E-commerce and Trade during Crisis Times: Firm-level Evidence from India, Indonesia and Mexico*

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Abstract

How did the possibility of engaging in E-commerce affect trade throughout the COVID crisis? Combining novel high-frequency firm-level customs data for India, Indonesia, and Mexico covering exports and imports with monthly measures of the use of E-commerce technologies within a firm's website, this paper measures the effect of E-commerce on trade during the COVID crisis. The results show that having E-commerce technology in place before COVID led to more resilience of firm trade in E-tradeable goods as the stringency of COVID-lockdown measures increased. We find a higher propensity to import for firms in all three countries and higher import values for India and Mexico. For India, we also find higher export values and export propensity. In contrast, we find no clear trade effects for firms of adopting E-commerce technology during COVID, despite many firms doing so in these three countries. The results indicate that the effects of technology adoption on trade take time to materialize, and may not help adopting firms to immediately weather a crisis, such as the COVID pandemic.

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1 Introduction

Online sales are an increasingly important part of business models around the world, with estimates suggesting in 2019 that 1.5 billion people shopped online with USD26.7 trillion global sales (UNCTAD, 2020). A large literature highlights the often sunk costs of matching and transacting across borders that prevent many firms from engaging in international trade (Anderson and Van Wincoop, 2004). However, these costs can be lower online (Goldfarb and Tucker, 2019). In particular, E-commerce can reduce the costs of matching and communicating with international sellers or distributors and transport companies, and similarly reduce the costs of acquiring information on customs procedures or seller or product quality (e.g. through online ratings systems). E-commerce may allow new firms to start trading and the existing traders to expand their market reach (Chen and Volpe Martinicus, 2022).

But how did the possibility of engaging in E-commerce affect trade throughout the COVID crisis? The outbreak of the pandemic was a major shock resulting in a substantial decline in global trade volumes between January and June 2020 (Brenton et al., 2022). Existing E-commerce users may have been partly insulated from the worst of the COVID trade shock, with lower costs of matching with new customers or suppliers in the face of disruption. For example, one Ningbo toy manufacturer partially offset falling COVID sales to Walmart and Target in the United States through new online sales to Brazil and Mexico[1]. Moreover, COVID-19 lockdowns and increased working from home forced many companies to adopt E-commerce technologies to reach their customers online. The rapid shift online may have allowed new firms to trade across borders.

In this paper we combine novel high-frequency firm-level customs data for India, Indonesia and Mexico covering exports and imports with monthly measures of the use of E-commerce technologies within a firm's website, to measure the effect of E-commerce on trade during the COVID crisis. We combine these data with measures of E-commerce tradeable products, to contrast the trade effects across different product types in a triple-differences estimation. We use E-commerce products defined by Ma et al. (2021) in our baseline analysis and consumer goods in the Appendix. Our analysis proceeds in two parts. First, we examine whether a firm's existing E-commerce use, prior to COVID, is correlated with improved trade performance of E-commerce tradeable products as the stringency of COVID lockdowns increases over time. Second, we examine whether firm adoption of E-commerce over an extended period including during COVID is correlated with improved trade performance of E-commerce tradeable products.

The triple differences (DDD) specification is estimated for each country and trade flow

[1] South China Morning Post, 2020

on data at the firm-HS 6-digit product-year-month level and includes firm, year-month and product fixed effects that control for firm or product-specific as well as high-frequency omitted variables that vary by country. One advantage of the DDD approach is that it does not depend on the two parallel trends assumptions for a causal interpretation, but rather a weaker identification assumption (Olden and Møen, 2022). For instance, we allow firms with and without technology to have different trends during COVID. Rather, identification requires that firms that adopt E-commerce and non-adopting firms would have a common trend in their trade of E-commerce tradeable products as a share of non-E-commerce products.

The results show that having E-commerce technology in place before COVID led to more resilience of firm trade in E-commerce products as the stringency of COVID-19 lockdown measures increased. We find a higher propensity to import for firms in all three countries, and higher import values for India and Mexico. For India we also find higher export values and export propensity, but not for Indonesia or Mexico. In contrast, we find no clear trade effects for firms of adopting E-commerce technology during COVID, despite many firms doing so in our three countries.

The paper next examines possible mechanisms for the distinction in results between existing E-commerce users prior to COVID and firms that adopted technology especially during COVID. Firms do not adopt technologies at random but because of the expected returns to doing so, thus pre-existing E-commerce users may have different characteristics to those that adopt out of necessity when lockdowns hit domestically. Alternatively, leveraging technology requires reorganization and can take time to materialize into performance changes, thus it may be too soon to measure any trade effects of COVID adoption. We do not find that pre-existing users and COVID adopters have significantly different characteristics, but rather find some support for the second mechanism. Even among pre-existing E-commerce users, those firms that used the technology earlier, more than one year before COVID, had more resilient trade than those that adopted in 2019.

This paper contributes to a literature examining links between firm-level technology and international trade. Micro-level studies for the United Kingdom, African countries and China by, respectively, Kneller and Timmis (2016), Hjort and Poulsen (2019) and Fernandes et al. (2019), show strong positive impacts of access and use of traditional or broadband internet on firms' propensity to export, export values, productivity, and employment. A much smaller literature focuses specifically on e-commerce as we do here. Lendle et al. (2016) show the eBay online platform alleviates some of the negative impact of geographic distance on international trade flows especially for differentiated products. Alcedo et al. (2021) use data from the Chinese AliExpress platform to show how buyer search costs and information frictions affect cross-border e-commerce. Ma et al. (2021) show that a Chinese policy to remove licensing and inspection requirements for e-commerce products led to large increases in imports of these goods. Carballo et al. (2022) find that participation in an online platform that provides trade information and information on potential trade partners, led to increased firm exports, particularly the trade of small firms and differentiated products, to less familiar destinations.

The paper adds to a growing literature on the impacts of COVID-19 on trade at the country-product level (Bas et al., 2023; Berthou and Stumpner, 2022; Bonadio et al., 2021; Demir and Javorcik, 2020; Espitia et al., 2022; Liu et al., 2022) or at the firm-level using panel data (Amador et al., 2023; Bricongne et al., 2021; de Lucio et al., 2022; Constantinescu et al., 2022; Lafrogne-Joussier et al., 2023). The studies show significant declines in trade the first semester of 2020 followed by partial recovery, indicating some adaptation by internationally integrated firms. Closest to our study is Constantinescu et al. (2022) that examines linkages between trade and digital technology adoption in face of the COVID-19 pandemic, relying on cross-sectional firm-level survey data for 45 countries. They show that globally engaged firms are recovering faster from COVID-19, possibly due to their heightened response in terms of finding novel ways to adapt supply chains even in the presence of lockdowns and uncertainty through increases in the use of digital technologies (and in product innovation).

This paper also contributes to a literature examining how COVID-19 spurred the growth of E-commerce or digital finance. The majority of these papers, especially focused on developing countries, consider country aggregates, rather than firm-level analysis as we do here. Fu and Mishra (2022) and Auer et al. (2022) show that the timing of COVID lockdowns across countries predicted increases in downloads of fintech apps and remote credit card retail payments. Bai et al. (2022) use Mastercard credit card data to show that online payments increased after COVID, with persistent increases in online retail and restaurant credit card payments. Ragoussis and Timmis (2022) use technology data from BuiltWith for 185 countries (the data used in this paper) and demonstrate the timing of COVID lockdowns predicts large increases in the share of websites with e-commerce or online payment functionality and these increases are especially acute for countries with the largest initial use of these technologies. Of particular relevance to our study, Apedo-Amah et al. (2020) use a World Bank firm-level survey of 51 developing countries to show large numbers of firms are increasing their use of digital platforms post-COVID.

The rest of the paper is organized as follows, the next section presents the data and descriptive trends in trade and technology use, the third section explains the empirical methodology, the fourth presents our results and the final section concludes.

2 Data and Descriptive Trends

High-frequency trade data from customs extracted from the S&P Global Market Intelligence's Panjiva trade data platform covering the universe of export and import transactions of India, Indonesia, and Mexico is used. The sample periods differ across countries: July 2018-December 2021 for India and Mexico and February 2019- June 2021 (imports) or September 2021 (exports) for Indonesia. The data includes information on the shippers (exporting firms) and the consignees (importing) for each transaction: their names and addresses (in most cases). We use machine learning and text analysis techniques to clean the firm names and assign a unique firm identifier to each name in order to construct for each country a high-frequency panel of firms engaged in exports or imports. The data includes Harmonized System 6-digit codes for the products traded (HS6 product in what follows) and the code for the partner country. For each country, we construct export and import values firm-HS6 product-month-year measured in US dollars. Details on data preparation and cleaning, in particular the fuzzy matching algorithms used to clean firm names and obtain unique firm identifiers are provided in the Appendix.

The quality of the data is assessed as in Fernandes et al. (2016) by a comparison of total exports and total imports obtained from aggregating the transaction-level data at year level with the total yearly exports and imports (excluding oil HS chapter 27) for each country from WITS/COMTRADE. For all countries, the ratios to WITS/COMTRADE in the period 2018-2021 are in the 93%-100% range for exports and 83%-98% for imports over the sample period.

In order to identify the digital technologies of the exporting and importing firms in India, Indonesia and Mexico, we match the firm-level trade data with monthly measures of firm E-commerce technologies from BuiltWith relying on firm names and addresses for the matching. The measures are obtained from the source-code information embedded in websites across the globe. As such, these measures reflect the presence of technology functionality (such as E-commerce capability), rather than the intensity of use of these technologies (such as the volume of E-commerce transactions). Websites are crawled such that each website is scraped every 1 to 4 weeks. The most popular websites defined by their Google PageRank (and likely those with the highest frequency of changes) are scraped every week. The BuiltWith data is available for all the near universe of websites around the world (roughly 550 million websites), and has been collected in the same manner from 2018 onwards. The set of websites is obtained from public secure socket layer (SSL) lists on a monthly basis. This became a de-facto public ledger of all secure websites (i.e. those with SSL certificates) since becoming a Google Chrome requirement in April 2018, so-called Certificate Transparency. BuiltWith also undertakes an extensive twice-yearly exercise to add additional websites based on following links within websites already in the data. Links pointing to websites not in the data are added.

