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The Resilience of Fashion Retail Stores

Victor Martínez-de-Albéniz[1], Diego Aparicio[1], and Jordi Balsach[1]

Abstract

Retail stores are an essential sales channel in the economy. What makes them resilient to external shocks? We propose a conceptual framework in which resilience is determined by (a) the intrinsic stability of the customer pool that the store serves and (b) the actions the store implements to cope with external shocks. We apply our framework to study the impact of COVID-19 pandemic on thousands of fashion stores across the world, using a novel high-frequency scraping method to infer daily sales. Our results indicate a severe impact of lockdown regulations, with remarkable store-level heterogeneity. Stores of smaller size, in high-income lower-density areas, catering to non-touristic demand, and not located in shopping malls were intrinsically more resistant to external shocks. Furthermore, stores that chose to be more differentiated (reduced assortment similarity) and to keep a fresher inventory (faster inventory days) were also able to attenuate the impact of the pandemic. Our framework can be useful for policymakers, who are interested in identifying and targeting most vulnerable businesses, as well as managers, who would like to build a network of stores sufficiently resistant to shocks.

Keywords

Retail, Fast-Fashion, Offline Stores, COVID-19, Lockdowns

JEL Classification Code: C8, D12, D22, L81, R3

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1 Introduction

> Crystal Mall's parking lots used to be so crowded that parents would line up to drop off their teenagers near one of the entrances rather than search for a spot. Now, the vast stretches of cracked pavement surrounding this 1980s-era regional mall on Connecticut's coast have more weeds than cars. Valued by an appraiser at $153 million as recently as 2012, Crystal Mall sold in June for just over $9.5 million in a foreclosure auction. (Wall Street Journal, 2023)

Brick-and-mortar stores remain the dominant sales channel in retail. In fact, flagship stores not only provide ease of access to the retailer's products, but also shape a brand's identity and add an experiential connection with the customer. However, rapid changes in the retail landscape, including the development of online channels and new technologies (Caro et al., 2020), have put into question the role of physical stores. Moreover, footfall—the count of consumers entering a store—keeps decreasing in all countries.

If these trends continue, which kinds of stores are more likely to survive? What makes some stores more resilient than others? We use the COVID-19 pandemic as a unique event to explore which elements make stores more resistant to external shocks. Indeed, the pandemic prompted us to challenge beliefs deeply embedded in our Folk Wisdom. For decades, retailers have taken at face value that signature stores in the busiest streets in Milan, Paris, New York, or Barcelona, are "the way to go." For instance, in 2014 Valentino opened a flagship store in the Fifth Avenue—an impressive store of 20,000 square-foot and three levels, right next to the MoMa. Stefano Sassi, then CEO of Valentino, said that Fifth Avenue "is the center of the world" and "having a store here is a key message to the market" (Wall Street Journal, 2014). Yet, Valentino closed its Fifth Avenue store in 2020, claiming that it was "no longer workable as a luxury destination" (Business Insider, 2020). This example suggests that we lack a full understanding of the factors that drive store resilience.

[1]IESE Business School, University of Navarra, Barcelona, Spain

Corresponding authors:
Diego Aparicio, IESE Business School, University of Navarra, Avenida Pearson 21, 08034 Barcelona, Spain.
Email: daparicio@iese.edu

The datasets and codes to reproduce the results of this paper are available here: https://doi.org/10.7910/DVN/PZC0N9.

In this article, we study the resilience of offline stores to external shocks. We examine the impact of the COVID-19 pandemic on two fashion retailers: Zara and Bershka. These two brands are among the largest ready-to-wear fashion brands worldwide, with combined sales of 21€ billion and 3,377 stores (Inditex Annual Report, 2019). While most readers are familiar with the unprecedented scale of COVID-19, it is helpful to recall a few key facts. COVID-19, caused by the SARS-CoV-2 virus, started as a health crisis—with over 775 million infected individuals and 7 million deaths as of October 2024. It has become the deadliest disease, surpassing the 1918 flu pandemic (National Geographic, 2021). Beyond public health outcomes, its worldwide spread in February 2020 led to major economic downturn caused by global, synchronized demand, and supply shocks (Guan et al., 2020). The International Monetary Fund estimates that the world economy declined 3.3% in 2020, for example, Spain -11.0%, the United Kingdom -9.9%, France -8.2%, Germany -4.9%, and the United States -3.5% (International Monetary Fund, 2021).

The pandemic forced national and local governments to implement drastic social and economic interventions in an effort to contain the spread of the virus (Brauner et al., 2021). A large body of literature examined the impact of these policies on health (Aleta et al., 2020; Chinazzi et al., 2020; Chiu et al., 2020; Glaeser et al., 2020; Salje et al., 2020). Studies have also used survey data, household scanner data, or proprietary transaction data to measure consumption patterns, often examining a single or a few countries (Adams-Prassl et al., 2020; Brinca et al., 2021; Carvalho et al., 2021; Chetty et al., 2020; Egger et al., 2021; Hwang et al., 2020; Josephson et al., 2021; Mueller et al., 2021; Sheridan et al., 2020). Moreover, Brodeur et al.'s (2021) literature review indicates that extant research on the economic consequences of COVID-19 has primarily examined macro indicators, such as GDP, local employment, job vacancies, or consumption across sectors of the economy. As a result, there is a gap in the literature to study, either theoretically or empirically, store-level supply and demand effects as well as factors that drive resilience across stores.

The recession in the retail economy, especially in fashion goods, was even more adverse compared to basic goods: fashion retail is typically classified as a highly cyclical industry, expanding rapidly when the economy is booming but retreating during recessions. Store demand was particularly affected, as it required consumers to travel to a store to physically touch and fit items (Bell et al., 2014; Chetty et al., 2020; Goolsbee and Syverson, 2021; Sheridan et al., 2020). News from landmark retailers inform us about the severe damage: Inditex and H&M decided to close 1,200 and 250 stores, respectively; J. Crew, Lord & Taylor, Century 21, Lucky Brand, Brooks Brothers, Neiman Marcus, Muji, and J.C. Penney all filed for bankruptcy in 2020. Moreover, the decline in retail was much larger than GDP contraction, in line with a remarkable heterogeneous sector-based and region-based impact (Chetty et al., 2020; Rosenthal et al., 2021).

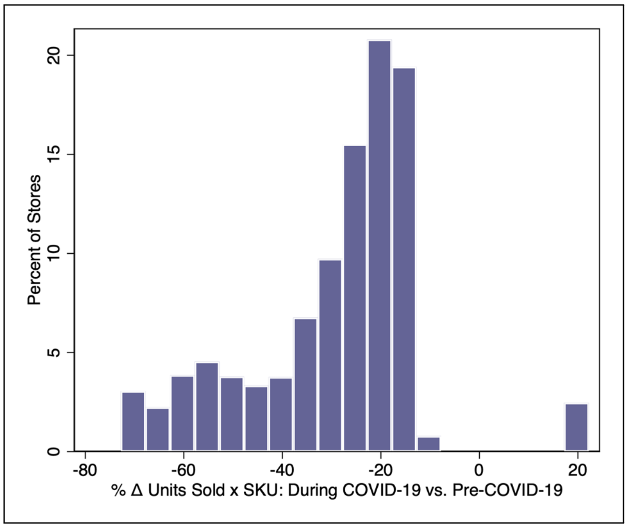

Figure 1. Great heterogeneity in the impact across stores.

Indeed, our data shows a severe aggregate decline in offline retail sales. We estimate that units sold declined 43% in 2020, and declined 53% in the (hardest) 6 months starting March 2020, using data from 3,142 stores throughout 97 countries (the Appendix A provides a global heat-map). These magnitudes echo the substitution patterns away from non-necessities and physical-contact products (Chetty et al., 2020). In contrast with existing studies of the economic consequences of COVID-19, we are interested in understanding its *heterogeneity across stores*.

Figure 1 illustrates the large variation across stores in the percentage change in units sold per SKU (stock-keeping-unit). It should be surprising to find effects that range from −90% to +20%. The impact is most pronounced in cosmopolitan cities like Madrid or London, as well as in smaller but touristic destinations like Algarve in Portugal or the Balearic Islands in Spain. Additionally, stores in non-urban spots experienced a modest decline in sales, possibly linked to inflows of population that fled cities, or to the redirection of shopping expenditure towards local stores instead of shopping while traveling. These patterns are consistent with a reallocation shock (Barrero et al., 2021) and with the value reversal city centers (Rosenthal et al., 2021). We observe that COVID-19 did not impact each store in the same way. But why? What makes stores more resilient to external shocks? This is the central question that we seek to answer in this article.

The concept of resilience has a long tradition in material sciences, biology, psychology, and more recently in management. In our context, we define resilience as the *ability of a store to recover from a large external disruption*. This definition mirrors the core ideas of supply chain resilience (Kleindorfer and Saad, 2005; Sheffi, 2015).[1] We develop a conceptual framework in which store resilience is a combination of market characteristics—defined as intrinsic resilience—and store strategies—defined as adaptive resilience. The former captures features that shape the pool of consumers it caters to, which is driven by both geography (e.g., population density or income) and store design (e.g., size and clustering with other urban amenities). The latter captures supply side flexibility to better cope with unpredictable market changes, through more personalized assortments and lower inventory assets (Fisher et al., 1997).

Our framework is guided by a novel empirical strategy, which can be summarized as follows:

1. We reconstruct store daily unit sales using high-frequency product inventory data collected via web-crawlers from two large brands: Zara and Bershka. The inventory is collected for thousands of stores throughout 20 countries.[2] By tracking the variation in units available of a particular product in a particular size at the store (e.g., a green sweater in size M), we recover sales on a daily basis. To the best of the authors' knowledge, no prior studies have used this approach. A remarkable advantage is the breadth and consistency across geographies: we construct product × store sales. This allows us to analyze store performance without geographical or temporal aggregation.
2. We track and encode non-health-related interventions across all sub-national regions (provinces or states within countries) in 20 countries. Critically, these policies are then mapped to the coordinates of each store. Said differently, we trace back the de-escalation plans that affected Miami and Los Angeles, and then assign those policies to a store in Miami and to another store in Los Angeles. Naturally, governments tailor their stay-at-home orders and de-escalation plans, however, we classify those into three stages that are overall consistent: strict lockdown (Spring or Fall), partial lockdown (Spring or Fall), and new normality.
3. We identify store characteristics and strategies which can attenuate or amplify demand swings from external shocks. In particular, we unpack the characteristics into: (a) store size, (b) store location (shopping mall or street), (c) market touristic intensity, (d) local population density (urban vs. rural), and (e) local population income. Additionally, we identify store operating choices in terms of (f) assortment overlap (similarity with global assortment) and (g) inventory speed (days of inventory).

Taking a step back, why is this empirical approach useful? One might be tempted to inform about retail sales using administrative data or company filings. However, most administrative records about the economy are reported at aggregated levels and with a substantial lag (Einav and Levin, 2014). This prevents to track behaviors across sectors and regions. Moreover, it is hard to compare apples-to-apples when the datasets between two countries are different. Furthermore, company filings are not sufficiently detailed. To illustrate, Inditex's public filings release sales records for Zara at the quarterly level—and even then, those records are worldwide. It is unfeasible to inform shopping patterns across countries or across stores. Instead, our data tracks daily store-level sales, allowing us to explain what are the features and actions that make the store more vs. less resilient. Daily variations in sales are connected to variations in shopping conditions, which have significantly varied across time and geography, allowing us to identify valuable cause-and-effect relationships.

