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Cost Pass-Through, Price Competition, and Market Power in Brick-and-Mortar Pharmacies: Evidence from Germany

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Cost Pass-Through, Price Competition, and Market Power in Brick-and-Mortar Pharmacies: Evidence from Germany

Maximilian Maurice Gail*

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Abstract

In the German pharmacy market, strictly regulated prescription (Rx) drug prices coexist with free pricing for over-the-counter (OTC) drugs. This paper investigates the extent of market power in the non-prescription segment (OTC drugs and non-pharmaceuticals) and explores the role of Rx drugs in facilitating this. Leveraging nearly a billion daily observations from over 6,300 pharmacies and 213,000 products (2018–2022), this study estimates wholesale-to-retail pass-through rates via an error correction model (ECM) and analyzes product-level markups (Lerner Indices). Results reveal asymmetric pass-through (*rockets and feathers*): retail prices adjust to cost increases faster than decreases, a dynamic driven by niche products while bestsellers exhibit pricing inertia. Long-run pass-through rates (1.3–1.7) indicate systematic cost overshifting. However, while OTC drugs sustain high long-run markups – corroborated by Lerner Indices that are 35 % higher than those of non-pharmaceuticals – non-pharmaceuticals face more competitive pricing dynamics, passing through cost decreases more aggressively than increases. Furthermore, a spatial analysis reveals that rural pharmacies exhibit higher long-run pass-through rates and appear to compensate for lower transaction volumes (−7.6 %) with markups 8.3 % higher than urban competitors, effectively nullifying aggregate gross profit differences. These spatial dynamics are characterized by rural pharmacies exhibiting greater short-run pricing inertia, followed by stronger long-run pass-through. The findings suggest that pharmacies leverage the regulated Rx segment to facilitate higher markups and systematic overshifting. Consequently, the financial viability of rural networks relies partially on this cross-subsidization from Rx drugs, a model facing risks from increasing digitization.

JEL codes: L11, L13, L42, L50, L51, L81, I11.

Keywords: Over-The-Counter Drugs, Cost Pass-Through Estimation, Pharmacy Market, Markups, Error Correction Model, Price Competition, Rockets and Feathers.

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1 Introduction

In recent decades, numerous European countries have liberalized their pharmacy markets to foster competition (see, e.g., López Vila et al., 2023; Martins et al., 2015). Economically, these reforms aimed to lower drug prices and improve access via several deregulatory measures: granting pricing autonomy for over-the-counter (OTC) medications, relaxing ownership and dispensing constraints (Lluch & Kanavos, 2010; Vogler et al., 2014), abolishing regional entry quotas (Heinsohn & Flessa, 2013), and reclassifying certain prescription drugs as OTC (Andersson & Hatziandreu, 1992). Germany aligned with this trend by implementing major reforms in 2004 (Heinsohn & Flessa, 2013; Stargardt et al., 2007).

Despite these regulatory shifts, rigorous empirical evidence on the evolution of competition in the pharmacy sector remains limited. International evidence utilizing micro-level data yields mixed conclusions. For instance, Moura and Barros (2020) report only modest price reductions in Lisbon, whereas reforms in Nordic markets fostered competition while precipitating consolidation (Anell, 2005; Anell & Hjelmgren, 2002). Broader European evidence similarly indicates that while liberalization improves access, it does not consistently lower consumer prices (Lluch & Kanavos, 2010; Vogler et al., 2014). Beyond Europe, Jo et al. (2022) reveal a critical trade-off in South Korea: while deregulation successfully reduced prices and improved access to the liberalized drugs, it accelerated the exit of incumbent pharmacies, thereby reducing overall consumer access to comprehensive pharmaceutical services. Most recently, Anderes (2026) highlights the structural vulnerability of traditional brick-and-mortar (B&M) pharmacies: after losing their local prescription (Rx) monopoly to self-dispensing physicians in specific Swiss regions, pharmacies suffered a permanent 9% profit decline alongside a 10% drop in Rx revenue. Driven by a 50% collapse in acute care sales, this shock forced a compensatory pivot toward non-drug health services.