The BuiltWith data contains rich information on up to 27,000 specific website technologies across 21 categories (at the granularity level of technology provider, e.g. Google or Shopify). We focus on two categories for our analysis: the presence of e-commerce functionality (reflecting the ability to sell online to customers either within the firm's website itself or links to e-commerce platforms) and online payment functionality (such as credit card payments or links to payment processors such as Paypal). Our technology measure reflects the presence of at least one e-commerce or payment technology in a firm's website in a given month.[2] Measures of e-commerce technologies embedded in a firm's website are likely to be a lower bound of all technology use, as firms can engage in e-commerce through social media or other digital platforms in addition to their own website. However, firm websites appear to reflect the bulk of e-commerce activity, for example, in Europe, for example, nearly 90% of firm e-commerce sales are through their own website rather than an online platform (Eurostat, 2020).

Additional firm-level information on NAICS industries and firm performance measures (like sales, employment, foreign ownership) is obtained from Aberdeen Ci Technology Database (CiTDB). This database is matched to the other data using firms names and addresses. The Aberdeen data uses Dun and Bradstreet as a sampling frame. The data has been shown to be virtually representative of the US firm distribution, and for developing countries has a close correlation after sectors with high levels of informality are excluded, like agriculture and construction (Barnatchez et al., 2017; Coscia et al., 2020).[3] Since our focus is only on trading firms, i.e. that tend to be at the top of the firm size distribution, coverage is less likely to be a concern. We use the NAICS industries to exclude from our sample firms in the public, education and the health sectors - because these firms are likely to be directly affected by government COVID response and are less likely to trade goods in any case.

BuiltWith contains information at the website-level and Panjiva and Aberdeen at the firm-level, and we use Google and Bing API to match these two data sets using firm names and addresses. We first match Panjiva and Aberdeen data. We clean and standardize the firm names and addresses in Panjiva and Aberdeen (e.g. removing common suffixes like "Ltd"), and convert the addresses to geographical coordinates in each using Google Places API, with Bing Maps API uses as a robustness for these coordinates. We match the Panjiva and Aberdeen firms by assigning probability weights using a combination of geographic proximity

[2] Our baseline measure assumes firms do not drop the technology once it is first observed, but results are robust to allowing for instances of dropping.

[3] The correlation with aggregate employment statistics exceeds 70% and 80% for Mexico and India respectively, Indonesia has a correlation of around 25%, see Coscia et al. (2020).

and semantic similarity of the firm names. We match the Panjiva-Aberdeen data to BuilWith using the company websites that are also obtained from Google Places API, after excluding links to social media sites. We undertook an extensive set of manual checks to validate the matches and improve the matching algorithm. Firstly, we randomly took a sample of 250 firms for each country and manually searched for each firm online to determine if the match to BuiltWith was correct. We find that 80% of matches were correct, 15% were false positives (i.e. the firm was matched to the wrong website) and 5% were false negatives (i.e. the firm had a website that wasn't found). Secondly, we manually examined nearly 100,000 cases of borderline matches to refine the matching algorithm and adjust the probability weights. Further details on the matching are in Appendix Section A.2.

The trade values in the matched data and original Panjiva sample are compared in Appendix Section A.3. Since not every firm has their own website, and several may rely on a social media presence, not every trading firm is expected to be in the matched data. In our manual checking this was found to be the case for 45% of the trading firms, which can be considered an upper bound benchmark matching rate. We match around 47% of Panjiva trading firms for India, 38% of firms in Indonesia, and 44% of firms for Mexico to the BuiltWith data. However, since larger firms are more likely to have a web presence, these matched firms account for around 65%, 58% and 52% of total trade value in India, Indonesia and Mexico respectively. Note that the match rates to all three datasets (i.e. Panjiva-Builtwith-Abeerdeen) is somewhat lower, especially for Mexico due to a small Aberdeen sample size.

Our analysis uses both differences in firm technology use and differences in e-tradeability of products, as discussed in Section 3. Specifically, we use e-commerce products defined by Ma et al. (2021) in our baseline analysis and consumer goods defined by Broad Economic Categories (BEC) in the Appendix. In 2016 China developed a Cross Border E-Commerce Retail Import Goods list that reflects HS 10-digit products that can be imported directly to Chinese consumers through online platforms or websites (see Ma et al. (2021)). Two channels of direct import are possible for these products: 1) direct shipment - where goods stored abroad are purchased online and imported directly to individual Chinese consumers and 2) bonded warehouse imports - where goods are bulk imported to China and stored in an approved warehouse, before being sold online and shipped directly to individual Chinese consumers. The classification has been updated slightly over time, we use the initial 2016 list, before our sample period.[4] We convert the 10-digit classification to the HS 6-digit level of our trade data, assuming that if any individual 10-digit product is included in the Cross-Border E-commerce list then the corresponding 6-digit good is E-tradeable.

[4]Our results are also robust to using the 2019 or 2020 updates to this classification

To capture the stringency of COVID lockdowns, we rely on the COVID stringency index from the Oxford COVID-19 Government Response Tracker. The index is a composite measure based on nine response indicators including school closures, workplace closures, and travel bans, scaled to take values from 0 to 100 with 100 indicating higher stringency. The index is available for each country daily and we take the monthly average.[5] The indexes are available for each country until the last month in the sample period: December 2021 for India and Mexico and September 2021 for Indonesia.

Table 1 presents some descriptive statistics on the samples covering all matched firms for each country's exports and imports separately. The number of firms is substantially larger in India, more than 27,000, than in either Indonesia or Mexico, between 2,400 and 4,300. Median trade values per firm-HS6 product-month are largest for Indonesian exports (about 14 thousand US dollars) and smallest for Mexican imports (about 2 thousand US dollars). Mean import values are similar across the three countries while mean export values are similar across Indonesia and Mexico and are substantially higher than mean imports. The distributions are highly right-skewed for both trade flows in all countries. On firm technology adoption, the samples include a larger share of observations for which the firm adopted E-payment or E-commerce in Mexico (about 30%) than in India and Indonesia (close to 17%). The samples include about one third of observations corresponding to E-tradeable goods but less than 20% corresponding to BEC consumer goods (with this type of goods being particularly less prevalent in the Mexico samples).

Table 1: Summary statistics for samples of all firms

		Export or Import Trade Value (USD)							
	No. Firms	p25	Median	p75	Mean	SD	Firm technology adoption pre-2019	E-tradeable Goods	BEC Consumer Goods
Indonesia									
Exports	2,250	$834.00	$14,128.15	$130,033.11	$666,919.7	$19,822,958	0.171	0.349	0.162
Imports	4,278	$775.83	$ 5,208.00	$ 31,852.22	$110,815.6	$ 2,366,617	0.169	0.271	0.053
India									
Exports	27,159	$687.20	$ 5,249.81	$ 35,216.75	$134,187.7	$ 1,734,736	0.154	0.384	0.186
Imports	28,022	$625.01	$ 4,801.50	$ 30,250.00	$107,118.3	$ 1,690,903	0.188	0.282	0.062
Mexico									
Exports	2,463	$247.96	$ 2,419.99	$ 26,685.68	$635,656.7	$11,491,128	0.299	0.347	0.072
Imports	3,618	$311.30	$ 1,988.29	$ 14,692.11	$109,330.7	$ 2,353,136	0.292	0.305	0.053

Notes: The summary statistics shown cover all types of firms in the matched samples: firms that never adopt digital technology as well as firms that adopt digital technology up to the end of 2018 or in 2019-2021. The summary statistics cover the July 2018-December 2021 period for India and Mexico, the February 2019-June 2021 period for Indonesia's exports and the February 2019-September 2021 period for Indonesia's imports. The firm technology adoption pre-2019, E-tradeable goods, and the BEC consumer goods variables are all indicator variables, and what is shown in the last three columns is the share of trade value for observations that have those variables equal to 1.

[5] See Oxford COVID-19 Government Response Tracker data. The index is described at: ourworldindata.org.

Table 2 presents descriptive statistics for the samples covering matched firms that do not adopt technology as well those that adopt digital technology in the period from mid-July to end-2021 for each country's exports and imports separately. The number of firms covered in these samples is smaller than in those described in Table 1 as these samples exclude firms that adopt technology prior to July 2018. Naturally, the rate of firm technology adoption is smaller in these samples than those in Table 1. The share of observations for which the firm adopted E-payment or E-commerce in Mexico (about 15%) is larger than the shares for India (close to 10%) and Indonesia (about 5%). The samples include about one third of observations corresponding to E-tradeable goods but less than 20% corresponding to BEC consumer goods.

Appendix Tables A.4 and A.5 show the number of firm-HS6 product-month-year observations and of products classified as E-tradeable goods and BEC consumer goods for both samples considered in Table 1 and 2, respectively. On average across the three countries out of more than 4,000 unique HS 6-digit codes, close to 1,000 are E-tradeable goods and close to 500 are consumer products.

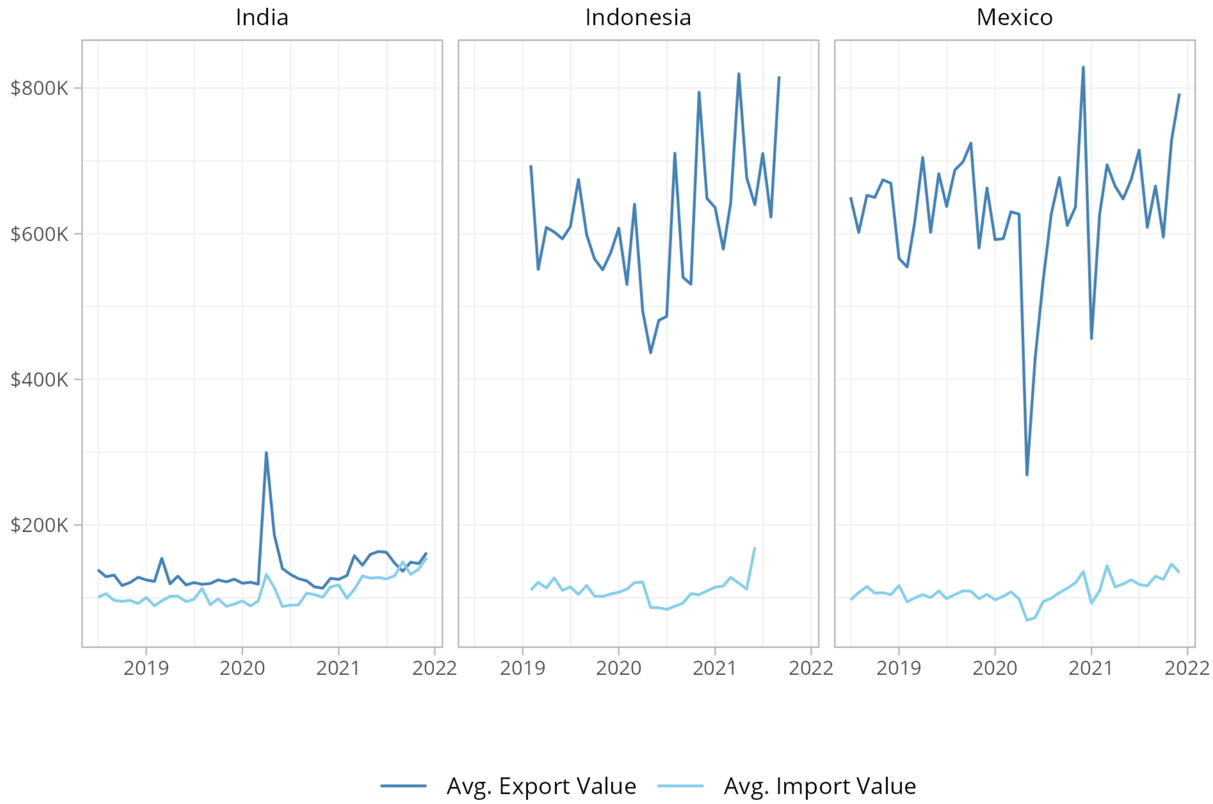
Table 2: Summary statistics for samples including firms that never adopt digital technology and firms that adopt digital technology in the mid-2018-2021 period