The findings of our work can be summarized as follows. First, we estimate the aggregate demand effects of the pandemic. Across 20 countries, we find that sales decreased −47% during 2020, and that a day of lockdown reduces store sales by −82%, a day of partial restrictions by −23%, and then a boost of +58% in a new normality day. These estimates are critical to inform policy-making decisions, such as the design, targeting, and scale of relief programs to businesses under water. It also informs managers about the links between policy, industry, and shopping habits (Mende et al., 2023).

Second, we unveil this broader sales perspective into the vast store heterogeneity (Figure 1). Our analysis of store-level heterogeneity reveals that large stores in shopping malls near touristic spots amplify the drop in retail sales—which is surprising because these types of stores were presumably the most profitable and appealing pre-COVID-19. On the other hand, rural, less densely populated, and wealthier areas attenuate those drops. Furthermore, stores that in 2019 had a lower assortment overlap as well as faster inventory rotation are more resilient to demand shocks—that is, by offering a set of products which are relatively more distinct compared to other stores in the country, or by decreasing the inventory days, signaling fresher, more up-to-date products, respectively. The link between store features and the pandemic continues even during the new normality period.

Our insights can be structured in a conceptual model of store resilience, made of (a) intrinsic store profile related to its local market characteristics, and (b) adaptive store actions that capture its operational "fitness." Collectively, they shape the stores' ability to recover from external disruptions. A visual summary of our conceptual model is shown in Figure 2.

We observe that resilient stores serve primarily to a captive local demand: it is away from a city center or touristic spot (and thus isolated from temporal one-off visitors), its customers are local (and presumably a portion of those have left the city for the countryside during the pandemic), and it is not a large or flagship or ambitious store. This store profile is inherently less exposed to external, systemic shocks—and therefore, its upward/downward sales fluctuations are more moderate. In contrast, less resilient stores tend to be large, next to touristic spots that welcome massive inflows of touristic and brief visitors per day, and are expensive to run. Its dependance to foreign, unloyal, and temporal demand makes the store more sensitive to shocks—and therefore its sales have been most adversely affected.

One may think of a store's exposure to external factors as a multiplier of sales: in booming periods, the store next to NYC's MoMA experiences above-average sales from

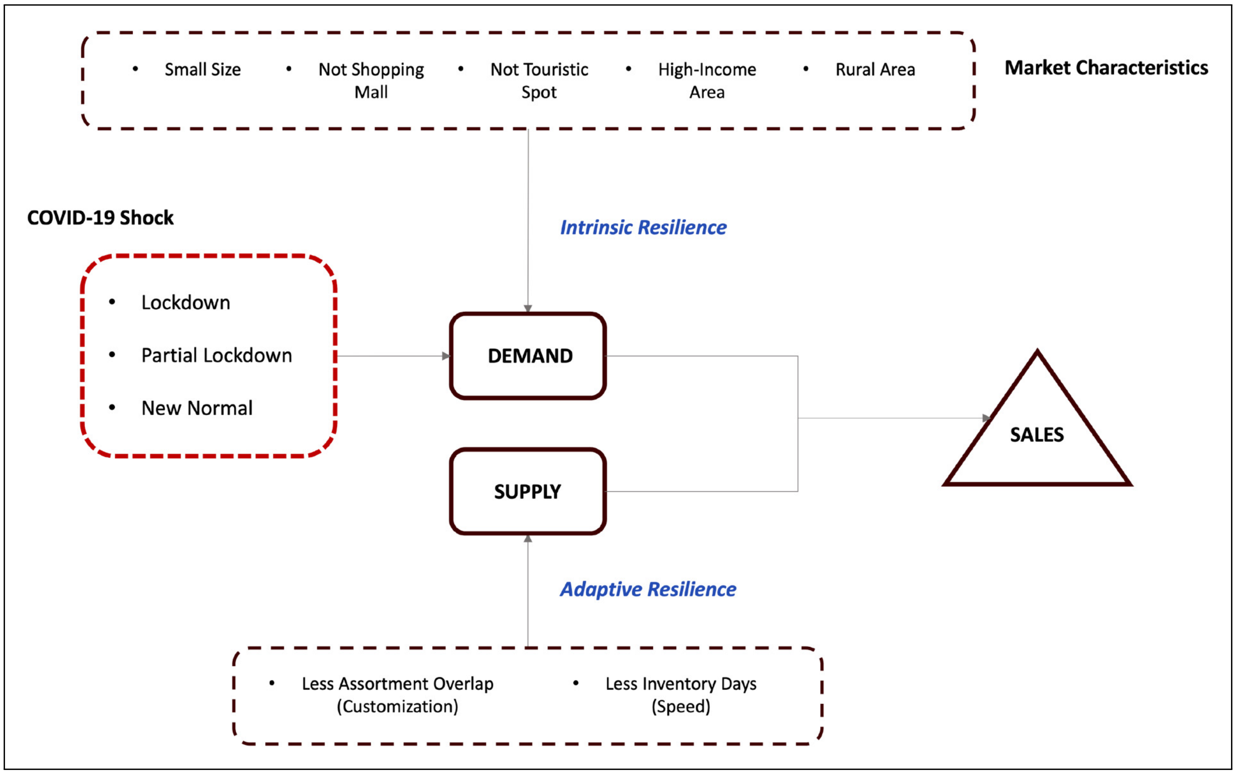

Figure 2. Framework of store resilience.

thousands of one-off visitors; however, during a macroeconomic disruption, its sales can decline considerably. Indeed, while local population has not significantly varied, travel restrictions removed a sizable fraction of demand—for example, total flights have declined 42% in 2020—exacerbating the losses in touristic stores.[3]

Furthermore, resilience is shaped by the stores' adaptive strategies: by offering a more differentiated assortment, curated to the (new) needs of the local demand, stores are able to more effectively convert potential customers into revenue. Note that multi-national retailers like Zara and Bershka do not produce items for a specific store or country.[4] While a store cannot completely "cherry pick" the assortment, there could still be meaningful store-level strategies in terms of the assortment overlap and inventory management—that is, the extent to which the products in the store are also found in other stores and the freshness or speed of inventory turnover, respectively. Indeed, Hwang et al. (2010), Boada-Collado and Martínez-de Albéniz (2020), and DeHoratius et al. (2023) reported assortment and inventory heterogeneity across stores. In our context, resilience drivers are identified in the pre-pandemic period, including the adaptive responses. Presumably, it is not realistic that a store manager can, say in the morning of a lockdown, all of a sudden change the assortment composition. Instead, inventory speed and assortment overlap are features that, although not completely static in time, already operated before the pandemic and were maintained during the period of study.

Third, while our study investigates what makes store-level sales more fragile, we also shed light on the brand (company-wide) actions which mitigate the impact brought by external shocks. Indeed, fashion retailers designed proactive, surprisingly fast strategies to cope with the pandemic: reduced assortment breadth (variety in the fashion catalog) and reduced overall inventory levels, suggesting a cost reduction across-the-board. Note that while all stores were inherently intertwined with these brand-level strategies, they still had some degrees of freedom to better cope with an external shock: as mentioned, we observe heterogeneity in terms of inventory speed and, most importantly, assortment overlap.

The remainder of the article is organized as follows. Section 2 describes the empirical setting and data. Section 3 shows the aggregate retail effects of COVID-19 and Section 4 unpacks the heterogeneity in store-level sales. Section 5 shows the brand-level strategies. Section 6 presents the robustness checks. Section 7 concludes the article with conclusion.

2 Data Description

We combine several datasets for our empirical analyses. We design a web-scraping algorithm that queries the corresponding websites of Zara and Bershka, and collects detailed inventory information for the offline stores. This inventory data at

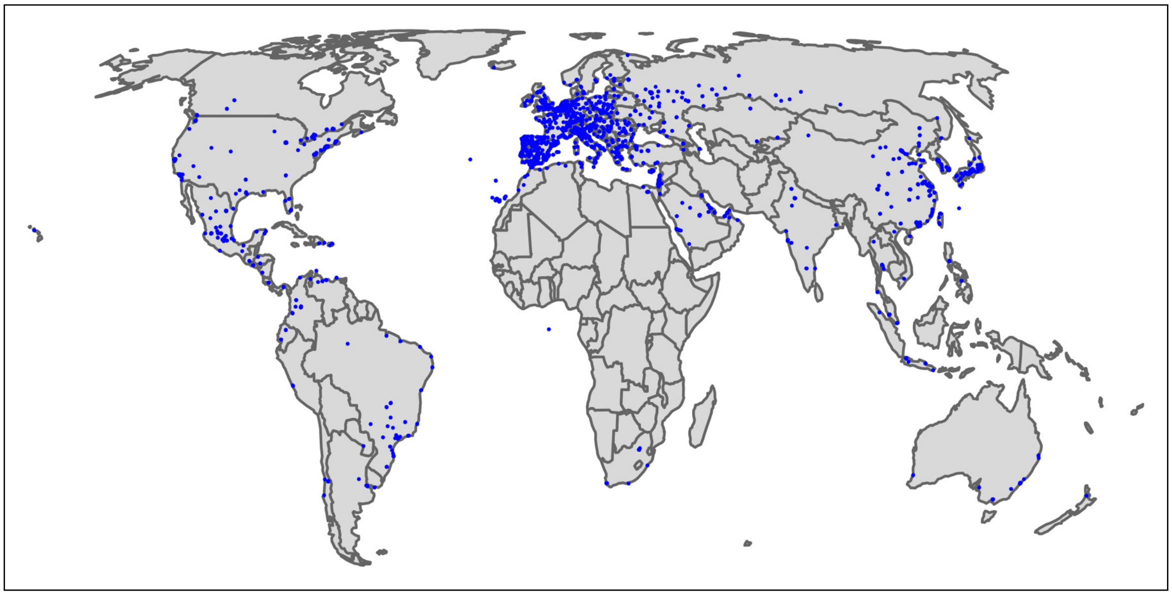

Figure 3. Map of physical stores.

the SKU level is used to *infer* sales at the store x day level. In the period of study, we identified a total of 3,142 stores worldwide, with almost 60% of them located in Europe. Figure 3 shows a visual representation of the retailers footprint.

We use inferred sales from 97 countries and 3,142 stores to motivate a global, descriptive view of the impact of COVID-19 on fashion retail (Appendix A). We then proceed to shed light on store-level heterogeneity using more detailed econometric models for 20 countries and 1,690 stores. We augment this data by mapping the location coordinates of each store with (a) governmental policies in that local area, (b) TripAdvisor reviews of touristic attractions nearby the store, and (c) COVID-19 infections recorded nearby the store. Next, we describe each dataset in greater detail.

2.1 Public Policy Phases and COVID-19 Cases

Lockdown and de-escalation phases have restricted stores' operating conditions and consumers' mobility. There are many examples familiar to the reader, including mobility restrictions across districts or states, reduced hours of operation in retail stores, social distancing, maximum number of shoppers at the same time, no fitting rooms, no dining inside restaurants. These have had a direct influence on the ability (and desire) to shop in physical stores (Goolsbee and Syverson, 2021; Mende et al., 2023). To estimate the effects of these policies on store-level sales (demand) and strategic decisions (supply), we track and encode daily sub-national government policies, which are then mapped to the store coordinates. We classify phases as follows:

- Lockdown: Strict mobility restrictions, stay-at-home orders, limited shopping non-necessities, travel bans, shorter hours of operation, restricted operating space, and social distancing.
- Partial lockdown: De-escalation phases following a strict lockdown, relaxed mobility restrictions, expanded hours and space of operation, and social distancing.
- New normal: "going back to normal" final phase of de-escalation (often the summer of 2020), social distancing, travel, and mobility restored.

