\tau_{ij,t}$ should take on or which trade cost proxies should be included is entirely up to the researcher. Consequently, the obtained results will drastically depend on these very assumptions. (Bosker and Garretsen, 2010). For example, who is to say that the chosen trade cost function should be identical for each country pair? Bosker and Garretsen (2010) note that the cost of distance is not necessarily the same across all countries in a sample. Indeed, one could argue that distance is far less costly in a country with many highly developed highways compared to a country lacking such infrastructure. The same logic could also be applied to countries along major inland waterways. Looking at this aspect alone, there are clearly many possible configurations to model trade costs in the context of this paper.

Furthermore, why does bilateral distance carry the same penalty between Germany and France as it does between Latvia and Lithuania? Why do the observable cost proxies enter the trade cost function additively? Frankly, the answer to these and many other questions that should be posed when reading this paper hark back to the existing gravity literature. Papers by the likes of Anderson and Wincoop (2004) provide the empirical foundation for this and many other works that are cited in this paper. As such, their choice of trade cost function also impacted the presented results. Still, it is not certain that the proposed functional form of their trade cost function is also optimal in the context of COVID-19 and the EU.

Novy's Relative Trade Cost Measure

For these reasons, and because reinventing the trade cost function is outside the scope of this paper, Novy's (2013) relative trade cost measure is also used to investigate trade costs. His method offers an attractive alternative to the theoretical gravity model by Anderson and Wincoop (2004) because it does not require the author to specify a trade cost function. Consequently, the whole debate about functional form and which proxies to include falls away. That said, utilizing this relative trade costs measure also comes with a few caveats that are worth discussing.

Looking more closely at the construction of the measure itself, an increase in relative trade costs during a given month does not necessarily mean that trade costs solely started to rise then. Novy's measure simply compares aggregate trade flow data at a particular point in time. It is plausible that aggregate trade data is slow to react to changes in freight rates or lockdown strictness. Thereby, Novy's measure may also be slow to pick up on rising road freight rates or lockdown strictness. For example, when Poland introduced mandatory temperature checks at border crossings, this resulted in border delays and possibly higher road freight rates (Graupner, 2021). If carriers charge a higher price to transport a good from A to B, exports already in transit will not be affected. As such, the simple fact that trade flows are slow to react to shipping rates inhibits Novy's measure from accurately pinpointing a rise in relative trade costs. Along these lines, the increase in relative trade costs observed towards the end of 2020 could theoretically reflect freight rate increases observed earlier in the year.

Next to time delays, changes in the calculated measure may also be picking up on factors entirely unrelated to trade costs. After all, who is to say that an increase in intranational relative to international trade is caused by higher trade costs. When the German automotive industry was forced to stop production for four weeks between March and April of 2020, car exports plummeted as inventories were quickly depleted (PricewaterhouseCoopers GmbH, 2020). Similarly, major supply chain disruptions in China delayed production for many EU companies, causing exports to dip (de Vet et al., 2021). If such events decrease bilateral relative to internal trade, Novy's measure would falsely interpret this change as rising trade costs. These examples highlight how the pandemic has the potential to increase Novy's relative trade cost measure without necessarily increasing trade costs.

Concluding Remarks & Suggestions for further Research

In closing, this paper paints two pictures of how trade costs could have developed in the EU during COVID-19. On the one hand, gravity estimates point towards an abrupt but short-lived rise in trade costs during the second quarter of 2020. On the other hand, Novy's relative trade cost measure suggests that trade costs were slow to react but increased gradually throughout 2020.

According to gravity estimates, bilateral distance became more costly to trade flows while sharing a common border became less beneficial between March and May of 2020. In the same timeframe, average lockdown strictness across the entire EU increased drastically. In March, this index rose from 6.59 to 48.91 before reaching an all-time high of 79.48 in April. Of course, it cannot be proven that lockdown strictness is causally related to distance becoming more costly and common borders becoming less beneficial to trade; However, it is interesting to see that the trade cost proxy coefficients follow an inverse relationship with average lockdown strictness across the EU.

In an attempt to capture the impact of lockdown strictness despite our fixed effects specification, a geometric average of bilateral strictness was constructed. The results indicate that the negative effect on trade from both the exporter and the importer being very strict increases as lockdown strictness rises in the EU. An additional point of strictness became more costly to trade as strictness increased, suggesting that lockdowns become increasingly effective at raising trade costs, the stricter they were. Intuitively, it makes sense that trade costs are impacted more after a certain threshold strictness, given that looser lockdowns may not impact trade costs at all.

Computing Novy's (2013) relative trade cost measure for each country separately suggests that trade costs rose gradually throughout 2020, unlike the gravity estimates which only indicate rising costs in the second quarter. Since the relative trade cost measure is simply the ratio of internal to international trade and does not contain any stochastic components, it provides concrete evidence that intranational trade rose relative to bilateral trade. Whether this shift in trade flows, equivalent to a rise in trade costs, is directly linked to higher lockdown strictness cannot not be proven. Still, these results could imply that trade costs did not react as quickly to the global pandemic as the gravity estimates might suggest.

Certainly, there are a variety of directions in which further research could steer the analysis presented thus far. Looking at the theoretical gravity model, it could be useful to experiment with additional trade cost proxies or change the functional form of the trade cost function altogether. For instance, one could control for more observables that may affect bilateral trade flows and are potentially correlated with other trade cost proxies. Variables such as infrastructure or the number of inland waterways come to mind here. Stepping away from the methodology used in this paper, it would be interesting to approach the research question with real data on trade costs. For example, one could compare the above-mentioned results with insights gained from freight rates or distribution costs to see how well bilateral distance proxies for transportation costs.

Appendix 1 – Graphs & Figures

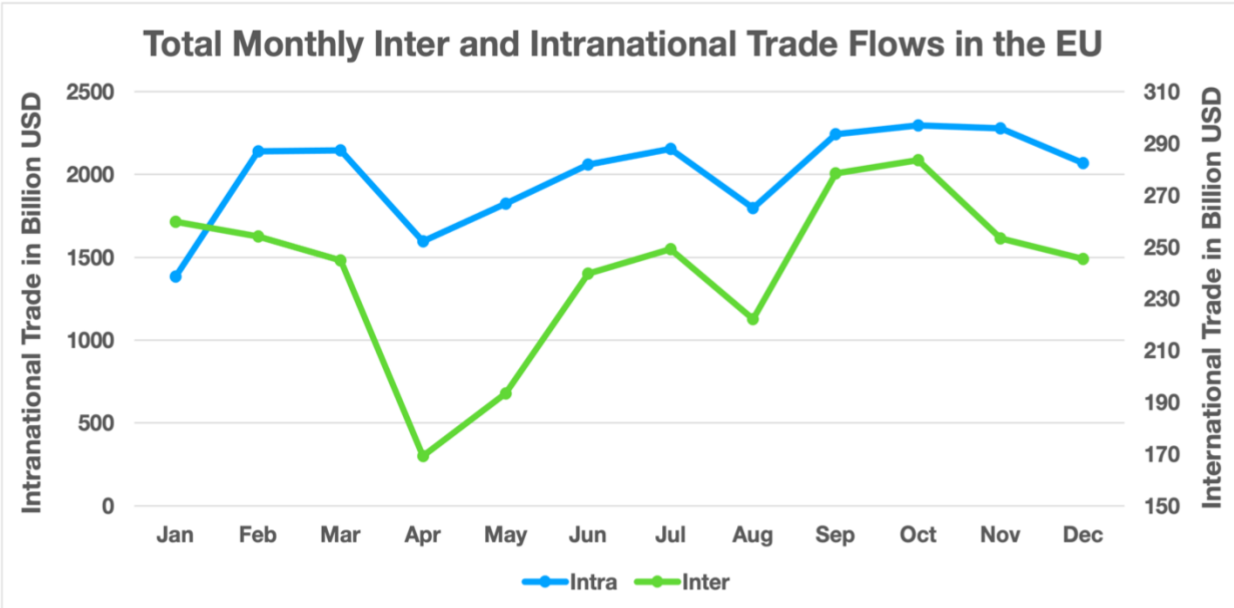

Figure 1: The development of intra and international trade flows across the EU. Each datapoint represents the sum of all intra or international trade in a specific month. The left Y-axis denotes the value of intranational trade in billion USD, while the right denotes international trade.