		Export or Import Trade Value (USD)							
	No. Firms	p25	Median	p75	Mean	SD	Firm technology adoption	E-tradeable Goods	BEC Consumer Goods
Indonesia									
Exports	1,930	$877.00	$16,068.61	$142,364.50	$688,817.70	$21,440,629	0.045	0.349	0.161
Imports	3,628	$816.82	$ 5,422.89	$ 32,895.75	$112,218.53	$ 2,552,736	0.054	0.264	0.049
India									
Exports	23,985	$749.94	$ 5,754.04	$ 38,118.44	$141,032.19	$ 1,796,577	0.086	0.373	0.176
Imports	24,790	$681.63	$ 5,168.10	$ 32,092.97	$112,991.00	$ 1,745,866	0.103	0.267	0.052
Mexico									
Exports	1,978	$275.01	$ 2,861.31	$ 33,050.21	$518,485.94	$ 8,149,436	0.152	0.342	0.066
Imports	2,893	$314.06	$ 1,972.19	$ 14,473.08	$ 88,795.32	$ 1,657,786	0.153	0.291	0.041

Notes: The summary statistics cover the July 2018-December 2021 period for India and Mexico, the February 2019-June 2021 period for Indonesia's exports and the February 2019-September 2021 period for Indonesia's imports. The firm technology adoption, the E-tradeable goods, and the BEC consumer goods variables are all indicator variables, and what is shown in the last three columns is the share of trade value for observations that have those variables equal to 1.

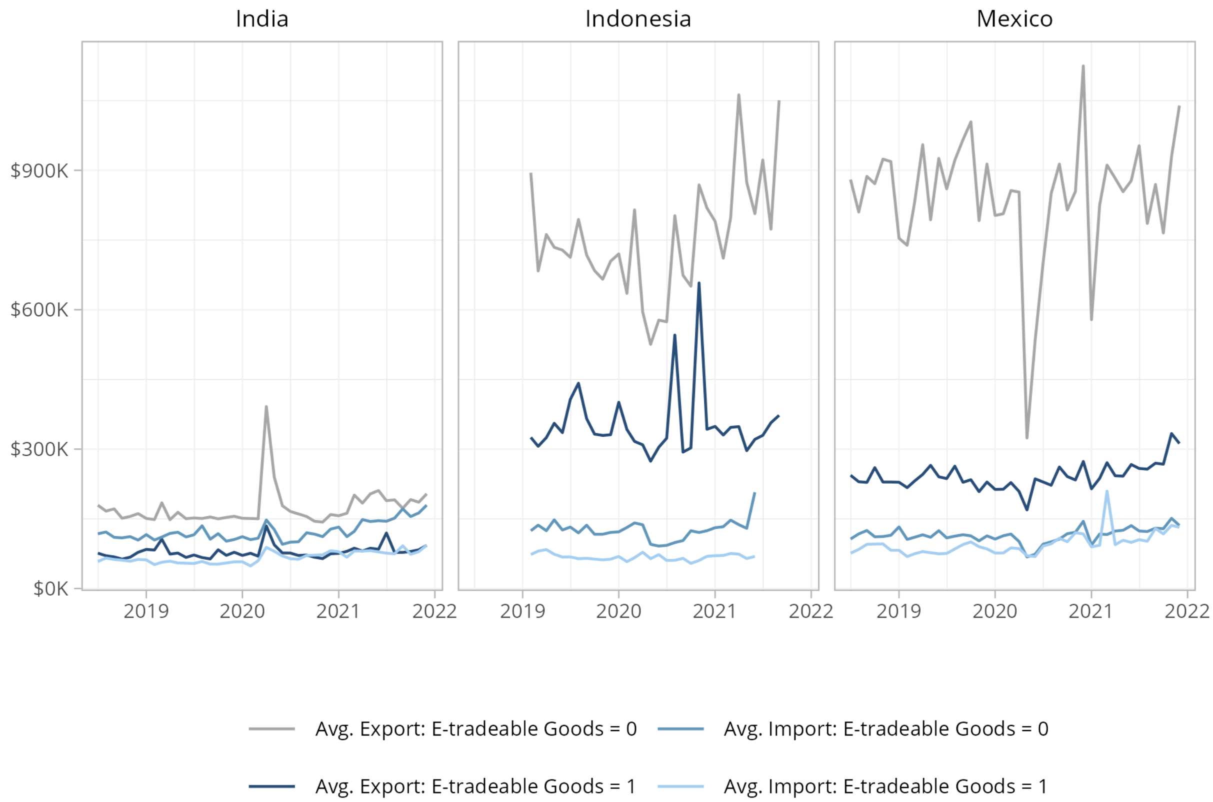
Figure 1 plots for each country average exports and imports at the firm-HS6 product-month level for the period ranging from July 2018 to December 2021. For Indonesia and Mexico average exports and to a lesser extent average imports show a strong dip at the onset of the COVID pandemic, in the first half of 2020. For India the timing of the COVID effects is different, with no initial dip but instead a strong increase around mid-2020 followed by a strong dip towards the end of 2020. Figure 2 shows average exports and imports separately for firm-HS6 product-month observations of E-tradeable goods versus firm-HS6 product-month observations of other goods. In all countries, average exports of E-tradeable goods are higher than those of other goods throughout the period, and they declined more strongly at the onset of COVID but also recovered substantially faster subsequently. Imports of E-tradeable goods do not differ much from imports of other goods in levels and trends over the period. In particular both types of imports experienced a decline in the first half of 2020 in Indonesia and Mexico and towards end 2020 in India.

Figure 1: Trends in firm-HS6 product-month-year average exports and imports



Notes: In each plot, the dark and light blue lines depict average firm-HS6 product-month-year export and import values (in US dollars), respectively. Sample periods are as follows: India and Mexico (July 2018 - December 2021), Indonesia's imports (February 2019 - June 2021) and Indonesia's exports (February 2019 - September 2021).

Figure 2: Trends in average firm-HS6 product-month-year exports and imports across E-tradeable goods and other goods

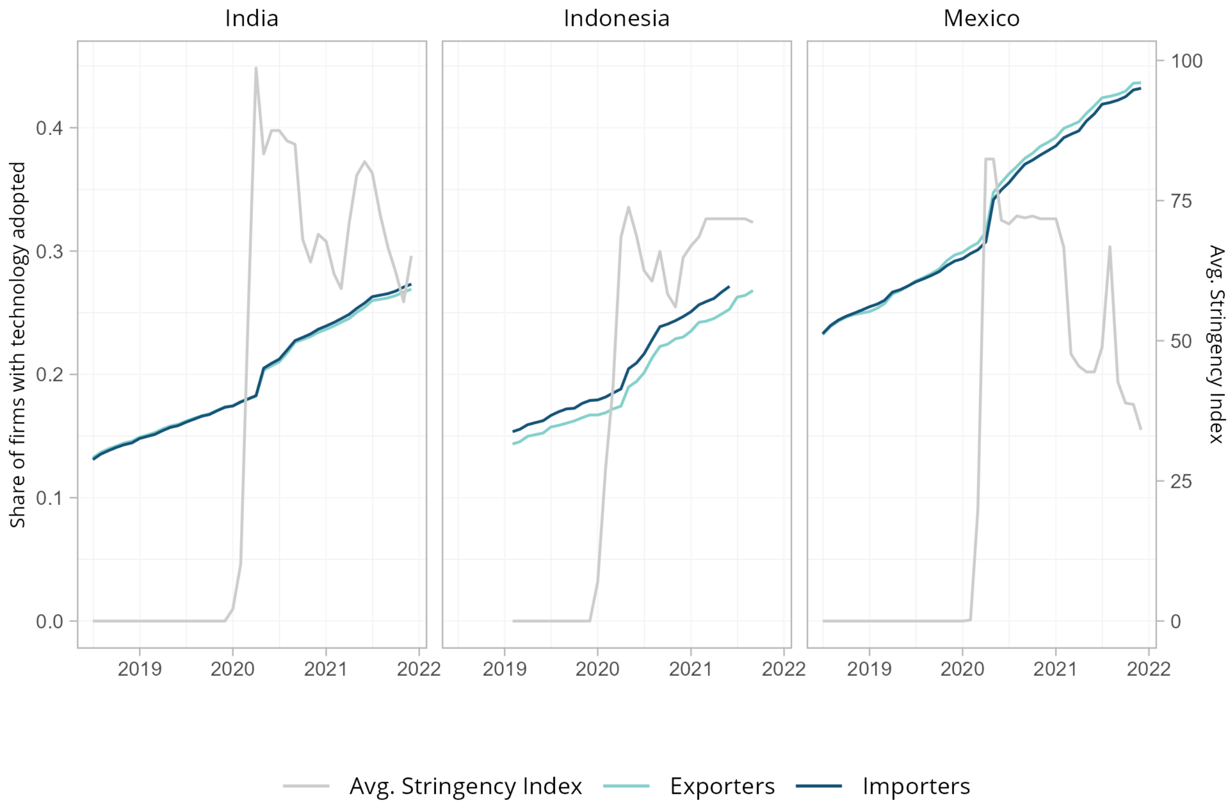


Notes: In each plot, the lightest blue line illustrates the average firm-HS6 product-month import value (in US dollars) for HS6 products classified as E-tradeable goods. The second lightest blue line represents the average firm-HS6 product-month import value for HS6 products not classified as E-tradeable goods. The darkest blue line denotes the average firm-HS6 product-month export value for products classified as E-tradeable goods. The grey line represents the average firm-HS6 product-month export value for HS6 products not classified as E-tradeable goods. Sample periods are as follows: India and Mexico (July 2018 - December 2021), Indonesia's imports (February 2019 - June 2021), and Indonesia's exports (February 2019 - September 2021)

Figure 3 presents the trends in firm digital technology adoption rates in the three countries for the period ranging from July 2018 to December 2021.[6] The outstanding pattern verified for the three countries, whether the sample of exporters or importers is considered, is an important increase in the rate of technology adoption as the COVID pandemic started. This higher rate continues to grow thereafter in all countries.