In Germany, previous research relied primarily on pharmacist surveys, which suggest that price competition is muted (Heinsohn & Flessa, 2013; Stargardt et al., 2007). However, such *stated preference* data often fails to capture the strategic realities and details revealed by actual transaction behavior captured by *revealed preference* data (see, e.g., Louviere et al., 2000, Chapter 8.2). Furthermore, reliance on aggregated data (e.g., price indices) risks severe bias. As demonstrated by Imbs et al. (2005) and Nakamura and Steinsson (2008), aggregation obscures micro-level heterogeneity, leading to biased estimates of price rigidity (Bogoev & Sergi, 2012; Pesaran & Smith, 1995). Consequently, this aggregation bias risks masking the true extent of local market power. For instance, Jo et al. (2022, Table 1) document that prior policy evaluations in the pharmacy market have predominantly relied on country-level data, which obscures micro-level heterogeneity. While Jo et al. (2022) advance this literature by utilizing pharmacy-panel data, they are limited to monthly aggregate revenues and annual city-level average prices of a representative sample of 50 OTC drugs.

In contrast, this paper bridges these gaps by analyzing a novel comprehensive proprietary dataset of transaction-level records from 9,231 B&M pharmacies between 2018 and 2022 (yielding a balanced panel of 6,338 pharmacies and covering approximately 213,000 unique products, comprising nearly a billion transactions). Unlike previous studies, these data allow for the precise observation of wholesale and retail prices, markups, and quantities of (almost) any product sold. A paramount strength of this dataset is that observing the exact wholesale price directly yields the economic marginal cost of dispensing a drug, eliminating the need for proxy variables or structural modeling, and allows for the measurement of the Lerner Index.[1] Furthermore, the high-frequency nature of the data permits the estimation of an asymmetric high-dimensional fixed effects error correction model (ECM) in the form of a non-linear autoregressive lag (NARDL) model (Balaguer & Ripollés, 2016; Salisu & Isah, 2017; Shin et al., 2014). Following the standard approach in the cost pass-through literature, this framework enables to explicitly measure both the speed of short-run adjustments and the magnitude of long-run pass-through. Specifically, by distinguishing between positive and negative cost shocks (e.g., Borenstein et al., 1997), dynamic pricing asymmetries (*rockets and feathers*) can be evaluated. Identification relies on the structural feature that individual pharmacies are atomistic and take product-specific wholesale prices as given. Since procurement terms with wholesalers are typically negotiated on an annual basis, high-frequency cost shocks are exogenous to idiosyncratic local demand. Crucially, the model includes pharmacy-by-product and time fixed effects, which absorb all time-invariant heterogeneity (such as location, quality, and brand loyalty) and common aggregate shocks. Consequently, the pass-through coefficients are identified solely from within-unit variation, orthogonal to static market power or spatial differentiation.

The analyses establish four primary stylized facts. First, the analyses reveal substantial pricing inertia and asymmetric pass-through, consistent with the *rockets and feathers* phenomenon (e.g., Bacon, 1991; Borenstein et al., 1997; Ritz, 2015; Tappata, 2009). Pharmacies transmit cost increases significantly faster than decreases, though the magnitude varies structurally by segment (OTC drugs and non-pharmaceuticals). For OTC drugs and non-

[1] The Lerner Index is calculated as $(P - W)/P$ (based on Lerner, 1934), where P denotes the retail price and W represents the wholesale price, which serves as a proxy for marginal cost. This relies on the assumption that other operating expenses (primarily personnel salaries, rent, and laboratory infrastructure) represent fixed common costs in both the short and long run that do not vary with the sale of an additional unit. Furthermore, marginal inventory holding costs are negligible; the German wholesalers typically guarantee deliveries up to three times daily, allowing pharmacies to operate on a just-in-time basis and minimizing the capital and space required for stock-keeping. See https://www.phagro.de/app/uploads/2021/06/Phagro-Broschüre-2021_web-1.pdf.

pharmaceuticals, adjustment dynamics align with the 2-to-1 ratio frequently documented in the literature for both wholesale cost and value-added tax shocks (e.g., Benzarti et al., 2020; Peltzman, 2000). Pharmacies pass through initial cost increases at rates of approximately 26 % for OTC drugs and 41 % for non-pharmaceuticals, compared to only 12 % and 23 %, respectively, for cost decreases. This disparity highlights that OTC pricing is notably stickier, suggesting that while cross-channel competition (from drugstores and general retailers) disciplines non-pharmaceutical pricing, the regulatory exclusivity of OTC drugs – which can only be purchased in pharmacies (see Section 2.2) – and their acute medical necessity allow pharmacies to protect margins from cost reductions. In the long run, however, this asymmetry disappears and pass-through rates exceed unity (overshifting), reaching approximately 1.5 for OTC drugs and 1.4 for non-pharmaceuticals.