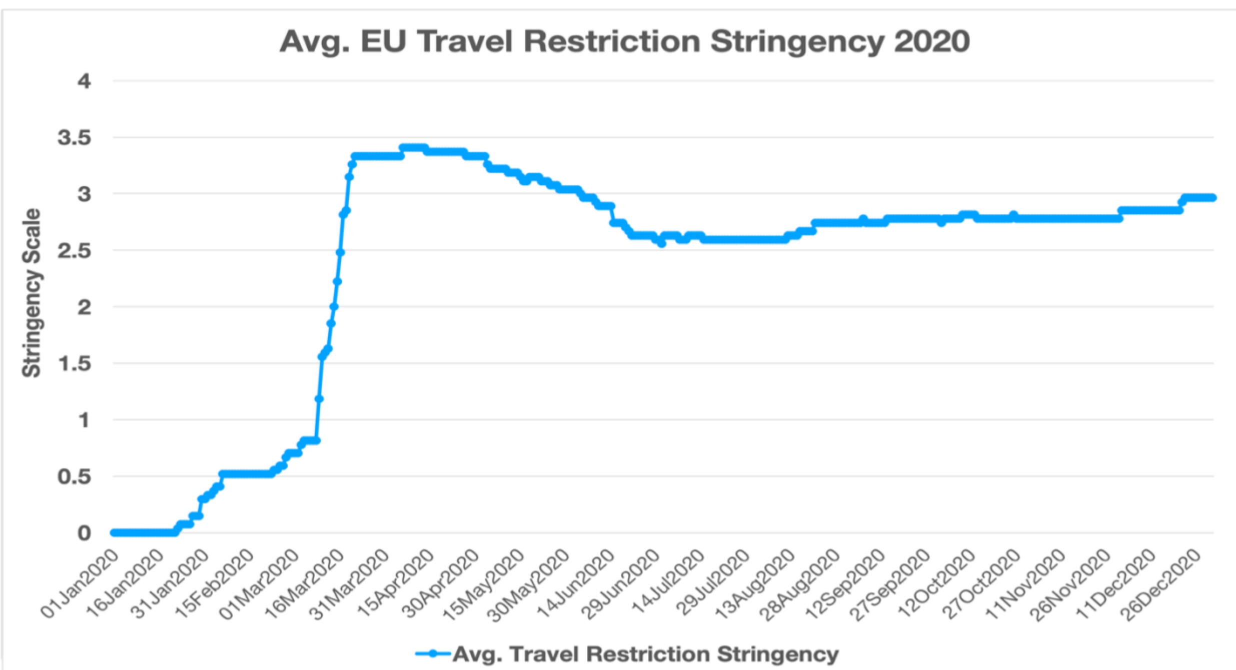

Figure 2: The development of the Oxford COVID-19 Government Response Tracker on international travel restrictions and average quarterly freight rates in the EU.

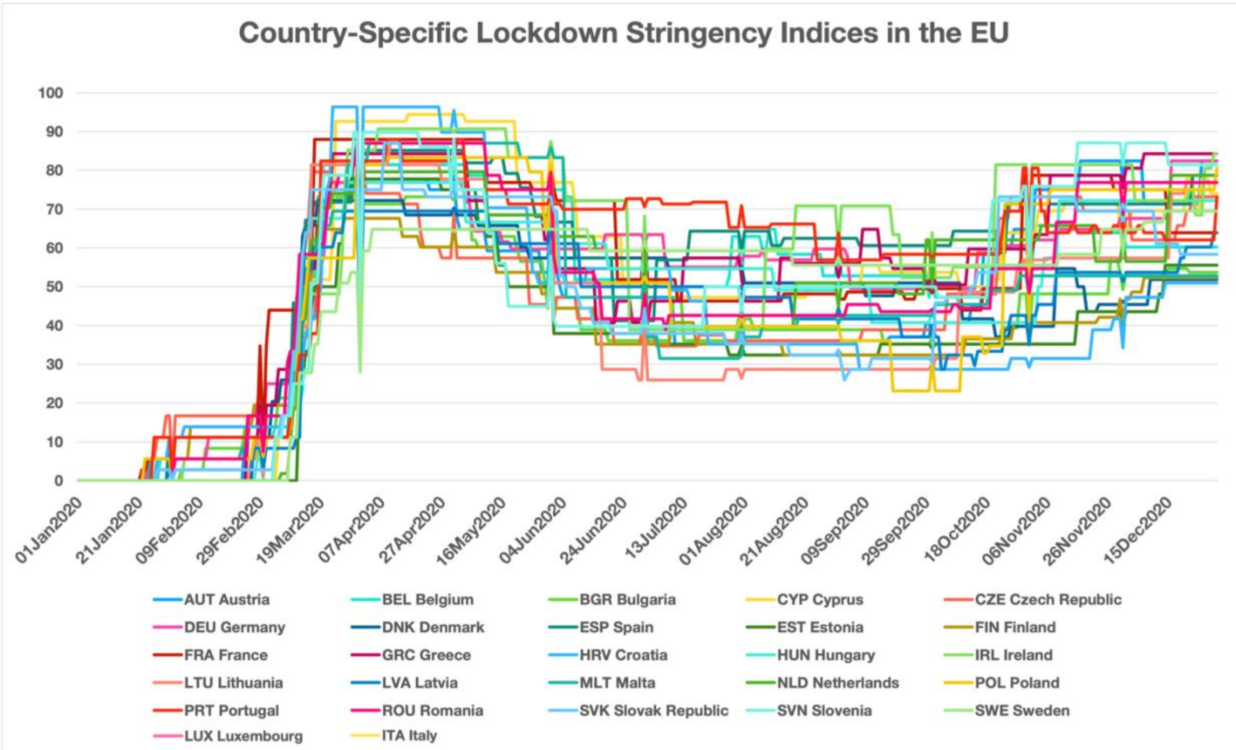

Figure 3: The development of country specific OxCGRT lockdown stringency indices in 2020.This index ranges from 0-100.

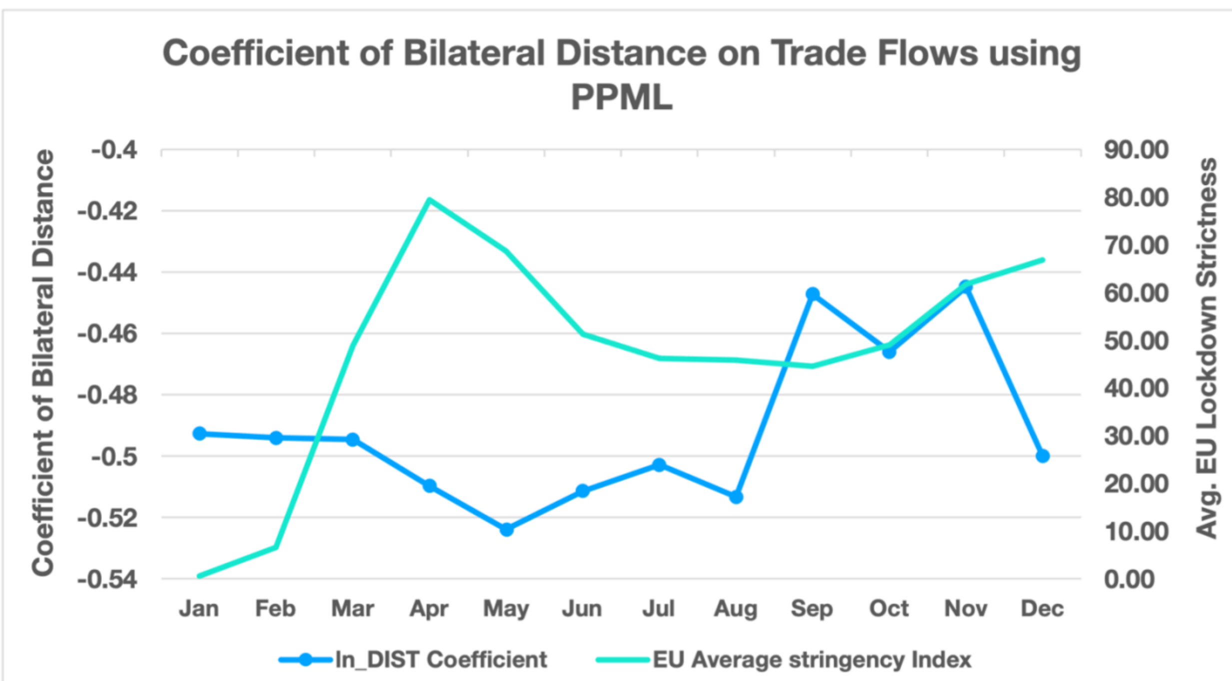

Figure 4: The coefficient of bilateral distance on trade flows and average EU lockdown strictness over the course of 2020 estimated using PPML regression and FE.

