Back to Trend: COVID Effects on E-commerce in 44 Countries

Joel Alcedo
Mastercard Ec. Institute

Prachi Mishra
Ashoka University

Alberto Cavallo
Harvard Business School

Antonio Spilimbergo
International Monetary Fund*

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Abstract

We study online spending shares in 44 economies and 26 industries during the COVID-19 pandemic, using online transaction data from Mastercard. The online shares of total credit card transactions surged during the pandemic during lockdowns, but since returned to pre-pandemic trends in most countries. The differences between countries are strongly correlated with the mobility and fiscal measures. There is little evidence of permanent structural changes in e-commerce spending patterns. Finally, we estimate that COVID-19-related restrictions on in-person spending imposed average welfare costs of 7 percent across countries.

Keywords: COVID-19; Technological Change; consumption; digitalization; E-commerce, welfare assessment
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*Joel Alcedo commenced research while at the Mastercard Economics Institute (email: joel.alcedo@mastercard.com). Alberto Cavallo is at Harvard Business School (email: acavallo@hbs.edu). Prachi Mishra is with the Ashoka University (email: prachi.mishra@ashoka.edu.in). Antonio Spilimbergo is with the Research Department at the International Monetary Fund (email: aspilimbergo@imf.org).

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1 Introduction

E-commerce experienced a dramatic surge when the COVID-19 pandemic began in early 2020.[1] Within weeks of widespread lockdowns and severe restrictions on in-person shopping, online transactions reached unprecedented levels in most economies. Although the media has extensively reported on this surge, academic research has largely neglected to document its magnitude and implications. Several critical questions remain: How extensive and widespread was the digitalization of consumption during this period? Where there notable differences emerge across countries and sectors? More importantly, did the pandemic fundamentally alter the trajectory of e-commerce, or was the surge merely a temporary deviation in the ongoing evolution toward digital retail? Finally, what were the welfare costs of restricting consumers from in-person purchases during the lockdowns?

This paper addresses these questions using a unique dataset provided by Mastercard©, which includes all transactions within its network. The sample encompasses 44 economies and 26 sectors where Mastercard represents a significant share of total card transactions, covering the period from January 2018 to January 2024. This time frame allows for a comprehensive analysis of online and in-person spending patterns over three years before and three years after the onset of the COVID-19 pandemic.

We find that although online spending shares surged during the pandemic, they dissipated in nearly all countries and sectors after three years, except in a few industries within the retail and healthcare sectors. Our findings suggest an important role for government transfers in sustaining spending in a context with severe mobility restrictions, with the effect on online spending shares waning as these two policies diminished over time.

Moreover, the temporary deviation from previous spending patterns suggests that mobility restrictions imposed welfare costs on consumers by limiting their access to in-person purchases. Using a simple theoretical framework, we estimate the implicit rise in transaction costs during lockdowns, as consumers incurred higher monetary or convenience-related costs when substituting in-person purchases with online alternatives. Our results suggest that, on average, the cost of in-person con-

[1] For the pre-pandemic period, the U.S. Census Bureau estimates that e-commerce rose from 5 percent in 2007 to 11 percent in 2019 (`https://www.census.gov/retail/index.html`).

sumption rose by 15 percent during the pandemic, leading to estimated welfare losses of 7 percent. The impact varied significantly across countries, with consumers in low-income and emerging markets facing higher effects due to more limited alternatives to in-person transactions.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data. Section 4 documents stylized facts, while Section 5 explores explanations for the observed patterns. Section 6 presents additional findings and Section 7 introduces an analytical framework to evaluate the welfare costs associated with the increased cost of in-person transactions. Finally, Section 8 concludes.

2 Related literature

This papers contributes to four strands of literature. First, it builds on research that quantifies the benefits of the internet for consumers. Classic studies such as Goolsbee and Klenow (2006), Brynjolfsson and Oh (2012), and Varian (2013) document the welfare gains from online access under normal conditions. More closely related to our work, Dolfen et al. (2020) use transaction-level credit card data to estimate that e-commerce accounted for 8% of U.S. consumption by 2017, generating an equivalent 1% permanent boost to consumption. However, while these studies focus on consumer benefits in steady-state conditions, recent research highlights the internet's role in enabling consumption resilience during extraordinary shocks, such as the COVID-19 pandemic. For example, Alipoura et al. (2022) use Mastercard transaction data to analyze geographic shifts in offline consumption in Germany following the pandemic. Similarly, Auer, Cornelli, and Frost (2023) document temporary changes in retail payment behavior across 18 countries, including spikes in cash circulation and card-not-present transactions during lockdowns. Our paper contributes to this literature by studying the persistence and quantifying the temporary welfare effects of these consumption shocks in a large number of countries and sectors.

Second, our paper relates to the extensive literature on the economic effects of COVID-19 (see Bloom, Fletcher, and Yeh, 2021; Chetty et al., 2020). Early studies predicted severe disruptions to retail industries (Roggeveen and Sethuraman, 2020), while subsequent research documented shifts in consumer behavior, such as panic buying, impulsive spending, and stockpiling (Wang, Shi, and Yuen, 2022). For instance, Moon, Choe, and Song (2021) examine how changes in consumption patterns contributed to the surge in e-commerce across various sectors in Korea during the pandemic. However, it remains unclear whether these behavioral changes are temporary responses or represent permanent shifts. Some scholars argue that pandemic-induced habits are likely to persist (Sheth, 2020), while others emphasize the unique circumstances of lockdowns, which left consumers with few alternatives (Keane and Neal, 2021). Shaw Norman (2022) discusses various factors explaining why the surge in online spending during COVID-19 might result in permanent shifts in consumer spending habits. Our paper complements this literature by examining key drivers of e-commerce spending and highlighting the short-run nature of these behavioral shifts in spending patterns.

Third, our paper connects to the literature on the pandemic's impact on technology adoption. Barrero, Bloom, and Davis (2023) show that working-from-home (WFH) persisted post-pandemic, though at lower levels than during lockdowns. They emphasize that pre-existing technologies—such as video conferencing and cloud-based collaboration tools—made WFH feasible, while lockdowns allowed employers and employees to "discover" these possibilities. Once this learning occurred, some WFH endured beyond the acute phase of the pandemic. E-commerce shares similarities with WFH, including pre-existing enabling technologies and a pandemic-driven surge in usage. However, unlike remote work, which was relatively uncommon before the pandemic, e-commerce was already well-established, leaving limited room for new learning. Overall, our findings suggest that the lockdowns did little to enhance consumers' familiarity with e-commerce, as most were already accustomed to it.

Finally, our paper contributes to the growing literature that leverages private data to enhance and complement traditional survey-based economic measurement. Notable examples include the use of online price data for inflation measurement in Cavallo (2013), as well as studies by Chetty et al. (2020) and Carvalho et al. (2020), which use high-frequency data to track economic activity in real time during the COVID-19 pandemic.[2] Closer to our work, Aladangady et al. (2019) use credit and debit card data to produce daily retail spending estimates that closely approximate official U.S. Census retail surveys. Our paper extends this literature by

[2]Other key examples include Choi and Varian (2012); Einav and Levin (2014); Glaeser, Kim, and Luca (2017); Abraham et al. (2020); Aladangady et al. (2019).

demonstrating how real-time credit card data can be used to measure e-commerce sales, improve understanding of consumption patterns during crises across many economies, and provide a simple framework for assessing welfare costs in near real time. This approach is particularly valuable for policymakers, as it equips them to respond more effectively to future events—such as pandemics—that may require prolonged lockdowns and restrictions on in-person purchases.

3 Data and Variable Construction

The digitalization of retail transactions (e-commerce) can be assessed using various metrics. While the total volume of online spending increased during the COVID-19 pandemic, overall consumer expenditure in the U.S. had recovered by early 2021. Thus, our analysis centers on the share of online spending, defined as the ratio of online transactions to total observable transactions. This metric captures both consumer and seller preferences as well as the constraints shaping online transaction behavior.

Credit and Debit Card Data

Our primary dataset comprises the universe of credit and debit card transactions processed through the Mastercard network between January 2018 and January 2024, spanning many economies and territories.[3] A detailed description of the data source and sample construction is provided in Online Appendix A, summarized here. The dataset adds value over publicly available statistics in three critical dimensions: coverage, frequency, and granularity. [4]

The raw data's unit of observation is a transaction between a cardholder and a merchant. Each transaction record includes detailed information such as the date and time of the transaction, the card type (credit, debit, or pre-paid), the merchant's location, the industry classification, the payment channel, and the transaction amount. The dataset also categorizes merchants using the standardized Merchant Category

[3]Nilson Report issue 1199 (June 2021) noted the global share of purchase transactions as Visa: 40 percent, UnionPay: 32 percent, Mastercard: 24 percent, and others: 4 percent.

[4]Note that a few countries, including the US and UK, produce official data for retail spending. Unfortunately we do not have a large cross country sample, also because countries may use different definitions. On the other hand, Mastercard data ensure cross-country consistency.

Codes (MCC), which classify businesses into 26 distinct sectors. This sectoral classification allows for a highly granular analysis of spending patterns across industries.

Key variables. Payments are categorized into online (e-commerce) and offline channels. Online transactions are defined as those where neither the cardholder nor the physical card is present at the point of sale. This broad definition includes internet-based transactions conducted via web browsers or mobile devices, recurring purchases, and in-app payments. Transactions that do not meet these criteria are classified as "offline."

To facilitate temporal analysis, the transaction-level data are aggregated on a monthly basis for each country in our sample. In our methodology, transactions are attributed to the country of the card's issuing bank, regardless of the merchant's geographical location. For each economy in the sample, the "online spending share" of total card consumption in economy c at time t is given by:

$$s_{c,t} = \frac{\text{Online Mastercard spending}_{c,t}}{\text{Total Mastercard spending}_{c,t}} \tag{1}$$

$s_{c,t}$ is calculated using monthly transaction-level data from Mastercard. We normalize all series to 100 before the pandemic and report the normalized shares.[5] Importantly, this allows us to compare the behavior of these shares over time across countries, particularly the degree of reversion to pre-pandemic trends. We also report deviations from pre-pandemic trends.

Representativeness. The 2018–2023 data universe contains an annual average of USD 6.2 trillion in network spending volume. Of these sales, roughly 48 percent were credit and charge transactions, and 52 percent were debit transactions. In 2023, approximately 2.9 billion cards were in force, accounting for 170.8 billion transactions.

Figure 1 presents Mastercard spending as a share of global GDP and global consumption (panels A and B, respectively). Mastercard transactions have steadily increased over time, rising from approximately 6.8 percent of global GDP in 2018 to 8.6 percent in 2023, and from 10.5 to 13.3 percent of global household consumption over the same period. Mastercard's growing share of overall consumption likely reflects, in part, the increasing importance of e-commerce, as we will see below.

[5] For confidentiality reasons, we are not able to publish the online shares at the country level. However, we can report the online shares (without normalization) at the sector level (Tables 4 and 5), and use these shares at the country-time level in the empirical analysis (Tables 2 and 3).

To ensure representativeness, we limit our sample to 44 economies where Mastercard holds a market share of more than 20 percent of total card transaction volume. Figure 2 shows that the online share patterns remain consistent even when using data from economies below this market share threshold.

We compare Mastercard's online spending shares with broader estimates derived from survey data that include other cards and payment methods. Figure 3 illustrates this comparison for the United States and the United Kingdom, where official survey estimates of "online retail spending" are published monthly by the US Census Bureau and the UK Office of National Statistics. Although differences in trend levels exist, the overall dynamic patterns are similar. Notably, the official data also suggest that the online spending share in both the United States and the United Kingdom returned to pre-COVID trend levels.

Data limitations. While card transactions are an increasingly important payment method in the retail and services sectors, datasets based on credit card transactions, including ours, have limitations. Certain market segments, such as vehicle sales, rental payments, and tuition, are underrepresented in card transaction data, as these purchases often involve bank-to-bank transfers such as automated clearing house (ACH) transfers. Conversely, card payments are the primary method of transacting online, leading to an over-representation of e-commerce relative to its share in aggregate household expenditures. Notably, despite these payment-format differences, the e-commerce shares derived from our database closely align with official statistics in markets where government agencies report e-commerce sales data on a low-frequency basis (Figure 3). In particular, despite some discrepancies in trends, the temporary deviations and lack of persistence in the online spending levels are similar across datasets. [6]

In addition to these limitations, while our data offer insights into transaction amounts, merchant categories, and payment channels, they lack certain details that could enhance our analysis. Specifically, although the credit card data capture aggregate transaction amounts, they do not include itemized information on individual purchases, such as product prices or quantities. Notably, the absence of Stock Keeping Unit (SKU) level data restricts our ability to examine detailed product pref-

[6] We also compute the trends using official data starting at different points in history; these broadly show that the Mastercard data is consistent with official data, and we observe similar back to trend dynamics, though indeed the levels and different, and above trend especially for the retail sector in the United States.

erences or assess price sensitivities at the product level.

Furthermore, demographic information about the cardholders—such as age, gender, income level, or educational background—is not available, as this information is securely managed by the consumer's bank and is not visible to Mastercard. This limitation restricts our ability to segment spending patterns by demographic groups or to explore how socioeconomic factors influence online versus offline purchasing behaviors. Additionally, the dataset lacks information on product quantities, preventing us from differentiating between high-value single-item purchases and multiple lower-value items within a single transaction.

4 Summary statistics and stylized facts

In this section, we present stylized facts on online shares across economies and sectors. Although the levels and dynamics differ, we find a surprising similarity in the transitory nature of the e-commerce surge across countries.

Online and total expenditures

Before examining the share of transactions occurring online, we first focus on the behavior of online and total expenditure separately. During the initial months of the pandemic, two forces were at work. On one hand, consumer spending declined, causing total expenditure to fall. On the other hand, the lockdowns forced the spending to move online. In some countries, this led to an immediate increase in online spending. In others, online expenditure also declined, but by less than total expenditure.