[6]Technology adoption rates are based on the samples of all exporters or all importers that are described in Table 1.

Figure 3: Firm technology adoption rates and COVID-19 stringency indexes



Notes: In each plot, the left y-axis shows the scale for the share of firms with the technology adopted and the right y-axis shows the scale for the average COVID-19 stringency index. The dark and light blue lines represent the adoption rates for importers and exporters, respectively. The grey line denotes the average COVID-19 Stringency Index. Sample periods are as follows: India and Mexico (July 2018 - December 2021), Indonesia's importers (February 2019 - June 2021) and Indonesia's exporters (February 2019 - September 2021).

3 Empirical Methodology

Our empirical analysis proceeds in two parts - distinguishing pre-2019 technology users and those that adopt especially during COVID. First, we examine whether a firm's pre-existing E-commerce use affects its resilience in terms of exports and imports to the COVID shock. Second, we focus on firms adopting E-commerce during COVID and how this affects their trade during the COVID period. As discussed in more detail below, for both sets of analyses we employ a triple-differences specification, contrasting the trade impacts across E-tradeable goods and other goods.

3.1 Role of firm pre-2019 technology use for firm trade

To understand the role that being an E-commerce technology user prior to 2019 plays in firms' trade resilience to the COVID shock, we estimate the following equation using data at the firm (i)-HS-6 digit product (p)-month-year level (t):

$$\begin{aligned} y_{ipt} = \alpha_0 + \alpha_1 tech_i \cdot covid_t + \alpha_2 covid_t \cdot etradeable_p + \alpha_3 tech_i \cdot covid_t \cdot etradeable_p \\ + FE_i + FE_p + FE_t + \epsilon_{ipt} \end{aligned} \tag{1}$$

We consider both the intensive margin of trade - the log values conditional on trade - and the probability of trading a given product - the extensive margin. For the intensive margin, y_{ipt} reflects the log value of firm i's imports (exports) of product p at time t, and for the extensive margin it is a dummy variable equal to one if product p is imported (exported) at time t. For the extensive margin using the set of all combinations of firms, months and HS6 product codes is computationally infeasible. Instead, we reflect the possibility of firms moving into more HS6 codes within the HS4 chapter they already trade in. Specifically, we calculate the extensive margin dummies using the set as all the possible HS6 codes for each firm that already trades at least one HS4 heading.

We employ triple differences that combine pre-existing differences in firm technology use, differences over time as COVID intensifies and differences across products that are E-tradeable or not. We define existing E-commerce technology users as those firms for whom the presence of E-commerce or Online Payment functionality was measured in their website up to the end of 2018 ($tech_i = 1$). We compare these pre-2019 technology users against all other firms, that is, firms that adopt E-commerce technology in 2019-2021 as well as firms that never adopt E-commerce technology in our entire sample period. We contrast the performance of pre-COVID technology users against that of other firms over time as COVID intensifies, measured by the Oxford University's COVID stringency index ($covid_t$). The final difference compares goods that are more easily E-tradeable ($etradeable_p$) to other goods. As defined in the previous section, our baseline measure E-tradeable goods is taken from Ma et al. (2021), and we examine robustness to using the BEC definition of consumer goods in the Appendix. We include firm, product and month-year fixed effects as denoted by FE_i, FE_p and FE_t, respectively.[7] Our coefficient of interest, the triple-difference, is given by α_3. We report robust standard errors that are clustered at the firm-product level.

Estimating the effects of firm technology on firm trade is of course subject to familiar

[7]The fixed effects for firms and products account for the levels of the variables entering the triple differences.

endogeneity concerns. Firms do not adopt technology at random, but because of the expected returns of doing so, and so technology use is often correlated with often unobservable firm characteristics like skills or management quality. Inclusion of firm and product fixed effects controls for any unobserved slow-moving firm or product specific factors. However, this does not control for time-varying unobservables, for instance if management quality is correlated with differential trade trends during COVID (Bloom et al., 2021), which motivates our triple difference (DDD) estimation that encompasses differences across product types.

One advantage of the DDD approach is that it does not depend on the two parallel trends assumptions for a causal interpretation, but rather a weaker identification assumption (as illustrated by Olden and Møen (2022)). Under this approach, we do not require that pre-COVID technology users and other firms have common trade trends during COVID in any given product type (e.g. for E-tradeable products) - that is, we can allow pre-COVID technology users and other firms to have differing trade trends during COVID. But rather, identification requires each group of firms to have a common trend in their trade of E-tradeable products as a share of non-E-tradeable products.

In examining potential mechanisms behind our results (Section 4.3) we examine whether there are heterogeneous impacts across earlier and later technology users - since technology can take time to materialize into performance effects. Specifically, we decompose the dummy variable ($tech_i = 1$) reflecting existing E-commerce technology before 2019, into the different years the technology was first used - 2018 adopters and 2017 (or earlier) adopters.

3.2 Role of firm technology adoption for firm trade

To understand the effect of the adoption of E-commerce technology on firms' subsequent trade performance, we estimate the following equation using data at the firm (i)-HS-6 digit product (p)-month-year level (t):

$$y_{ipt} = \alpha_0 + \alpha_1 tech_{i,t-2} + \alpha_2 tech_{i,t-2} \cdot etradeable_p + FE_i + FE_p + FE_t + \epsilon_{ipt} \tag{2}$$

We employ triple differences that combine changes in firm technology use over time (compared to non-adopters) with differences across products that are E-tradeable or not. The outcome (y_{ipt} denotes measures of the intensive and extensive margins of trade as defined earlier. The variable $tech_{i,t-2}$ reflects the time-varying presence of E-commerce or Online Payment functionality within a firm's website, which we lag two months since any trade impacts are unlikely to be instantaneous.[8] The variable $tech_{i,t-2}$ takes the value one for months after the technology is first detected and zero otherwise. We restrict the sample to

[8]In unreported results we consider robustness to alternative lag lengths with similar findings.

only include firms that do not have the technology at the end of 2018 (so it excludes the pre-existing E-commerce technology users considered in the previous sub-section). Therefore our sample contrasts the trade performance of firms adopting the technology during 2019-2021 and those that never adopt. Our estimation measures trade impacts for technology adopting firms, which are mostly comprised of firms adopting post-COVID despite our inclusion of pre-COVID periods in the estimation (recall the large increases in technology adoption post-COVID in Figure 3).

Our coefficient of interest, the triple-difference, is given by α_2. As in the previous section, $etradeable_p$ reflects the measure E-tradeable goods (or consumer goods in the Appendix) and we include firm, product and month-year fixed effects as denoted by FE_i, FE_p and FE_t, respectively. Under our triple difference approach, identification requires firms that adopt technology and do not adopt to have a common trend in their trade of E-tradeable products as a share of non-E-tradeable products.

4 Results

In this section, we present the results from studying the effects of existing digital technology use and new digital technology adoption on firm trade.

4.1 Results on the role of firm pre-COVID technology use for firm trade

In this section, we investigate whether firms that had adopted E-payment or E-commerce technology before 2019 were better equipped to mitigate the impacts of COVID on their trade outcomes.

The results in Table 3, columns 1 and 2, show that among Indian firms that had already adopted E-payment or E-commerce by 2019 as monthly COVID stringency increased, those that traded E-tradeable goods experienced a 0.3% rise in imports and a 0.1% rise in exports compared to those trading other goods. We find a similar effect for Mexican firms that import E-tradeable goods (columns 3 and 4) but no effect for Indonesian firms (columns 5 and 6).

Using consumer goods as an alternative measure of e-tradeability we find somewhat stronger results, a 0.4% to 0.6% increase in firm imports in India, Indonesia and Mexico, and a 0.2% and 0.6% rise in Indian and Indonesian firm exports respectively (see Appendix Table A.6). We do not find an association with Mexican firm exports.

Table 3: COVID stringency and firm trade at intensive margin - mediating role of digital technology use and E-tradeable goods

	India		Mexico		Indonesia	
	Log. Imports	Log. Exports	Log. Imports	Log. Exports	Log. Imports	Log. Exports
Firm technology adoption pre-2019 × COVID stringency index	-0.001***	0.000	-0.001**	0.000	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
COVID stringency index × E-tradeable Goods	0.000	0.000**	-0.001*	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Firm technology adoption pre-2019 × COVID stringency index × E-tradeable Goods	0.003***	0.001**	0.003***	0.000	0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Num. Obs.	2,575,520	2,205,440	2,258,374	500,300	1,164,711	231,536
R-squared	0.436	0.467	0.323	0.428	0.382	0.564
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The variable Firm technology adoption pre-2019 is a dummy equal to 1 if the company adopted the E-payment or E-commerce technology up to December 2018 and 0 if not. The sample period for the regressions is July 2018-December 2021 for India and Mexico, February 2019-June 2021 for Indonesia's exports and February 2019-September 2021 for Indonesia's imports. Clustered-standard errors at the firm-product level. *p<0.1; **p<0.05; ***p<0.01.

This pattern of results is similar at the extensive margin of firm trade. Columns (1) and (2) of Table 4, show that Indian firms that had already adopted E-payment or E-commerce by 2019 experienced a 0.011% increase in the propensity to import and a 0.005% increase in the propensity to export any HS 6-digit E-tradeable good as COVID stringency increased. Similar to the intensive margin results for Mexico, we find that Mexican firms experience a 0.018% increase in the propensity to import E-tradeable goods but no corresponding changes in the propensity to export such goods as the pandemic unfolds. Indonesian firms also experience a 0.015% increase in the propensity to import E-tradeable goods.

Employing consumer goods as an alternative measure of e-tradeability we find similar results, an increase in the propensity of both Indian firms to export and import consumer goods products and Mexican firm imports of these goods, but no relationship for Indonesian firm trade propensity (see Appendix Table A.7). We do not find an association with Mexican firm export propensity.