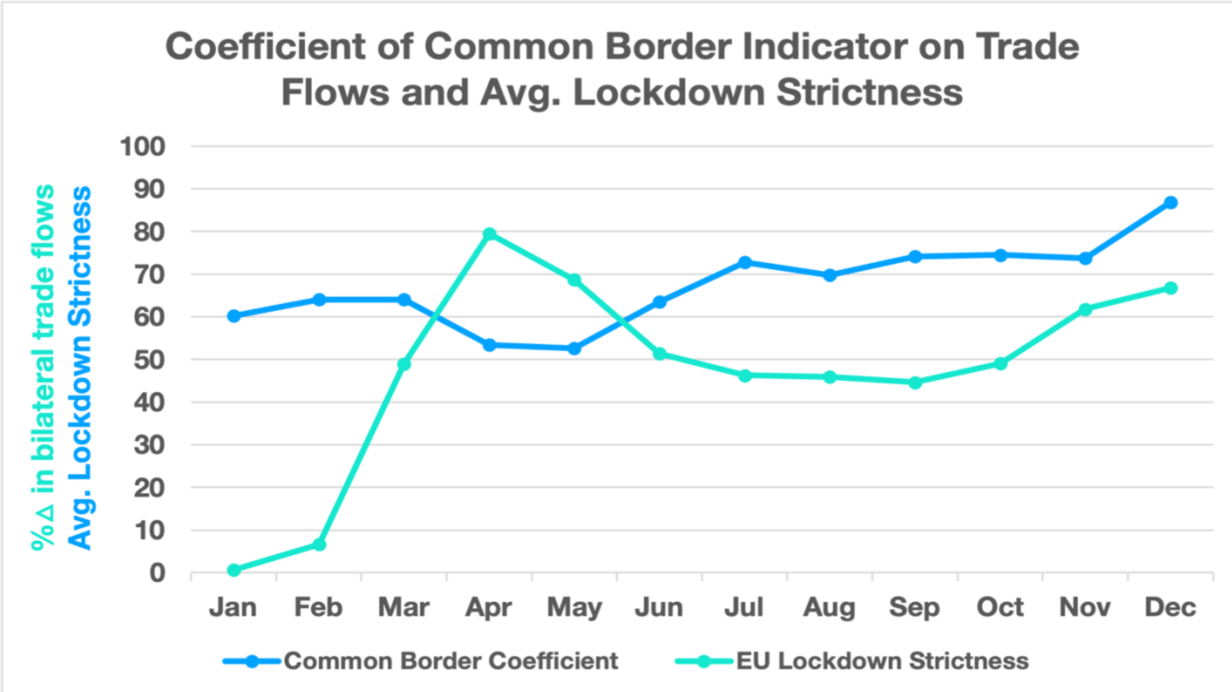

Figure 5: The coefficient of the common border indicator on trade flows over the course of 2020 along with average EU lockdown strictness. The vertical axis denotes the percentage change in bilateral trade flows if a country pair shares a common border. This because the coefficient is transformed via $[e^{coefficient} - 1] \times 100$ into percentage change. The same scale is used to denote average lockdown strictness on a scale of 0-100.

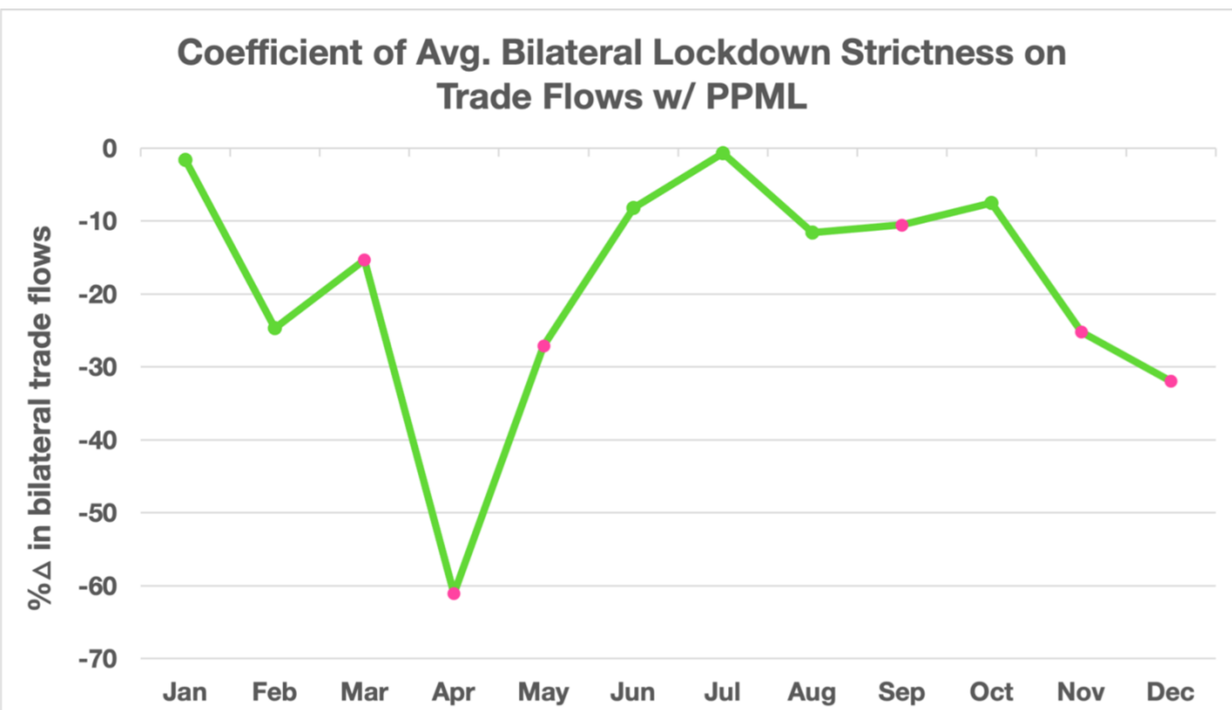

Figure 6: The coefficient of average bilateral lockdown strictness on trade flows over the course of 2020. The vertical axis denotes the % change in bilateral trade flows if average bilateral

lockdown strictness rises by one point. This because the coefficient is transformed via $[e^{coefficient} - 1] \times 100$ *into percentage change. Estimated using PPML regression with FE. Significant coefficients are denoted in pink.*

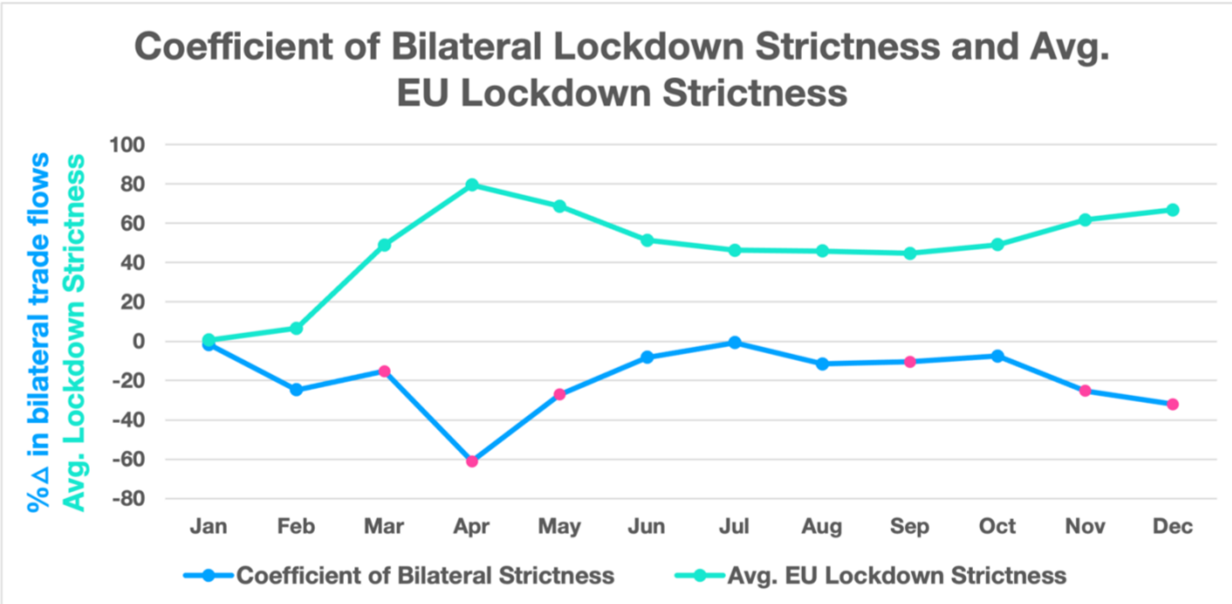

Figure 7: The coefficient of average bilateral lockdown strictness on trade flows over the course of 2020. The vertical axis denotes the % change in bilateral trade flows if average bilateral lockdown strictness rises by one point. This because the coefficient is transformed via $[e^{coefficient} - 1] \times 100$ *into percentage change. Significant coefficients of bilateral strictness are denoted in pink.*