While most stores may have experienced the three phases, the empirical strategy exploits *temporal and geographical variation*. That is, we construct (inferred) sales before and during each of those phases for a given store in Miami, which experiences a different de-escalation timing to a store in Boston or Madrid. We are mindful that a partial phase in Paris may not be the same as a partial phase in Lille. For example, stores in Paris might be required to restrict the selling space to X squared feet (and not in Lille). We do our best to carefully encode phases as parsimoniously as possible, acknowledging that it is beyond the scope of our paper to further dissect policy heterogeneity across regions.

We urge the reader to be mindful that the household mindset during 2020 was quite different from today. Back then, the public at large could only speculate about when vaccination might be completed, how effective such vaccines would be, and when the virus would be more or less contained. In fact, the first vaccination phase started in December 2020 (New York Times, 2020). When a local government instituted a lockdown, it was seen both as a costly and necessary decision, plus it was unclear which lockdown would really be the "last lockdown."

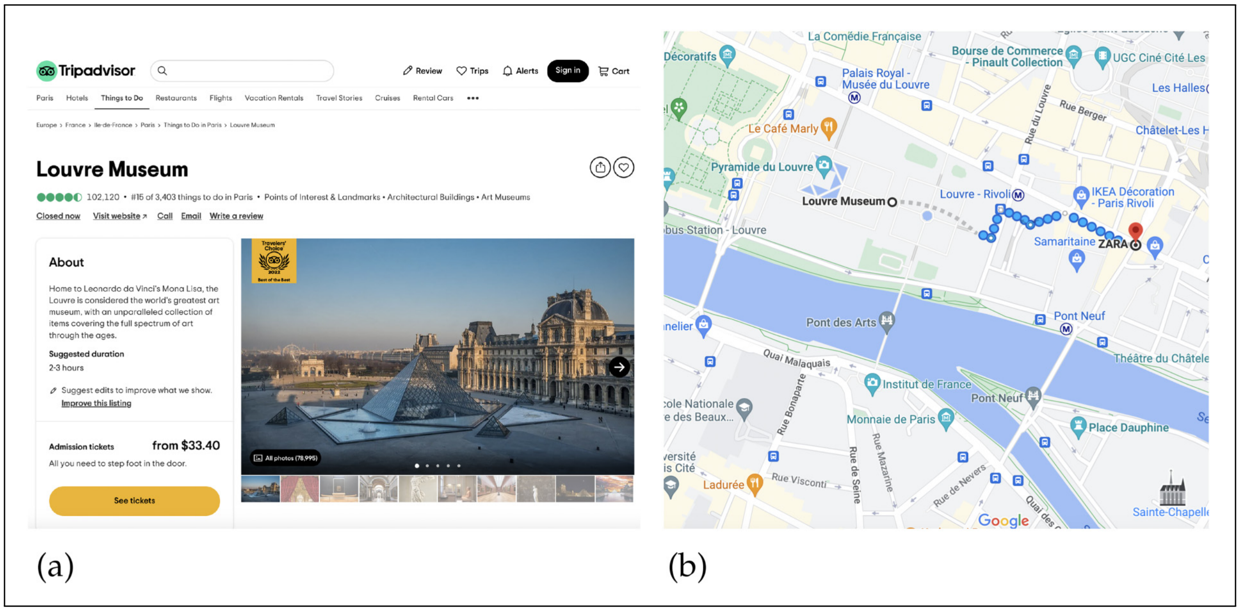

Figure 4. TripAdvisor data mapped to the store coordinates: Louvre Museum↔Zara. (a) Louvre Museum in Paris and (b) a Zara store within 0.2 miles.

In addition to regional de-escalation phases, we collected time-varying COVID-19 infections at the finest geographical level possible for all 20 countries. This dataset is also mapped with the store location to capture the local spread (and contagion concerns) of the virus nearby the store. The E-Companion provides details of the data sources.

2.2 TripAdvisor

TripAdvisor is a leading review website. We collect TripAdvisor review data for all main attractions in our 20 countries. In total, we have data for 268,273 distinct attractions. For each attraction, we use its latitude and longitude to map its proximity to a Bershka or Zara store, and focus on attractions that are within 0.5 km (0.3 miles) of the store.

Figure 4 provides the visual guidance. We collect review data from the Louvre Museum in Paris, see Panel (a). The Louvre is among the highest-ranked attractions, with 100,000+ TripAdvisor reviews, welcoming 45,000 people on a crowded day pre-COVID. Presumably, those visitors positively spillover a retail store nearby (Leonardi and Moretti, 2022). Thus, we ask: is there a store nearby? Panel (b) shows that the answer is yes. There is a Zara store located 350 m (0.2 miles) away. Having geo-localized each store and each attraction, we can map the number of attractions and reviews for each store in our data.

The TripAdvisor data is used to construct a measure of touristic exposure. Importantly, there is a great variation in the proximity to touristic spots across stores. It is helpful to crystalize some examples. A store in Florence has 315,377 total reviews for 588 attractions within 5 km, another store in Amsterdam has 180,049 reviews for 337 attractions within 5 km, but stores in Bordeaux or Burlington have <70 reviews. While TripAdvisor data may miss some points of interest and it is a static snapshot (e.g., does not capture time-varying trends), it appears to be a well-suited empirical strategy to characterize which stores cater to touristic customers versus local customers (Aparicio et al., 2025).

2.3 Store Features

To unpack what features of a store attenuate or amplify external shocks, we construct a rich set of store-level covariates. As visualized in Figure 2, we denote some of these features as intrinsic resilience and others as adaptive resilience. We report robustness operationalizations in Section 6.

- Shopping mall: Whether the store is located in a shopping mall or out in the street. This feature captures spillovers from nearby stores and demand aggregator locations (Ellickson et al., 2020).
- Touristic spot: We use TripAdvisor's number of attractions and number of reviews within 0.5 km to inform the degree of touristic demand. A store is classified as touristic if it belongs to the highest quartile in the brand × country in terms of reviews.
- Store size: We use the store assortment size (defined below) as a measure of size. A store is classified as large if its assortment is above the median assortment size in the brand × country. We also re-define size using the number of units sold pre-COVID-19. This captures differences in store

size within a country. For example, a store in Ireland's Dublin has 0.13 median daily units sold per-SKU (assortment of 1,100 products), while another store in Ireland's Newbridge has 0.03 sales per-SKU (600 products). The E-Companion reports the histogram of the median daily units sold per-SKU.

- High-income area: We use TripAdvisor reviews to obtain the ratio of restaurants with fine dining to overall restaurants within 0.5 km of the store. A store is classified as high-income when its ratio is above the median. To illustrate its effectiveness, consider a few examples: in France, the top store according to this ratio is located in Paris' Champs Elysées (nearby Louis Vuitton and several 5-star hotels); in the United Kingdom, the top store is located across London's Hyde park (nearby the Mandarin Oriental and Belgravia); in the United States, the third store is located in NYC's Fifth Avenue. Similarly, stores in Greenwich and McLean—known to be among the wealthiest cities in the United States—are classified as high-income stores.
- Rural area: We use the number of restaurants (as per TripAdvisor) to inform whether the store is located in a rural or urban area. A store is classified as rural when its measure within 5 km is below the median in the country. As an alternative measure, we use the population density. This feature speaks to the customer-type and travel distances to access a store (Huff, 1964; Lim et al., 2021). Once again, there is great dispersion in the stores' centricity. To illustrate, our data covers a store in Canada's Toronto (density of 3,000/km^2), but also stores in Canada's Saint-Bruno-de-Montarville (density of 600/km^2) or U.S.' Oak Brook (density of 395/km^2).
- Inventory days: The freshness or speed of inventory turnover can be an important operational lever (Cachon and Swinney, 2009). Intuitively, when a store's inventory is moving, the store can bring new items to the store to more effectively match supply and demand; in contrast, slow-moving stores are "stuck" selling the same products at slower speeds, thus impeding to rotate the variety. We operationalize inventory days as follows:

$$\text{Inventory Days}_{i,t} = \frac{\sum_k Inventory_{i,t,k}}{\sum_k PastSales_{i,t,k}}, \quad (1)$$

  where the inventory days for store i on date t is the ratio of the average inventory depth and number of daily per-SKU units sold during the previous two weeks (e.g., $PastSales_{i,t,k} = 1/14 \sum_{t'=t-14}^{t-1} Sales_{i,t,k}$ denotes the latter). The inventory depth for store i on date t is defined as the ratio of total units in-stock divided by the number of available SKUs. Hence, Inventory Days$_{i,t}$ represents the number of days that a product will remain in stock, the usual metric for inventory investments. Recall that we estimate equation (1) using data pre-COVID-19, to capture behaviors that already existed before the disruption. A store features low inventory days when its measure is below the median. The median inventory days and depth is 16 days and 2 units, respectively.
- Assortment overlap: The flexibility to offer "better" (more relevant) options in the assortment—that is, tapping current needs—can explain the relative strength to navigate an external disruption. For example, a store in Tampa (Florida) may be used to tailoring the assortment to its local demand, and thus more easily accommodate shifting customer behavior during the pandemic, compared to a store in Fifth Avenue, which may serve the needs of its temporal, touristic demand. We operationalize assortment overlap as follows:

$$\text{Assortment Overlap}_i = \sum_{j \neq i \in S} \frac{A_i' A_j}{||A_i|| \cdot ||A_j||} \frac{1}{\#j \in S}, \quad (2)$$

  where the assortment overlap for store i is computed as the cosine similarity between store i's assortment vector A_i and store j's assortment vector A_j (following Hwang et al. (2010)), and then averaged across stores. The vector A_i has length K (i.e., the number of distinct items in the brand × country) and one element in A_i is the proportion of time that store i offered item k relative to the entire time the item was observed. Once again, the assortment overlap is computed pre-COVID-19. The measure in equation (2) ranges from 0 to 1, with higher values indicating greater assortment similarity with other stores. A store features low assortment overlap when its measure is below the median. The average overlap is 0.59, indicating meaningful non-overlapping products across stores.

Collectively, this feature set captures important store heterogeneity. To illustrate, the 25th and 90th percentile store have an estimated assortment size of 800 and 4,600 products, respectively. To provide visual intuition for some of these operationalizations, Figure 5 shows the distribution across stores for (a) the number of touristic attractions nearby the store, (b) the number of TripAdvisor reviews, (c) population nearby the store, (d) assortment size, (e) inventory days, and (f) assortment overlap.[5] While some interdependence may exist (e.g., best-selling stores may have more resources to improve inventory decisions), there is abundant variation across features (the correlation matrix is shown in the E-Companion).

2.4 Inferring Sales From High-Frequency Store Inventory Changes

We collect data from two leading fashion brands: Zara and Bershka. We design web-scraping algorithms that collect three main pieces of information:

1. Brand data: Brand assortment catalog. It is time-varying but not store-specific.
2. Store data: Location (time-static) and products available (time-varying).