Overall, we find strong evidence across countries that firm imports of E-tradeable goods were more resilient to the COVID shock compared to those of other goods. Specifically for India, we find evidence that both the imports, as well as the exports of E-tradeable goods were more resilient.

Table 4: COVID stringency and firm trade at extensive margin - mediating role of digital technology use and E-tradeable products

	India		Mexico		Indonesia	
	Import Propensity	Export Propensity	Import Propensity	Export Propensity	Import Propensity	Export Propensity
Firm technology adoption pre-2019 × COVID stringency index	-0.00003***	-0.00002*	-0.00005***	-0.00002	-0.00001	-0.00009
	(0.00001)	(0.00001)	(0.00002)	(0.00002)	(0.00003)	(0.00011)
COVID stringency index × E-tradeable Goods	-0.00007***	-0.00004***	-0.00014***	-0.00007***	-0.00001	0.00009
	(0.00001)	(0.00001)	(0.00002)	(0.00002)	(0.00002)	(0.00011)
Firm technology adoption pre-2019 × COVID stringency index × E-tradeable Goods	0.00011***	0.00005***	0.00018***	0.00007	0.00015***	-0.00002
	(0.00002)	(0.00001)	(0.00004)	(0.00006)	(0.00005)	(0.00012)
Num. Obs.	99,999,522	79,418,640	43,128,750	11,329,164	24,584,692	5,019,264
R-squared	0.065	0.075	0.118	0.123	0.096	0.136
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The variable Firm technology adoption pre-2019 is a dummy equal to 1 if the company adopted the E-payment or E-commerce technology up to December 2018and 0 if not. The sample period for the regressions is July 2018-December 2021 for India and Mexico, February 2019-June 2021 for Indonesia's exports and February 2019-September 2021 for Indonesia's imports. Clustered-standard errors at the firm-product level. *p<0.1; **p<0.05; ***p<0.01.

4.2 Results on the role of firm technology adoption for firm trade

In this section, instead of looking at the effects on trade for firms with pre-2019 E-commerce technology use, we study whether digital technology adoption affects firm trade. Since the effects of technology on trade can take some time to materialize, we allow for a two-month lag in the impact of technology adoption on firm trade at either the intensive margin in Table 6 or the extensive margin in Table 5. For firms who adopted technology 2 months ago, we compare their exports and imports on average across all goods, and then separately identify effects for those of E-tradeable goods. Across the three countries, we find almost no conclusive evidence of a differential effect of technology adoption on firm exports and imports of E-tradeable products. For Mexico, while technology adoption does foster firm exports on average in column 4 of Table 6, there is no differential benefit for E-tradeable goods. For Indonesia, even though there is a weak positive average effect of digital technology adoption on exports at the intensive margin (Table 5, column 6), the effect is negative for E-tradeable goods. The same is verified for exports at the extensive margin (Table 6, column 6). For India, there is evidence of growth in the trade of E-tradeable goods compared to other goods after the firm adopts digital technologies but only at the extensive margin.

Overall, the evidence suggests that there is no conclusive relationship between lagged technology adoption and firm trade in our three countries' samples.

Table 5: Lagged digital technology adoption and firm trade at intensive margin

	India		Mexico		Indonesia	
	Log. Imports	Log. Exports	Log. Imports	Log. Exports	Log. Imports	Log. Exports
Firm technology adoption 2-month lag	0.025	-0.032	-0.027	0.155***	0.031	0.134
	(0.022)	(0.030)	(0.028)	(0.051)	(0.030)	(0.090)
Firm technology adoption 2-month lag × E-tradeable Goods	-0.028	0.018	0.071	-0.115	-0.006	-0.376**
	(0.042)	(0.046)	(0.057)	(0.105)	(0.068)	(0.182)
Num. Obs.	2,162,521	1,922,861	1,678,466	367,750	964,661	191,478
R-squared	0.444	0.47	0.335	0.44	0.393	0.587
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The sample period for the regressions is July 2018-December 2021 for India and Mexico, February 2019-June 2021 for Indonesia's exports and February 2019-September 2021 for Indonesia's imports. Clustered-standard errors at the firm-product level. *p<0.1; **p<0.05; ***p<0.01.

Table 6: Lagged digital technology adoption and firm trade at extensive margin

	India		Mexico		Indonesia	
	Import Propensity	Export Propensity	Import Propensity	Export Propensity	Import Propensity	Export Propensity
Firm technology adoption 2-month lag	-0.00056	-0.00060	0.00003	0.00041	-0.00261	0.00083
	(0.00065)	(0.00055)	(0.00090)	(0.00211)	(0.00192)	(0.00590)
Firm technology adoption 2-month lag × E-tradeable Goods	0.00226**	0.00231**	-0.00059	-0.00470	0.00470	-0.01354***
	(0.00102)	(0.00102)	(0.00198)	(0.00288)	(0.00410)	(0.00506)
Num. Obs.	86,846,928	69,771,870	33,694,962	8,733,480	20,804,600	4,176,480
R-squared	0.063	0.076	0.117	0.123	0.098	0.143
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Clustered-standard errors at the firm-product level. *p<0.1; **p<0.05; ***p<0.01. The sample period for the regressions is July 2018-December 2021 for India and Mexico, February 2019-June 2021 for Indonesia's exports and February 2019-September 2021 for Indonesia's imports.

4.3 Potential mechanisms

In this section, we investigate the potential mechanisms behind our main results: Why do we see pre-2019 technology users' trade outcomes being partially insulated from the effects of COVID, but firms adopting technology (especially heavily during COVID) do not seem to display any changes in trade patterns?

We first investigate if the selection of firms is driving these results, that is, are firms adopting technology early inherently different from firms adopting technology later? A literature has shown that users of digital technologies tend to be larger, more productive and more likely to export, but these differences are much more pronounced for more advanced technologies (like those related to data and Artificial Intelligence) rather than those related to E-commerce (Cirera et al., 2022; Haller and Siedschlag, 2011; Zolas et al., 2021).

To conduct this investigation, we consider two main categories of firms: (i) firms that adopted technology up to December 2019, that we designate as "old adopters" and (ii) firms that adopted technology from January 2020 to December 2021 (or the last sample month for Indonesia) that we designate as "COVID adopters". And we also consider two additional sub-categories of COVID adopters: (i) firms that adopted technology from January 2020 to December 2020 that we designate as “COVID early adopters” and (ii) firms that adopted technology in 2021 that we designate as “COVID late adopters”.[9]

Table 7 provides no evidence that old adopters are inherently bigger and hence more productive firms. If anything, there is mild evidence that firms who adopted technology during the COVID period are slightly bigger in terms of both imports and exports (columns 2 and 5) in India and Indonesia. Table 8 also does not show any size differences between early COVID adopters and late COVID adopters. Finally, Table 9 shows that even among pre-COVID old adopters, there are no consistent size differences between firms that adopted in 2017, 2018, or 2019 and those that adopted even earlier. Overall, we conclude that the selection of larger (and hence more productive) firms into technology adoption is not driving our results.

Table 7: Average firm trade size pre-COVID and digital technology adoption

	India		Mexico		Indonesia	
	Log. Imports	Log. Exports	Log. Imports	Log. Exports	Log. Imports	Log. Exports
COVID Adopter	0.082	0.114*	-0.003	0.001	0.258*	0.259
	(0.080)	(0.066)	(0.097)	(0.172)	(0.156)	(0.416)
Num. Obs.	114,708	77,392	101,695	21,675	43,602	6,872
R-squared	0.21	0.191	0.185	0.275	0.239	0.439
Product FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The coefficients shown are based on a regression of firm total trade pre-COVID on a “COVID Adopter” dummy variable equal to 1 if the firm adopted digital technology between January 2020 and December 2021, and 0 if the firm is an “Old Adopter”, meaning that it adopted the digital technology before January 2020. The estimating samples include only firms classified as either “COVID Adopters” or “Old Adopters” and the sample period is pre-COVID, spanning from July 2018 to December 2019 for India and Mexico, and from February 2019 to December 2019 for Indonesia. Clustered standard errors at the firm level. *p<0.1; **p<0.05; ***p<0.01.

[9] These categories of firms differ slightly from those used in previous sections but are more adequate to identify the mechanisms.

Table 8: Average firm trade size pre-COVID and types of COVID adopters

	India		Mexico		Indonesia	
	Log. Imports	Log. Exports	Log. Imports	Log. Exports	Log. Imports	Log. Exports
COVID Early Adopter	-0.005	-0.107	0.034	-0.165	-0.080	0.138
	(0.129)	(0.102)	(0.169)	(0.251)	(0.189)	(0.469)
Num. Obs.	43,299	28,647	31,048	6,928	15,783	2,437
R-squared	0.258	0.262	0.259	0.398	0.337	0.614
Product FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The coefficients shown are based on a regression of firm total trade pre-COVID on a "COVID Early Adopter" dummy variable equal to 1 if the firm adopted digital technology during 2020, and 0 if the firm is a "COVID Late Adopter", meaning that it adopted digital technology in 2021. The sample includes only firms classified as either "COVID Early Adopters" or "COVID Late Adopters" and the sample period is pre-COVID, spanning from July 2018 to December 2019 for India and Mexico, and from February 2019 to December 2019 for Indonesia. Clustered standard errors at the firm level. *p<0.1; **p<0.05; ***p<0.01.

Table 9: Average firm trade size pre-COVID and types of old adopters

	India		Mexico		Indonesia	
	Log. Imports	Log. Exports	Log. Imports	Log. Exports	Log. Imports	Log. Exports
2017-Adopter	-0.052	0.132	-0.004	0.488*		
	(0.155)	(0.144)	(0.165)	(0.268)		
2018-Adopter	-0.172	0.252**	-0.089	0.392*	-0.295	-0.043
	(0.130)	(0.103)	(0.162)	(0.234)	(0.298)	(0.630)
2019-Adopter	-0.106	0.225	-0.108	0.021	-0.199	-0.373
	(0.135)	(0.145)	(0.162)	(0.251)	(0.144)	(0.434)
Num. Obs.	71,409	48,745	70,647	14,747	25,819	4,255
R-squared	0.218	0.207	0.19	0.305	0.263	0.507
Product FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The coefficients shown are based on a regression of firm total trade pre-COVID on dummy variables "2017-Adopter", "2018-Adopter" and "2019-Adopters" equal to 1 if the firm adopted digital technology in the respective year, and 0 otherwise. The baseline category comprises firms that adopted digital technology before 2017 for India and Mexico and before 2018 for Indonesia. The sample includes only old adopters and the sample period for the regressions is pre-COVID, spanning from July 2018 to December 2019 for India and Mexico, and from February 2019 to December 2019 for Indonesia. Clustered standard errors at the firm level. *p<0.1; **p<0.05; ***p<0.01.