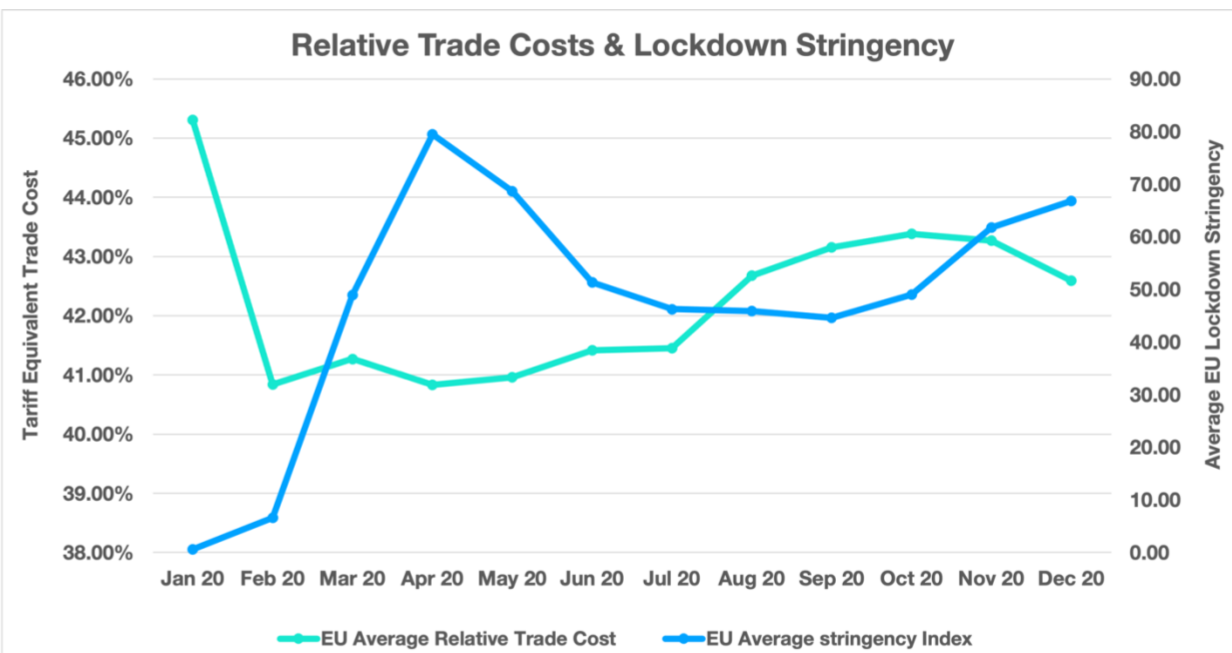

Figure 8: The development of Novy's relative trade cost measure and lockdown stringency over the course of 2020. Both measures are reported as EU-wide averages.

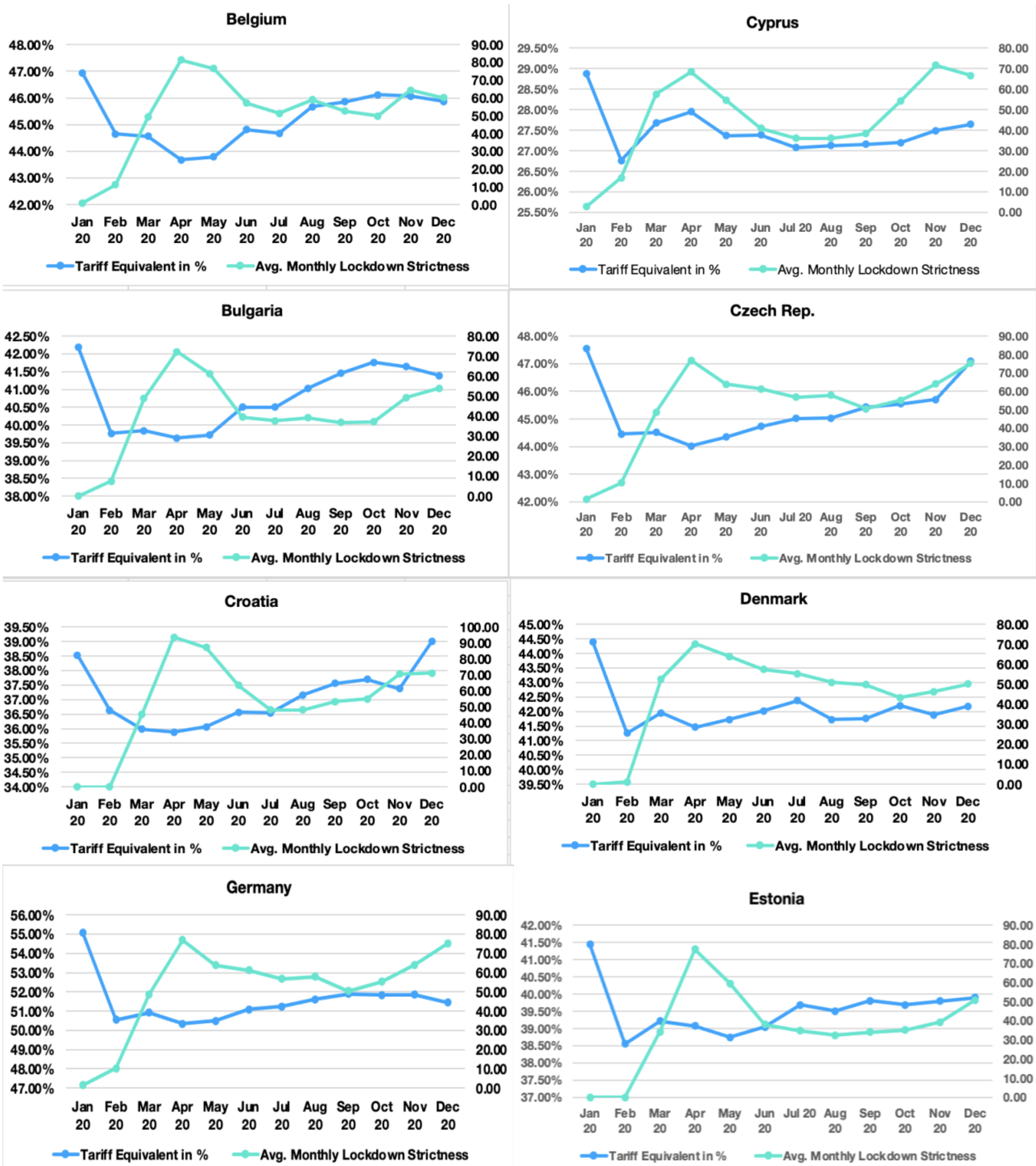

Figure 9: The development of Novy's country-specific relative trade cost measure along with average monthly lockdown strictness across the EU.

Figure 9: The development of Novy's country-specific relative trade cost measure along with average monthly lockdown strictness across the EU.