These short-run dynamics are consistent with theoretical models in which frictions, such as menu or search costs, delay short-run price cuts (e.g., Hellerstein, 2008; Loy et al., 2016; Nakamura & Zerom, 2010; Varian, 1980). By contrast, for systematic long-run overshifting, standard oligopoly models show that systematic long-run pass-through relies on four components: the elasticities of demand and marginal cost (supply), the curvature of demand, and the intensity of competition (Ritz, 2024; Weyl & Fabinger, 2013). Under monopoly or monopolistic competition with constant marginal costs, however, the role of demand elasticity vanishes, and systematic overshifting relies entirely on a log-convex demand curvature (Bulow & Pfleiderer, 1983; Mrázová & Neary, 2017). Because pharmacies purchase drugs directly from wholesalers and face negligible stocking or inventory costs, their marginal costs can be assumed to be constant (see Footnote 1). Consequently, log-convexity may play an important role in explaining the observed overshifting. Economically, log-convexity can reflect *fat tails* in the distribution of consumer valuations (Gabaix et al., 2016; Weyl & Fabinger, 2013), meaning that as prices rise, the remaining consumer base becomes increasingly price-insensitive, making it optimal for firms to overshift costs. This theoretical mechanism perfectly aligns with the finding that more rural pharmacies can sustain higher unit markups and exhibit higher long-run pass-through rates (see following stylized facts).

Second, contrary to the premise that rural pharmacies are financially disadvantaged by lower consumer density (which results in lower turnover and reduced economies of scale), they offset structurally lower transaction volumes (-7.6 %) by setting OTC unit markups approximately 8.3 % higher than their urban competitors. Consequently, total gross profits in more rural pharmacies are statistically indistinguishable from those in urban locations. This aligns with the structural analysis of Schaumans and Verboven (2008, p. 969), who demonstrate that while general entry liberalization is feasible, maintaining geographic coverage in smaller markets requires shielding profitability, potentially through nonuniform (higher) markups. The empirical evidence presented here highlights that a functionally equivalent mechanism operates in the segment of OTC-drugs and non-pharmaceuticals: rural incumbents, which are shielded from the profit-eroding effects of entry typically found in denser markets, leverage their local market power to extract rents through higher OTC and non-pharmaceutical prices, possibly to satisfy their solvency constraint. This power may be grounded in the regulated Rx segment – which generates approximately 75 % of a pharmacy's gross profits (see Section 3.3) – acting as a strategic *traffic builder* (Dhar & Hoch, 1997). By serving as a regulated anchor that draws consumers to the pharmacies, it may induce them to bundle Rx prescriptions with OTC and non-pharmaceutical products to minimize search and travel costs. This conjecture is corroborated by descriptive evidence indicating that approximately one-fifth of OTC and non-pharmaceutical sales stem from such joint purchases (see Section 3.3). Theoretically, such a finding is consistent with models of *one-stop shopping* and multi-product search frictions (e.g., Florez-Acosta & Herrera-Araujo, 2020; Klemperer, 1995; Lal & Matutes, 1994; Messinger & Narasimhan, 1997; Zhou, 2014). This mechanism may allow incumbents to extract higher margins from OTC drugs and non-pharmaceuticals compared to the absence of such a regulated anchor, which may be consistent with the theoretical models featuring, search-constrained, captive and uninformed consumers (e.g., Bliss, 1988; Ronayne & Taylor, 2022; D. O. Stahl, 1989; K. Stahl, 1982; Varian, 1980). The critical reliance on this regulated anchor is empirically validated by Anderes (2026), who demonstrates that exogenous shocks to Rx footfall cause severe profit erosion for pharmacies. Applied to this study, this highlights the threat to the viability of the cross-subsidization model.