We next investigate whether our results are driven by the fact that it takes time for digital technology adoption to translate into increased firm trade. The literature has established that translating technology adoption into productivity gains requires reorganization of firm processes, which can take years to fully materialize (Brynjolfsson and Hitt, 2003; Bresnahan et al., 2002; Canzian et al., 2019; DeStefano et al., 2020; Leung, 2004). To do this, we study whether, as firms faced increased COVID stringency, those who were early technology adopters (adopters before 2017, during 2017, or 2018) saw larger increases in trade during COVID compared to the group of firms that adopted the technology from January 2019 onwards or never adopted it.

Table 10 provides evidence that firms who adopted technology early (in 2017 or before for India and Mexico and 2018 or before for Indonesia; during 2017 for India and Mexico; and during 2018 for India, Mexico, and Indonesia) had a significantly higher propensity to import E-tradeable goods as COVID stringency increased compared to the control group facing the same level of COVID stringency. Early adopters in India and Mexico also witnessed a significantly higher propensity to export E-tradeable goods as COVID stringency increased compared to the baseline firms.

Table 11 shows that among firms who adopted technology early (in 2017 or before for India and Mexico and 2018 or before for Indonesia; during 2017 for India and Mexico; and during 2018 for India, Mexico, and Indonesia) Indian firms have significantly higher value of E-tradeable goods imports as COVID stringency increased compared to the control firms. We find similar effects for Mexican firms but only for the earliest technology adopters (pre-2017). We do not observe any such effects for Indonesian firms, for whom we do not have pre-2017 data. Consistent with our earlier findings in the paper, most of these effects show up in firm imports rather than exports.

Table 10: COVID stringency and firm trade at extensive margin - different types of pre-2019 technology adopters

	India		Mexico		Indonesia	
	Import Propensity	Export Propensity	Import Propensity	Export Propensity	Import Propensity	Export Propensity
COVID stringency index × E-tradeable Goods	-0.00007***	-0.00004***	-0.00014***	-0.00007***	-0.00001	0.00009
	(0.00001)	(0.00001)	(0.00002)	(0.00002)	(0.00002)	(0.00011)
Pre-2017 Adopter × COVID stringency index	-0.00004***	-0.00003**	-0.00009***	-0.00002		
	(0.00001)	(0.00001)	(0.00003)	(0.00003)		
Pre-2017 Adopter × COVID stringency index × E-tradeable Goods	0.00013***	0.00006***	0.00028***	0.00007		
	(0.00002)	(0.00002)	(0.00007)	(0.00008)		
Pre-2018 Adopter × COVID stringency index					-0.00002	-0.00005
					(0.00005)	(0.00010)
Pre-2018 Adopter × COVID stringency index × E-tradeable Goods					0.00020***	0.00004
					(0.00006)	(0.00012)
2017-Adopter× COVID stringency index	-0.00005**	-0.00001	-0.00002	-0.00005		
	(0.00003)	(0.00001)	(0.00002)	(0.00004)		
2017-Adopter× COVID stringency index × E-tradeable Goods	0.00013*	0.00003	0.00013*	0.00027*		
	(0.00008)	(0.00003)	(0.00007)	(0.00015)		
2018-Adopter × COVID stringency index	-0.00002	0.00001	-0.00002	0.00000	0.00001	-0.00014
	(0.00001)	(0.00001)	(0.00002)	(0.00003)	(0.00005)	(0.00015)
2018-Adopter × COVID stringency index × E-tradeable Goods	0.00007**	0.00005**	0.00008	-0.00002	0.00009	-0.00010
	(0.00003)	(0.00002)	(0.00005)	(0.00007)	(0.00006)	(0.00013)
Num. Obs.	99,999,522	79,418,640	43,128,750	11,329,164	24,584,692	5,019,264
R-squared	0.065	0.075	0.118	0.123	0.096	0.136
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The regression sample comprises both "Pre-2019 Adopters" and "Non-Pre-2019 Adopters". The "Pre-2019 Adopters" category includes pre-2017, 2017, and 2018 adopters for India and Mexico, and pre-2018 and 2018 adopters for Indonesia. The "Non-Pre-2019 Adopters" category encompasses firms that either never adopted the e-commerce or e-payment technology or adopted it from 2019 onwards. The baseline category is "Non-Pre-2019 Adopters". The sample period for the regressions is July 2018-December 2021 for India and Mexico, February 2019-June 2021 for Indonesia's exports and February 2019-September 2021 for Indonesia's imports. Clustered-standard errors at the firm-product level. *p<0.1; **p<0.05; ***p<0.01.

Table 11: COVID stringency and firm trade at intensive margin - different types of pre-2019 technology adopters

	India		Mexico		Indonesia	
	Log. Imports	Log. Exports	Log. Imports	Log. Exports	Log. Imports	Log. Exports
COVID stringency index × E-tradeable Goods	-0.00023	-0.00047**	-0.00059*	-0.00014	0.00018	-0.00037
	(0.00023)	(0.00022)	(0.00033)	(0.00074)	(0.00032)	(0.00120)
Pre-2017 Adopter× COVID stringency index	-0.00107***	0.00025	-0.00137**	0.00034		
	(0.00040)	(0.00051)	(0.00065)	(0.00133)		
Pre-2017 Adopter× COVID stringency index× E-tradeable Goods	0.00201***	0.00114	0.00304**	-0.00158		
	(0.00072)	(0.00085)	(0.00143)	(0.00275)		
Pre-2018 Adopter × COVID stringency index					0.00008	0.00268
					(0.00076)	(0.00233)
Pre-2018 Adopter × COVID stringency index × E-tradeable Goods					0.00088	-0.00425
					(0.00150)	(0.00296)
2017-Adopter× COVID stringency index	-0.00266**	-0.00028	-0.00117	0.00074		
	(0.00122)	(0.00096)	(0.00078)	(0.00163)		
2017-Adopter× COVID stringency index × E-tradeable Goods	0.00568***	0.00213	0.00277	0.00055		
	(0.00177)	(0.00146)	(0.00173)	(0.00272)		
2018-Adopter× COVID stringency index	-0.00059	-0.00030	-0.00045	-0.00007	-0.00084	-0.00052
	(0.00055)	(0.00057)	(0.00055)	(0.00125)	(0.00099)	(0.00170)
2018-Adopter× COVID stringency index × E-tradeable Goods	0.00194*	0.00109	0.00200	-0.00005	0.00107	0.00199
	(0.00102)	(0.00093)	(0.00129)	(0.00246)	(0.00161)	(0.00301)
Num. Obs.	2,575,520	2,205,440	2,258,374	500,300	1,164,711	231,536
R-squared	0.436	0.467	0.323	0.428	0.382	0.564
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The regression sample comprises both "Pre-2019 Adopters" and "Non-Pre-2019 Adopters". The "Pre-2019 Adopters" category includes pre-2017, 2017, and 2018 adopters for India and Mexico, and pre-2018 and 2018 adopters for Indonesia. The non-pre-2019 adopters category encompasses firms that either never adopted the e-commerce or e-payment technology or adopted it from 2019 onwards. The baseline category is "Non-Pre-2019 Adopters". The sample period for the regressions is July 2018-December 2021 for India and Mexico, February 2019-June 2021 for Indonesia's exports and February 2019-September 2021 for Indonesia's imports. Clustered-standard errors at the firm-product level. *p<0.1; **p<0.05; ***p<0.01.

5 Conclusions

The COVID crisis constituted a substantial trade shock for firms. What started as a disruption to trade in parts and components from China transformed into a broader trade shock throughout 2020-2021. At the same time, lockdowns proliferated around the world, which led to a wave of firms adopting E-commerce technologies to reach customers remotely that were increasingly stuck at home. But how did the adoption of E-commerce affect the ability to reach customers abroad? Specifically, how did the possibility of engaging in E-commerce affect firm trade throughout the COVID crisis? And how did the trade performance differ across pre-existing E-commerce users and the waves of new adopters during COVID? This paper seeks to tackle these questions.

Since the COVID shock affected firms in multiple dimensions, disentangling causal effects is not straightforward. To do so we leverage granular and high-frequency firm-product customs and technology data to measure the effect of E-commerce on trade during the crisis. Firstly, this allows us to control for a rigorous set of fixed effects, to control for unobserved month and year, firm-level or product-level potential confounders. Secondly, we employ a triple differences estimation, leveraging differences not only across firms based on their technology use over time, but also differences across the online tradeability of HS-6 digit products. This approach has the advantage of allowing to control for differential effects of COVID across technology users and non-users, for instance, because of their different productivity or locations.

The results show that having E-commerce technology in place before COVID led to greater resilience of firm trade in E-tradeable goods as the stringency of COVID-lockdown measures increased. We find a higher propensity to import for firms in all three countries and higher import values for India and Mexico. For India, we also find higher export values and export propensity. In contrast, we find no clear trade effects for firms adopting E-commerce technology during COVID, despite many firms doing so in these three countries. The results indicate that the effects of technology adoption on trade take time to materialize and may not help adopting firms to immediately weather a crisis, such as the COVID pandemic.

These findings have several potential policy implications. Firstly, the rapid adoption of E-commerce technologies demonstrates that many firms had the prerequisites in place to adopt. In recent years the development of off-the-shelf E-commerce websites and platforms, the spread of digital financial services like mobile money, have dramatically increased the accessibility of E-commerce. At the same time, both selling and buying online requires relatively slow internet speeds and the rapid diffusion of mobile internet has widened access to the broadband required. That we see so many firms adopting E-commerce as COVID hits and their customers shift online, points to adoption barriers surrounding demand, rather than infrastructure or internal capabilities. This contrasts with much of the policy discussion of technology adoption in developing countries that has focused on infrastructure - for basic technologies like E-commerce, incentives rather than infrastructure appear to be the main constraint.

Our findings that technology adoption has little trade impact during COVID, but earlier adoption matters for resilience, are consistent with the literature on technology and productivity, which suggests that costly and time consuming reorganization and redesign of business processes are needed to turn adoption into productivity gains (Brynjolfsson and Hitt, 2003; Bresnahan et al., 2002; Leung, 2004). Simply bolting E-commerce onto existing business models is unlikely to achieve much, but rather productivity is achieved through digitizing in-house processes, taking advantage of online data to improve customer service or product quality, more targeted advertising online and improved management of inventory or supply chains. The literature finds that firms that tend to adopt earlier also tend to make such complementary investments - and these are often better managed firms to start with. The policy focus needs to go beyond only encouraging adoption towards ensuring firms make the organizational changes to turn this into performance gains.