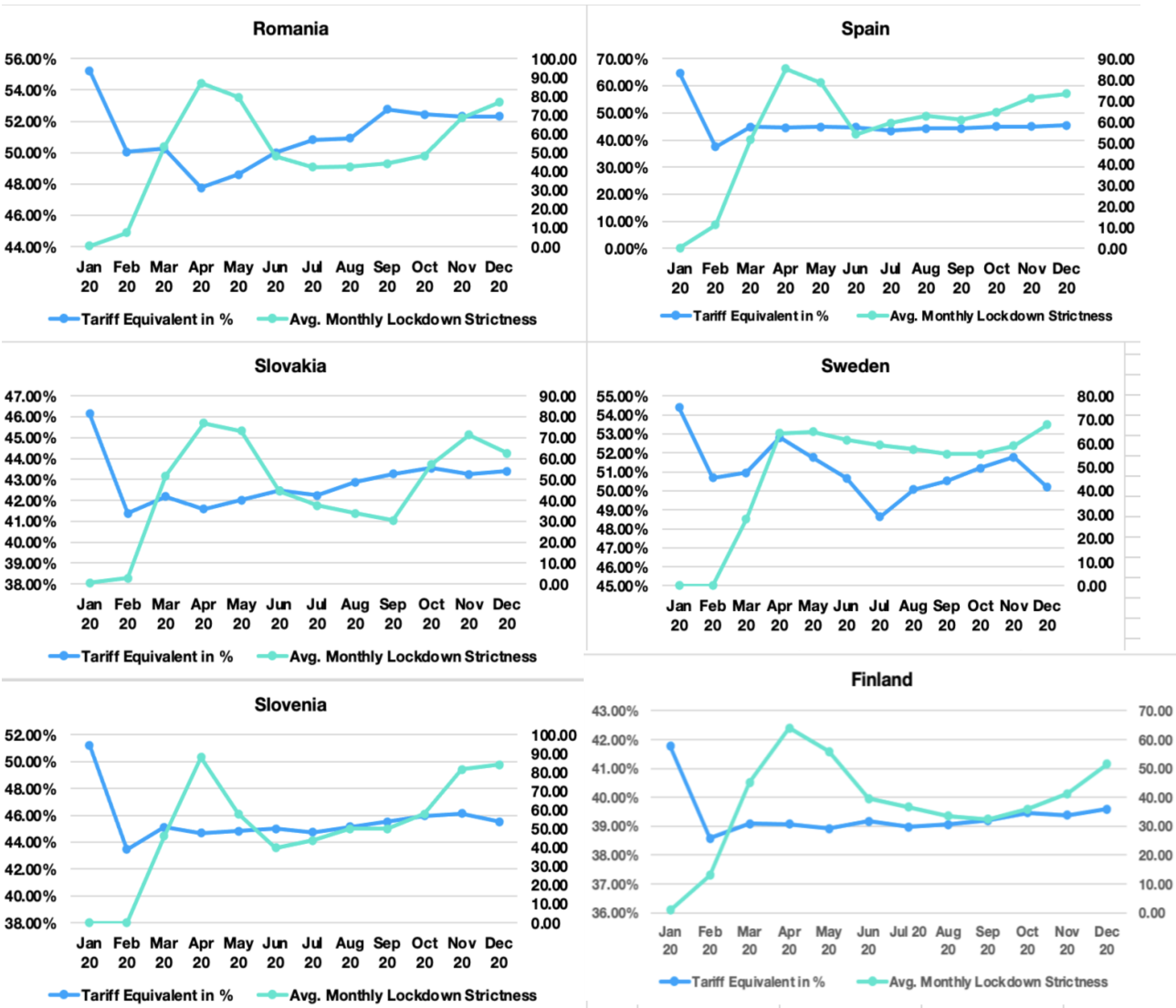

Figure 9: The development of Novy's country-specific relative trade cost measure along with average monthly lockdown strictness across the EU

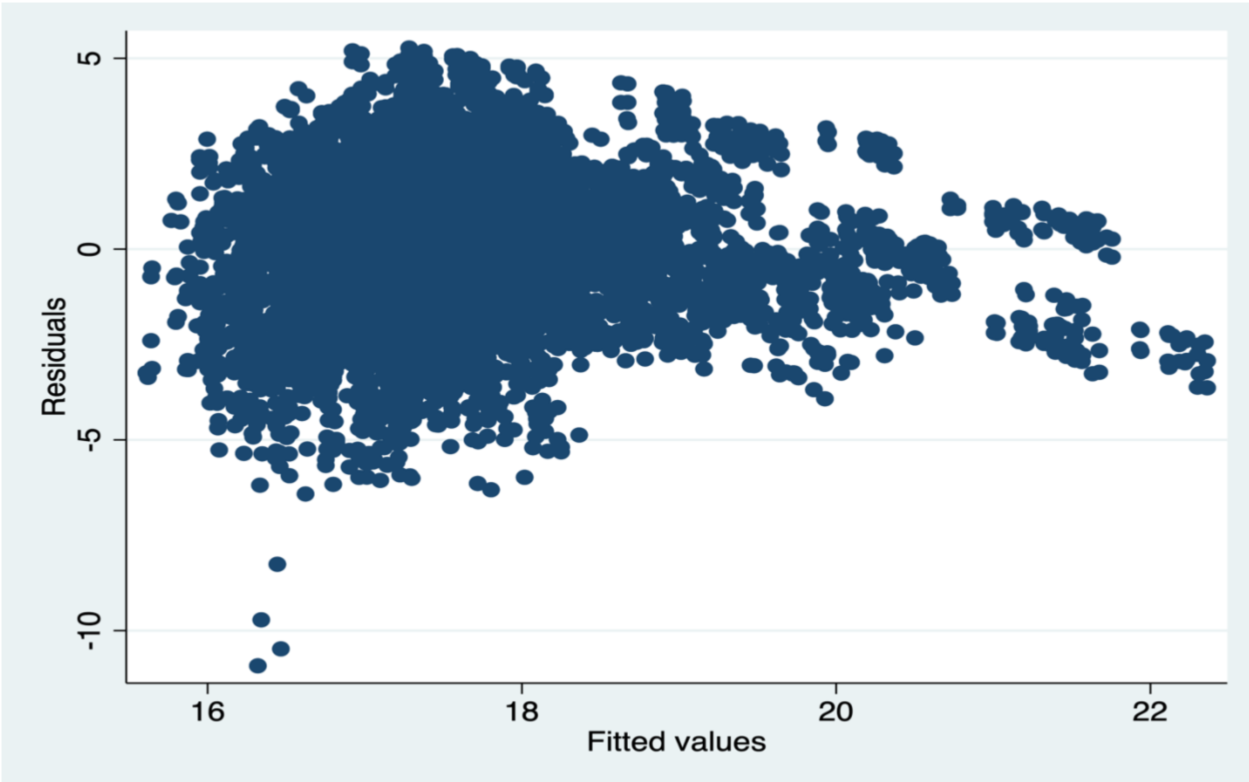

Figure 10: Plot of the OLS residuals versus the fitted values of the natural logarithm of trade flows. This picture suggests we have heteroskedasticity.

Appendix 2 – Tables

Table 2
Summary statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Bilateral trade	8424	3.63e+08	1.01e+09	4.81e+05	1.12e+10
Internal trade	276	9.67e+10	2.39e+11	9.30e+08	2.90e+12
DIST	8424	1259.019	773.9303	0	3766.31
CBD	8424	.0554278	.2288272	0	1
COMLANG	8424	.0240833	.153317	0	1
avg_bilateral_stringency	8424	46.76598	23.7267	1	95
EURO	8424	.4892896	.4999155	0	1

Table 3
PPML regression with exporter and importer fixed effects showing the relationship between bilateral trade flows and all five trade cost proxies for 2020 as a whole. Fixed effects are omitted for brevity.

trade	Coef.	Robust Std. Err	t	P>|t|	[95% Conf. Interval]	
ln_DIST	-.5501483	.0685123	-8.03	0.000	-.6844299	-.4158667
CBD	.4645731	.1066398	4.36	0.000	.255563	.6735833
COMLANG	.1976175	.2705264	0.73	0.465	-.3326045	.727839
EURO	-.057076	.153117	-0.37	0.709	-.3571798	.2430278
avg_bilateral_stringency	-.0420018	.0145595	2.88	0.004	-.0134657	.070538
_cons	19.23189	.6976332	27.57	0.000	17.86456	20.59923

Table 4
PPML regression with exporter and importer fixed effects showing the relationship between bilateral trade flows and all five trade cost proxies for 2020 on a monthly basis. Fixed effects are omitted for brevity.