Third, regarding cost pass-through, market power seems to drive a distinct temporal pattern: rural pharmacies display stronger short-run inertia followed by greater long-run markup expansion. This divergence is statistically significant for non-pharmaceuticals (approximately 1.35 vs. 1.38 for urban and rural pharmacies, respectively), while for OTC drugs, the effect is only weakly significant despite a comparable economic magnitude (approximately 1.44 vs. 1.46). This finding highlights that pharmacies protected by spatial barriers are potentially not compelled to absorb cost shocks but instead leverage local power to pass on cost volatility. This behavior mirrors findings in other industries characterized by high fixed costs and capacity constraints, such as cement (Miller et al., 2017), gas stations (Stolper, 2024) and solar leasing (Pless & Van Benthem, 2019). Overshifting is also found in many other industries such as a variety of retail goods (Besley & Rosen, 1999), alcoholic beverages (Kenkel, 2005; Young & Bielińska-Kwapisz, 2002) and cigarettes (Delipalla & O'Donnell, 2001), where imperfect competition, log-convex demand, a convex-cost structure or spatial frictions facilitate systematic cost overshifting into higher equilibrium prices to insulate margins (see, e.g., Miravete et al., 2023; Ritz, 2024; Stolper, 2024; Weyl & Fabinger, 2013).

In the pharmacy context, this pricing power may be functionally necessary: facing high fixed operating costs – including mandatory staffing and laboratory infrastructure – that must be recovered across a constrained transaction volume, incumbents are compelled to exploit the unregulated OTC segment (even extending to non-pharmaceuticals). This aligns with the *waterbed effect* observed in many industries such as telecommunications (Genakos & Valletti, 2011), and mirrors the regulatory spillovers documented in pharmaceutical manufacturing (Dubois & Lasio, 2018), where price constraints in one segment alter equilibrium pricing in others (e.g., to cover common fixed costs). Theoretically, this dynamic arises naturally in multi-product firms (such as pharmacies) facing common fixed costs (Schiff, 2008) and follows retail pricing models where incumbents cross-subsidize infrastructure by concentrating markups on their least price-sensitive products (Bliss, 1988).

Fourth, market power is highly heterogeneous across the product portfolio, revealing a strategic segmentation between bestseller and niche items. While the overall asymmetry is driven predominantly by niche products, bestsellers exhibit distinct pricing inertia and higher long-run pass-through rates. This inertia is consistent with *add-on pricing* strategies (Ellison, 2005) or the fairness-based theory of price rigidity (Rotemberg, 2005), where firms maintain stable nominal prices to avoid triggering customer anger. However, the substantial long-run overshifting suggests that once prices do adjust, pharmacies exploit brand loyalty associated with bestseller drugs to pass on cost shocks. This mirrors the behavior documented by Granlund and Bergman (2018), where high-visibility brand-name drugs adjust significantly slower to shocks than generics. Conversely, non-pharmaceuticals exhibit a long-run reverse asymmetry (cost decreases are passed on more strongly than increases), consistent with their role as a secondary *traffic builder* fighting against competition from drugstores. Thus, the *rockets and feathers* effect is not a uniform friction (such as expected from menu costs for printing labels), but seems to be a targeted strategy maximizing rent extraction where consumer attentiveness is lowest.

The remainder of this paper is organized as follows. Section 2 details the institutional setting of the German pharmacy market. Section 3 describes the data, data handling and presents the descriptive statistics. Section 4 outlines the identification strategy used to isolate short- and long-run cost pass-through (CPT) asymmetries, as well as structural heterogeneity across pharmacies and product ranks. Section 5 reports the estimation results, where Section 5.1 provides the main CPT results, Section 5.2 provides robustness, Section 5.3 explores structural heterogeneity, and Section 5.4 examines the spatial dimension of market power, linking urbanization levels to markup strategies, profitability, and CPT dynamics. Section 6 discusses the broader economic implications and acknowledges methodological limitations. Finally, Section 7 summarizes the findings and concludes.

2 Institutional Background

Although this analysis draws on the German pharmacy market, its findings can be generalized to other countries as this framework mirrors the structural environment found in 24 out of 30 European nations (López Vila et al., 2023). While the OTC segment is liberalized in the majority of member states (e.g., Italy, Portugal, and Greece), the market for Rx drugs remains heavily regulated across most European healthcare systems to ensure uniform access and affordability. In Germany, as in many peer countries (e.g., Austria, Belgium, France, Spain, Denmark), pharmacies are bound by fixed (statutory) prices or strict reimbursement limits for Rx drugs (see, Vogler et al., 2011, 2014), effectively eliminating price competition in this segment. Consequently, this common regulatory asymmetry likely allows for the transfer of findings and implications to other regulated pharmacy markets.