Since the reorganization needed to leverage technology incurs both time and sunk costs, this highlights the importance of longer-term policies to create an environment favourable to these organizational investments. For instance, policies to create the digital and management skills needed are likely to help, as are those to spur competition, strengthening incentives for firms to reorganize and facilitating reallocation of scarce resources to the most innovative firms. The COVID crisis created the incentive for many firms to shift online, but the incentives to reorganize and reap the potential dividends depend on the broader business environment. Reactive policies responding to crises are no doubt important for mitigating some of their adverse impacts, but reaping the potential upside from crises also depends on longer-term broader reforms.

Given the richness of the data employed here, several possible extensions are likely to be fruitful directions for future work. Firstly, our analysis points to differences in returns to technology over time and the need for complementary investments. One could examine which firm characteristics affect these returns over time and utilize measures of complementary investments in IT human capital available in the Aberdeen data. Secondly, although we employ a novel triple differences estimation, the measurement of causal effects could be strengthened by using plausibly exogenous instrumental variables. Possible candidates could include sub-national variations in broadband infrastructure or industry differences in the importance of E-commerce. Finally, the Panjiva data contains rare information on both the importing firm and exporting firm (in the same transaction) that could be exploited to analyze the largely unexplored topic of how technology diffuses through international supply chains and what are potential policies that can spur such diffusion.

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A Appendix

A.1 Panjiva Trade Data

Our analysis relies on transaction-level trade data for India, Indonesia, and Mexico obtained from the S&P Global Market Intelligence's Panjiva data platform. Exporting and importing firms are identified by their names but firm names are noisy: names appear with multiple spellings or with spelling errors and some entries under firm names are not proper names but are instead a number or an address. In brief, the steps for the cleaning of names are as follows:

1. Eliminate from the list of firm names those entries that are not proper names (numbers, addresses, and the expressions 'NIL', 'N/A', or 'To the order').

2. Remove from the actual firm names a list of stop words or geographic stop words and any symbol (that is not a letter nor a number). The list of stop words was selected based on text analysis indicating the most common words appearing in firm company names, such as 'corporation', 'international', 'limited', 'llc'. We also remove from the firm names prefixes and suffixes for example 'co', 'sa' or 'pvc'.

3. Based on the list of pre-processed firm names obtained after Step 2, we use N-gram similarity (using cosine distance metrics) to identify potential pairs of similar firm names (using a lower similarity threshold of 0.6 where 1 means two names are identical).

4. The potential pairs of similar firm names identified in step 3 go through an algorithm to more precisely determine if they are really similar based on Levenshtein distance (i.e., a measure of the similarity between two strings). Cutoffs to determine what is a "small" distance between pairs of names are determined through machine learning algorithms based on subsamples of firm name pairs whose similarity was determined through manual inspection.

5. The pairs of similar firm names as identified in Step 4 are then sorted alphabetically so as to identify neighbor names (names that appear in consecutive rows after sorting) and correct any potentially similarity that may have been missed in Step 4.

6. The algorithms in Step 4 above generate some "big groups" of firm names considered to be similar because they share several common words. To break up these "big groups", firm names are sorted alphabetically within each group and if two consecutive firm names do not have sufficiently similar pre-processed names (as captured by a cutoff in the Levenshtein distance) the group is "broken" at that place so two separate groups of similar firm names result .

7. After similar firm names are identified from all steps above and are assigned a temporary unique numeric identifier, firm names are sorted alphabetically but also based on the firm address. If two consecutive names have similar addresses and similar names and did not have the same unique numeric identifier they will be joined in a a new final unique numeric identifier.

The steps above are applied to clean the names of exporting and importing firms in India, Indonesia, and Mexico. Some transactions are made by firms whose names indicate they are courier companies. Since these transactions are made for a third party, frequently individuals and since the total trade value is negligible respect we dropped all observations.[10] To focus on true commercial export and import transactions by firms, we attempt to identify transactions conducted by either individuals or by official entities (e.g., government departments, embassies, inspection agencies) based on the names indicated or on complementary information included in the Panjiva database. Such observations account for a very small total trade value in each of the countries. After incorporating unique identifiers for firms, the export and import data sets are subject to a series of cleaning procedures as detailed in Fernandes et al. (2016), namely dropping the very few observations for which trade value is 0 or missing, HS 6-digit product codes are missing or not part of the HS 2017 revision list, partner country is missing or is the own country (this may indicate transactions made with Special Economic Zones but this cannot be systematically assessed, so the information cannot be used). The quality of the data is assessed as in Fernandes et al. (2016) by a comparison of total exports and total imports obtained from aggregating the transaction-level data at year level with the total yearly exports and imports for the three countries obtained from COMTRADE/WITS (World Integrated Trade Solution). Focusing on the period used for regressions, the ratios to COMTRADE/WITS in 2018-2021 range from 92% to 100% for exports and 91% to 100% for imports. To obtain our final data sets, we eliminate exports and imports of oil (HS chapter 27), which is generally not well captured in transaction-level customs data sets. Moreover, to focus on true commercial export and import transactions by firms, we also drop from the data sets transactions of currency paper notes (HS 490700) that are conducted only by countries' central banks, transactions of arms and ammunition (HS chapter 93), and for India transactions of diamonds and precious metals and stones (HS chapter 71) because they are inconsistently reported over time in the Panjiva data. Export and import values are measured in United States Dollars.

A.2 Firm-Level Data Matching

The analysis requires matching the firm-level trade data from Panjiva, to firm-level data from Aberdeen and website-level information on technology usages from BuiltWith. At its core, the objective of the matching process is to create two datasets. The first dataset aims to correctly match as many Panjiva firms to their counterparts in the Aberdeen data. This makes it possible to link Aberdeen firm characteristics with trade outcomes derived from the Panjiva data. The second dataset matches as many Panjiva firms to the Builtwith dataset. This allows the measurement of technology adoption as captured by Builtwith to be included in the model. This section outlines, in a non-technical way, the probabilistic matching process used to combine three different datasets. This overview simplifies the process, leaving out country-specific coding choices and the reasons behind all coding decisions. Differences in the ratio of Panjiva to Aberdeen firms in the two datasets for different countries affected the matching process. For example, there were more firms in the Panjiva data for Mexico, while

[10] The complete list of names dropped at this step for each country are available from the authors upon request.

the numbers were about equal for Indonesia, and there were more firms in the Aberdeen data for India compared to the Panjiva data.

To begin with, data from Panjiva was cleaned and prepared for matching. This involved removing companies without an ID, as well as rows that were entirely blank except for the ID. The remaining company names were then cleaned, standardized, and common suffixes like '.ltd' were eliminated. Following this data pruning, the information was transformed into a wide-format representation, where each row corresponds to a single Panjiva ID (specific to this project. Consequently, multiple company names (due to different spellings) and addresses (owing to various locations) may be linked to a single ID.

We used the Google Places API to add more information to the Panjiva data to add two types of data crucial for the matching:

1. The geographical coordinates (longitude and latitude) of the companies, allowing us to use location data in the matching process; and

2. Additional company information like telephone numbers and website URLs, which was especially important for matching Panjiva data with the Builtwith dataset. Alongside the Google Maps Places API, the Bing Maps API was also employed to provide an alternative estimate of the company's location, as a robustness check. In instances where multiple results were returned by the Bing API, we retained only the result with the highest confidence level.

The next step involved the cleaning and preparation of the Aberdeen dataset. The process followed roughly the same steps used for the Panjiva data, but without the use of the Google Maps API. The Aberdeen dataset already contained many contact details, thus rendering this step unnecessary. The data from different files were loaded, merged, and transformed into a wide-format structure, such that each row represented a single primary ID. The data was structured to ensure that the most recent data for each company was retained (if there is data for more than one year)

Due to the computational complexity inherent in many-to-many matching, the Panjiva and Aberdeen datasets were matched in multiple stages. Initially, firms located closest to each other were matched, with the geographic restriction gradually relaxed to a wider radius (up to 25km, computed using the Haversine formula) to enable more matches. After this initial matching, an automatic scoring algorithm was used to retain the best match for each Panjiva firm. Besides geographic distance, variations of firm names (both cleaned and uncleaned) were used to match firms across datasets. The Levenshtein Edits Distance was used to account for misspellings and minor differences in firm name recording across datasets. Additional data such as phone numbers, website URLs, and parent enterprise information were also employed in the matching process when available. In case Panjiva firm matched to multiple Aberdeen firms with the same certainty, the largest of the Aberdeen firms, as measured by firm revenue, was maintained.

The process to match the Panjiva-Aberdeen data with the Builtwith dataset is described below:

1. We dropped unwanted URLs, such as those from platforms that are used as a company website but are not owned by the company (like 'Facebook.com/COMPANYNAME').

2. We then cleaned the remaining URLs with a custom URL cleaning function and compiled them into a single file. This file was then matched with the complete Builtwith database.

All programming is done in R (version 4.1.2) either on a local Windows machine or, for the larger data processing, a Azure Databricks environment (version 4.0.4).

We undertook an extensive set of manual checks to validate the matches and improve the matching algorithm. Firstly, we randomly took a sample of 250 firms from each country and then manually searched each firm online to determine if the match or non-match was correct. 80% of cases were correct, 15% were false positives (i.e. the firm was matched to the wrong website) and 5% were false negatives (i.e. the firm had a website that wasn't found). Secondly, we manually examined nearly 100,000 cases of borderline matches to refine the matching algorithm and adjust the probability weights. Further details on the matching are in the Appendix.

A.3 Matching Rates Panjiva Trade Data, Aberdeen and BuiltWith

Table A.1: India - Panjiva total trade value and number of firms matched to BuiltWith and Aberdeen datasets by year

		% Matched Aberdeen	% Matched BuiltWith	% Matched Both
Panel A: Matching Rates in Terms of Total Trade Value				
Import Trade Value				
2018	$127,536,290,663	43.57	65.15	31.72
2019	$253,506,184,609	44.25	65.14	32.61
2020	$217,302,910,739	43.42	66.89	33.16
2021	$306,430,535,564	42.60	66.81	33.14
Export Trade Value				
2018	$111,567,497,569	48.98	65.14	35.52
2019	$249,244,905,936	48.57	64.43	34.92
2020	$234,417,237,312	47.48	64.79	35.31
2021	$311,344,269,990	46.03	64.94	34.56
Panel B: Matching Rates in Terms of Number of Firms				
Number of Importers				
2018	92,226	37.24	47.39	22.51
2019	121,290	35.84	45.81	21.28
2020	111,422	36.22	47.46	21.89
2021	117,362	34.47	47.04	20.94
Number of Exporters				
2018	84,194	38.77	48.66	23.93
2019	116,038	36.56	46.75	22.13
2020	113,853	36.35	47.60	22.20
2021	124,529	34.91	47.46	21.42

Note: Sample used of Panjiva imports and exports dataset covers the period between July 2018 and Dec 2021.