These two cases are illustrated in Figure 4, which shows the total and online spending for the US and Brazil. Since consumer spending is seasonal, we present seasonally adjusted indices using X13-ARIMA. In both countries, online spending was significantly higher three years after the pandemic began. However, the short-term dynamics differed. The US represents a case where online expenditure increased despite the contraction in total spending. In contrast, online expenditure in Brazil declined but fell by less than total expenditure. As a result, the share of online expenditure rose in both countries.[7]

[7] We further note that the increase in online spending was not caused by a contraction in the availability of cash (which can only be used offline). We explored indicators for cash availability in the US

Online shares in 44 countries

Next, we document stylized facts on the evolution of online shares in 44 countries. We report the shares at two points in time: the peak relative to the 2019 average and the most recent available data. Our analysis focuses on deviations during the COVID-19 pandemic relative to economy-specific trends. In all cases, the pre-COVID trend is estimated for each economy using a regression of online shares on a monthly time trend for the period between 2018 and 2019.

Figure 5 provides two examples of the dynamic behavior of the online share $s_{c,t}$ in the retail sector (solid line) compared to the pre-COVID-19 trend in each economy (dashed line). In the United States, the online share of retail spending peaked shortly after the pandemic began, increasing by nearly 30 percent. This share rose again during subsequent waves of COVID-19 cases and eventually reverted to the level predicted by the pre-COVID trend by early 2023.[8] In Brazil, the online share initially followed a similar pattern but fell in 2022, but it is now below the level predicted by pre-pandemic trends.

Figure 6 (panel A) shows the deviation from trend and its distribution in the retail sector across our sample of countries. The evidence is striking: not only has the online share in retail returned to trend for the median country, but it is very close to trend for countries in the 75th percentile and significantly below trend for those in the 25th percentile. Figure 6 (panel B) further shows that 61 percent of markets are at or below their pre-COVID trend (deviation from pre-COVID trend ≤ 0 percent). Importantly, while the bottom 25th percentile are below trend, the top 75th percentile are above, we observe similar back to trend dynamics for the entire

and Brazil. In both countries, cash availability increased at the onset of the pandemic, reflecting the effects of expansionary monetary policies. It continued to grow in the US while partially retracting in Brazil. Similarly, ATM withdrawals from Mastercard, a flow measure that reflects consumer preferences for holding cash, increased in mid-2020 and early 2021 for the US, peaking at levels 40 to 55 percent higher than pre-pandemic. In Brazil, ATM withdrawals fell by about 40 percent in 2020, in line with the decline in total expenditure, but increased thereafter, returning to pre-pandemic levels by the end of 2022.

[8] Note that the US Census Retail Sales Report uses a slightly different definition than the data used by Mastercard. Specifically: the Census data include restaurants, which are excluded from Mastercard data; the Census data include large durable goods (e.g., vehicles), which are underrepresented in Mastercard data; the Census data estimate sales across all payment forms (including cash), whereas Mastercard data are limited to Mastercard payment products; and the Census data cover all sales channels, while Mastercard focuses exclusively on card activity, as cards are the primary payment form online. These definitional differences explain why the online shares differ slightly. In particular, the Census reports that the online share remains about 2 percentage points above trend post-pandemic, whereas Mastercard data show it returning to trend.

distribution, which is a key stylized fact we document in the paper.

Table 1 summarizes the dynamic behavior of the online share for our sample of 44 economies. Results are ordered by the latest deviation relative to pre-COVID trends. The shares reported in Column 1 are normalized to the average level for 2019, meaning these numbers are indices relative to pre-pandemic levels. Column 2 reports the online shares in April 2023 (latest available), while Column 3 shows differences relative to pre-pandemic trends.

As shown at the bottom of the table, on average, the online share rose by 52 percent at its peak and then declined to 31 percent in 2023. While current levels are 31 percent higher than before the pandemic, they are, in fact, 1 percentage point below the average level predicted by pre-pandemic trends. Median values reflect a similar story of a sharp surge followed by a gradual return to trend over time.

The global (weighted) average difference between the online shares and the predicted pre-crisis trends, both at the peak and in the latest data, highlights the transitory nature of the online surge.[9] At its peak, the share of total transactions was 3.1 percentage points higher than the pre-crisis trend, but it declined to just 0.6 percentage points by April 2023. Globally, therefore, on average, only one-fifth of the peak deviation persists in the latest data.

Although, on average, countries have returned to the levels predicted by pre-pandemic trends, there are still significant differences across countries, as shown in the last column of Table 1. In 30 percent of economies, these deviations remain numerically positive, though small and close to zero in all cases. However, for some smaller economies, such as Bahrain, Croatia, and Slovenia, the shares are significantly higher.[10] In contrast, most other economies, including the United States and many developed economies, now have online shares that are nearly at or significantly below the predicted pre-COVID trend levels.

We also estimate an AR(1)1 model for deviations in online shares from pre-Covid trends for each country . An estimated coefficient corresponding to the AR(1) term smaller (in absolute value) than 1 indicates transient behavior. A coefficient close

[9]The average global deviation is calculated using the following four steps: i) calculate the deviations of the online shares from trend for each economy (as reported in Table 1), ii) compute the weight of each "economy-wide deviation" as the share of Mastercard spending in that economy over total global spending, iii) multiply each economy-wide deviation by its respective weight, using the Q3 2021 weight, and iv) compute the weighted sum, which is defined as the average global deviation.

[10]Note that some cross-sectional variation was normal even before the pandemic. The cross-sectional variation after COVID-19 is smaller than it was pre-pandemic.

to 1 indicates a more permanent departure from trend. For all countries (with the exception of Luxembourg), the absolute values of the estimates coefficients are less than one, consistent a transient behavior. For several countries, the AR1 coefficients are close to 1, meaning that it takes longer for several countries to revert to the mean. [11]

5 Empirical framework

The previous section argues that e-commerce shares surged at the onset of the pandemic but quickly returned to pre-COVID-19 trends, with some heterogeneity across economies.

What explains the heterogeneity across economies in the level of the spike and persistence of online shares? Figure 7 illustrates the strong correlation between global online shares and the strictness of COVID-19 pandemic movement restrictions, as measured by Google's index of residential mobility. This correlation was particularly pronounced during the second quarter of 2020, when lockdowns severely restricted mobility in most economies. However, the correlation weakened as the pandemic progressed. This pattern is consistent with the declining impact of COVID-19 lockdowns and other restrictions on economic activity over time, as economic agents adapted to the constraints (see, e.g., European Central Bank, 2021).

As the pandemic (and the attendant lockdowns) evolved other confounding factors were ongoing. In particular, countries implemented ambitious fiscal packages which differed in magnitude, in timing, and in sectors targeted. At the same time, underlying conditions, including internet penetration, were different across countries. These endogenous and pre-existing factors interacted with the mobility, creating very different relationship between online spending and mobility across countries.

To explore this issue more systematically, we estimate a panel regression of the deviation in online shares from the predicted pre-COVID-19 trends on mobility, fiscal support during COVID-19, and other covariates. The estimating equation is specified as follows:

[11] Luxembourg is also peculiar in that the post -Covid online share is much lower than the pre-covid share Table 1 so the AR(1) coefficient for Luxembourg may capture country specific dynamic, possibly unrelated to the Covid shock.

$$\Delta s_{c,t} = MOB_{c,t} + \text{New covid cases}_{c,t} + \text{Covid fiscal spend}_{c,t} \times MOB_{c,t} + \\ + \text{PreCovid trend online share}_c + \text{Internet Penetration}_c + \\ + \text{Per capita GDP}_c + \pi_t + \varepsilon_{c,t} \tag{2}$$

$s_{c,t}$, as defined in Equation (1), represents the online spending share in country c at time t. Given the time-invariant cross-sectional differences in pre-existing capabilities in purchasing online , we estimate the regression in changes. The dependent variable is measured as the change in online shares for a given year-month relative to the previous month, and time-varying explanatory variables are also measured in differences. Time fixed effects are included in all regressions; however, country fixed effects are not included, as several controls are time-invariant and the dependent variable is in change.[12] $MOB_{c,t}$ represents the Google residential mobility index, which increases with the stringency of pandemic restrictions. Residential mobility on any given day of the week is measured as the percentage change from a baseline value, defined as the median value for the corresponding day of the week during the 5-week period Jan 3–Feb 6, 2020. The mobility variable is extrapolated beyond September 2022, when Google stopped producing the data.

GDP per capita, measured in constant 2017 PPP international dollars, is sourced from the IMF World Economic Outlook (WEO). Covid Fiscal spend$_{c,t}$ reflects fiscal measures implemented by countries in response to the COVID-19 pandemic. This variable includes various types of fiscal support—such as above-the-line measures, below-the-line measures, and contingent liabilities—and is sourced from the 2021 IMF Fiscal Monitor database.

In the baseline specification, Covid Fiscal spend$_{c,t}$ varies only by country and includes "discretionary" fiscal measures implemented since January 2020, covering measures for 2020, 2021, and beyond. The results are qualitatively similar if we instead use a continuous measure, such as the overall government fiscal balance at the annual level, sourced from the IMF World Economic Outlook (see Table 4 and the discussion below). Note that we also include the interatction between the fiscal variable and mobility to account for the fact that the effect of the extrardinary fiscal

[12]The main findings are robust to estimation in levels (Table 3). The only time-varying variables are Google mobility and the number of new cases. The results reported in Column (1) of Table 2 remain robust when country fixed effects are included.

measures depends on the stringency of the lockdown

We assume that lockdown measures and fiscal support are exogenous, i.e., they are not influenced by (changes in) the e-commerce share. This assumption is reasonable given that the variables in the regressions are measured in differences. The ability to expand e-commerce, the level of fiscal support, and the extent of lockdowns may be correlated with country-specific characteristics, but these effects cancel out when variables are differenced.

Table 2 reports the regression results. Summary statistics for all variables used in the regressions are provided in Table A1. Column [1] shows that residential mobility and pandemic intensity, measured by the number of new cases, correlate positively with deviations from trend in the latest data.

In Column [2], we include additional controls. Residential mobility and pandemic intensity remain significant drivers of online shares. Richer economies also appear to return faster to pre-pandemic trends as indicated by the negative coefficient on per capita income, though the estimates are statistically indistinguishable from zero.

In Column [3], we include the interaction of fiscal support during COVID-19 with the severity of restrictions. The interaction term is positive and statistically significant at conventional levels. Greater fiscal support was associated with higher online shares when restrictions were more severe. This suggests that government transfers supported spending by increasing consumption, which, in the presence of pandemic restrictions, could primarily occur online.

Notably, the average effect of fiscal spending on online shares (evaluated at the average change in mobility) is also positive in Column [3]. The average change in mobility in the sample is 36.6 percentage points. Thus, the average effect of fiscal spending on e-commerce shares can be computed as $-0.0009+36.6\times0.0060=0.22$.[13] Furthermore, a one percentage point (pp) higher change in residential mobility is associated with a 0.4 percentage point higher increase in the online share gap, almost double the average effect of a one percentage point higher fiscal support.

[13] The average month-on-month change in Residential Mobility over our sample period, until September 2022 (the last month for which data are available), is 36.6 percentage points.

Firm and Consumer Online Capabilities

One potential explanation for the rise in online shares observed during the pandemic is that consumers and firms learned to transact online. In fact, a "collateral benefit" of the lockdown period could have been that many buyers and sellers would be obliged to learn online shopping by necessity; a permanent legacy of the pandemic would be a more widespread use of online shopping (Shaw Norman (2022)). However, the lack of persistence in the surge in online shares suggests that this online capability was likely not a binding constraint.

To explore this further, we develop two new monthly measures of online learning at the country level. The first is "Firm capability," defined as the proportion of active firms that have ever sold online since the start of the sample in 2019. This measure captures the idea that sellers who learned to transact online and set up the necessary infrastructure have incurred the fixed costs and can continue conducting online transactions in the future.

The second measure is "Consumer capability," defined as the proportion of active consumers who have ever bought online, building on the same concept. Figure 8 plots the median (over countries) consumer and firm capability measures over time. On average, these measures of online capability have steadily increased, suggesting that online capabilities are now more widespread than ever before. Remarkably, firms seem to have reacted proportionally more during covid than consumers. However, the fact that the share of online transactions has fallen from its peak, despite this increase in capability, may not, therefore, support the argument that technological constraints were binding on average.

At the same time, such constraints could still play a role in explaining some of the differences observed across countries. We included these measures of online capabilities in the regressions reported in Table 2, Column [4].[14] We find that the estimated coefficient on firm capability is positive and statistically significant, while the coefficient on consumer capability is statistically indistinguishable from zero.

[14] The number of observations decreases in Column [4] due to insufficient information to compute consumer and firm capabilities. Appendix Table A1 replicates Table 2, repeating all specifications on the smaller sample. The results remain robust.

Robustness checks

Table 3 presents additional robustness checks to confirm the results reported in Table 2. Column [1] repeats the final column from Table 2 as the baseline. Columns [2]–[3] include alternative measures of mobility: "retail" and "grocery & pharmacy," which are negatively correlated with pandemic restrictions. Column [4] uses the Oxford Stringency Index.

Retail mobility is defined by Google as "mobility trends for places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters." Grocery & pharmacy mobility is defined by Google as "trends for places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies." The Oxford Stringency Index, formally known as the Oxford COVID-19 Government Response Tracker's (OxCGRT) Stringency Index, is a composite measure developed by researchers at Oxford University to track the strictness of government policies in response to the COVID-19 pandemic. Finally, Column [5] excludes the internet penetration variable to test the robustness of the results.

Columns [6]–[7] employ alternative specifications: in Column [6], changes are measured over a 12-month period, while Column [7] estimates the regression in levels rather than changes. The findings remain broadly similar, particularly the result that government transfers increased online consumption, especially during times of high mobility restrictions, which continues to be strong and robust.

Notably, the estimated coefficients on online capabilities are not robust to alternative specifications. Overall, we interpret the evidence as providing little support for the presence of significant learning effects.

Table 4 uses a continuous fiscal spending measure, i.e., the overall fiscal balance from the IMF, instead of the discretionary fiscal support variable at the country level used in Table 2. The government balance, while having the advantage of being time-varying, also includes existing automatic stabilizers in addition to discretionary measures. Moreover, a lower fiscal balance implies higher fiscal support during the pandemic. The results are qualitatively similar to those in Table 2. In particular, the estimated coefficient on *Residential mobility* $\times$ *Government fiscal balance* is negative and statistically significant. These estimates reinforce the finding that greater fiscal support (or a lower fiscal balance) was associated with higher online shares during periods of severe mobility restrictions. Thus, the results provide additional evidence that government transfers supported spending by increasing consumption, which, given pandemic restrictions, could largely occur online.