Specifically, the German pharmacy market is characterized by a strict regulatory dichotomy that shapes local competition. Uniform pricing laws for Rx drugs eliminate price competition, forcing pharmacies to rely on the liberalized OTC market to exercise local pricing strategies. Furthermore, pharmacies compete on several non-price dimensions. As detailed by Albrecht et al. (2020, pp. 59–64), these include service quality (e.g., counseling intensity, courier services), assortment depth, and strategic location choice. Crucially, while the transaction-level data cannot capture unobservable service dimensions like counseling, it perfectly isolates the intersection of two primary strategic levers: pricing behavior for OTC and non-pharmaceutical products, and spatial differentiation. The following sections outline these regulatory constraints, ownership structures, and competitive dynamics shaping the German pharmacy market that underpin the empirical framework employed in this analysis.

2.1 Regulatory Framework and Ownership Structure

The German pharmacy market operates under a strict regulatory regime that was fundamentally reshaped by the Statutory Health Insurance Modernization Act (*Gesundheitsmodernisierungsgesetz*, GMG) in 2004. Despite liberalization measures that legalized mail-order dispensing (see Section 2.3), the market remains highly fragmented due to the persistence of prohibition of third-party ownership (*Fremdbesitzverbot*). This regulation bans corporate chains, restricting ownership exclusively to licensed pharmacists (*approbated pharmacists*). While the 2004 reform relaxed the *one-pharmacist, one-pharmacy rule* (*Mehrbesitzverbot*) to allow ownership of up to four locations (one main pharmacy and three branches), these branches must be located in close geographic proximity.[2] Consequently, the local markets consist en-

[2] Branch pharmacies must be located in the same county (*Landkreis*) or independent city, or in a directly adjacent county (§ 2(4) ApoG (*Apothekengesetz*)).

tirely of independent small-to-medium B&M pharmacies, distinguishing it from the corporate chain models prevalent elsewhere in Europe.[3]

Following the 2004 reform, the number of pharmacies peaked at 21,602 in 2008 as owners utilized the new branch regulations. However, a steady consolidation has since reduced this number to 16,601 by 2025 (a decline of $\approx$ 23 %), raising concerns regarding healthcare access in rural areas.[4]

2.2 Price Regulation

A defining feature of the market is the dual regulatory regime governing Rx- and OTC drugs, which imposes distinct constraints on competition. First, the Rx segment is subject to a fixed prices regime. Under the Medicinal Products Price Ordinance (*Arzneimittelpreisverordnung*), pharmacies must charge a uniform, nationwide fixed price for prescription medications, effectively eliminating price competition.[5] Second, the OTC segment is liberalized, allowing pharmacies to set consumer prices autonomously while benefiting from a "pharmacy-only" distribution restriction.[6] This distinguishes OTC drugs from non-pharmaceutical products; while the latter complement a pharmacy's assortment, they face direct cross-channel competition from drugstores and general retailers, whereas OTC drugs remain within a protected regulatory segment.

Crucially, this deregulation extends to the upstream wholesale market. While wholesale prices for Rx drugs are strictly regulated – imposing a fixed surcharge and capping discounts – the procurement of OTC products is free from such restrictions.[7] This asymmetry typically allows high-volume pharmacies (often located in urban areas or as mail-order pharmacies) to negotiate lower unit costs for OTC inventory, whereas the fixed-price Rx margin serves as the foundation covering fixed operational costs (labor, rent,

[3]See, López Vila et al. (2023) for a European comparison, noting that 17 of 30 countries permit pharmacy chains.

[4]See Appendix Figure D.1. For discussions on supply security, see (Albrecht et al., 2020; Knobloch & Schröder, 2023, 2024).

[5]See § 78 AMG (*Arzneimittelgesetz*). Furthermore, for statutory health insurance patients (90 % of German patients), out-of-pocket costs are capped at a standardized co-payment (typically € 5–10), rendering demand effectively price-inelastic.

[6]See § 43 AMG.