trade	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf. Interval]	
ln_DIST_202001	-.4926844	.0636626	-7.96	0.000	-.6312858	-.3817328
ln_DIST_202002	-.4940196	.0612133	-8.05	0.000	-.6129949	-.3730432
ln_DIST_202003	-.4946224	.0622569	-7.94	0.000	-.6166437	-.3726011
ln_DIST_202004	-.5097107	.0591885	-8.61	0.000	-.625718	-.3937034
ln_DIST_202005	-.5239052	.061792	-8.48	0.000	-.6450153	-.4027951

ln_DIST_202006	-.5113545	.070347	-7.27	0.000	-.6492322	-.3734769
ln_DIST_202007	-.5028696	.0614892	-8.18	0.000	-.6233863	-.382353
ln_DIST_202008	-.5132438	.0653064	-7.86	0.000	-.6412421	-.3852456
ln_DIST_202009	-.4471983	.0662283	-6.75	0.000	-.5770034	-.3173932
ln_DIST_202010	-.4660308	.0630999	-7.39	0.000	-.5897044	-.3423572
ln_DIST_202011	-.4448116	.0671988	-6.62	0.000	-.5765188	-.3131044
ln_DIST_202012	-.4998738	.0692455	-7.22	0.000	-.6355925	-.3641552
CBD_202001	.4714934	.1099041	4.29	0.000	.2560854	.6869014
CBD _202002	.4949627	.1029156	4.81	0.000	.2932518	.6966736
CBD _202003	.494599	.109758	4.51	0.000	.2794772	.7097208
CBD_202004	.4276902	.1048807	4.08	0.000	.2221277	.6332526
CBD _202005	.422615	.1156128	3.66	0.000	.1960181	.649212
CBD _202006	.4915089	.1092464	4.50	0.000	.2773899	.7056279
CBD _202007	.5470069	.112073	4.88	0.000	.3273478	.766666
CBD _202008	.5291317	.1087979	4.86	0.000	.3158918	.7423715
CBD _202009	.5545488	.1061187	5.23	0.000	.3465601	.7625376
CBD _202010	.556586	.1107101	5.03	0.000	.339598	.7735739
CBD_202011	.5523203	.1331688	4.15	0.000	.2913143	.8133264
CBD _202012	.6251517	.1219346	5.13	0.000	.3861642	.8641391
COMLANG_202001	.1034073	.2625792	0.39	0.694	-.4112386	.6180531
COMLANG_202002	.1950081	.2357521	0.83	0.408	-.2670576	.6570738
COMLANG_202003	.1127369	.255326	0.44	0.659	-.3876929	.6131667
COMLANG_202004	.1404445	.2387456	0.59	0.556	-.3274883	.6083772
COMLANG_202005	.1658029	.2476496	0.67	0.503	-.3195814	.6511872
COMLANG_202006	.1412418	.2700113	0.52	0.601	-.3879705	.6704542
COMLANG_202007	.2066884	.2580059	0.80	0.423	-.2989939	.7123706
COMLANG_202008	.0747433	.2882985	0.26	0.795	-.4903114	.6397979
COMLANG_202009	.2315516	.2376724	0.97	0.330	-.2342777	.6973808
COMLANG_202010	.2734156	.2293463	1.19	0.233	-.1760949	.7229262
COMLANG_202011	.206723	.2806545	0.74	0.461	-.3433496	.7567956
COMLANG_202012	.0093493	.2987152	0.03	0.975	-.5761217	.5948203
EURO_202001	.0159426	.1537611	0.10	0.917	-.2854237	.3173089
EURO_202002	.0092886	.1449447	0.06	0.949	-.2747978	.2933751
EURO_202003	.0041801	.1505192	0.03	0.978	-.2908321	.2991923
EURO_202004	-.0161254	.1501836	-0.11	0.914	-.3104797	.278229
EURO_202005	.086855	.1690528	0.51	0.607	-.2444825	.4181924
EURO_202006	.0300411	.1544264	0.19	0.846	-.272629	.3327113
EURO_202007	.0147167	.1587358	0.09	0.926	-.2963998	.3258332
EURO_202008	-.0093545	.1610565	-0.06	0.954	-.3250193	.3063104
EURO_202009	.000014	.1541609	0.00	1.000	-.3021357	.3021637
EURO_202010	-.0202043	.1653514	-0.12	0.903	-.3442871	.3038786
EURO_202011	.002721	.1749601	0.02	0.988	-.3401944	.3456364
EURO_202012	-.0601458	.1616556	-0.37	0.710	-.3769849	.2566933
avg_bilateral_stringency_202001	-.2832736	.8201054	-0.35	0.730	-1.890651	1.324103
avg_bilateral_stringency_202002	.0162675	.0142821	1.14	0.255	-.0117249	.04426
avg_bilateral_stringency_202003	.1664014	.0264388	6.29	0.000	.1145823	.2182205
avg_bilateral_stringency_202004	.9434991	.1237447	7.62	0.000	.7009639	1.186034
avg_bilateral_stringency_202005	.3163341	.1316106	2.40	0.016	.058382	.5742862

avg_bilateral_stringency_202006	-.085419	.1065275	-0.80	0.423	-.294209	.123371
avg_bilateral_stringency_202007	.0071741	.0583508	0.12	0.902	-.1071913	.1215396
avg_bilateral_stringency_202008	-.123102	.0748453	-1.64	0.100	-.269796	.0235921
avg_bilateral_stringency_202009	.1114209	.0541926	2.06	0.040	.0052054	.2176364
avg_bilateral_stringency_202010	.0779341	.0928377	0.84	0.401	-.1040245	.2598927
avg_bilateral_stringency_202011	.2909108	.0857638	3.39	0.001	.1228168	.4590048
avg_bilateral_stringency_202012	.3852264	.16376	2.35	0.019	.0642628	.70619
_cons	-11.06624	11.26164	-0.98	0.326	-33.13864	11.00616

Table 5

Novy's Relative Trade Cost Measure for all countries in the sample, Jan – Dec 2020

Period	Belgium	Bulgaria	Croatia	Republic of Cyprus	Czech Rep.	Denmark	Estonia	Finland	Germany
Jan 20	46.93%	42.19%	38.53%	28.88%	47.54%	44.40%	41.44%	41.77%	55.08%
Feb 20	44.65%	39.76%	36.63%	26.76%	44.45%	41.25%	38.55%	38.57%	50.54%
Mar 20	44.57%	39.84%	35.98%	27.68%	44.51%	41.95%	39.22%	39.09%	50.92%
Apr 20	43.68%	39.63%	35.88%	27.95%	44.01%	41.46%	39.07%	39.07%	50.34%
May 20	43.79%	39.71%	36.06%	27.37%	44.35%	41.72%	38.74%	38.91%	50.48%
Jun 20	44.81%	40.50%	36.57%	27.39%	44.73%	42.02%	39.04%	39.17%	51.08%
Jul 20	44.68%	40.51%	36.54%	27.08%	45.02%	42.38%	39.68%	38.97%	51.24%
Aug 20	45.68%	41.04%	37.16%	27.12%	45.03%	41.73%	39.50%	39.06%	51.62%
Sep 20	45.86%	41.45%	37.55%	27.16%	45.42%	41.75%	39.81%	39.20%	51.89%
Oct 20	46.12%	41.77%	37.69%	27.20%	45.55%	42.20%	39.69%	39.47%	51.84%
Nov 20	46.07%	41.64%	37.37%	27.49%	45.70%	41.89%	39.80%	39.38%	51.86%
Dec 20	45.87%	41.39%	39.00%	27.64%	47.09%	42.18%	39.90%	39.60%	51.45%
Average	**45.23%**	**40.79%**	**37.08%**	**27.48%**	**45.28%**	**42.08%**	**39.54%**	**39.35%**	**51.53%**

Table 5 - Continued

Novy's Relative Trade Cost Measure for all countries in the sample, Jan – Dec 2020

Period	Greece	Hungary	Italy	Latvia	Lithuania	Luxembourg	Netherlands	Poland
Jan 20	42.24%	49.48%	69.19%	40.71%	41.50%	38.19%	50.60%	47.85%
Feb 20	38.23%	45.07%	43.71%	38.21%	39.06%	36.41%	47.51%	44.96%
Mar 20	38.64%	45.67%	43.92%	38.49%	39.72%	36.44%	47.92%	45.12%
Apr 20	38.13%	45.10%	43.45%	38.46%	39.29%	36.42%	47.38%	44.48%
May 20	38.68%	45.19%	43.54%	38.25%	39.37%	36.54%	47.56%	44.59%
Jun 20	39.28%	45.83%	43.86%	37.94%	39.57%	36.92%	48.25%	44.96%
Jul 20	39.43%	45.62%	44.13%	38.48%	39.55%	36.77%	48.54%	45.07%
Aug 20	38.43%	45.91%	44.45%	38.95%	39.98%	36.83%	49.37%	45.88%
Sep 20	39.46%	46.34%	45.16%	39.66%	40.70%	37.03%	49.72%	46.74%
Oct 20	38.65%	46.17%	45.16%	39.72%	40.53%	37.64%	49.70%	46.75%
Nov 20	39.34%	46.47%	44.42%	39.89%	40.84%	37.27%	49.99%	46.61%
Dec 20	39.27%	46.06%	45.18%	36.98%	40.53%	38.00%	49.37%	45.68%
Average	**39.15%**	**46.08%**	**46.35%**	**38.81%**	**40.05%**	**37.04%**	**48.83%**	**45.72%**

Table 5 - Continued

Novy's Relative Trade Cost Measure for all countries in the sample, Jan – Dec 2020