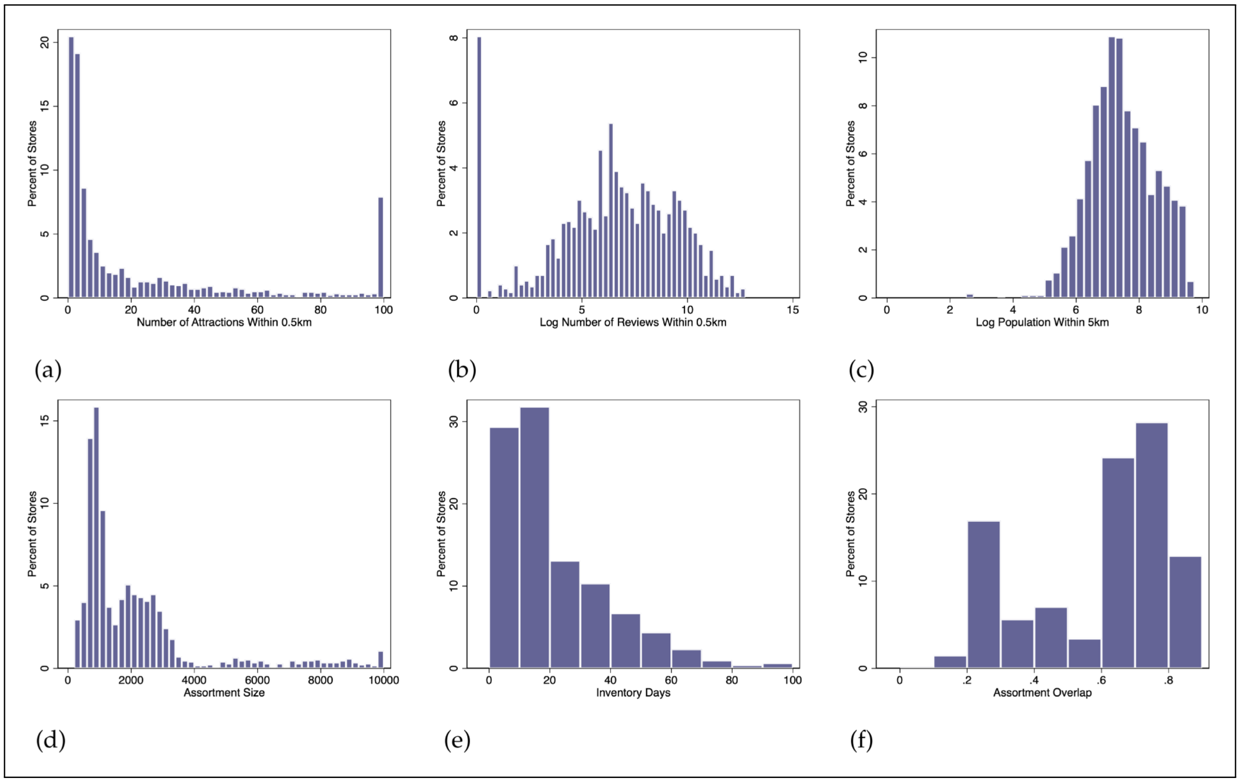

Figure 5. Strong variation in store characteristics: (a) touristic attractions, (b) TripAdvisor reviews, (c) population, (d) assortment size, (e) inventory days, and (f) assortment overlap.

3. Inventory data: Units available for a specific SKU x store x date. A SKU represents a unique product identifier (e.g., a green sweater size M).

The data spans from early March 2019 to end of December 2020, with a daily and sometimes intra-day frequency. Our dataset covers 49,964 products (broadly defined, i.e., different kinds of sweaters) and 393,558 SKUs (narrowly defined, i.e., unique combinations of model, color, and size). Zara and Bershka are known to have an extraordinary large assortment (Aparicio and Rigobon, 2023). For instance, we estimate that Zara's average catalog on a given day has ∼12,000 SKUs.

With this empirical setting in mind, the algorithm for data collection works as follows:

- Step 1: Retrieve all SKUs of the catalog for brand b at time t. Sample a subset of SKUs in that catalog—in general the top listed 200 items per category.
- Step 2: Retrieve the inventory available for each SKU in that subset (Step 1) in store i of brand b at time t.
- Step 3: Repeat Step 2 query for all stores.
- Step 4: Repeat Steps 1 to 3 over time.

It is helpful to note that not all SKUs sampled (Step 1) are available in all stores. A given store may offer more specialized products, be smaller (there is not have enough space for certain products), or products may be sold out in that store. This temporal variation in the offer set allows us to infer the store assortment size. Intuitively, it is unfeasible to web-scrape the entire offer from the store (e.g., 10,000 SKUs); however, by observing the variation in the share of the catalog offered by the store, we can construct a measure of store assortment size. Furthermore, we utilize the first and last dates in which we observed the product in the store. Thus, we define a store × date measure of assortment size as the number of products that have been introduced and are yet not discontinued (i.e., date t is higher than the start date of a product and lower than its end date), which is then scaled by the number of products queried in that store × date. To construct a time-invariant measure of store-level size based on the assortment (Figure 5), we use the 75% percentile of the store × date assortment.

Figure 6 visualizes the data collection effort. Imagine we are interested in collecting inventory for the dresses category. As mentioned, we collect the IDs for the top 400 products in the grid (top-left). This maps Step 1 above. Then, the algorithm visits the product page (top-right) and clicks a size and availability (bottom-left). Then, the algorithm selects a store (bottom-middle) and reads the HTML code (bottom-right) to recover the number of units available. In a nutshell, repeating the query for multiple products and over consecutive days allows us to recover changes in inventory—and thus, changes in units sold.

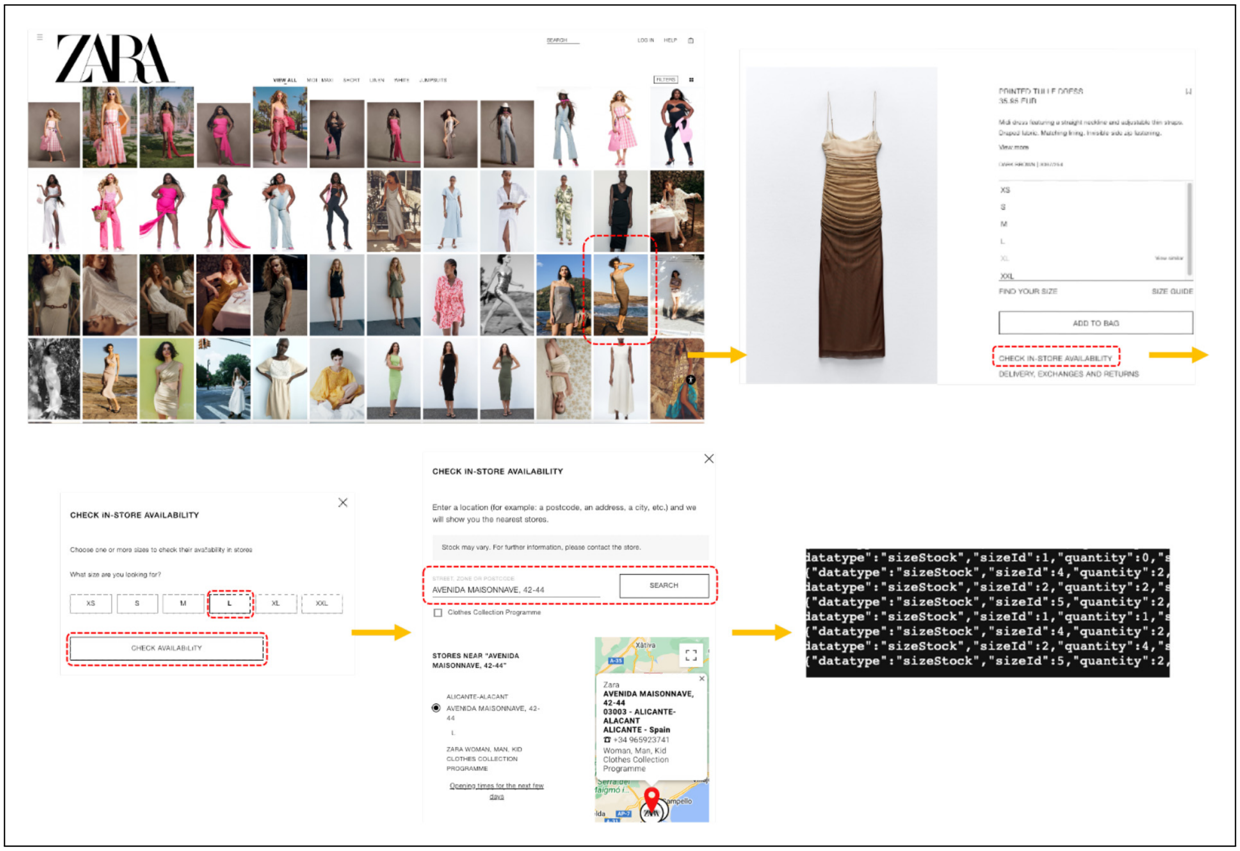

Figure 6. Example—Web-scraping inventory for stock-keeping-unit (SKU) × store.

Table 1. Example—Changes in inventory levels.

Store ID	Product x Color	Size ID	t_1	q_1	t_2	q_2	Change
686	00364326712	1	2019-12-12 12:25:15	0	2019-12-14 13:32:48	0	0
686	00364326712	1	2019-12-14 13:32:48	0	2019-12-16 03:56:29	2	2
686	00364326712	1	2019-12-16 03:56:29	2	2019-12-17 07:30:34	2	0
686	00364326712	1	2019-12-17 07:30:34	2	2019-12-18 11:14:37	1	−1
686	00364326712	1	2019-12-18 11:14:37	1	2019-12-19 5:23:03	1	0
…	…	…	…	…	…	…	…

Inventory changes can be closely linked to sales changes: when inventory for a specific SKU × store decreases, a sale most likely occurred. Indeed, to infer units sold, we compute the difference in SKU inventory depth for store i between times t_1 and t_2. Table 1 shows the structure of the data. A single observation represents the amount of stock (q) for SKU on time 1 (t_1), and the amount of stock on time 2 (t_2), where t_2 is the next observation for the same SKU × store. As per Table 1, it is clear that we identify two types of events: (a) positive differences in inventory (i.e., replenishments—unknown sales in that interval); and (b) negative differences in inventory. The latter cases are classified as sales events.

There are additional operationalizations. While we might neglect units sold when there are product refills (usually large and unusual positive numbers), given the low frequency of refill events (compared to the greater frequency of events of units sold), accounting for refills yields minimal differences. Moreover, we control for irregularity in the intervals between SKU-timestamps. If the interval between two SKU-timestamps is too wide, the sales records become noisier. Therefore, we consider a sale if the time difference between two inventory points is less than 3 days.[6] Finally, we eliminate the last observed inventory levels which are often larger drops and represent product discontinuities rather than sales.