6 Heterogeneity across Sectors

In this section, we analyze the impact of the pandemic on specific sectors, focusing on those most affected. The reason is that the covid pandemic and attending policy measures affected sectors in a differential way so that the dynamics could be driven by only few sector.s

Table 5 provides a detailed snapshot of online spending shares by sector, illustrating key trends.[15] The table shows the online share by sector pre-COVID, at the peak, at the latest time, and the difference between the latest observation and the pre-COVID trend. Among these sectors, restaurants and bars, which are all person-incentive sectors disproportionally hit during the covid pandemic, exhibited the largest increase in online spending shares, rising over 25 percentage points—from 7.3 percent in 2019 to 28.4 percent at the peak. Services and retail categories also experienced substantial increases, though smaller than those for restaurants and bars. By January 2024, however, the deviation from pre-COVID trends had turned negative for all sub-sectors, including restaurants and bars, retail, and services.

These broad categories mask substantial heterogeneity across subsectors. Table 6 reports the difference between the latest online shares and the pre-crisis trend for 26 disaggregated sectors in our dataset. Notably, sectors such as auto rental, clothing stores, drug stores, and electrical appliances continue to report high online shares. Some of these sectors, particularly drug stores, had relatively low pre-COVID-19 e-commerce shares. In contrast, the share of online spending in services—specifically hotel-motel, recreation, mail order, and other transport—has fallen significantly below pre-pandemic trends.

[15]Sectoral averages are calculated by computing a weighted average of the deviation in the online share from the trend at the economy-sector level, with weights based on the share of Mastercard spending in the economy-sector relative to global spending in that sector. Notably, some sectors (e.g., airlines and travel agencies) typically exhibit very high online penetration; for these, we introduce an upper limit on the pre-pandemic time trend, constraining the value below 100% (since e-commerce shares cannot exceed 100%). The industries whose online penetration reached this upper limit are included in Table 5. These include, for example, "mail order," "airline," "travel agencies," and "utilities." As our methodology for estimating the online share applies a scaling factor of (total card spending / total consumption), the scaled online shares for these industries converge to the upper limit of card spend/total consumption when the 100% threshold is reached.

As with economy-wide results, there is divergence across sectors in pre-COVID trends. On average, sectors that were leaders in e-commerce before COVID-19 reported mildly higher increases in online shares (Figure 9). Most of the increase during the peak occurred in sectors with mid-range pre-COVID online shares. Sectors such as health care, electrical appliances, and sporting goods-toys reported the largest increases relative to pre-crisis trends.

These effects appear to be largely transitory, consistent with the evidence at the economy-wide level (Figure 10). However, certain sectors—especially in retail, such as drug stores, clothing stores, and electrical appliances—deviate from this pattern. The temporary nature of the surge is particularly pronounced in industries with higher pre-pandemic e-commerce shares, as well as in sectors such as travel and entertainment.

Finally, Figure 11 shows the deviation of e-commerce shares from trend for key sectors, along with their distribution, across our sample of 44 countries. There is notable variation across sectors. For restaurants, the peak increase in e-commerce shares is the highest across the distribution. In contrast, for some retail sectors, such as food, the online share has returned to trend for the median country but remains well above trend for countries in the 75th percentile.

Overall, the sectoral evidence supports the main findings of this paper: (i) there is significant divergence across sectors in e-commerce shares; (ii) sectors that were early adopters of e-commerce reported mildly higher peak increases during COVID-19; and (iii) despite the sharp acceleration, the effects appear to be largely transitory, with some exceptions in sectors such as retail and healthcare.

7 Assessment of the welfare costs

This section provides a theoretical framework to assess the welfare costs of the observed patterns. The existing literature primarily focuses on the benefits of e-commerce, emphasizing that it provides consumers with greater choice. For example, Dolfen et al. (2020) document that e-commerce accounted for 8 percent of consumption by 2017, yielding a 1 percent boost to consumption. However, existing frameworks, which focus on the benefits of increased consumer choice or reductions in transaction costs, are not well-suited to analyze the welfare costs arising from restrictions on consumer choice during the pandemic. This section introduces a framework and a calibration exercise to evaluate the welfare implications of the sudden surge and subsequent return to trend in online shares.

The framework

The framework focuses on consumers' choices between buying online and in-person. Goods and services purchased online and in-person differ both because of the types of goods purchased and because, even for identical goods, the services attached to buying online versus in-person differ.

To capture this choice, we posit a constant elasticity of substitution (CES) utility function subject to a budget constraint:

$$U = (\lambda x^{\rho} + (1-\lambda) y^{\rho})^{\frac{1}{\rho}} \qquad \text{s.t.} \qquad p_x x + p_y y = I \tag{3}$$

where x is the bundle of goods purchased in-person and y is the bundle of goods purchased online. p_x and p_y are the respective price indices, and I is the total nominal amount spent. λ is the (time-invariant) share parameter, reflecting (country-specific) preferences for online versus in-person spending. $\frac{1}{1-\rho}$ is the (time-invariant) elasticity of substitution between online and in-person purchases.

The consumers optimize the optimal share of online purchases[16]:

$$S^* \equiv \frac{p_y y^*}{I} = \frac{1}{1 + \left(\frac{\lambda}{1-\lambda}\right)^{\frac{1}{1-\rho}} \left(\frac{p_y}{p_x}\right)^{\frac{\rho}{1-\rho}}} \tag{4}$$

The optimal online share S^* depends on the parameters ρ and λ, as well as the relative price $\frac{p_y}{p_x}$ of online versus in-person purchases. Crucially, these prices represent not only the cost of the (bundle of) goods but also the relative convenience costs. For example, buying online may offer greater variety and avoids in-person interactions, whereas purchasing in-person allows consumers to directly inspect merchandise and involves personal contact.

[16] Detailed derivations are shown in Appendix.

The consumers' welfare can be assessed looking at the indirect utility function[17]:

$$U = \frac{1}{p_y} \frac{I}{1 + \left(\frac{\lambda}{1-\lambda}\right)^{\frac{1}{1-\rho}} \left(\frac{p_y}{p_x}\right)^{\frac{\rho}{1-\rho}}} \left[\lambda \left(\frac{\lambda}{1-\lambda} \right)^{\frac{\rho}{1-\rho}} \left(\frac{p_y}{p_x} \right)^{\frac{\rho}{1-\rho}} + 1 - \lambda \right]^{\frac{1}{\rho}} \tag{5}$$

The indirect utility function can further be written in terms of online share S^*.

$$U = \frac{IS^*}{p_y} \left[\lambda \left(\frac{\lambda}{1-\lambda} \right)^{\frac{\rho}{1-\rho}} \left(\frac{p_y}{p_x} \right)^{\frac{\rho}{1-\rho}} + 1 - \lambda \right]^{\frac{1}{\rho}} \tag{6}$$

The indirect utility decreases as prices rise. Similarly, it can be shown from Equation (4) that welfare, as measured by indirect utility, decreases when the prices of both offline and online bundles increase. As discussed earlier, these prices may include convenience costs, which can fluctuate significantly (even temporarily) during lockdowns.

The cost of online purchases (p_y) has been steadily declining over time, following a long-term trend driven by consumers becoming more familiar with online technology, merchants expanding their online offerings, and improvements in home delivery logistics. From the previous sections, we approximate this trend as linear. Moreover, we assume that this linear trend remained unchanged after the pandemic. However, during the the COVID-19 pandemic, the cost of in-person purchases (p_x) spiked temporarily both for compulsory lockdowns and because of fear of in-person interactions (which limited inperson buying on top of legal restrictions to mobility)

Calibration

How can we calibrate the parameters in Equation (3) given that only the online share S^* is observable?[18] We focus on total spending, as in the previous sections.

We use the pre-pandemic period to calibrate the key parameters of the model. As a benchmark, we set the value of ρ to $\frac{2}{3}$ (corresponding to an elasticity of substitution of 3). The share parameter λ is calibrated to match the share of online spending in 2018 for each country. We also assume that the drop in p_y, the price

[17] Derivations are in the appendix.

[18] The literature on online and offline markets from the supply-side perspective is large and expanding; fewer studies have focused on the demand side. Exceptions include Zhang and Demirkan (2021) and Fassnacht and Unterhuber (2016), though these studies focus on specific markets.

of online purchases, explains the increase in the online share. The upward trend in the online share is observed in (almost) all countries, and the yearly increase in the share is consistent with a 2 percent annual decline in p_y. These values align with the observed online share in 2018 and its trend growth.

During the pandemic, we assume the cost of in-person purchases (p_x) increased. While p_x is not directly observable, it can be inferred from the online share using Equation (3). Table A2 summarizes the assumptions and data sources used to calibrate the parameters.

Using the framework, we calculate the optimal online share, the implicit cost of in-person transactions during the pandemic, and, crucially, the welfare loss due to the restriction. Table 8 reports the welfare effects derived from the calibration exercise. An average imputed increase in the cost of in-person transactions by 15 percent raised the calibrated online share to match the actual increase in online share. The estimated welfare loss from this imputed price increase is 7 percent.

These averages, however, mask significant differences across countries. In advanced economies, the average imputed increase in the cost of in-person transactions was 9 percent, whereas in emerging and developing economies (EMDEs), the imputed costs rose by 25 percent. These differences resulted in varying welfare losses: 7 percent in advanced economies and 10 percent in EMDEs.

Sensitivity to parameters

The results from the simulation exercise are subject to several caveats. A key parameter is the elasticity of substitution, $\frac{1}{(1-\rho)}$, which is set at 3 in the baseline calibration. In the US, a lower elasticity of substitution (e.g., 2) would require a larger increase—24 percent—in the price of in-person purchasing during the pandemic to generate the observed increase in the online share. A lower elasticity would also result in a larger welfare loss, estimated at about 11 percent. Furthermore, it would imply an (implausibly) larger rate of decrease in the price of online expenditure to match the observed trend in online shares before and after the pandemic.

Another critical parameter is the share parameter, λ. A larger λ, all else equal, implies a higher proportion of purchases made in person. We calibrate λ to match the initial share of online spending. For the US, a value of 0.54 yields the observed online spending share of 39 percent. Using different values for λ would alter the calibrated share but would not significantly affect the welfare estimates.

Caveats and Extensions

The above framework is simple, transparent, and delivers clear results. However, the assessment is based on a series of assumptions.

First, it assumes that all effects of the lockdowns are captured by an increase in the cost of in-person purchases, p_x, which includes not only monetary costs but also convenience costs and health risks associated with in-person shopping. However, other key parameters could have changed during the pandemic, including the crucial elasticity of substitution, $\frac{1}{1-\rho}$. The exercise relies on the standard assumption of model stability, which is common in most calibration exercises. Furthermore, the fact that the online share returned to its pre-pandemic trend may suggest that the pandemic did not fundamentally alter the underlying dynamics of online versus in-person purchasing behavior. Second, the estimated welfare losses are based on the relative prices of online and in-person transaction costs. We assume that during the pandemic only the cost of in-person transactions increased, while the cost of online transactions followed its pre-pandemic trend. This assumption is supported by the observation that the online share returned to its pre-pandemic trend after the pandemic. If the cost of online transactions had been permanently affected, the online share would not have reverted to its prior trend. Conversely, if the cost of online transactions had decreased during the pandemic, the welfare losses would have been lower than the estimates provided above.

Third, for simplicity, the model considers only one good, which should be interpreted as a bundle of goods. The same framework can be applied to specific goods or sectors, with each having its own sector-specific parameters ρ and λ. For example, in the travel sector, λ would be very low due to the already high share of online purchases, and ρ would also be low given the limited substitutability between online and in-person purchases in this sector.

Fourth, a striking finding of our empirical analysis is that the online share reverted to its pre-2020 trend after the pandemic ended. This suggests that the underlying forces driving the transition to a more online-oriented economy remained unchanged. Notably, the transition did not accelerate, and there was no ratchet effect, implying a lack of significant learning. Reflecting this insight, the framework excludes any explicit learning effects and instead assumes a gradual decline in the costs of online purchases. This reflects buyers (and sellers) progressively becoming more familiar with online shopping. While the framework does not model this explicitly, it is plausible that different generations exhibit varying propensities to buy online, and the observed increase in online share may simply reflect compositional effects as younger, more online-savvy generations replace older ones.

Fifth, the framework assesses only the welfare losses arising from the increase in in-person transaction costs during the pandemic. However, the pandemic affected welfare through several other channels. For instance, income effects played a significant role, as did shortages of goods. Other studies have examined these key issues. This paper is the first to provide a framework for assessing welfare losses through this specific channel, leaving these additional aspects for future research.

Sixth, we replicate the exercise focusing solely on retail purchases and show the results in Appendix Table A3. The advantage of this approach is that the goods purchased are more homogeneous, reducing sensitivity to composition effects. The disadvantage is that the data are noisier, possibly due to classification issues. Nonetheless, the results are qualiatively similar, though the magnitude of the welfare loss is larger: the average welfare loss is 13 percent, compared to 7 percent when total spending is analyzed.

Finally, the welfare losses are calculated only for credit card users. In some low-income countries, such as Somalia, Zimbabwe, and Cambodia, credit card users represent a small share of the population. Consequently, the largest estimated welfare losses for these countries should be interpreted with caution, as they do not necessarily reflect losses for the entire population.

8 Conclusions

During the COVID-19 pandemic, online purchases surged in nearly all economies. This paper systematically documents the extent of this surge using a unique, large dataset covering 44 economies and 26 sectors over a period of nearly three years before and after the pandemic. The analysis reveals significant heterogeneity across countries and sectors in the pre-COVID trends of online spending shares. While online spending shares surged universally during the pandemic, these increases largely reversed as the crisis subsided, with a few exceptions in sectors such as retail and healthcare, where the shifts appear more enduring.

The lack of persistence in online spending shares is surprising and runs counter to popular expectations. A common narrative in the media suggested that the pandemic accelerated digitalization by compelling consumers to adopt new digital skills, with the assumption that these changes would have lasting effects. While our findings confirm the rapid uptake of e-commerce during the pandemic, they provide little evidence of enduring changes driven by ”learning-by-locking” effects. Instead, the data suggest that consumer behavior reverted to pre-pandemic trends once restrictions eased.