Period	Portugal	Romania	Slovakia	Slovenia	Spain	Sweden	EU Average
Jan 20	43.14%	55.24%	46.14%	51.22%	64.58%	54.40%	45.30%
Feb 20	38.96%	50.06%	41.38%	43.45%	37.52%	50.68%	40.84%
Mar 20	39.17%	50.25%	42.18%	45.10%	44.80%	50.96%	41.27%
Apr 20	37.80%	47.76%	41.58%	44.68%	44.54%	52.79%	40.83%
May 20	39.09%	48.59%	42.02%	44.84%	44.88%	51.76%	40.96%
Jun 20	39.59%	50.00%	42.45%	45.00%	44.62%	50.66%	41.41%
Jul 20	39.20%	50.82%	42.24%	44.75%	43.32%	48.62%	41.45%
Aug 20	39.49%	50.92%	42.87%	45.16%	44.31%	50.07%	42.67%
Sep 20	40.31%	52.75%	43.26%	45.51%	44.32%	50.53%	43.15%
Oct 20	40.89%	52.44%	43.55%	45.95%	44.95%	51.20%	43.38%
Nov 20	41.00%	52.32%	43.25%	46.13%	45.04%	51.76%	43.27%
Dec 20	39.99%	52.31%	43.39%	45.53%	45.44%	50.20%	42.59%
Average	**39.89%**	**51.12%**	**42.86%**	**45.61%**	**45.69%**	**51.14%**	**42.26%**

Table 6

Regression of all trade cost proxies on the relative trade cost measure for each individual month of 2020.

Trade Cost Proxies	2020-01	2020-02	2020-03	2020-04	2020-05	2020-06	2020-07	2020-08
ln(Distance)	0.0607***	0.0169	0.0299***	0.0330***	0.0275**	0.0182	0.0083	0.0183
	(0.018)	(0.0118)	(0.0126)	(0.0119)	(0.012)	(0.011)	(0.012)	(0.012)
Common Border	0.1148***	0.0818***	0.1072***	0.1042***	0.1048***	0.0965***	0.0878***	0.0875***
	(0.040)	(0.023)	(0.023)	(0.022)	(0.022)	(0.024)	(0.026)	(0.029)
Common Language	-0.0054	0.0597*	0.0438	0.055*	0.0371	0.0157	0.0213	0.0414
	(0.036)	(0.031)	(0.031)	(0.029)	(0.031)	(0.032)	(0.038)	(0.043)
Currency Union	0.0054	-0.035***	-0.028***	-0.025*	-0.028**	-0.025*	-0.0216	-0.030**
	(0.018)	(0.0118)	(0.0126)	(0.0119)	(0.012)	(0.011)	(0.012)	(0.012)
Average Bilateral Stringency Index	0.052***	0.0037***	0.0006	-0.002**	0.0006	0.004***	0.0044***	0.0059***
	(0.0188)	(0.0011)	(0.0008)	(0.001)	(0.001)	(0.0007)	(0.0007)	(0.0008)
Constant	0.0662	0.3428	0.2458**	0.4397	0.245	0.1580	0.2244	0.1082
Observations	253	253	253	253	253	253	253	253
R^2	0.0737	0.0898	0.10622	0.10249	0.10445	0.10199	0.10159	0.09706

Table 6 - Continued

Regression of all trade cost proxies on the relative trade cost measure for each individual month of 2020 - Continued

Trade Cost Proxies	2020-09	2020-10	2020-11	2020-12	Pooled for 2020
ln(Distance)	0.0244*	0.0393***	0.0420***	0.0433***	0.0368***
	(0.013)	(0.014)	(0.015)	(0.016)	(0.003)
Common Border	0.1007***	0.0929***	0.0985***	0.1333***	0.1104***
	(0.03)	(0.027)	(0.027)	(0.030)	(0.007)
Common Language	-0.014	0.1466***	0.1304	0.0581	0.0507***
	(0.040)	(0.040)	(0.044)	(0.048)	(0.010)

Currency Union	**-0.036 (0.014)	**-0.033 (0.016)	-0.027 (0.017)	***-0.059 (0.018)	-0.0274*** (0.004)
Average Bilateral Stringency Index	0.0061*** (0.0009)	0.0030*** (0.0008)	0.0015** (0.0006)	0.0047*** (0.001)	-0.00007 (0.0001)
Constant	0.062	0.089	0.116	-0.120	0.2405***
Observations	253	253	253	253	3036
R^2	0.10002	0.10569	0.10986	0.1081	0.11398

Table 7

Comparison between the predicted relative trade cost measure for 2020 and the calculated relative trade cost measure for 2020

	Denmark	**Finland**	**Germany**	**Italy**	**Sweden**
Calculated Trade Cost Measure for 2020	42.08%	39.35%	51.53%	46.35%	51.14%
Predicted Trade Cost Measure for 2020	57%	59%	47%	73%	63%
Difference	**-14.92%**	**-19.65%**	**4.53%**	**-26.65%**	**-11.86%**

Notes: The predicted relative trade cost measure is an extrapolation of the trade cost development between 1970-2000 from Novy (2013). The calculated relative trade cost measure is from this paper.

Table 8

OLS regression with exporter and importer fixed effects showing the relationship between bilateral trade flows and all five trade cost proxies for 2020 as a whole. Fixed effects are omitted for brevity.

ln_trade	Coef.	Robust Std. Err	t	P>|t|	[95% Conf. Interval]	
ln_DIST	-1.311397	.0745787	-17.58	0.000	-1.457836	-1.164958
CBD	.2039658	.1840842	1.11	0.268	-.1574925	.5654241
COMLANG	.1437551	.3340091	0.43	0.667	-.512088	.7995982
EURO	-.0422022	.0911959	-0.46	0.644	-.2212698	.1368655
avg_bilateral_stringency	-.0021395	.0007372	2.90	0.004	-.0035871	-.0006919
_cons	24.91281	.6543379	38.07	0.000	23.62799	26.19764

Table 9

OLS regression with exporter and importer fixed effects showing the relationship between the natural logarithm of bilateral trade flows and all five trade cost proxies for each individual month of 2020. Fixed effects are omitted for brevity.

ln_trade	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf. Interval]	
ln_DIST_202001	-1.006743	.2478685	-4.06	0.000	-1.49341	-.5200765
ln_DIST_202002	-1.000971	.242762	-4.12	0.000	-1.477611	-.5243296
ln_DIST_202003	-1.011345	.2471928	-4.09	0.000	-1.496686	-.5260049
ln_DIST_202004	-.9834651	.2352247	-4.18	0.000	-1.445307	-.5216231
ln_DIST_202005	-1.000854	.2395569	-4.18	0.000	-1.471202	-.5305061
ln_DIST_202006	-.9807243	.2399631	-4.09	0.000	-1.45187	-.5095789
ln_DIST_202007	-1.010766	.2398946	-4.21	0.000	-1.481777	-.5397552
ln_DIST_202008	-.9972192	.2490578	-4.00	0.000	-1.486221	-.5082172
ln_DIST_202009	-.9437328	.2477541	-3.81	0.000	-1.430175	-.4572905
ln_DIST_202010	-.9292112	.2444526	-3.80	0.000	-1.409171	-.4492509
ln_DIST_202011	-.939378	.2448414	-3.84	0.000	-1.420102	-.4586544
ln_DIST_202012	-.9369525	.2898003	-3.23	0.001	-1.505949	-.3679562
CONTIG_202001	.517616	.3253768	1.59	0.112	-.1212313	1.156463
CONTIG_202002	.4965659	.3192867	1.56	0.120	-.1303242	1.123456
CONTIG_202003	.5010707	.3229322	1.55	0.121	-.1329769	1.135118
CONTIG_202004	.5622186	.3066681	1.83	0.067	-.039896	1.164333
CONTIG_202005	.5371395	.3158001	1.70	0.089	-.0829049	1.157184
CONTIG_202006	.5325355	.3144358	1.69	0.091	-.0848303	1.149901
CONTIG_202007	.5593202	.3171292	1.76	0.078	-.0633337	1.181974
CONTIG_202008	.6251013	.3356517	1.86	0.063	-.0339199	1.284123
CONTIG_202009	.6682864	.3281021	2.04	0.042	.0240881	1.312485
CONTIG_202010	.6470619	.3268648	1.98	0.048	.0052928	1.288831
CONTIG_202011	.6521993	.3533447	1.85	0.065	-.0415606	1.345959