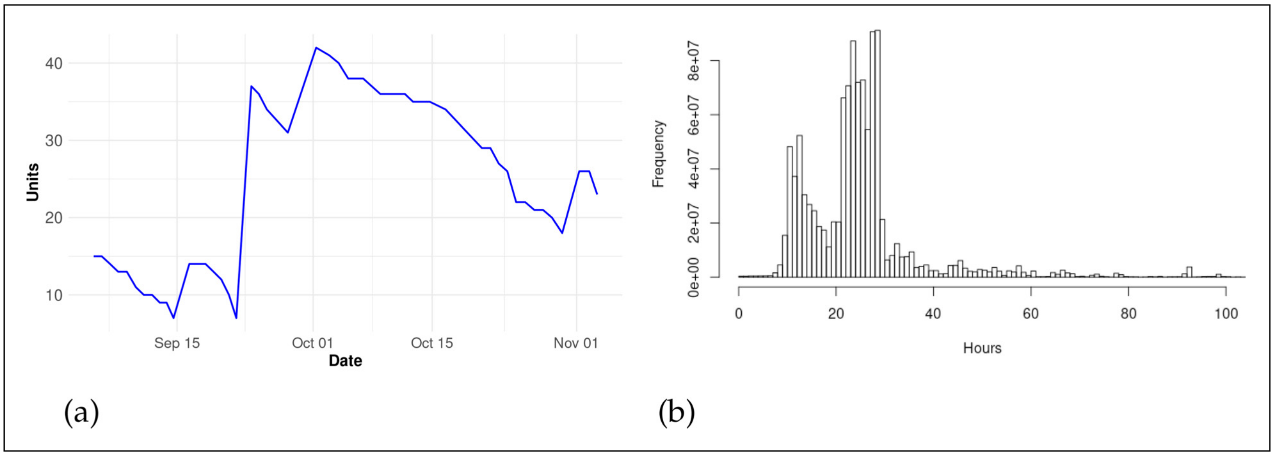

Figure 7. Illustration of the inventory behavior at the store: (a) inventory of one stock-keeping-unit (SKU) in one store and (b) timelapses between inventory readings.

We aggregate store-date-SKU sales—inferred from changes in inventory levels—to the store-date level. In particular, we define a measure of total sales at the store-date level as follows:

$$\text{Sales}_{i,t} = \frac{\sum_k -\Delta Inventory_{i,t,k}}{ProductsObserved_{i,t}} \times \frac{Assortment_{i,t}}{ProductsQueried_{i,t}}, \quad (3)$$

where $\sum_k -\Delta Inventory_{i,t,k}$ represents units sold for store i and date t, as captured by the sum of (negative) inventory changes across all products k. Said differently, $\Delta Inventory_{i,t,k}$ represents the negative inventory variation for product k in store i and date t (e.g., a variation of -2 means that 2 units of item k were sold). Note that in periods when we are able to collect data for more (less) products, then the corresponding units sold will be higher (lower). Thus, we normalize by the number of products for which we collected inventory changes in store i on date t. In other words, $\frac{\sum_k -\Delta Inventory_{i,t,k}}{ProductsObserved_{i,t}}$ can be interpreted as the velocity of sales (units per inventory). Finally, per-SKU sales are scaled by store i's assortment and the number of products queried for a measure of total store sales. Importantly, $\text{Sales}_{i,t}$ is systematically comparable across stores and over time.

For completeness, Figure 7 visualizes the patterns of the data process. We focus on the inventory readings for a single SKU at a single store over time. Panels (a) and (b) show the typical inventory levels over time, and the distribution of timelapses (difference in consecutive timestamp readings) between inventory readings, respectively.

To summarize, we construct a novel dataset obtained through large-scale web-crawlers that collect daily inventory levels—sometimes hourly—from two leading international fashion brands. The data spans 49,964 products (393,558 SKUs including product × color × size), 630 days between 13 March 2019 and 31 December 2020, and 1,690 physical stores in 20 countries. The median store assortment size is 1,500 products, the median per-SKU units sold is 0.05, and the median inventory depth is 2 units. The E-Companion reports additional data statistics.

2.5 Sales Data Validation

One might wonder whether this big data effort is needed at all. Why not simply use publicly available financial filings to recover sales patterns? The reason is that the publicly available data is extremely broad (and reported with a delay). Inditex's filings report the overall sales of Zara and Bershka—but those filings neither report sales at the daily or weekly or monthly level, nor sales at the store or state or country level. A key methodological contribution of our work is to set forward an empirical strategy that infers sales at the store-day level which is apples-to-apples comparable over time and across stores throughout countries.

Several facts about our data provide a compelling "validation" as an effective sales indicator.

1. Our baseline measure of sales at the store-day level clearly captures the disruption caused by COVID-19 in March of 2020. To illustrate, Figure 8 plots the daily measure of sales for two stores: a store in Madrid and a store in Athens. We see a dip around mid-March, exactly when a lockdown was instituted (gray area)—while hard to see, the lockdown timing differs between these stores. The median units sold before (blue) versus during (red) COVID-19 depict a sharp decline in sales.
2. The measure of positive sales correlates with Inditex's store sales. Panel (a) of Figure 9 reports Inditex's number of open stores during 2020 (open defined as positive sales). Panel (b) shows a qualitatively consistent pattern with our sales data.
3. Inditex reports that sales in Spain decreased by 33% in 2020, and that offline sales in Inditex decreased by ∼45%

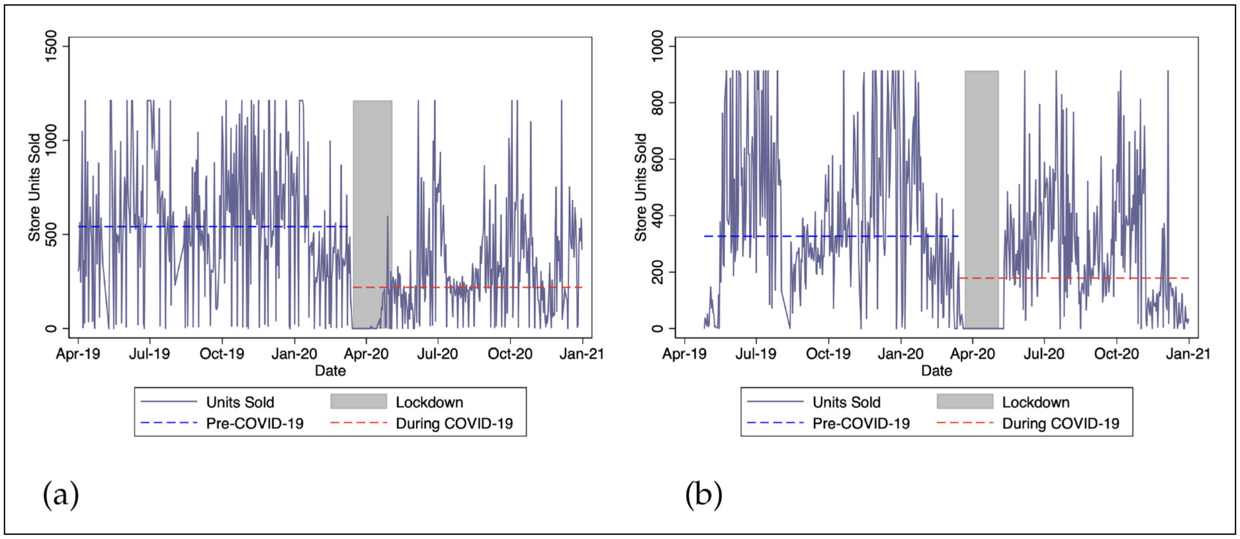

Figure 8. Store sales—Examples: (a) store in Madrid and (b) store in Athens.

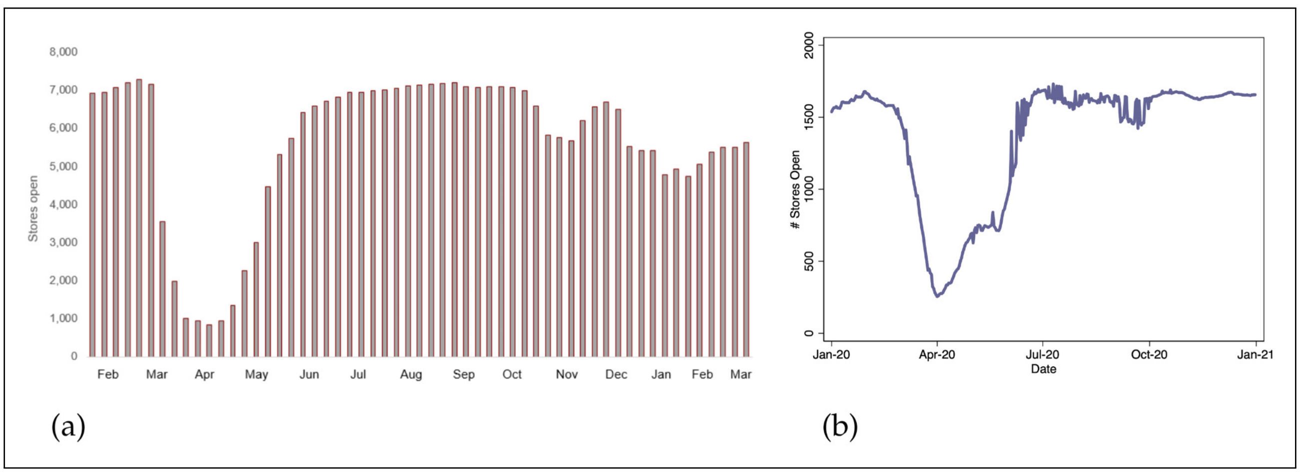

Figure 9. Stores—Open and close: (a) Inditex filings and (b) Inferred store open/close.

worldwide. Similarly, we estimate that units decreased by 18% in Spain, and worldwide sales declined 43% in 2020 and 53% in the (hardest) 6 months starting March 2020. While we should not expect a 1-to-1 mapping—we cover Zara and Bershka in 20 countries, not the entire business group worldwide—our magnitudes are remarkably consistent.

4. Inditex operated 7,469 stores by the end of 2019 and 6,477 by 2021 (a relative decrease of 13%). Similarly, we estimate that there were 1,904 active Berhska and Zara stores by the end of 2019, but that number decreased to 1,628 two years later (a 14% decrease). Once again, the relative decrease is extremely similar.

In sum, this evidence collectively provides a compelling case for using web-scraped inventory changes to capture true sales taking place at offline stores. We provide a caveat that our measure of inferred sales include physical sales made in the store, as well as any online order fulfilled from that store, which is a minor but growing fulfillment method for fashion retailers (Glaeser et al., 2019; Lim et al., 2020; Martínez-de Albéniz, 2019). Inditex reports rolling-out its "Single Inventory System" (SINT), which allowed Inditex "to fulfill e1.2 billion online sales from our stores" (Inditex Annual Report, 2020). However, this represents just 5% of the sales in 2020.[7]

Table 2. Store-level sales effects.