What explains these patterns? In the initial phase of the pandemic, the demand for e-commerce surged relative to in-person commerce as lockdowns and mobility restrictions constrained traditional shopping options. Crucially, the interaction between restricted mobility and government transfers drove this temporary shift. Mobility restrictions forced consumers online, while fiscal transfers supported spending. However, as restrictions eased and fiscal support diminished, these effects waned, leading online spending shares to revert to their pre-pandemic trends.

Despite the overall reversion to pre-pandemic trends, some heterogeneity persists: in 30 percent of economies, online spending shares remain higher than pre-pandemic levels. Additionally, the expansion of e-commerce appears more durable in certain sectors, particularly retail and healthcare. These results may reflect extensive margin effects, where new and younger customers continue to engage in online shopping. With travel and gathering restrictions lifted and government transfers ceased globally, understanding the long-term implications of these shifts remains a critical area for future research.

Finally, we use a simple framework to quantify the welfare costs arising from mobility restrictions during lockdowns, which severely limited in-person purchases. Our analysis estimates these welfare costs at approximately 10 percent in 2020.

Overall, the findings highlight significant inertia in consumer spending patterns. While COVID-19 led to a temporary surge in e-commerce, spending behaviors largely reverted to pre-pandemic trends as the crisis subsided. In this sense, there is little evidence to support the notion of a “long COVID” effect on e-commerce.

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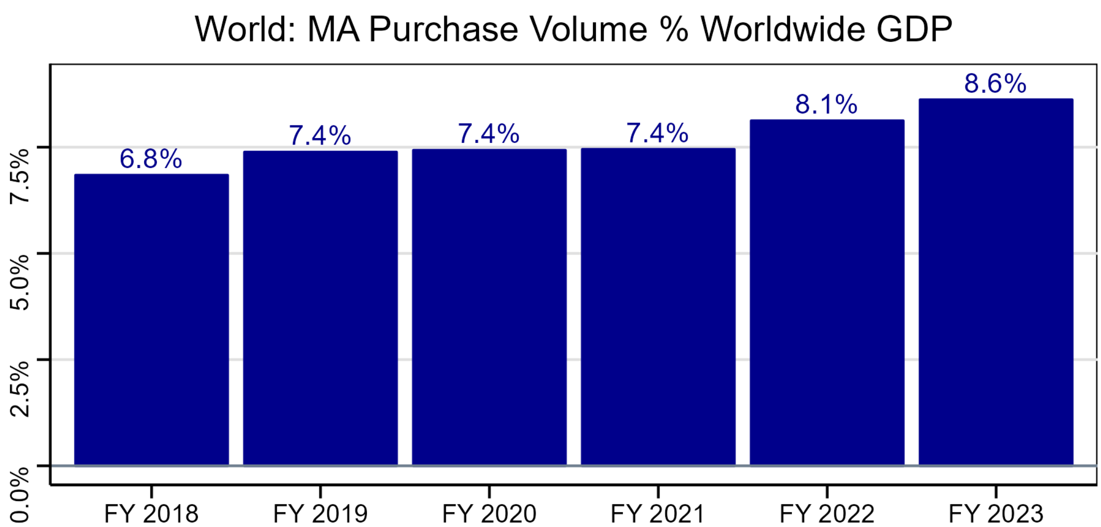
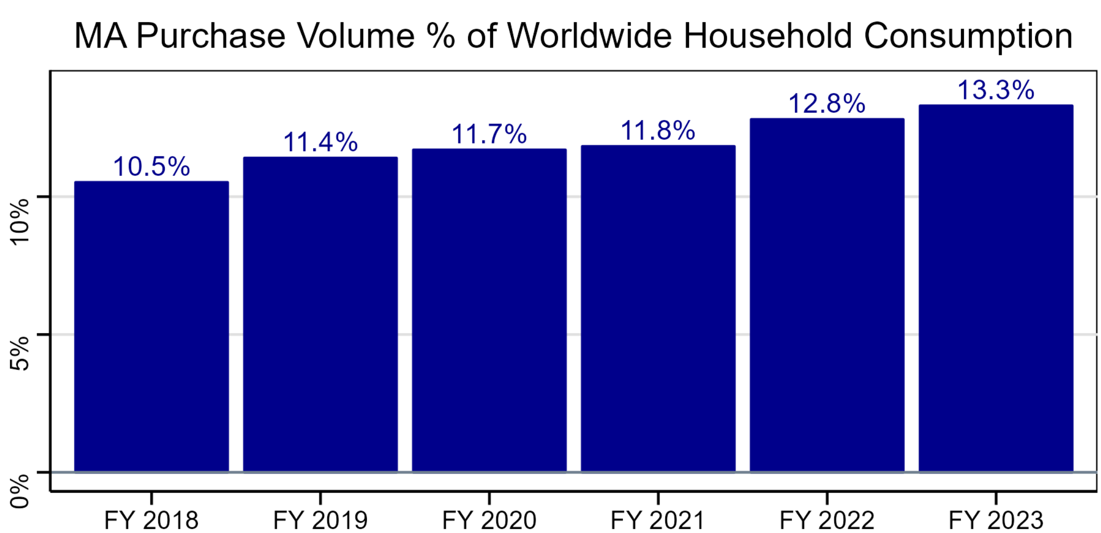
Figure 1: Mastercard purchase volume

(a) Panel A. percent of global GDP



(b) Panel B. percent of global consumption



Note: Mastercard credit and debit card volumes (based on public records found here: https://investor.mastercard.com/financials-and-sec-filings/quarterly-results/default.aspx), and global GDP is from Oxford Economics. Global household consumption is from the IMF.

Figure 2: Mastercard's Market Share Cut-off

We limit our sample to economies where Mastercard has a significant market share in order to be sure to have a representative sample. Changing this cutoff value has little impact on our results. To show this, we computed the online share for economies where Mastercard has a small share of the card market and compared it to the results we can obtain from the 44 economies included in our sample. Figure B1 shows that online shares between these two groups are highly correlated, with a correlation coefficient of 0.97.

(a) Online shares in economies where Mastercard has $\geq 20\%$ and $< 20\%$ market share.

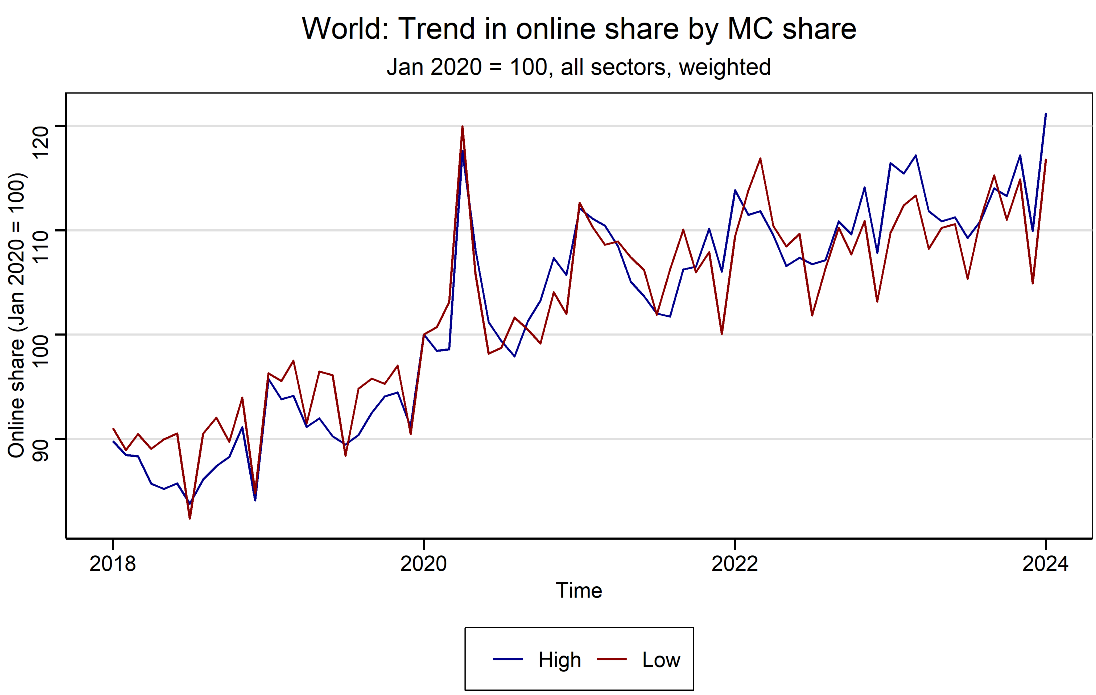
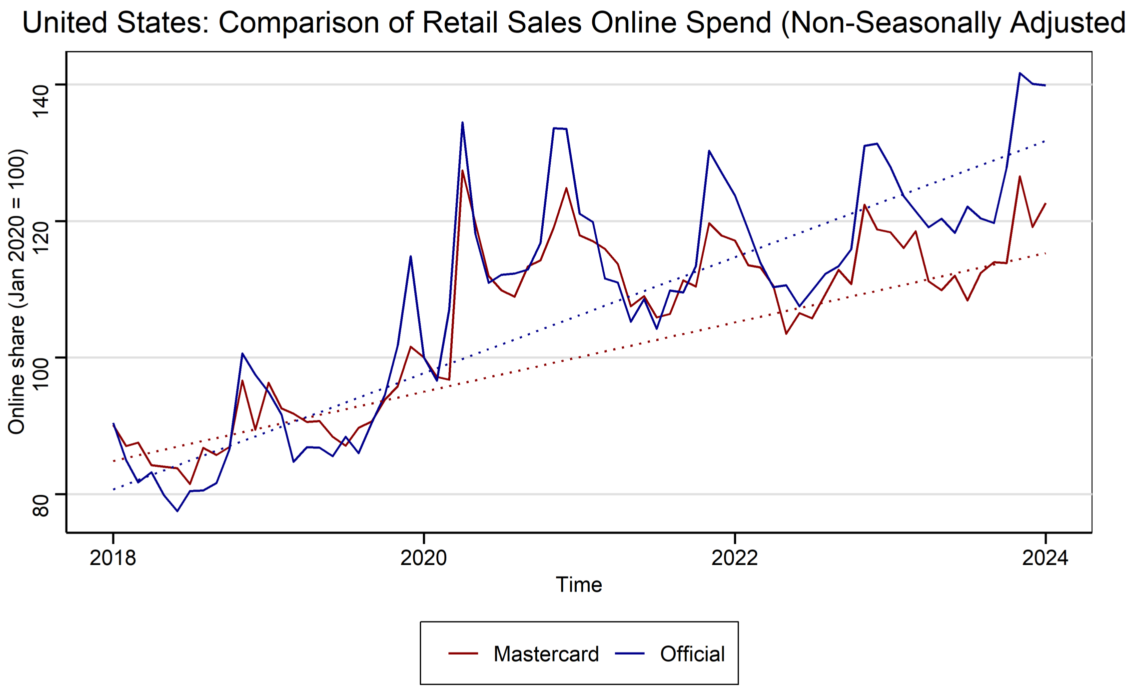


Figure 3: Online shares in retail sales in the United States and the United Kingdom. Comparison between modeled estimates and national statistics.



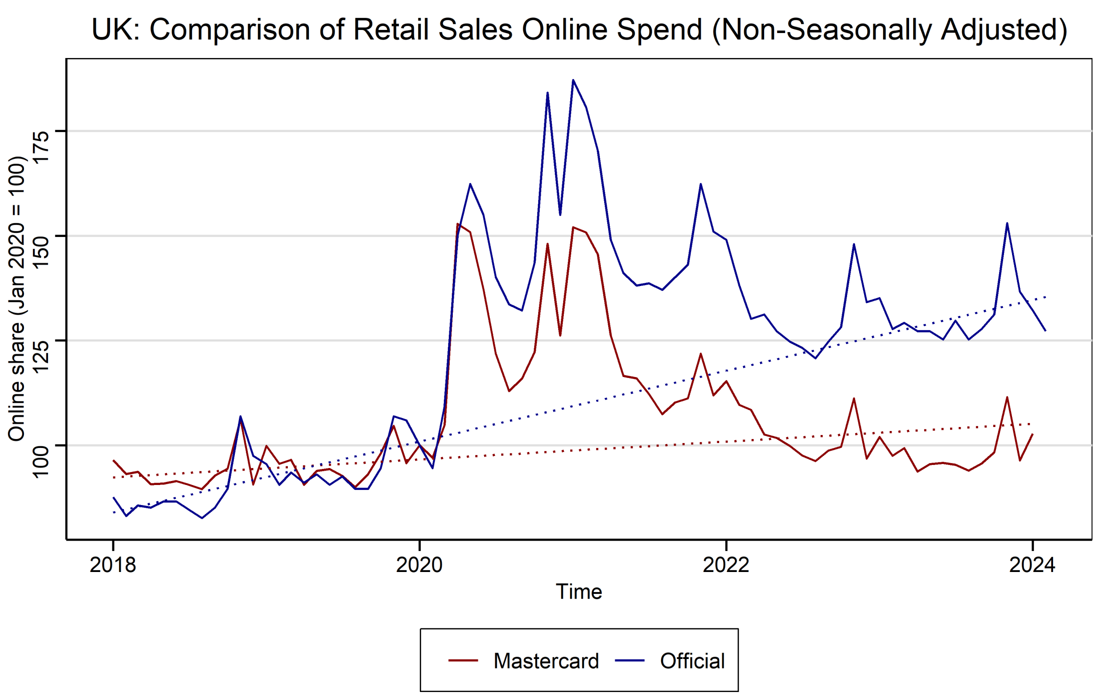
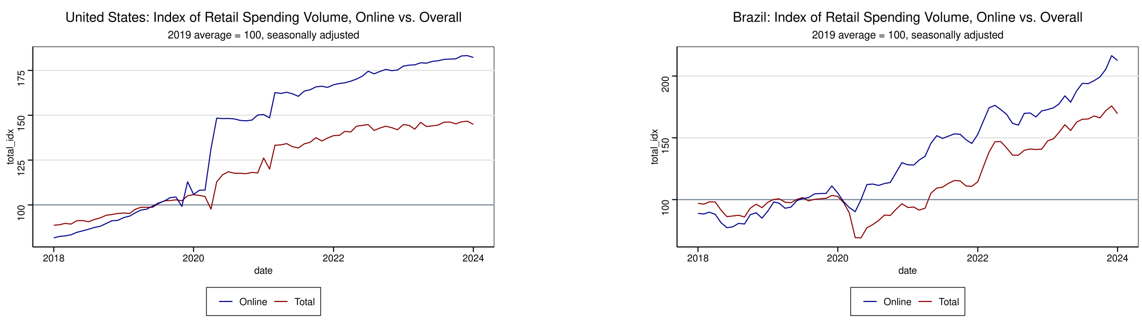
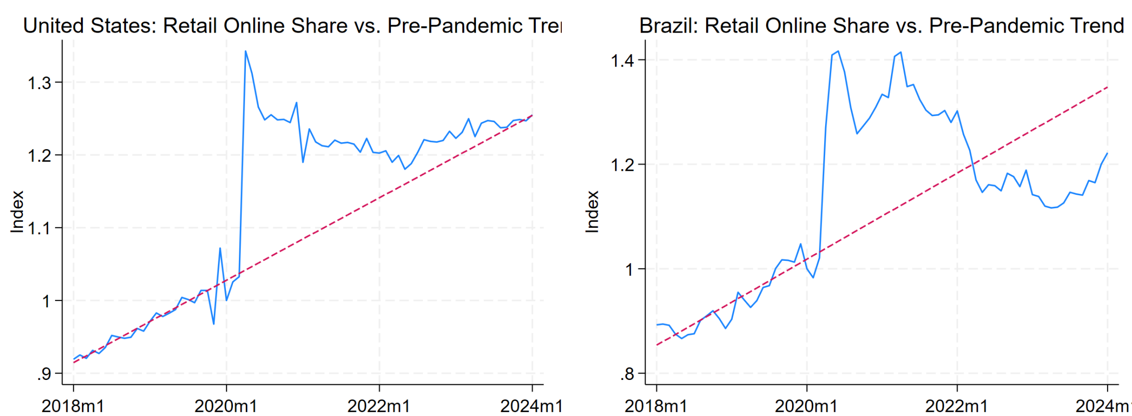