Table A.2: Mexico - Panjiva total trade value and number of firms matched rates to BuiltWith and Aberdeen datasets by year

		% Matched Aberdeen	% Matched BuiltWith	% Matched Both
Panel A: Matching Rates in Terms of Total Trade Value				
Import Trade Value				
2018	$200,958,172,502	31.06	52.84	22.26
2019	$386,948,465,511	30.54	51.77	21.61
2020	$339,049,722,858	30.15	51.20	21.15
2021	$436,713,856,170	29.62	52.43	20.93
Export Trade Value				
2018	$216,740,349,751	36.00	53.88	27.60
2019	$438,015,696,665	34.41	53.65	26.52
2020	$405,696,201,793	33.30	52.26	24.86
2021	$470,775,779,378	32.73	52.70	24.34
Panel B: Matching Rates in Terms of Number of Firms				
Number of Importers				
2018	44,506	13.12	44.47	8.48
2019	50,833	12.39	44.05	7.99
2020	47,940	12.54	44.89	8.20
2021	48,084	12.21	45.20	8.06
Number of Exporters				
2018	21,844	15.02	43.10	9.71
2019	26,537	14.03	42.31	9.06
2020	26,203	14.15	42.84	9.15
2021	26,415	13.70	42.98	9.09

Note: Sample used of Panjiva imports and exports dataset covers the period between July 2018 and December 2021.

Table A.3: Indonesia - Panjiva total trade value and number of firms matched rates to BuiltWith and Aberdeen datasets by year

		% Matched Aberdeen	% Matched BuiltWith	% Matched Both
Panel A: Matching Rates in Terms of Total Trade Value				
Import Trade Value				
2019	$111,689,365,252	65.16	61.17	45.65
2020	$121,889,448,906	63.49	59.72	42.90
2021	$ 75,789,780,848	64.64	60.13	44.43
Export Trade Value				
2019	$117,213,032,387	66.47	55.43	40.62
2020	$160,785,569,164	57.58	51.71	36.46
2021	$137,153,786,021	67.86	61.05	45.59
Panel B: Matching Rates in Terms of Number of Firms				
Number of Importers				
2019	31,045	28.41	38.71	15.78
2020	32,782	26.87	38.22	15.16
2021	28,283	27.83	39.63	16.10
Number of Exporters				
2019	13,801	33.33	38.24	18.75
2020	14,590	31.73	37.44	18.02
2021	13,729	31.33	37.56	18.01

Note: The Panjiva import dataset spans the period from February 2019 to June 2021, whereas the Panjiva export dataset covers the interval from February 2019 to September 2021.

A.4 Additional Summary Statistics

Table A.4: Firm-HS6 product-month-year observations and number of products classified as E-tradeable goods and BEC consumer goods - Sample with all firms

	E-tradeable Goods	BEC Consumer Goods
Panel A: Indonesia		
Exports		
No. Observations	80,767	37,463
No. HS6 Products	869	470
Imports		
No. Observations	315,478	61,413
No. HS6 Products	925	485
Panel B: India		
Exports		
No. Observations	847,415	409,572
No. HS6 Products	937	498
Imports		
No. Observations	726,718	159,011
No. HS6 Products	924	494
Panel C: Mexico		
Exports		
No. Observations	173,510	36,239
No. HS6 Products	827	412
Imports		
No. Observations	689,123	119,624
No. HS6 Products	907	479

Note: Firm-HS6 product-month-year observations and the number of products classified as E-tradeable and BEC consumer goods - Sample includes all firms: never-adopters, technology adopters during the analysis period (July 2018-December 2021 for India and Mexico, February 2019-June 2021 for Indonesia's Exports, and February 2019-September 2021 for Indonesia's Imports), and adopters before the analysis period.

Table A.5: Firm-HS6 product-month-year observations and number of products classified as E-tradeable goods and BEC consumer goods - Samples including firms that never adopt digital technology and firms that adopt digital technology in the mid-2018-2021 period

	E-tradeable Goods	BEC Consumer Goods
Panel A: Indonesia		
Exports		
No. Observations	66,865	30,858
No. HS6 Products	861	466
Imports		
No. Observations	254,867	47,737
No. HS6 Products	915	476
Panel B: India		
Exports		
No. Observations	718,179	337,857
No. HS6 Products	928	494
Imports		
No. Observations	576,439	112,189
No. HS6 Products	919	493
Panel C: Mexico		
Exports		
No. Observations	125,645	24,341
No. HS6 Products	779	368
Imports		
No. Observations	487,835	69,103
No. HS6 Products	876	450

Note: This table shows the firm-HS6 product-month-year observations and number of products classified as E-tradeable goods and BEC consumer goods - Samples include firms that never adopted the technology and firms that adopted the technology throughout the analysis period (July 2018-December 2021 for India and Mexico, February 2019-June 2021 for Indonesia's Exports, and February 2019-September 2021 for Indonesia's Imports)

A.5 Additional Results

Table A.6: COVID stringency and firm trade at intensive margin - mediating role of digital technology use and BEC Consumer Goods

	India		Mexico		Indonesia	
	Log. Imports	Log. Exports	Log. Imports	Log. Exports	Log. Imports	Log. Exports
Firm technology adoption pre-2019 × COVID stringency index	-0.001**	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
COVID stringency index × BEC Consumer Goods	-0.001**	-0.001***	-0.002*	-0.001	-0.001	-0.002
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Firm technology adoption pre-2019 × COVID stringency index × BEC Consumer Goods	0.005***	0.002***	0.004**	0.000	0.006***	0.006**
	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)
Num. Obs.	2,575,520	2,205,440	2,258,374	500,300	1,164,711	231,536
R-squared	0.436	0.467	0.323	0.428	0.382	0.564
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The variable Firm technology adoption pre-2019 is a dummy equal to 1 if the company adopted the E-payment or E-commerce technology before 2019 and 0 if not. The sample period for the regressions is July 2018-December 2021 for India and Mexico, February 2019-June 2021 for Indonesia's exports and February 2019-September 2021 for Indonesia's imports. Clustered-standard errors at the firm-product level. *p<0.1; **p<0.05; ***p<0.01.

Table A.7: COVID stringency and firm trade at extensive margin - mediating role of digital technology use and BEC Consumer Goods

	India		Mexico		Indonesia	
	Import Propensity	Export Propensity	Import Propensity	Export Propensity	Import Propensity	Export Propensity
Firm technology adoption pre-2019 × COVID stringency index	-0.00002*	-0.00001	-0.00002*	0.00000	0.00002	-0.00009
	(0.00001)	(0.00001)	(0.00001)	(0.00002)	(0.00004)	(0.00012)
COVID stringency index × BEC Consumer Goods	-0.00006***	-0.00006***	-0.00008**	-0.00004	-0.00006*	0.00009
	(0.00002)	(0.00001)	(0.00003)	(0.00003)	(0.00003)	(0.00014)
Firm technology adoption pre-2019 × COVID stringency index × BEC Consumer Goods	0.00006**	0.00006***	0.00014*	0.00002	0.00010	-0.00006
	(0.00003)	(0.00002)	(0.00008)	(0.00008)	(0.00009)	(0.00016)
Num. Obs.	99,999,522	79,418,640	43,128,750	11,329,164	24,584,692	5,019,264
R-squared	0.065	0.075	0.118	0.123	0.096	0.136
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The variable Firm technology adoption pre-2019 is a dummy equal to 1 if the company adopted the E-payment or E-commerce technology before 2019 and 0 if not. The sample period for the regressions is July 2018-December 2021 for India and Mexico, February 2019-June 2021 for Indonesia's exports and February 2019-September 2021 for Indonesia's imports. Clustered-standard errors at the firm-product level. *p<0.1; **p<0.05; ***p<0.01.

Table A.8: Lagged digital technology adoption and firm trade at intensive margin - BEC Consumer Goods

	India		Mexico		Indonesia	
	Log. Imports	Log. Exports	Log. Imports	Log. Exports	Log. Imports	Log. Exports
Firm technology adoption 2-month lag	0.017	-0.035	-0.007	0.136***	0.013	0.047
	(0.019)	(0.027)	(0.022)	(0.041)	(0.031)	(0.083)
Firm technology adoption 2-month lag × BEC Consumer Goods	-0.012	0.045	0.020	-0.333**	0.223	-0.224
	(0.082)	(0.060)	(0.151)	(0.159)	(0.160)	(0.218)
Num. Obs.	2,162,521	1,922,861	1,678,466	367,750	964,661	191,478
R-squared	0.444	0.47	0.335	0.44	0.393	0.587
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The sample period for the regressions is July 2018-December 2021 for India and Mexico, February 2019-June 2021 for Indonesia's exports and February 2019-September 2021 for Indonesia's imports. Clustered-standard errors at the firm-product level. *p<0.1; **p<0.05; ***p<0.01.

Table A.9: Lagged digital technology adoption and firm trade at extensive margin - BEC Consumer Goods

	India		Mexico		Indonesia	
	Import Propensity	Export Propensity	Import Propensity	Export Propensity	Import Propensity	Export Propensity
Firm technology adoption 2-month lag	0.00010	-0.00019	-0.00005	-0.00022	-0.00227	-0.00009
	(0.00066)	(0.00055)	(0.00085)	(0.00226)	(0.00207)	(0.00643)
Firm technology adoption 2-month lag × BEC Consumer Goods	-0.00183	0.00153	-0.00069	-0.00569	0.00916	-0.02326***
	(0.00168)	(0.00137)	(0.00434)	(0.00439)	(0.00951)	(0.00677)
Num. Obs.	86,846,928	69,771,870	33,694,962	8,733,480	20,804,600	4,176,480
R-squared	0.063	0.076	0.117	0.123	0.098	0.143
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The sample period for the regressions is July 2018-December 2021 for India and Mexico, February 2019-June 2021 for Indonesia's exports and February 2019-September 2021 for Indonesia's imports. Clustered-standard errors at the firm-product level. *p<0.1; **p<0.05; ***p<0.01.