	Log Units Sold		
	(1)	(2)	(3)
Post	−0.294***		
	(0.004)		
Lockdown		−1.717***	
		(0.011)	
Partial Lockdown		−0.259***	
		(0.005)	
New Normal		0.459***	0.454***
		(0.005)	(0.005)
Lockdown Spring			−2.981***
			(0.022)
Partial Spring			−0.351***
			(0.011)
Lockdown Fall			−0.863***
			(0.011)
Partial Fall			−0.245***
			(0.005)
Constant	−2.740***	−2.695***	−2.601***
	(0.003)	(0.003)	(0.003)
Observations	846,878	846,878	846,878
R^2	0.604	0.625	0.633
AIC	3,020,700	2,974,536	2,957,370
Store FE	Yes	Yes	Yes
Country × Brand × Week FE	Yes	Yes	Yes
Country × Brand × Day FE	Yes	Yes	Yes

Notes: AIC = Akaike information criterion; FE = fixed effect. Robust standard errors in parenthesis. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

3 Aggregate Demand Effects

We begin our empirical analysis by examining aggregate demand effects from COVID-19. To build intuition for the analyses that follow, we first estimate a simple fixed-effects model for the average effect to retail consumption. In particular:

$$\ln(Sales)_{i,t} = \alpha_0 + \beta_1 \text{Post}_t + \psi_{c,b,w} + \phi_{c,b,d} + \gamma_i + \varepsilon_{i,t}, \quad (4)$$

where $\ln(Sales)_{i,t}$ denotes total units sold by store i on date t, Post_t denotes an indicator variable that takes value 1 starting March 2020, and $\varepsilon_{i,t}$ are residuals. We include a stringent set of fixed effects: $\psi_{c,b,w}$ accounts for country × brand × week number (e.g., Germany–Bershka–Week16) fixed effects, $\phi_{c,b,d}$ accounts for country × brand × day of the week (e.g., Germany–Bershka–Thursday) fixed effects, and γ_i accounts for store i fixed effects. We note that $\psi_{c,b,w}$ and $\phi_{c,b,d}$ are relevant to control for seasonality patterns in fashion retail and company-wide changes. The unit of analysis in equation (4) is a store-date.

The results are shown in Table 2. Column (1) shows that sales decreased 25% starting February 2020 ($-0.25=\exp(-0.294)-1$, $[-0.30, -0.29]$ 95% CI). However, these effects are expected to vary significantly upon the operating conditions. Thus, we estimate a model to capture the effects of non-health-related interventions. In particular:

$$\ln(Sales)_{i,t} = \alpha_0 + \beta_1 \text{Lockdown}_{i,t} + \beta_2 \text{Partial}_{i,t} + \beta_3 \text{New Normal}_{i,t} + \psi_{c,b,w} + \phi_{c,b,d} + \gamma_i + \varepsilon_{i,t}, \quad (5)$$

where $\ln(Sales)_{i,t}$ denotes the total units sold for store i on date t; $\text{Lockdown}_{i,t}$, $\text{Partial}_{i,t}$, or $\text{New Normal}_{i,t}$ denote an indicator variable that takes value 1 when store i on date t is on a lockdown, partial, or new normal phase, respectively. As before, the unit of analysis in equation (5) is a store-date.

Column (2) shows that a lockdown decreases store daily sales by 82% and a day with partial restrictions decreases sales by 23%. We observe a boost in sales once restrictions are lifted and the de-escalation phase reaches the new normality. We further expand equation (5) to distinguish between Spring versus Fall lockdowns and partial phases. As we might anticipate, column (3) shows that the effects are more adverse in the Spring—when the pandemic was just taking

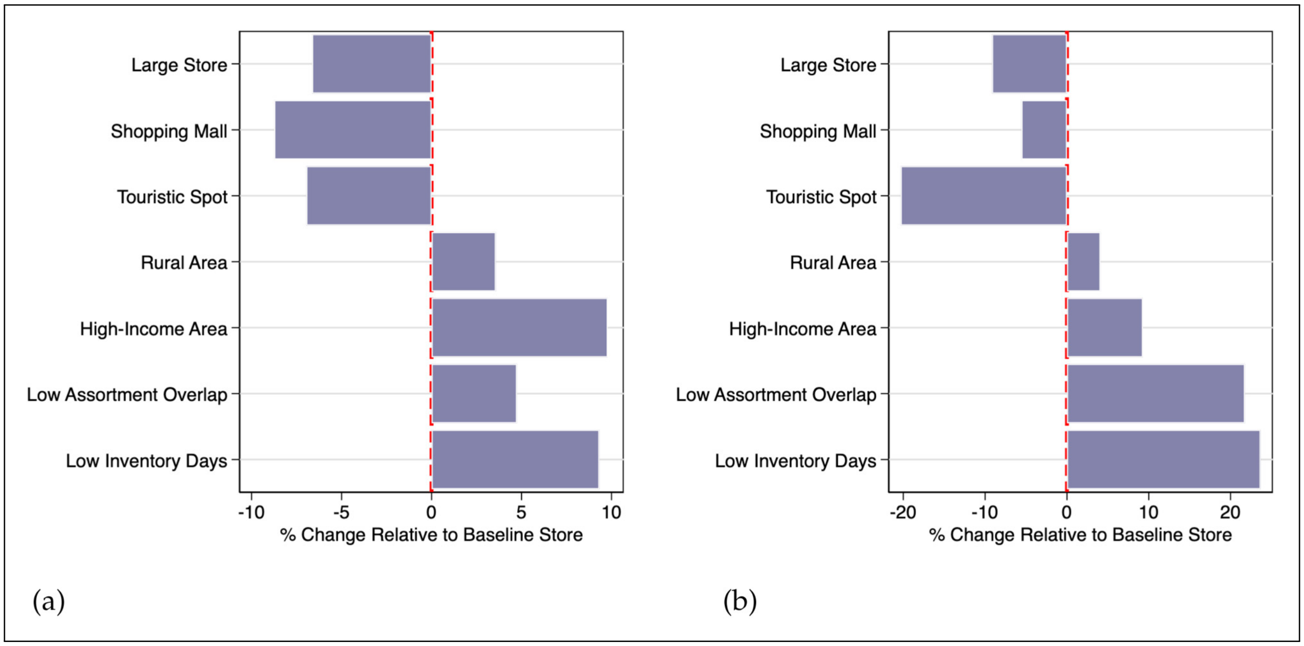

Figure 10. Store resilience: (a) partial lockdown and (b) new normality.

off and non-health-related interventions were most prohibitive of non-essential consumption. For instance, a day of partial mobility reduced sales by 30% in the Spring versus 22% in the Fall. We should also consider that, while local governments eased shopping conditions during Spring, households' uncertainty and health concerns might have also (relatively) improved. Consistent with the idea that fear to the spread of the virus (importantly, nearby the store location) demotivates consumption, we find a negative relationship between (log) infections and store sales. The results are discussed in Section 6.

The analyses so far shed light on the severe impact that COVID-19 had to retail sales in brick-and-mortar stores. However, these estimates mask the heterogeneity that exists across stores. Indeed, we have seen in Figure 1 notable disparities in how different stores were affected by the pandemic. We explore store heterogeneity next.

4 What Makes a Store Resilient?

We seek to understand the store characteristics that help explain the heterogeneous effects to COVID-19. As mentioned in Section 2.3, we unpack store-level characteristics into: (a) size of store, (b) shopping mall or street access, (c) touristic spots, (d) rural, less densely populated areas, (e) high-income areas, (f) inventory speed, and (g) assortment overlap. As summarized in Figure 2, we denote (a) to (e) as intrinsic resilience, and (f) and (g) as adaptive resilience.

We estimate the following model:

$$\begin{aligned}\ln(Sales)_{i,t} &= \alpha_0 + \beta_1 \text{Lockdown}_{i,t} + \beta_2 \text{Partial}_{i,t} \\ &+ \beta_3 \text{New Normal}_{i,t} + \sum_{f \in F} 1_{\text{Feature}_i = f} \\ &\times \left(\lambda_{1,f} \text{Lockdown}_{i,t} + \lambda_{2,f} \text{Partial}_{i,t} + \lambda_{3,f} \text{New Normal}_{i,t} \right) \\ &\psi_{c,b,w} + \phi_{c,b,d} + \gamma_i + \varepsilon_{i,t}, \end{aligned} \tag{6}$$

where $\ln(Sales)_{i,t}$, $\text{Lockdown}_{i,t}$, $\text{Partial}_{i,t}$, and $\text{New Normal}_{i,t}$ follow the notation used in equation (5). Our interest lies in the interaction terms between each of these non-health-related policies and feature $f \in F$.[8] As before, $\psi_{c,b,w}$, $\phi_{c,b,d}$, and γ_i denote the full set of high-dimensional fixed effects, namely country-brand-week, country-brand-day-of-the-week, and store, respectively. As shown by the Akaike information criterion (AIC), the moderators included in equation (6) marginally lift the explained variance.

As part of the robustness checks, we estimate a mixed effects (mixture regression) model to account for unobserved store feature heterogeneity, allowing for random coefficients at the store-level. The estimates, reported in the E-Companion, are similar. Additionally, in Section 6, we report various robustness checks using alternative specifications as well as alternative feature operationalizations. Overall, we find a similar pattern of findings.

The coefficients of interest are shown in Figure 10.[9] The full model estimates are reported in Table 3. Here, we focus on the partial lockdown and new normality periods—recall that the

Table 3. Fixed effects model.

	Log Units Sold (1)
Lockdown	−1.954***
	(0.023)
Lockdown × Large Store	0.008
	(0.015)
Lockdown × Shopping Mall	−0.016
	(0.016)
Lockdown × Touristic Area	−0.065***
	(0.019)
Lockdown × Rural Area	0.026*
	(0.015)
Lockdown × High-Income Area	0.191***
	(0.016)
Lockdown × Low Assortment Overlap	0.118***
	(0.015)
Lockdown × Low Inventory Days	0.232***
	(0.016)
Partial	−0.275***
	(0.014)
Partial × Large Store	−0.092***
	(0.009)
Partial × Shopping Mall	−0.122***
	(0.011)
Partial × Touristic Spot	−0.096***
	(0.011)
Partial × Rural Area	0.046***
	(0.009)
Partial × High-Income Area	0.121***
	(0.010)
Partial × Low Assortment Overlap	0.061***
	(0.009)
Partial × Low Inventory Days	0.116***
	(0.010)
New Normal	0.361***
	(0.014)
New Normal × Large Store	−0.066***
	(0.008)
New Normal × Shopping Mall	−0.039***
	(0.010)
New Normal × Touristic Spot	−0.153***
	(0.011)
New Normal × Rural Area	0.028***
	(0.009)
New Normal × High-Income Area	0.063***
	(0.010)
New Normal × Low Assortment Overlap	0.141***
	(0.008)
New Normal × Low Inventory Days	0.153***
	(0.009)
Constant	−2.702***
	(0.003)
Observations	846,878
R^2	0.626
AIC	2,972,422
Store FE	Yes
Country x Brand x Week FE	Yes
Country x Brand x Day FE	Yes

Notes: AIC = Akaike information criterion; FE = fixed effect. Robust standard errors in parenthesis. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

massive drop during the full lockdown tends to dominate any secondary effect (Table 2).[10] Surprisingly, the features that one would imagine make the store more profitable are those driving a more adverse decline in retail activity. More specifically, large and best-selling stores experience lower sales in partial and new normality periods. Similarly, stores closer to the highest ranked touristic attractions—prime locations, expensive to run, flagship stores—also observe a larger drop in retail sales. Stores located inside shopping malls also experience a more adverse effect—possibly due to more stringent regulations in large closed spaces as well as increased risk of contagion in high-traffic areas. On the other hand, high-income and rural areas safeguard stores from external shocks. Once again, these stores receive substantially fewer daily visitors than urban, touristic stores—however, its demand is less sensitive to external shocks. In terms of adaptive actions, we find that lower assortment overlap (i.e., more specialized products) and faster, fresher inventories drive higher sales.