Figure 4: Retail spending during the pandemic



Notes. Figure 1 reports retail spending, seasonally adjusted using X13-ARIMA SEATS, adjusted with data starting in 2014.

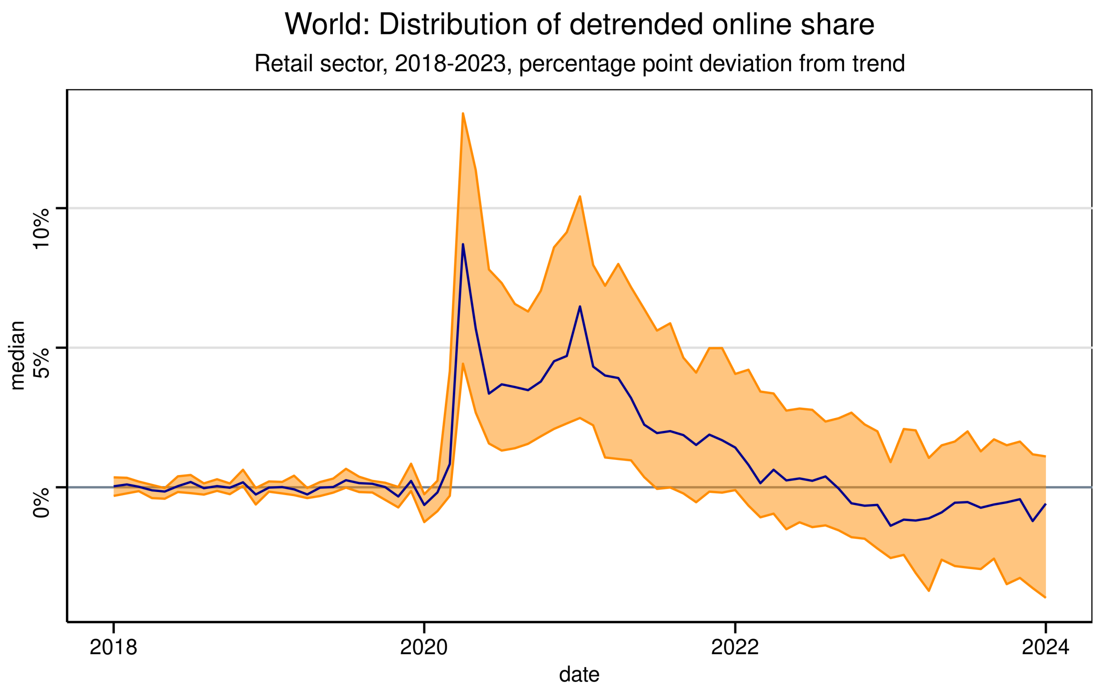
Figure 5: Examples of Retail Online Spending Share During COVID



Notes: The "online spending share" of total card consumption in the retail sector in a given year is defined by Equation (1) in the text, as $s_{c,t} = \frac{\text{Online Mastercard spending}_{c,t}}{\text{Total Mastercard spending}_{c,t}}$. The online share indexed to January 2020=1. The data is seasonally adjusted using X-13 ARIMA-SEATS.

Figure 6: Distribution of retail online share across countries (deviation from trend)

(a)



(b)

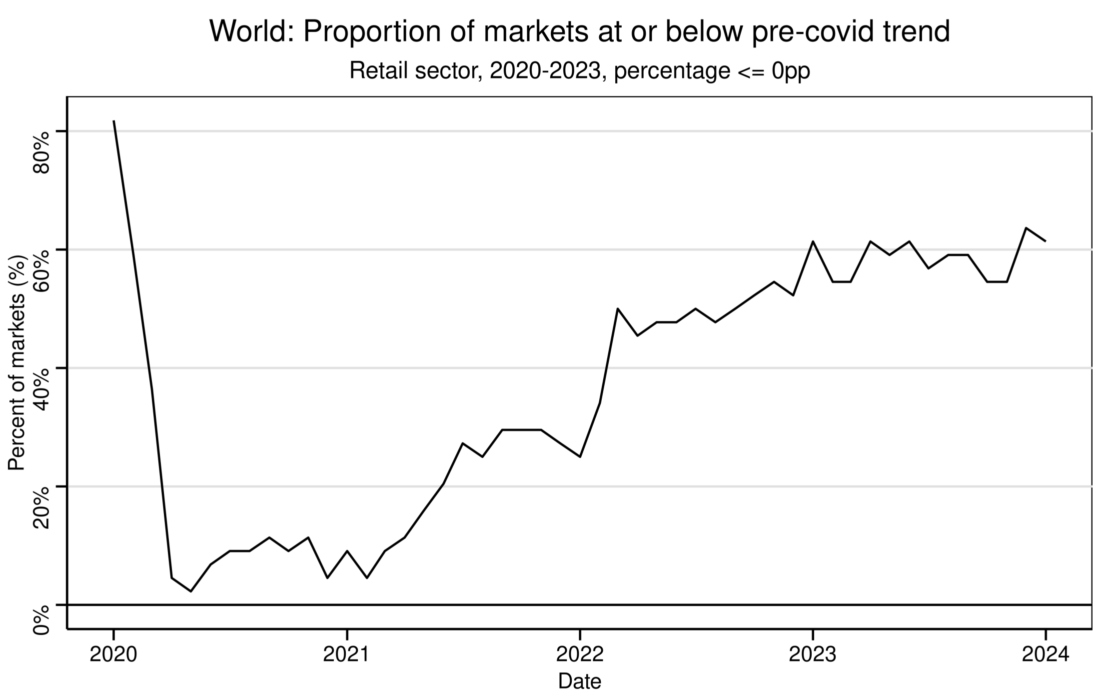
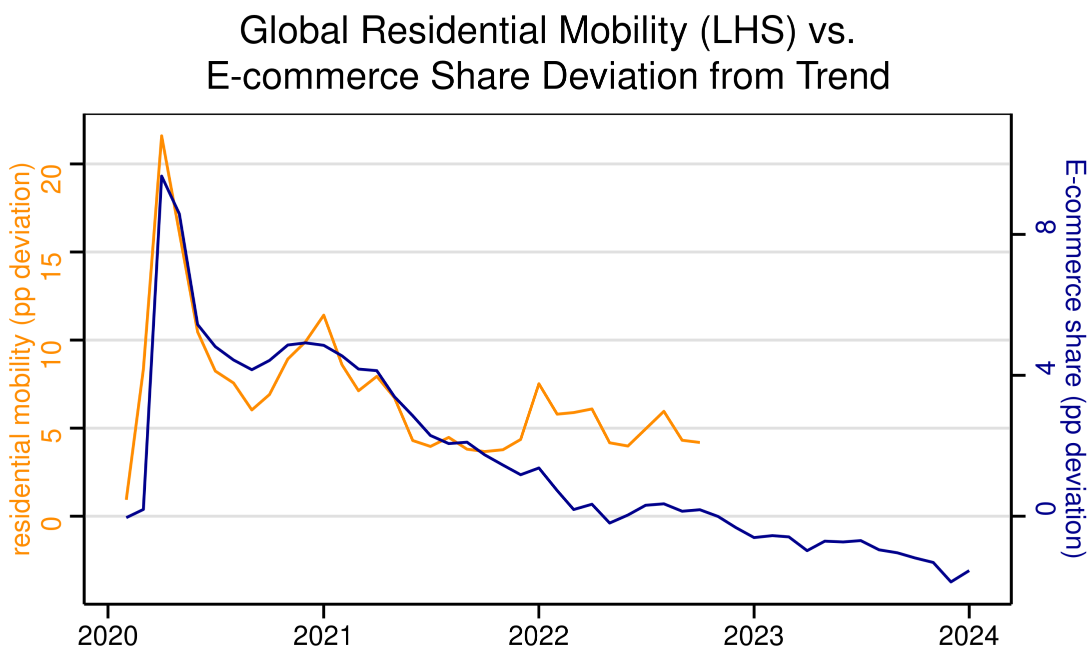
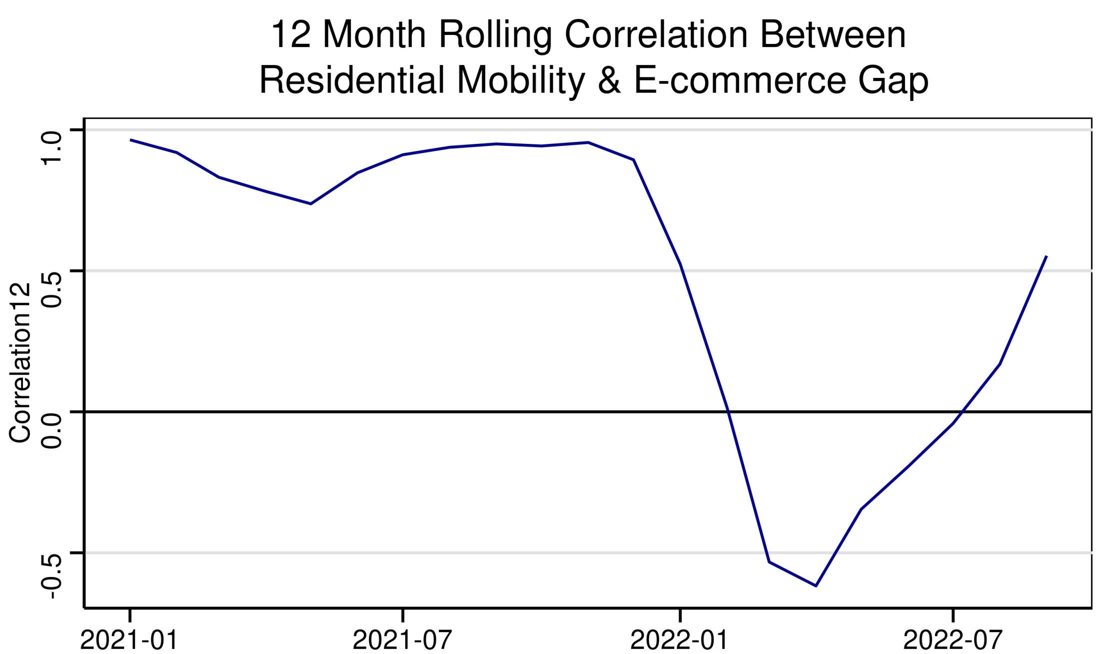


Figure 7: Residential mobility (time spent at home) vs. e-commerce deviation from trend

(a)

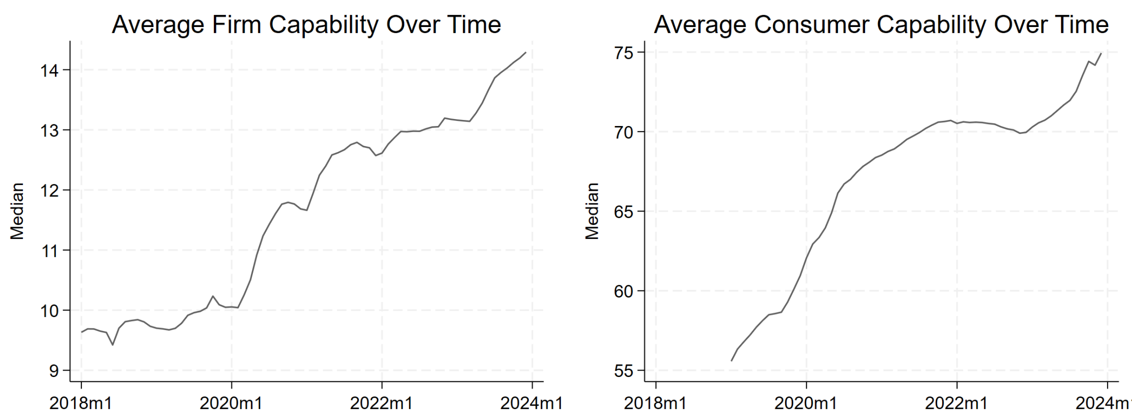


(b)



Notes: E-commerce gaps are seasonally adjusted to account for spikes around the holidays. Both the global residential mobility and E-commerce gaps are computed by taking an equal weight average for the 44 economies in our sample. Google COVID-19 Mobility Reports Discontinued in October 2022.