CONTIG_202012	.5507204	.3563773	1.55	0.123	-.1489936	1.250434
COMLANG_202001	.2816009	.3654327	0.77	0.441	-.4358925	.9990943
COMLANG_202002	.2874773	.3603794	0.80	0.425	-.4200945	.9950491
COMLANG_202003	.3054898	.3764672	0.81	0.417	-.4336689	1.044648
COMLANG_202004	.1577998	.3397622	0.46	0.642	-.5092919	.8248916
COMLANG_202005	.2495992	.3475493	0.72	0.473	-.4327819	.9319804
COMLANG_202006	.2579536	.3499917	0.74	0.461	-.429223	.9451302
COMLANG_202007	.2467679	.3539773	0.70	0.486	-.448234	.9417698
COMLANG_202008	.0520198	.3803824	0.14	0.891	-.694826	.7988656
COMLANG_202009	.0432696	.3668223	0.12	0.906	-.6769523	.7634916
COMLANG_202010	.0767619	.3845159	0.20	0.842	-.6781996	.8317234
COMLANG_202011	.1018412	.3768768	0.27	0.787	-.6381219	.8418042
COMLANG_202012	.3470961	.3693926	0.94	0.348	-.3781723	1.072364
EURO_202001	-.031438	.1063306	-0.30	0.768	-.2402084	.1773324
EURO_202002	-.0476233	.1098135	-0.43	0.665	-.2632319	.1679853
EURO_202003	-.0010374	.1058386	-0.01	0.992	-.2088417	.2067669
EURO_202004	-.0121473	.1034954	-0.12	0.907	-.215351	.1910564
EURO_202005	.0374874	.1022392	0.37	0.714	-.1632497	.2382246
EURO_202006	.0501207	.1038726	0.48	0.630	-.1538237	.2540651
EURO_202007	-.012124	.1079804	-0.11	0.911	-.2241335	.1998855
EURO_202008	-.033498	.1107566	-0.30	0.762	-.2509585	.1839624
EURO_202009	.0525724	.1064852	0.49	0.622	-.1565015	.2616463
EURO_202010	.0220743	.1190819	0.19	0.853	-.211732	.2558806
EURO_202011	-.0192721	.1216638	-0.16	0.874	-.2581478	.2196036
EURO_202012	.0151374	.1214905	0.12	0.901	-.2233979	.2536727
avg_bilateral_stringency_202001	.2012132	.648558	0.31	0.756	-1.072171	1.474597
avg_bilateral_stringency_202002	.015741	.0161523	0.97	0.330	-.0159726	.0474545
avg_bilateral_stringency_202003	.1047317	.0589691	1.78	0.076	-.0110486	.220512
avg_bilateral_stringency_202004	.3376824	.1449113	2.33	0.020	.0531624	.6222023
avg_bilateral_stringency_202005	.0875063	.0802131	1.09	0.276	-.0699848	.2449974
avg_bilateral_stringency_202006	.0731604	.0627817	1.17	0.244	-.0501057	.1964265
avg_bilateral_stringency_202007	-.0403236	.0469569	-0.86	0.391	-.1325193	.051872
avg_bilateral_stringency_202008	.0507025	.0534196	0.95	0.343	-.054182	.155587
avg_bilateral_stringency_202009	.1003802	.0469275	2.14	0.033	.0082424	.1925179
avg_bilateral_stringency_202010	.1308693	.0755405	1.73	0.084	-.0174475	.2791862
avg_bilateral_stringency_202011	.0923439	.0513334	1.80	0.072	-.0084445	.1931322
avg_bilateral_stringency_202012	-.011075	.0820752	-0.13	0.893	-.1722221	.150072
_cons	11.8322	7.521958	1.57	0.116	-2.936472	26.60087

Appendix 3 – Calculations

Calculations 1

Full calculations to show that sharing a border or language is systematically related to a higher relative trade cost measure $\tau_{ij,t}$.

All four trade cost functions:

$$\ln t_{ij,t} = \beta_1 \ln DIST_{ij} + \beta_2 CBD_{ij} + \beta_3 CLG_{ij} + \beta_4 EUR_{ij} + \beta_5 INDEX_{ij,t}$$

$$\ln t_{jj,t} = \beta_1 \ln DIST_{ji} + \beta_2 CBD_{ji} + \beta_3 CLG_{ji} + \beta_4 EUR_{ji} + \beta_5 INDEX_{ji,t}$$

$$\ln t_{ii,t} = \beta_1 \ln DIST_{ii} + \beta_2 CBD_{ii} + \beta_3 CLG_{ii} + \beta_4 EUR_{ii} + \beta_5 INDEX_{ii,t}$$

$$\ln t_{jj,t} = \beta_1 \ln DIST_{jj} + \beta_2 CBD_{jj} + \beta_3 CLG_{jj} + \beta_4 EUR_{jj} + \beta_5 INDEX_{jj,t}$$

Taking the natural logarithm to the right-hand side:

$$t_{ij,t} = \ln DIST_{ij}{}^{\beta_1} \exp\left(\beta_2 CBD_{ij} + \beta_3 CLG_{ij} + \beta_4 EUR_{ij} + \beta_5 INDEX_{ij,t}\right)$$

$$t_{ji,t} = \ln DIST_{ji}{}^{\beta_1} \exp\left(\beta_2 CBD_{ji} + \beta_3 CLG_{ji} + \beta_4 EUR_{ji} + \beta_5 INDEX_{ji,t}\right)$$

$$t_{ii,t} = \ln DIST_{ii}{}^{\beta_1} \exp\left(\beta_2 CBD_{ii} + \beta_3 CLG_{ii} + \beta_4 EUR_{ii} + \beta_5 INDEX_{ii,t}\right)$$

$$t_{jj,t} = \ln DIST_{jj}{}^{\beta_1} \exp\left(\beta_2 CBD_{jj} + \beta_3 CLG_{jj} + \beta_4 EUR_{jj} + \beta_5 INDEX_{jj,t}\right)$$

$Plug\ expressions\ for\ t_{ii,t}, t_{jj,t}, t_{ij,t}, t_{ji,t}\ into\ \tau_{ij,t} = \left\{\left(t_{ij,t}t_{ji,t}\right)/\left(t_{ii,t}t_{jj,t}\right)\right\}^{1/2} - 1$

$$\tau_{ij,t} = \left(\frac{DIST_{ij}DIST_{ji}}{DIST_{ii}DIST_{jj}}\right)^{\beta_1} \frac{\exp\left(\beta_2 CBD_{ij}+\beta_3 CLG_{ij}+\beta_4 EUR_{ij}+\beta_5 INDEX_{ij,t}+\beta_2 CBD_{ji}+\beta_3 CLG_{ji}+\beta_4 EUR_{ji}+\beta_5 INDEX_{ji,t}\right)}{\exp\left(\beta_2 CBD_{ii}+\beta_3 CLG_{ii}+\beta_4 EUR_{ii}+\beta_5 INDEX_{ii,t}+\beta_2 CBD_{jj}+\beta_3 CLG_{jj}+\beta_4 EUR_{jj}+\beta_5 INDEX_{jj,t}\right)}$$

$$\tau_{ij,t} = \left(\frac{DIST_{ij}DIST_{ji}}{DIST_{ii}DIST_{jj}}\right)^{\beta_1} \exp\left(\beta_2 CBD_{ij} + \beta_3 CLG_{ij} + \beta_4 EUR_{ij} + \beta_5 INDEX_{ij,t} + \beta_2 CBD_{ji} + \beta_3 CLG_{ji} + \beta_4 EUR_{ji} + \beta_5 INDEX_{ji,t} - \beta_2 CBD_{ii} - \beta_3 CLG_{ii} - \beta_4 EUR_{ii} - \beta_5 INDEX_{ii,t} - \beta_2 CBD_{jj} - \beta_3 CLG_{jj} - \beta_4 EUR_{jj} - \beta_5 INDEX_{jj,t}\right)$$

$$\begin{aligned}\tau_{ij,t} = \left(\frac{DIST_{ij}DIST_{ji}}{DIST_{ii}DIST_{jj}}\right)^{\beta_1} & exp\{\beta_2\left(CBD_{ij} - CBD_{ii} + CBD_{ji} - CBD_{jj}\right) \\ & + \beta_3\left(CLG_{ij} - CLG_{ii} + CLG_{ji} - CLG_{jj}\right) + \beta_4\left(EUR_{ij} - EUR_{ii} + EUR_{ji} - EUR_{jj}\right) \\ & + \beta_5\left(INDEX_{ij} - INDEX_{ii} + INDEX_{ji} - INDEX_{jj}\right)\}\end{aligned}$$

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