Resilient stores are specializing on serving a local "captive" demand (Bell and Lattin, 1998; Ho et al., 1998; Lim et al., 2021). These stores are small and far away from city centers, and its demand is local and presumably there are few stores nearby. That is, there is a single Zara or Bershka store in the city, and thus travel distance makes shoppers relatively more loyal to a particular store (Bell et al., 1998; Cachon, 2014; Singh et al., 2006). Stores catering to a captive demand need to be more customer-centric, namely better adjust variety to the current needs of the customer, thereby contributing to a higher resilience.

In contrast, less resilient stores sell to a large demand, absorbing positive spillovers from nearby attractions, businesses, and urban amenities (Davis et al., 2019; Ellickson et al., 2020; Leonardi and Moretti, 2022). Although potential demand is large, the customer base is constantly changing: those who enter the store are temporal shoppers passing by. These stores function as demand aggregators and cater to a "blockbuster" clientele, that is, stores are less attached to local customer needs. Stores located nearby the highest ranked attractions in the country are expensive to run—prime locations—and are often seen as signature stores: Fifth Avenue (New York), Passeig de Gràcia (Barcelona), Champs-Elysées (Paris), or Via Monte Napoleone (Milan). For decades retailers unquestionably embraced these locations: any brand wanted "to be there." However, these characteristics also make the store relatively more dependent on constantly recycling one-off visitors—and that may be unfeasible when shocks reduce travel, tourism, or urban mobility.

We can extend this set of insights into a broader conceptual framework, as we anticipated in Figure 2 in the introduction. This allows us to take a step back from Zara and Bershka, and set forward generalizable knowledge that speaks to retail businesses operating brick-and-mortar stores. We expect our framework to be generalizable in at least two dimensions, namely other offline settings—for example, general impulse

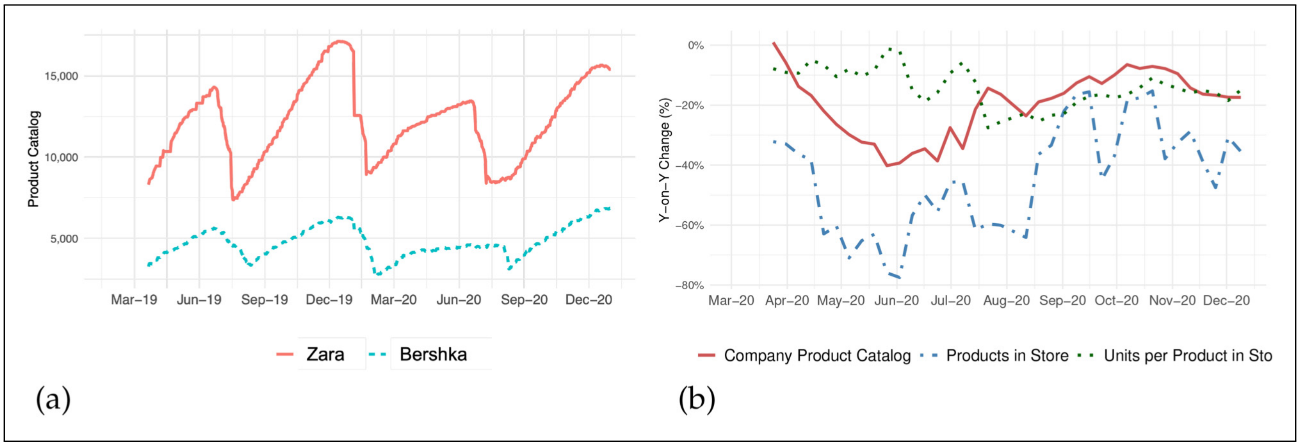

Figure 11. Brand-level reduction in catalog: (a) product catalog and (b) products in the store.

product retailing, office spaces, co-working spaces, restaurants or entertainment—as well as other large macroeconomic shocks that shake the profitability of a store.

In terms of managerial implications for operating brick-and-mortar stores, we overall conclude that features which more effectively "sync" with local demand enhance resilience. This includes (a) decisions related to where open the store—geography, density, street access—as well as (b) decisions to how operate the store—variety and speed. This finding can be somewhat counterintuitive. One might speculate that "generalist" stores may be more resilient by offering best-selling items to catch-all audience, meanwhile "specialist" stores are more sensitive to shifts in demand tastes. However, the ability to operate high-velocity inventories as well as curate their variety to the current needs of the customer are mutually reinforcing factors that increase resilience to external disruptions. That is, faster-moving inventories allow the store to get rid of unsold stock, then allowing the store to bring more up-to-date variety. For instance, during periods of partial mobility restrictions, it was likely more pertinent to offer comfortable home-wear over the latest trendy items, as nightclubs were entirely closed.

Once again, these ideas are not exclusive to the fashion industry. Managers may want to think in which ways their businesses can further customize for the loyal consumer. For restaurants, this may imply offering take-out when dine-in is not possible or making swift changes to the menu, for example, bringing seasonal and local ingredients to the table—even if this means sacrificing the "best-seller" dishes. For ice-cream shops, this may imply rotating flavors more frequently to maintain sense of novelty. For brands of consumer goods, this may imply considering retail outlets other than department stores and shopping malls, for example, small, temporary pop-up stores.

Interestingly, the value of a specialized store can be related studies in ecology showing that specialist species can sometimes outperform generalist species (Bascompte and Jordano, 2007; Levins, 1968). Indeed, Bascompte and Scheffer (2023) described that "increasing heterogeneity of the species" and "allowing variability" are ways to enhance the resilience of an ecological network. An intuitive phrase often used is "jack-of-all-trades is master of none." As explained by Remold (2012), "the core of this idea is that generalists bear some cost in each environment they can use, such that a specialist on a given environment will always be able to outcompete a generalist sharing that environment." For our purposes, we see this link to nature as a motivation to take the learnings from our work and apply them in diverse business settings.

These insights bring important managerial implications for the optimal mix of stores, for spatial competition in retail (Ellickson et al., 2020; Lim et al., 2021), for thinking as stores through the lens of risk versus reward, and for the complex externalities in the geography of retail (Glaeser et al., 2019; Huff, 1964). Going forward, business owners might want to tone down the number of flagship stores as well as look with better eyes spots that are less ambitious but bring stability to the portfolio of sales (Cachon, 2014)—stores that cater to a local, small, and loyal demand.

5 Brand-Level Strategies: Shrinking the Catalog

So far, we have discussed store-level resilience to external disruptions. A related question of interest to managers and policymakers is whether retailers implemented any brand-wide strategic actions to better cope with the pandemic. Figure 11 shows the evidence that they actually did.[11] In Panel (a), we observe that both Zara and Bershka started to reduce the assortment variety as early as February 2020. This occurs as a result of launching *fewer new products* to the market. By April 2020, the product catalog was about 15% smaller compared to the same period in 2019. Even as of December 2020, the variety offered remained below a year before.

In Panel (b), we more closely examine the behaviors of twelve stores located in Spain. Two findings are noteworthy: (a) stores reduced variety of products echoing the company-wide catalog reduction; and (b) they also reduced the amount of inventory in stock, most likely anticipating a contraction in the demand. The dotted line indicates that, starting March 2020, the inventory depth remained below 2019. These behaviors suggest that some companies were able to respond surprisingly rapidly to the shocks associated with COVID-19, consistent with theories of optimal assortment management and the practice of the fast-fashion business model (Caro and Gallien, 2007, 2010; Caro et al., 2020; Caro and Martínez-de Albéniz, 2015).

The timing of these responses is worth discussing. A strict, national-wide full lockdown (in which stores were required to close) occurred between March and April in Spain. Consistent with the fact that no consumption in the offline stores was possible, Panel (b) shows fairly stable inventory levels in this period, due to the inability to remove inventories from the stores. It was only once stores were able to operate under the new capacity and schedule guidelines that inventory levels were adjusted downward, by selling and not replenishing stock at the same rate. On the other hand, product variety was reduced much more quickly. Indeed, while in 2019 new products arrived during the season, this product updating was significantly shrunk in 2020. The company's strategies via quantity and variety reduction remained throughout the year. In particular, we estimate a 20% decrease in assortment breadth and a 15% decrease in the inventory depth of those products.

This evidence is meaningful because it suggests that businesses lacking this kind of operational fast-response might have experienced a more profound effect. For instance, rapidly cutting back company-wide per-product inventory depth minimizes excessive inventory that must later be sold at deep markdowns. Going forward, we might expect further developments in omnichannel operations and higher flexibility in shrinking/expanding assortments throughout the season (Bell et al., 2014; Cachon, 2020; Gallino and Moreno, 2018; Lim et al., 2020).

Finally, despite some evidence of brand-level strategies, the store-level measures of adaptive resilience are relatively consistent over time. To see this, we compare the assortment overlap as well as the inventory days before and during the pandemic. More specifically, a simple OLS regression shows that the coefficients are 0.96 ($p < 0.001$) and 0.74 ($p < 0.001$) for assortment overlap and inventory days, respectively, when the pre-pandemic feature predicts the post feature. Importantly, it informs that the abilities to fast-response and customize are determined prior to the external disruption and beyond the brand strategies. Therefore, it is difficult to disentangle risk mitigation actions vs. risk management actions. In other words, adaptive resilience seems a consequence of preparedness.

6 Robustness Checks

Our main results remain unchanged in many robustness checks. We mention the analyses here and discuss them in detail in the E-Companion.

1. COVID-19 Infections Nearby the Store. We show the amplifier role of COVID-19 infections, namely an increase of infections nearby the store reduces sales.
2. Brand-Specific Catalog. We report similar findings when controlling for the brand-wide catalog variety.
3. Alternative Delta Period of 4 Days. We report similar findings when re-constructing our sales measure using a delta period of at most 4 days.
4. Alternative Measure of Store Assortment Overlap. We redefine assortment overlap as follows:

$$\text{Assortment Overlap}_i = \sum_{t\in T_i}\sum_{k\in K_{i,t}} \frac{\sum_{i'\neq i\in S_t} \mathbb{1}_{\{k,t\}\in\{i',t\}}}{\# i' \in S_t} \frac{1}{\# K_{i,t}} \frac{1}{T_i}, \quad (7)$$

   where the assortment overlap for store i on date t is defined as the share of other stores in the same brand x country that also sell item k on date t (i.e., $\frac{\sum_{i'\neq i\in S_t} \mathbb{1}_{\{k,t\}\in\{i',t\}}}{\# i' \in S_t}$), then averaged across all items k sold by store i on date t, and then averaged across time. Thus, higher values indicate greater similarity with other stores.
5. Alternative Measure of Rural Area. We use the population density nearby the store.
6. Alternative Measure of Store Size. We use store-level sales in the pre-pandemic period.
7. Alternative Measure of High-Income Area. We use TripAdvisor's number of fine dining restaurants nearby the store.
8. Alternative Measure of Touristic Spot. We use TripAdvisor's number of attractions nearby the store.
9. Alternative Measure of Inventory Speed. We use store-level inventory depth in the pre-pandemic period.
10. High versus Low Sales Variability Pre-COVID-19. We show that sales variability pre-COVID-19 amplifies sales drops during the external shock.
11. Duration of Lockdown Phase. We show that the strength of the lockdown period slightly attenuates external shocks.