Figure 8: Firm and Consumer Capability Over Time



Notes. "Firm capability" is defined at the country-time level, as the proportion of active firms that ever sold online since the start of the sample in 2018. "Consumer capability" is defined as the proportion of active consumers that ever bought online. Figure 5 plots the median consumer and firm capability measures over time.

Figure 9: Peak versus pre-COVID trend in online spending shares across sectors

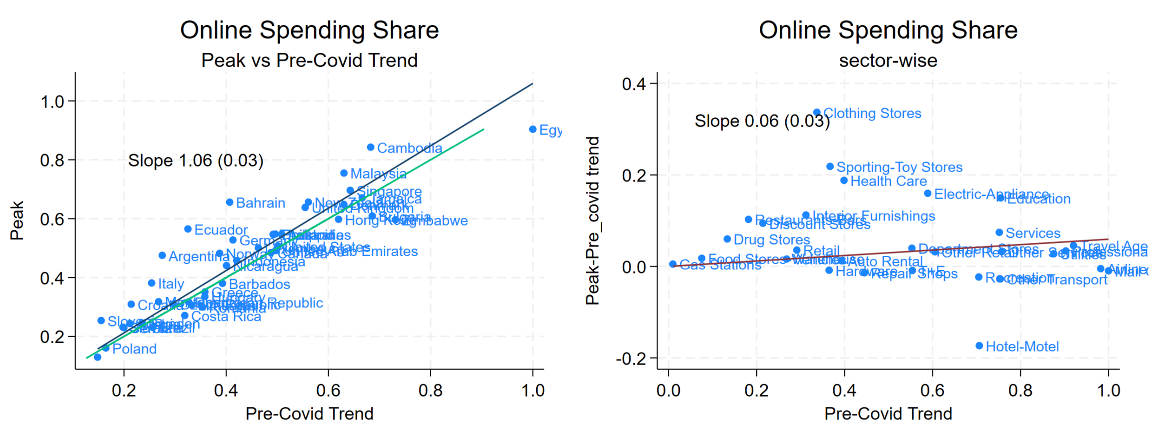
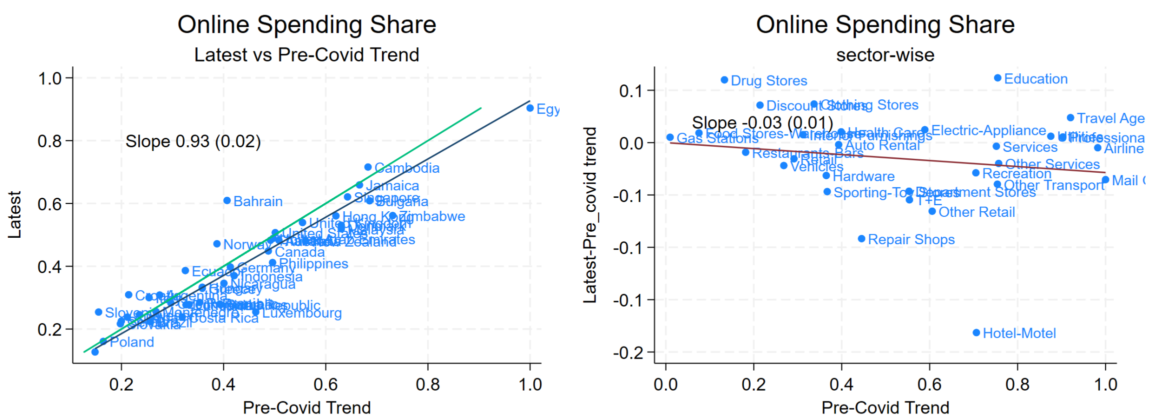


Figure 10: Latest versus pre-COVID trend in online spending shares across sectors



Notes: "Latest" refers to online spending share in April 2023. The pre-COVID trend is estimated in each sector using a regression of monthly online shares on a time trend between 2018-2019.

Figure 11: Distribution of retail online share across countries and sectors (deviation from trend)

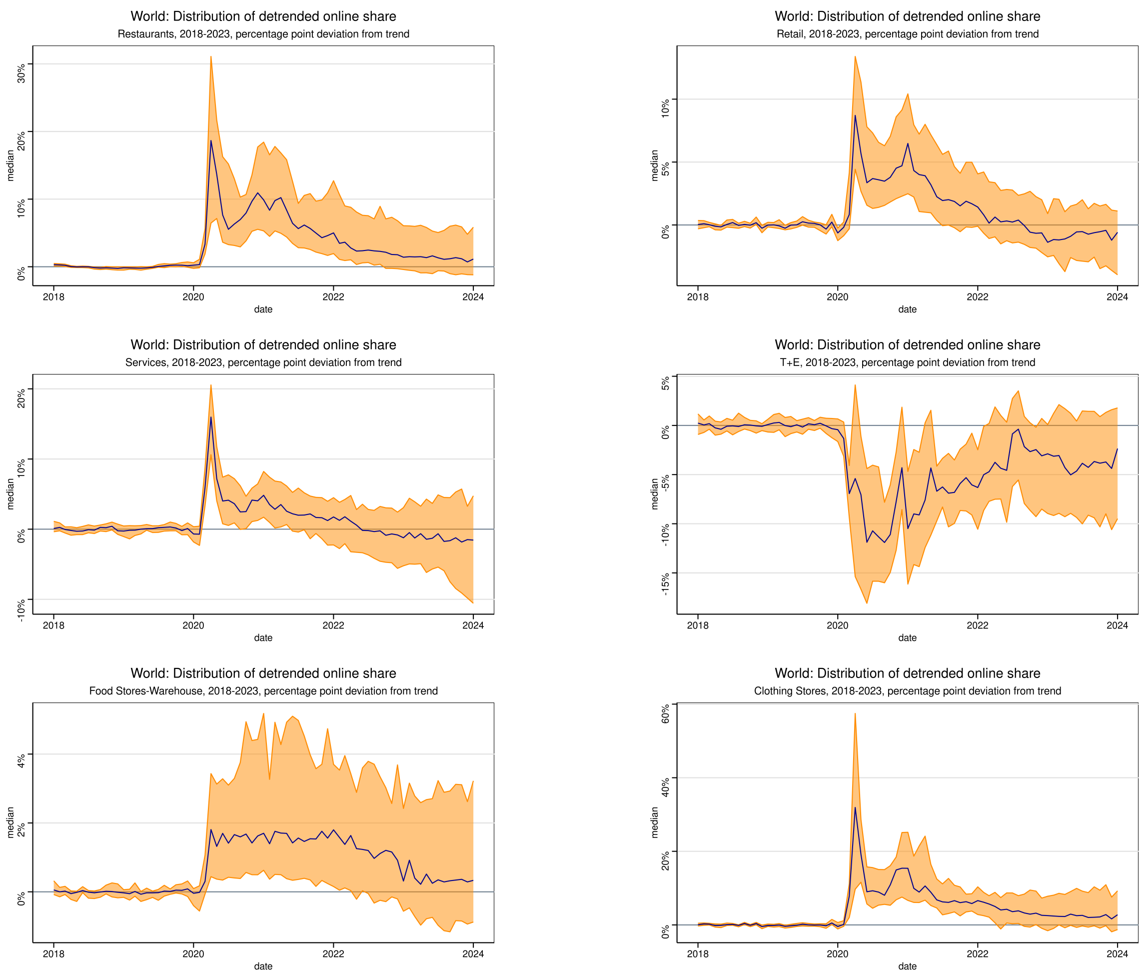


Table 1: Online Spending Share During COVID-19 in all Economies in the Sample [latest = Jan 2024]

Economy	Crisis peak (relative to 2019)	Latest	Latest minus pre-COVID trend
Slovenia	2.08 (2022/01)	2.11	0.87
Croatia	2.71 (2022/01)	2.39	0.70
Bahrain	1.81 (2022/02)	1.64	0.54
Austria	1.6 (2022/03)	1.58	0.25
Slovakia	1.82 (2022/02)	1.72	0.25
Italy	1.55 (2022/01)	1.27	0.24
Norway	1.22 (2022/02)	1.20	0.22
Serbia	1.74 (2022/01)	1.59	0.16
Cambodia	1.53 (2021/07)	1.35	0.15
Ecuador	1.86 (2022/01)	1.20	0.14
Argentina	1.55 (2022/01)	1.00	0.09
United Arab Emirates	1.31 (2021/02)	1.34	0.07
Sweden	1.19 (2022/01)	1.17	0.05
Poland	1.73 (2022/02)	1.65	0.03
United States	1.24 (2022/01)	1.21	0.02
Jamaica	1.14 (2022/01)	1.13	0.01
United Kingdom	1.26 (2022/01)	1.09	0.01
Montenegro	1.94 (2022/01)	1.53	0.01
Germany	1.45 (2022/03)	1.12	0.01
Czech Republic	1.89 (2022/02)	1.65	-0.01
Thailand	1.64 (2022/03)	1.38	-0.02
Singapore	1.33 (2022/02)	1.17	-0.03
Indonesia	1.55 (2022/02)	1.33	-0.03
Greece	1.63 (2022/01)	1.50	-0.04
Australia	1.18 (2022/01)	1.02	-0.07
Canada	1.32 (2022/01)	1.20	-0.08
Lithuania	1.33 (2022/02)	1.26	-0.12
Egypt	1.63 (2022/02)	1.50	-0.13
Nicaragua	1.21 (2021/09)	0.95	-0.14
Denmark	1.21 (2022/02)	1.01	-0.14
Bulgaria	1.25 (2022/01)	1.19	-0.15
Dominican Republic	1.28 (2022/01)	1.12	-0.15
New Zealand	1.35 (2022/03)	0.97	-0.17
Hungary	1.71 (2022/01)	1.50	-0.17
Brazil	1.32 (2022/02)	1.20	-0.19
Malaysia	1.74 (2022/03)	1.16	-0.23
Philippines	1.6 (2022/01)	1.13	-0.24
Netherlands	1.47 (2022/02)	1.27	-0.29
Zimbabwe	1.35 (2021/12)	1.26	-0.29
Romania	1.52 (2022/02)	1.36	-0.29
Costa Rica	1.28 (2022/02)	1.11	-0.31
Barbados	1.31 (2022/01)	0.93	-0.35
Luxembourg	1.4 (2022/01)	0.71	-0.54
Mean	1.52	1.31	-0.01
Median	1.47	1.21	-0.03
Standard Deviation	0.30	0.31	0.26

Notes. For each economy in the sample, the "online spending share" of total card consumption in any economy for a given year is defined by Equation (1) in the text, as $s_{c,t} = \frac{\text{Online Mastercard spending}_{c,t}}{\text{Total Mastercard spending}_{c,t}}$. "Latest" is the online share in January 2024 indexed to January 2020=1. Country-wise daily new covid cases data from www.ourworldindata.org. Monthly average of daily new cases are taken; month and year with the highest average is defined as peak. The peak is measured relative to the average online share in the economy for 2019.

Table 2: Correlates of deviation in online shares from the predicted pre-COVID trends

Dependent variable: Month-on-month change in online share gap (in pp)

	[1]	[2]	[3]	[4]
Residential Mobility, monthly avg %	0.350***	0.352***	0.283***	0.276***
	[0.040]	[0.040]	[0.050]	[0.050]
New Covid Cases per million, logs	0.031	0.022	0.014	0.013
	[0.020]	[0.030]	[0.030]	[0.030]
Pre-covid trend online share		-0.004	-0.004	-0.002
		[0.000]	[0.000]	[0.000]
COVID Fiscal spending as % 2019 GDP		-0.000	-0.001	-0.001
		[0.000]	[0.000]	[0.010]
Internet penetration, 2019 (%)		0.002	0.002	0.002
		[0.010]	[0.010]	[0.010]
Residential mobility * Fiscal spending, 2019			0.006***	0.007***
			[0.000]	[0.000]
GDP per capita-2019, in ’000’		-0.002	-0.002	-0.000
		[0.000]	[0.000]	[0.000]
Firm capability (%)				0.447
				[0.580]
Consumer capability (%)				0.074
				[0.190]
r2	0.42	0.42	0.42	0.45
N	1827	1827	1827	1446
Time FE	Yes	Yes	Yes	Yes
# countries	43	43	43	34
# months	46	46	46	46

Notes: Variables in differences are online share, Residential Mobility, Firm and Consumer Capabilities. The differences are computed by taking first difference month over month. Residential mobility on any given day of the week is measured as the percentage change from the baseline value, which is defined as the median value, for the corresponding day of the week, during the 5-week period Jan 3–Feb 6, 2020. The mobility variable is extrapolated beyond September 2022 when Google stopped producing the data. GDP per capita is in $, constant prices, PPP 2017 international dollars, taken from the IMF WEO. “Firm capability”, defined at the (country, time) level, as the proportion of active firms that ever sold online since the start of the sample in 2018. “Consumer capability” is defined as the proportion of active consumers that ever bought online. Figure 5 plots the median consumer and firm capability measures over time. Robust standard errors in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels.