7 Discussion and Implications

We used a novel approach to infer sales at the store-day level, consistent across countries, and with sufficient time and store-level granularity. This data allowed us to identify which features make stores more resilient. Our main result is that size, touristic spots, and locations inside shopping malls *exacerbate* the drop in store sales, while rural and high-income areas *attenuate* those effects. We also observe that more resilient stores have lower assortment overlap and lower inventory days—that is, they offer a relatively more distinct variety and operate faster, fresher inventories, respectively. In other words, while stores are tied to their upstream decisions (e.g., brand catalog), they still possess some degrees of freedom to increase resilience from local operational choices.

Our findings provide generalizable insights in at least two domains: industry and policy. Our data covers fashion brands, but there are no structural differences with other retail industries that operate brick-and-mortar stores. Our framework of intrinsic and adaptive resilience speaks to restaurants, department stores, consumer electronics, fitness clubs, furniture or design shops. All these industries are shaped by (a) urban economics decisions, such as customer-type (basket size, repurchase frequency, travel distance, and demographics) and store-type (location, shopping mall, access, and size), as well as (b) supply-side decisions of relative variety and assortment freshness. In a similar vein, we focus on the COVID-19 shock, but we expect our findings to apply to large, non-idiosyncratic macroeconomic shocks. Our findings are not country-specific but rather encompass 20 countries, of all which experienced similar non-health-related policies. This consistency adds external validity to other shocks in which store functionality and shopping habits are driven by a set of shared policies.

Some of our empirical results challenge established Folk Knowledge about offline stores. To begin with, flagship stores were often conceived as "live proof" of success. In the words of Valentino's CEO, signature stores send a "key message to the market." A brand prides itself of operating a flagship store in New York, in Barcelona, in Tokyo, or in London—especially if those stores are right next to landmark spots. These kinds of stores are often large and expensive to run, but pay off because they welcome thousands of shoppers every day due to their proximity to many touristic attractions. For instance, the Louvre received 45,000 visitors on a busy day pre-pandemic—many of which are likely to spillover a Zara nearby. However, this volatile exposure can make such store more sensitive to external shocks, namely, it multiplies demand swings.

On the other hand, resilient stores are less ambitious endeavors: not gigantic spaces, not prime locations, away from urban centers, and with street access. These features make the store ideal to serve a captive demand—and as a result, customers tend to be more local and loyal. Stores in Elche (Spain) or McLean (the United States) probably do not receive many tourists, thereby buffering the gains and the losses. Additionally, specialized stores in terms of relatively more curated assortment as well as faster inventory days experienced a less adverse decline in sales and a faster recovery during the pandemic.

What can managers learn from the results covering Zara and Bershka presented in this article? In other words, what can managers do to strengthen store resilience? It is helpful to distinguish between structural and tactical actions. Borrowing a term from the Finance literature, our findings suggest that managers should start thinking about the "risk-portfolio optimization" for their stores. A manager should ask: What mix of stores is the optimal mix for my business? Do I want all my stores to be in flagship locations? Our findings suggest that the answer is no. Indeed, judging from the recent wave of retailers shutting down stores or filing bankruptcy, managers may have overlooked this simple, yet fundamental question. There is a Marketing role that a signature store conveys to the market—customers and competitors—and those return-on-investment economics are complex to quantify. However, it seems unlikely that only operating flagship stores is the optimal mix. Instead, the right mix might also include local stores that cater to a local and captive demand, which safeguards from external shocks and charts a more sustainable way of business.

This structural analysis of the retail configuration does not, however, allow managers to tactically react to external shocks. Our results establish that managers still possess several degrees of freedom to increase store resilience. Some of these actions include contracting/expanding the brand-wide catalog variety throughout the season, adjusting inventory days, and the flexibility to update the store assortment overlap (or relative novelty). We are mindful that this is not straightforward to implement: at the corporate level, it implies granting greater power to store-level decisions, which might be harder and less efficient to plan. Although this de-centralization may seem less cost-effective, it enhances the resilience of brick-and-mortar stores. We find that keeping lighter inventories and tuning the store-level assortment (dis)similarity with other stores might be a great lever to respond to the interplay between fashion trends, external shocks, and customer changes.

Finally, our findings open up new avenues for research in retail management in marketing, operations, and urban economics. While our study examined two leading fashion brands, future research could expand our line of work by considering other firms in fashion, other industries (e.g., restaurants), as well as other macroeconomic shocks or additional datasets that complement web-scraped high-frequency inventories. It would also be interesting to establish the dynamics between store-resilience and cross-channel substitution into online retail (Hwang et al., 2020). Furthermore, the interaction of the retail store with its physical surroundings—for example, stores and services, transportation, pedestrian, or vehicle traffic—seems an important element that affects the number of potential shoppers and lies at the heart of our proposed conceptual framework. It is thus likely that the observed resilience of the store extends beyond it and encompasses the "human habitat" around it: establishing a broader measure of resilience would advance our understanding of urban spaces.

Appendix A

Figure A1 provides a visual perspective for 3,142 stores throughout 97 countries. To simplify, we restrict attention to the average year-on-year variation in units sold, experienced by the stores during November 2020.

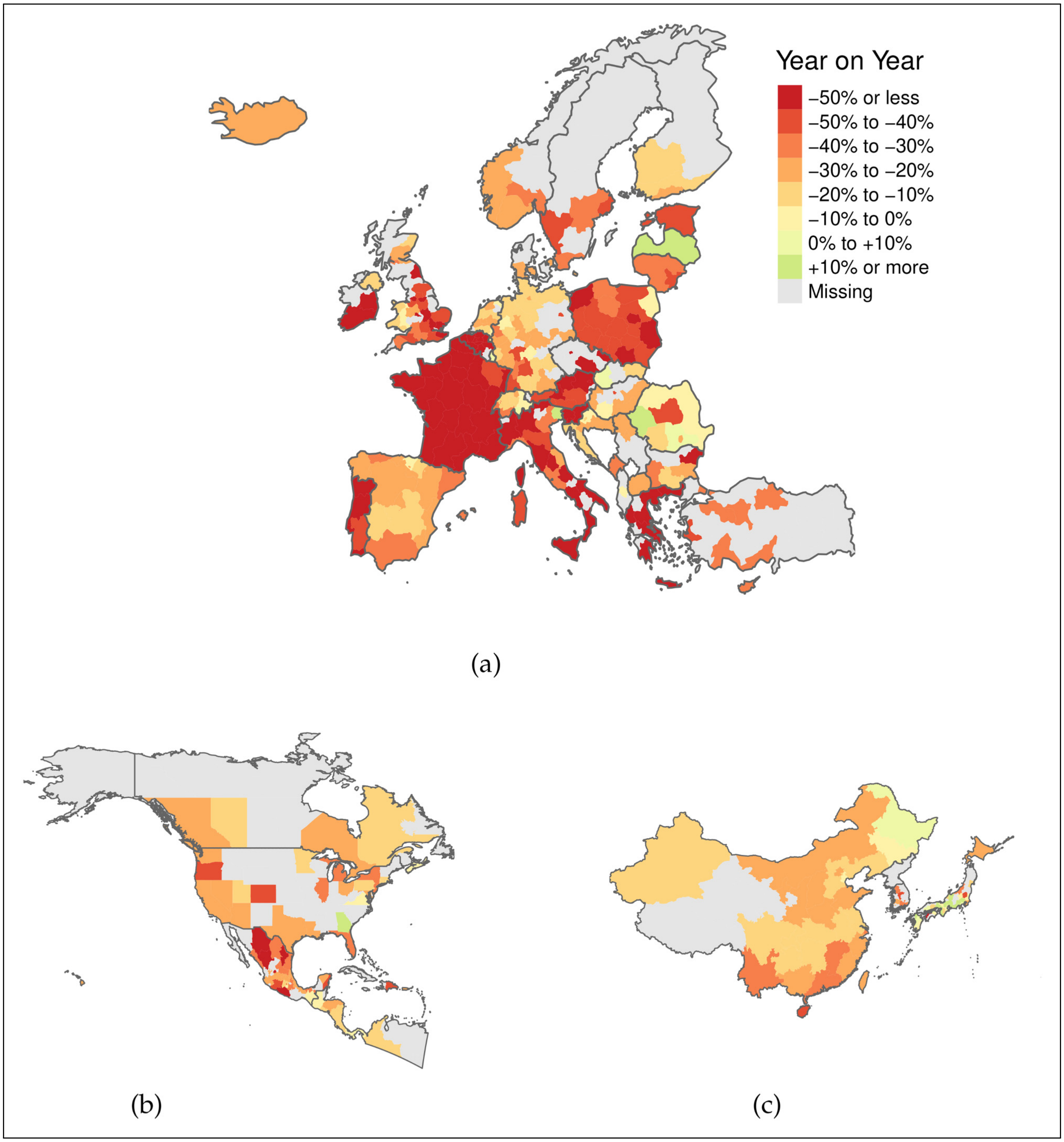

Figure A.1. Global map Nov-20 versus Nov-19: % change in total units sold per store: (a) Europe, (b) North America, and (c) East Asia.

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ORCID iD

Victor Martnez-de-Albéniz https://orcid.org/0000-0001-8391-2205
Diego Aparicio https://orcid.org/0000-0003-4964-6745

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Notes

1. There is some resemblance to the ideas of resilience in ecology, defined as "the capacity of a system to persist with and adapt to change" (Nyström et al., 2019). There is also resemblance to psychology, which considers resilience as the combination of a "personal trait" as well as a "dynamic process of change" (Olsson et al., 2015).
2. The countries are Austria, Belgium, Canada, Denmark, France, Germany, Greece, Ireland, Israel, Italy, Japan, Mexico, the Netherlands, Norway, Poland, Portugal, Spain, Sweden, the United Kingdom, and the United States.
3. Estimated using airport traffic data from 20 countries. Chinazzi et al. (2020), Glaeser et al. (2020), and Brinkman and Mangum (2021) also reported vast decreases of travel within the city. Indeed, flight noise has decreased so drastically that scientists have been able to recover natural earth seismic signals, previously confounded with human noise (Lecocq et al., 2020).
4. To provide a visual intuition for the uniform assortment, consider the screenshots in the E-Companion. We observe the same denim shoes across countries in Zara's online store.
5. The E-Companion reports the distribution of inventory depth.
6. Section 6 reports the robustness specifications using a delta period of 4 days.
7. We do not find evidence that offline store fulfillment of online orders was systematically correlated with COVID-19 interventions.
8. To illustrate, when $f = \text{Mall}$, then we have the interaction between $\text{Lockdown}_{i,t}$ and Mall_i, between $\text{Partial}_{i,t}$ and Mall_i, and between $\text{New Normal}_{i,t}$ and Mall_i (all of which are indicator variables in this case). Note that the main effects of features $f \in F$ are absorbed by the store fixed-effects, but the interaction with the regulation (our object of interest) is identified.
9. All coefficients are statistically significant at the 1% level. The estimates are expressed relative to the baseline store. For example, the coefficient for new normality × high-income is shown as $(\exp(\hat{\beta}_3 + \hat{\lambda}_{3,\text{High-Income}}) - 1) * 100 - (\exp(\hat{\beta}_3) - 1) * 100$.
10. For completeness, the interaction terms for the lockdown period are visualized in the E-Companion.
11. The comparison is shown year-on-year to account for seasonality.

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