Table 3: Correlates of deviation in online shares from the predicted pre-COVID trends. Robustness

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
	Baseline	Retail mob	Grocery and phar	Ox str	Ex internet	Yoy	Level
Mobility, monthly avg %	0.276***	-0.084***	-0.076***	0.053***	0.276***	0.168***	0.133***
	[0.050]	[0.020]	[0.020]	[0.020]	[0.050]	[0.030]	[0.030]
New Covid Cases per million, logs	0.013	0.004	0.039	0.057	0.016	0.218***	0.112
	[0.030]	[0.030]	[0.030]	[0.040]	[0.030]	[0.070]	[0.080]
Pre-covid trend online share	-0.002	0.000	0.001	0.000	-0.002	-0.060***	-0.064***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.010]	[0.010]
COVID Fiscal spending as % 2019 GDP	-0.001	-0.003	-0.001	0.001	-0.001	-0.019	0.045***
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
Internet Penetration, 2019 (%)	0.002	-0.001	-0.001	0.001		0.037***	0.035**
	[0.010]	[0.010]	[0.010]	[0.010]		[0.010]	[0.020]
Mobility * Fiscal spending, 2019	0.007***	-0.001*	-0.002***	0.002***	0.007***	0.005***	0.006***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
GDP per capita-2019, in '000'	-0.000	0.001	-0.001	-0.002	0.001	0.010	0.037**
	[0.000]	[0.000]	[0.000]	[0.010]	[0.000]	[0.010]	[0.020]
Firm capability (%)	0.447	0.540	0.984	0.832	0.442	0.081	-0.090***
	[0.580]	[0.640]	[0.620]	[0.730]	[0.580]	[0.090]	[0.020]
Consumer capability (%)	0.074	-0.008	0.097	-0.023	0.071	0.222***	0.093***
	[0.190]	[0.200]	[0.210]	[0.230]	[0.190]	[0.050]	[0.010]
r2	0.45	0.41	0.38	0.39	0.45	0.38	0.30
N	1446	1446	1446	1136	1446	1083	1461
Country FE	No	No	No	No	No	No	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# countries	34	34	34	34	34	34	34
# months	46	46	46	46	46	46	46

Notes: Column [1] repeats the baseline specification (column [4]) in Table 2. Columns [2]-[3] includes alternative measures of mobility (retail, and grocery and pharmacy, which are negatively correlated with pandemic restrictions) and Column [4] uses the Oxford stringency measure. Retail mobility is defined by Google as "mobility trends for places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters". Grocery & pharmacy mobility is defined by Google as "trends for places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies". The Oxford Stringency Index, formally known as the Oxford COVID-19 Government Response Tracker's (OxCGRT) Stringency Index, is a composite measure developed by researchers at Oxford University to track the strictness of government policies in response to the COVID-19 pandemic. Column [5] drops the internet penetration variable. Columns [6]-[7] employ alternative specifications – with changes measured over 12-month period, and estimation in levels rather than changes respectively. In all columns excluding Columns [6—[7], variables in differences are online share, Residential Mobility, Firm and Consumer Capabilities. The differences are computed by taking first difference month over month. In Column [6], online shares, and consumer and firm capabilities are in differences, computed as 12-month changes. In Column [7], all variables are in levels. Residential mobility on any given day of the week is measured as the percentage change from the baseline value, which is defined as the median value, for the corresponding day of the week, during the 5-week period Jan 3–Feb 6, 2020. The mobility variable is extrapolated beyond September 2022 when Google stopped producing the data. GDP per capita is in $, constant prices, PPP 2017 international dollars, taken from the IMF WEO. "Firm capability", defined at the (country, time) level, as the proportion of active firms that ever sold online since the start of the sample in 2018. "Consumer capability" is defined as the proportion of active consumers that ever bought online. Figure 5 plots the median consumer and firm capability measures over time. Robust standard errors in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels.

Table 4: Correlates of deviation in online shares from the predicted pre-COVID trends: Robustness to continuous fiscal measure

Dependent variable: Month-on-month change in online share gap (in pp)				
	[1]	[2]	[3]	[4]
Residential Mobility, monthly avg %	0.3500***	0.3539***	0.2920***	0.3122***
	[0.04]	[0.04]	[0.04]	[0.04]
New Covid Cases per million, logs	0.0306	0.0286	0.0219	0.0266
	[0.02]	[0.02]	[0.02]	[0.03]
Pre-covid trend online share		-0.0032	-0.0034	-0.0014
		[0.00]	[0.00]	[0.00]
Government fiscal balance		-0.0034	-0.0017	-0.0051
		[0.01]	[0.01]	[0.01]
Internet penetration, 2019 (%)		0.0021	0.0023	0.0016
		[0.01]	[0.01]	[0.01]
Residential mobility * Government fiscal balance			-0.0145***	- 0.0150***
			[0.01]	[0.01]
GDP per capita-2019, in ’000’		-0.0019	-0.0018	-0.0006
		[0.00]	[0.00]	[0.00]
Firm capability (%)				0.8331
				[0.58]
Consumer capability (%)				0.1451
				[0.22]
r2	0.42	0.43	0.44	0.46
N	1827	1601	1601	1355
Time FE	Yes	Yes	Yes	Yes
# countries	43	43	43	34
# months	46	46	46	46

Notes: Variables in differences are online share, Residential Mobility, Firm and Consumer Capabilities. The differences are computed by taking first difference month over month. Residential mobility on any given day of the week is measured as the percentage change from the baseline value, which is defined as the median value, for the corresponding day of the week, during the 5-week period Jan 3–Feb 6, 2020. The mobility variable is extrapolated beyond September 2022 when Google stopped producing the data. GDP per capita is in $, constant prices, PPP 2017 international dollars, taken from the IMF WEO. “Firm capability”, defined at the (country, time) level, as the proportion of active firms that ever sold online since the start of the sample in 2018. “Consumer capability” is defined as the proportion of active consumers that ever bought online. Figure 5 plots the median consumer and firm capability measures over time. Robust standard errors in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10 percent levels.

Table 5: Divergence Across Selected Sectors

sector	2019 average	Peak crisis	Latest	Latest vs pre-covid trend
All Categories	35.9	45.4	45.2	-2.1
Restaurants-Bars	7.3	28.4	17.2	-0.9
Retail	21.8	32.7	27.6	-1.5
Services	67.6	82.6	74.8	-0.3

Notes to Tables 5 and 6. Sectoral averages are created by computing a weighted average of the deviation in online share from the trend at the economy-sector level, where the weights are the shares of Mastercard spending in the economy-sector as a ratio of global spending in that sector. Notably, there are few sectors (e.g. airlines and travel agencies), with typically very high online penetration; for these we introduce an upper limit on the pre-pandemic time trend, constraining the value below 100% (as eCommerce shares cannot exceed 100%). The industries whose online penetration has achieved the upper limit are included in Table 5. These include, for example, "mail order", "airline", "travel agencies", and "utilities". As our methodology for estimating online share applies a scaling factor of (total card spending / total consumption), the scaled online shares for these industries will converge to an upper limit of card spend/total consumption when the 100% threshold is met. The data is seasonally adjusted using seasonally adjusted using X13-ARIMA SEATS, adjusted with data starting in 2014.

Table 6: **Heterogeneity across sectors in persistence of online shares**

	2019 average	Peak crisis	Latest	Latest vs pre-covid trend	Rank
Education	73.24	90.45	81.67	6.19	1
Drug Stores	10.31	19.33	19.33	6.00	2
Clothing Stores	22.59	67.40	37.39	3.69	3
Discount Stores	15.86	30.84	25.00	3.58	4
Travel Agencies	86.07	96.61	94.43	2.39	5
Electric-Appliance	45.65	74.88	60.13	1.23	6
Health Care	34.37	58.69	40.90	1.03	7
Food Stores-Warehouse	4.92	9.32	8.46	0.92	8
Interior Furnishings	21.88	42.46	31.97	0.76	9
Utilities	84.77	90.32	88.16	0.61	10
Professional Services	85.46	93.66	90.83	0.54	11
Gas Stations	0.48	1.49	1.49	0.52	12
Auto Rental	30.11	40.55	39.11	-0.19	13
Airline	93.10	97.73	97.73	-0.49	14
Restaurants-Bars	7.32	28.43	17.23	-0.92	15
Other Services	65.02	78.91	73.70	-1.99	16
Vehicles	19.60	28.44	24.64	-2.19	17
Recreation	60.29	68.20	67.62	-2.88	18
Hardware	27.36	35.65	33.34	-3.14	19
Mail Order	97.96	99.05	96.47	-3.53	20
Other Transport	66.81	72.66	71.43	-3.97	21
Department Stores	28.51	59.28	50.65	-4.64	22
Sporting-Toy Stores	27.26	58.56	32.03	-4.68	23
Other Retail	46.21	63.78	54.02	-6.55	24
Repair Shops	32.50	43.13	35.35	-9.17	25
Hotel-Motel	38.59	53.31	52.48	-18.15	26
All Categories	35.91	45.39	45.19	-2.13	

Table 7: Heterogeneity across sectors in persistence of online shares

Parameter	value	Notes
Elasticity of substitution $\left(\equiv \frac{1}{1-p}\right)$	3	Studies suggest a high elasticity of substitution between online and in- person purchases. As robustness we also try a value of 2 (see discussion)
Share parameter ($\equiv \lambda$)	Average: .58 Range: .48-.70	The value of λ is country-specific and is set so that the calibrated online share in 2018 matches the actual share
Average percent annual decrease in price in online purchases (p_y)	2 percent	This number is consistent with direct empirical observation. Another validation is given by the fact that a 2 percent decrease in online price is consistent with the increase in the pre-covid online shares
(implicit) Increase in in-person price (p_x) during the pandemic (March -December 2020)	Average: 15 percent Range: 7- 103 percent	An average 15 percent increases in the (implicit) cost of in-person purchases matches the observed increase in the share of online purchases between March and December 2020. With the Exception of Egypt (103) and Zimbabwe (40) all countries are well below 30 percent

Table 8: Estimated Welfare Losses

	Online share 2019	Online share 2020 (March -December)	Difference	Implied increase in cost for in-person purchase	Estimated welfare loss
Australia	46	48	2	2	0
Austria	15	16	1	4	-3
Bahrain	36	44	8	15	-7
Barbados	29	30	1	1	0
Brazil	18	21	4	15	-11
Bulgaria	49	55	7	20	-8
Cambodia	55	70	15	37	-10
Canada	37	41	4	11	-6
Costa Rica	21	25	3	14	-9
Croatia	11	15	3	25	-18
Czech Republic	16	22	5	27	-18
Denmark	54	55	1	3	0
Dominican Republic	25	29	4	11	-7
Ecuador	30	42	12	25	-13
Egypt	55	77	22	103	-23
Germany	36	38	2	3	-1
Greece	22	24	2	13	-9
Hong Kong	43	49	5	17	-7
Hungary	20	23	4	21	-14
Indonesia	30	34	4	13	-8
Italy	25	27	3	4	-2
Jamaica	59	61	2	4	0
Lithuania	23	22	-1	1	0
Luxembourg	36	36	0	3	-1
Malaysia	43	53	10	29	-12
Montenegro	16	18	1	10	-7
Netherlands	9	8	-1	-3	3
New Zealand	49	49	0	0	1
Nicaragua	36	41	5	9	-4
Norway	39	38	-1	-7	5
Philippines	34	45	11	29	-14
Poland	9	10	1	11	-9
Romania	20	24	5	25	-16
Serbia	13	14	0	6	-5
Singapore	52	63	11	26	-9
Slovakia	13	14	2	11	-9
Slovenia	12	14	2	8	-6
Somalia	37	41	3	31	-16
Sweden	21	19	-1	-7	6
Thailand	33	39	6	19	-10
UAE	38	39	1	4	-2
United Kingdom	51	57	7	12	-4
United States	41	45	4	9	-4
Zimbabwe	44	55	11	40	-16
Average	32	36	4	15	-7
Advanced economies	31	33	3	9	-5
EMDE	37	44	8	25	-10

Notes. For each economy in the sample, we report the online share in 2019 ($s_{c,2019}$) the online share in 2020 between March and December ($s_{c,2020}$). The difference between the two, the imputed increase in in-person transaction cost, and the estimate welfare loss given the increase in in-person transaction cost as described in the main text.

Appendix

Tables

Summary Statistics (based on Table 2 Column 4)

Variable	Obs	Mean	Std. Dev.	Min	Max
Online share gap (online share-trend) (in pp), SA	1,082	-0.0195	3.022	-19.27	24.61
Residential Mobility, monthly avg %	1,082	0.128	4.110	-15.55	34.06
New Covid Cases per million, logs	1,082	7.127	2.417	-1.715	12.07
Pre-covid trend online share	1,082	44.36	18.10	14.84	100
COVID Fiscal spending as % 2019 GDP	1,082	13.67	10.81	1.149	43.39
GDP per capita-2019, in '000'	1,082	36.59	21.93	2.779	97.34
Residential mobility * Fiscal spending, 2019	1,082	0.995	71.95	-567.3	844.8
Firm capability (%)	1,082	0.0719	0.164	-0.401	1.379
Consumer capability (%)	1,082	0.228	0.392	-3.613	2.842
Internet penetration, 2019 (%)	1,082	78.52	18.00	26.59	99.70

Notes: Variables in differences: online share gap (LHS), Residential Mobility, Firm and Consumer Capabilities (RHS). First difference month over month.

Table A1: Robustness Constant Sample

	[1]	[2]	[3]	[4]
Residential Mobility, monthly avg %	0.3643***	0.3655***	0.2748***	0.2763***
	[0.04]	[0.04]	[0.05]	[0.05]
New Covid Cases per million, logs	0.0353	0.0249	0.012	0.0134
	[0.03]	[0.03]	[0.03]	[0.03]
Pre-covid trend online share		-0.0024	-0.0026	-0.0019
		[0.00]	[0.00]	[0.00]
COVID Fiscal spending as % 2019 GDP		-0.0022	-0.0029	-0.001
		[0.01]	[0.01]	[0.01]
Internet penetration, 2019 (%)		0.0012	0.0015	0.0018
		[0.01]	[0.01]	[0.01]
Residential mobility * Fiscal spending, 2019			0.0072***	0.0070***
			[0.00]	[0.00]
GDP per capita-2019, in '000'		0.0005	0.001	-0.0002
		[0.00]	[0.00]	[0.00]
Firm capability (%)				0.447
				[0.58]
Consumer capability (%)				0.0743
				[0.19]
r2	0.4329	0.4333	0.4451	0.4456
N	1446	1446	1446	1446
Country FE	No	No	No	No
Time FE	Yes	Yes	Yes	Yes
# countries	43	43	43	34
# months	46	46	46	46

Notes: Variables in differences: online share (LHS), Residential Mobility, Firm and Consumer Capabilities (RHS). First difference month over month.

Table A2: Heterogeneity across sectors in persistence of online shares - Retail Only

Parameter	value	Notes
Elasticity of substitution $\left(\equiv \frac{1}{1-p}\right)$	3	Studies suggest a high elasticity of substitution between online and in- person purchases. As robustness we also try a value of 2 (see discussion)
Share parameter ($\equiv \lambda$)	Average: .63 Range: .51-.74	The value of λ is country-specific and is set so that the calibrated online share in 2018 matches the actual online share
Average percent annual decrease in price in online purchases (p_y)	2 percent	This number is consistent with direct empirical observation. Another validation is given by the fact that a 2 percent decrease in online price is consistent with the increase in the pre-covid online shares
(implicit) Increase in in-person price (p_x) during the pandemic (March -December 2020)	Average: 24 percent Range: 1- 250 percent	An average 24 percent increases in the (implicit) cost of in-person purchases matches the observed increase in the share of online purchases between March and December 2020. With the Exception of Cambodia , Somalia, and Zimbabwe all countries are below 50 percent

Table A3: Estimated Welfare Losses - Retail Only

	Online share 2019	Online share 2020 (March -December)	Difference	Implied increase in cost for in-person purchase	Estimated welfare loss
Australia	27	32	5	12	-7
Austria	13	15	2	8	-6
Bahrain	13	22	9	32	-20
Barbados	22	23	1	1	-1
Brazil	10	14	3	19	-14
Bulgaria	43	52	9	17	-7
Cambodia	47	70	23	57	-16
Canada	19	26	7	27	-16
Costa Rica	10	14	4	20	-15
Croatia	5	7	2	23	-17
Czech Republic	13	18	5	28	-19
Denmark	41	43	2	4	-2
Dominican Republic	12	16	4	15	-11
Ecuador	18	27	9	24	-15
Egypt	10	12	2	20	-15
Germany	34	39	5	6	-3
Greece	9	11	2	12	-10
Hong Kong	35	44	9	20	-10
Hungary	11	14	3	19	-14
Indonesia	21	31	9	34	-19
Italy	20	26	6	14	-9
Jamaica	20	22	2	3	-2
Lithuania	12	13	1	3	-3
Luxembourg	28	34	6	14	-8
Malaysia	26	39	13	33	-17
Montenegro	6	7	1	6	-5
Netherlands	5	6	1	8	-7
New Zealand	32	35	4	9	-5
Nicaragua	28	37	10	25	-14
Norway	24	29	6	13	-8
Philippines	15	28	13	49	-27
Poland	6	8	2	17	-13
Romania	9	12	4	17	-13
Serbia	6	6	1	8	-7
Singapore	35	51	15	40	-17
Slovakia	9	12	3	25	-18
Slovenia	8	12	4	24	-17
Somalia	40	61	21	68	-23
Sweden	12	14	2	8	-6
Thailand	15	25	10	44	-25
United Arab Emirates	12	17	6	40	-25
United Kingdom	37	48	12	24	-11
United States	25	31	5	15	-9
Zimbabwe	39	72	33	150	-36
Average	20	27	7	24	-13
Advanced economies	21	26	5	17	-10
EMDE	22	32	10	37	-17
EMDE (ex Zimbabwe)	21	29	9	30	-15

Notes. For each economy in the sample, we report the online share in 2019 ($s_{c,2019}$) the online share in 2020 between March and December ($s_{c,2020}$). The difference between the two, the imputed increase in in-person transaction cost, and the estimate welfare loss given the increase in in-person transaction cost as described in the main text.

A Detailed overview of database used in our study.

Payment Channels and the Scope of Study

Payments can occur through a variety of channels, including cash, card, check, and deposits. This study focuses on aggregated & anonymized card transactions within the Mastercard network. A related database from Mastercard was used by Mian, Rao, and Sufi (2013).

Although card transactions mainly serve the retail and services sector, specific segments like vehicle sales are underrepresented as deposits often take precedence over card payments.

Card payments are the predominant method for online transactions, translating to over-representativeness of e-commerce relative to household expenditures in aggregate. Although this translates to an inherent payment form bias, e-commerce shares in our database align well in markets whose official statistics agencies report e-commerce sales.

Our study adds value by providing a more granular look into the transience of e-commerce spend across different industries and many more markets than is typically not readily available.

A.0.1 Data Structure & Dimensionality

- **Payment Channels:** A significant component of our study is defining online spending. For this purpose, we categorize E-commerce as transactions where neither the cardholder nor the card are physically present. In transactions where tap to pay is initiated via a mobile wallet with a linked card, which represent a small portion of aggregate volumes, the card itself is not physically present. Examples include shopping for apparel through a website, prepaying for automotive fuel through a mobile app, purchasing an airline ticket online and ordering food over the phone using a credit card, elaborated upon in table A4.

- **Localization:** The data is measured relative to the card's issuing bank country. For instance, a transaction made using a Canadian card for an online purchase from a U.S. merchant will be attributed to Canada, regardless of the merchant's location.

- **Sectoral Definitions & Industry Representativeness:** Industries in our dataset are categorized using Merchant Category Codes (MCC), a standard in the card payments industry. MCCs are assigned at the firm level, meaning all transactions—whether online or in-person—are classified under the firm's primary business activity. For example, if a firm predominantly engaged in mail order sales also operates a physical storefront, its in-person transactions would still be categorized as mail order. While MCCs can be mapped to other classifications like NAICS or SIC, the core insights of our study remain consistent regardless of the classification used. It's important to note that card payment data exclude cash transactions and sectors where card payments are uncommon, such as rent or large automotive sales.

The database offers details on:

- Date & time: the date and time in which the transaction occurred.
- Type of card: whether the card is a credit, debit, or pre-paid card.
- Merchant location: what is the address on record for the merchant where the transaction took place?
- Industry classification: what industry is the merchant classified as.
- Channel: whether the payment was an online or brick & mortar transaction.
- Transaction amount: the value of the transaction made.

Importantly, Mastercard does not have access to the following dimensions:

- Cardholder-specific details, like location, income, or account balances.
- Breakdown of individual items or SKUs in a purchase. Mastercard only observes the total payment amount.

A detailed description of what can be observed in payment data follows the ISO 8583 international standard[19], which outlines the data formats and fields used in financial transaction messaging. This standard specifies the structure for exchanging payment-related information across different systems, ensuring interoperability

[19] https://www.iso.org/obp/ui/#iso:std:iso:8583:-1:ed-1:v1:en

and accuracy in processing transactions.In the context of this research, an aggregated and anonymized dataset provided by Mastercard was studied. The dataset contains no personally identifiable information about individual consumers, merchants, or financial institutions.

A.0.2 Mastercard's Reach

The Mastercard network has a presence in 210 countries and territories, connected to 20,000 financial institutions and over 80 million merchant locations with more than 2.9 billion cards in force. In 2022, Mastercard processed approximately 125.7 billion transactions, amounting to a total value of nearly 8.2 trillion U.S. dollars from purchases and cash disbursements.

Table A4: Examples of in-store and online sales

Sector	Example of in-store sale	Example of online sale
Airline	Purchasing flight tickets at an airline ticket desk	Paying for a flight online at the airline's booking site
Auto Rental	Renting a vehicle at the rental counter in person	Booking a rental car via the company's website
Clothing Stores	Trying on and purchasing apparel at a physical store	Buying apparel from the retailer's e-commerce website
Department Stores	Shopping for clothing and housewares at a department store	Ordering from the department store's e-commerce platform
Discount Stores	Buying household items at a discount store	Ordering discounted household goods through a store app
Drug Stores	Buying over-the-counter medication at a local pharmacy	Ordering prescription refills through the pharmacy's website
Education	Purchasing textbooks at a campus bookstore	Enrolling in an online course or paying tuition fees online
Electric-Appliance	Buying a television at a big-box electronics store	Ordering a home appliance from an online retailer
Food Stores	Purchasing groceries in a warehouse club	Ordering groceries for home delivery on the warehouse's website
Gas Stations	Filling the tank and paying at the station's register	Prepaying for gas through a mobile app linked to a card
Health Care	Paying for a doctor's visit at a clinic	Booking a telemedicine consultation or settling bills online
Hardware	Buying tools at a physical hardware store	Ordering home-improvement supplies from the store's website
Hotel-Motel	Reserving and paying for a room at a hotel front desk	Booking a stay through the hotel's website or an aggregator
Interior Furnishings	Selecting furniture in-store	Placing an online order for furniture on the company's website
Mail Order	Picking up merchandise at a mail-order company's local outlet	Purchasing goods by placing an online or catalog order
Other Services	Paying for a haircut at a barbershop	Paying for remote or online professional services via website
Other Transport	Buying a train ticket at the station's ticket office	Booking bus or train tickets through a transportation app
Professional Services	Paying in person for consulting at an office	Paying for an online consulting session by credit card
Recreation	Buying an event ticket in person at a box office	Booking tickets or classes through an online ticketing system
Repair Shops	Paying for a car repair at the mechanic's garage	Paying a service deposit or scheduling repairs online
Restaurants-Bars	Dining in and paying the bill at a restaurant	Placing a delivery or pickup order on the restaurant's app
Other Retail	Purchasing goods from a local specialty shop	Ordering products online from the same specialty retailer
Sporting-Toy Stores	Selecting sporting goods or toys in a physical store	Buying sports equipment or toys on the retailer's website
Travel Agencies	Booking a vacation package at a travel agency storefront	Purchasing airline tickets through the agency's website
Utilities	Paying a utility bill at a physical service kiosk	Paying for utilities online via the provider's portal
Vehicles	Purchasing a car at a local dealership	Placing a deposit or buying a car from an online marketplace

B Technical appendix

This appendix contains the derivation for the calibration discussed in the main text.

Define the amount of good in person as x and the amount of goods purchased online as y. The two (bundle of) goods are imperfect substitutes. The consumer maximizes their utility:

$$U = (\lambda x^\rho + (1-\lambda) y^\rho)^{\frac{1}{\rho}} \quad \text{s.t.} \quad p_x x + p_y y = I \tag{A1}$$

The Lagrangian for the maximization problem is:

$$L = \left[\frac{\lambda x^\rho + (1-\lambda) y^\rho}{2} \right]^{\frac{1}{\rho}} + \gamma \left[I - p_x x - p_y y \right] \tag{A2}$$

where $Z \equiv \frac{\lambda x^\rho + (1-\lambda) y^\rho}{2}$.

The first-order conditions are:

$$\frac{\partial L}{\partial x} = 0 \qquad MU_x - \gamma p_x = 0$$

$$\frac{\partial L}{\partial y} = 0 \qquad MU_y - \gamma p_y = 0$$

$$\frac{MU_x}{p_x} = \frac{MU_y}{p_y}$$

$$\frac{\frac{1}{\rho} Z^{\frac{1}{\rho}-1} \cdot \lambda \rho x^{\rho-1}}{\frac{1}{\rho} Z^{\frac{1}{\rho}-1} (1-\lambda) \rho \gamma^{\rho-1}} = \frac{p_x}{p_y}$$

$$\frac{\lambda}{1-\lambda} \left(\frac{x}{y} \right)^{\rho-1} = \frac{p_x}{p_y} \tag{A3}$$

$$\frac{x}{y} = \left(\frac{p_x}{p_y} \cdot \frac{1-\lambda}{\lambda} \right)^{\frac{1}{\rho-1}} \tag{A4}$$

Substituting in the budget constraint:

$$p_x \left(\frac{p_x}{p_y} \cdot \frac{1-\lambda}{\lambda} \right)^{\frac{1}{\rho-1}} y + p_y y = I \tag{A5}$$

$$y = \frac{1}{p_y} \frac{I}{\frac{p_x}{p_y} \left(\frac{p_x}{p_y} \cdot \frac{1-\lambda}{\lambda} \right)^{\frac{1}{1-\rho}} + 1} \tag{A6}$$

$$y = \frac{1}{p_y} \frac{I}{\left(\frac{p_x}{p_y} \right)^{\frac{\rho}{1-\rho}} \left(\frac{1-\lambda}{\lambda} \right)^{\frac{1}{1-\rho}} + 1} \tag{A7}$$

Online share of spending:

$$S \equiv \frac{p_y y}{I} = \frac{1}{1 + \Lambda \left(\frac{p_y}{p_x} \right)^{\frac{\rho}{1-\rho}}} \tag{A8}$$

where $\Lambda \equiv \left(\frac{\lambda}{1-\lambda} \right)^{\frac{1}{1-\rho}}$.

We observe only S (the share of online expenditure). From that, we can deduce $\frac{p_y}{p_x}$. From equation (A8):

$$1 + \Lambda \left(\frac{p_y}{p_x} \right)^{\frac{\rho}{1-\rho}} = \frac{1}{S} \tag{A9}$$

$$\left(\frac{p_y}{p_x} \right)^{\frac{\rho}{1-\rho}} \Lambda = \frac{1}{S} - 1 \tag{A10}$$

$$\left(\frac{p_y}{p_x} \right)^{\frac{\rho}{1-\rho}} = \frac{1-S}{S\Lambda} \tag{A11}$$

$$\frac{p_y}{p_x} = \left(\frac{1-S}{S\Lambda} \right)^{\frac{1-\rho}{\rho}} \tag{A12}$$

$$p_x = p_y \left(\frac{S\Lambda}{1-S} \right)^{\frac{1-\rho}{\rho}} \tag{A13}$$

To calculate the welfare effect, we need to calculate how utility changes with the (implicit) increase in price of buying in person.

Deriving the indirect Utility.

Substituting in the utility function (A1) the equilibrium condition (A4):

$$U = [\lambda x^\rho + (1-\lambda) y^\rho]^{\frac{1}{\rho}}$$

$$x = y\left(\frac{p_y}{p_x}\right)^{\frac{1}{1-\rho}}\Lambda$$

$$\frac{x}{y} = \left(\frac{p_x}{p_y}\cdot\frac{1-\lambda}{\lambda}\right)^{\frac{1}{\rho-1}} \tag{A14}$$

$$U = \left[\lambda y^{\rho}\Lambda^{\rho}\left(\frac{p_y}{p_x}\right)^{\frac{\rho}{1-\rho}} + (1-\lambda)y^{\rho}\right]^{\frac{1}{\rho}} \tag{A15}$$

$$U = y\left[\lambda\Lambda^{\rho}\left(\frac{p_y}{p_x}\right)^{\frac{\rho}{1-\rho}} + (1-\lambda)\right]^{\frac{1}{\rho}} \tag{A116}$$

Using equation (A9):

$$U = \frac{IS}{p_y}\left[\lambda\Lambda^{\rho}\left(\frac{p_y}{p_x}\right)^{\frac{\rho}{1-\rho}} + (1-\lambda)\right]^{\frac{1}{\rho}} \tag{A17}$$

Note that (A17) is not strictly speaking an indirect utility because it is a function of share (but writing this way makes the interpretation easier).