[7]For Rx drugs, wholesalers are capped at a 3.15 % surcharge plus a fixed fee of € 0.70. While volume-based discounts (Skonti) were common during the sample period, a 2024 Federal Court of Justice (BGH) ruling has since declared them largely impermissible, retroactively highlighting the regulatory tightness of the segment. (BGH, judgment of 08.02.2024 - I ZR 137/23). See, https://juris.bundesgerichtshof.de/cgi-bin/rechtsprechung/document.py?Gericht=bgh&Art=en&Datum=Aktuell&Sort=12288&nr=137213&pos=9&anz=1370&Blank=1.pdf and https://www.pharmazeutische-zeitung.de/bgh-sieht-skonto-als-rabatt-145378/. In contrast, OTC procurement allows for any negotiated volume-based rebates.

mandated emergency services, and compliance).[8]

One argument from the literature suggests that pharmacies could utilize the liberalized OTC segment to compete on price and attract customers (Albrecht et al., 2020, p. 37-38). As Albrecht et al. (2020, p. 58-60 and 65) highlight, aggressive OTC pricing may serve as a lever to capture the demand for *bundled* (joint) purchases, thereby securing the associated Rx prescriptions, which cannot be discounted directly, or additional OTC drugs. However, this mechanism may also operate in reverse. Instead of using OTC drugs to attract Rx volume, pharmacies may leverage the Rx prescription to increase margins on OTC drugs and non-pharmaceuticals. Thus, the necessity of the Rx visit and fixed prices may create a captive consumer base, allowing the pharmacy to extract rents through higher margins on the secondary OTC purchase (due to one-stop shopping). Consequently, where local competition is limited – typically in rural areas – margins are expected to be systematically higher. The empirical occurrence of such bundled purchases will be analyzed in Section 3.3, while the analysis of local competition is conducted in Section 5.4.

2.3 Online Competition and the Limits of Local Market Power

The liberalization of mail-order dispensing in 2004 introduced a structural break in the pharmacy market, establishing an *outside option* for consumers that constrains the pricing power of local pharmacies. While B&M pharmacies remain legally tethered to physical locations (§ 11a ApoG), large foreign incumbents (e.g., DocMorris, Shop-Apotheke) have captured significant market share by leveraging economies of scale to undercut local prices. This outside option is critical for the subsequent analysis because even the most spatially rural local pharmacy can be expected to face competition from these ubiquitous mail-order pharmacies.

Data confirms that mail-order pharmacies aggressively target the more price-elastic OTC segment. On average, online competitors offer discounts of approximately 28 % below the recommended retail price whereas B&M pharmacies only discount by 9 % (Albrecht et al., 2020, p. 38). Leveraging economies of scale, superior management and marketing resources (Albrecht et al., 2020, p. 16-17), these entrants have expanded rapidly in the OTC

[8] The wholesale market is a highly concentrated oligopoly (market shares in 2024: Phoenix (30%), Alliance Healthcare (24%), NOWEDA (24%), Sanacorp (17%) and Pharma Privat (5%), see https://www.rebmann-research.de/teil-6-der-pharmazeutische-grosshandel-ist-mehr-als-nur-zulieferer-von-apotheken). Evidence on details of negotiations between wholesalers and B&M pharmacies is scarce, but information suggests that wholesalers exhibit substantial negotiation power and negotiations usually occur once for the succeeding year (establishing the overall purchasing conditions). See, e.g., https://www.apotheke-adhoc.de/nachrichten/detail/markt/treuhand-konditionen-besser-verhandeln/ and https://www.apotheke-wirtschaft.de/heftarchiv/2018/03/wie-sie-sich-am-besten-vorbereiten.html.

segment. Over the last decades, their market share in the OTC segment has surged from 5 % in 2008 to 22.7 % by 2024 (ABDA, 2021, 2025; Statista, 2024a). In contrast, their share of the Rx market remains marginal (0.9 %–1.4 %) due to the urgency of acute care and regulatory barriers (ABDA, 2024, 2025). This dichotomy reinforces the mechanism described above: while B&M pharmacies retain the Rx volume due to immediate availability, their ability to cross-subsidize this service via high OTC margins is constantly threatened by the lower-priced online alternatives (see discussion in Section 6).

The competitive balance between B&M pharmacies and foreign mail-order rivals was significantly disrupted by a 2016 ruling of the European Court of Justice (ECJ). The Court held that imposing German fixed-price regulations on foreign mail-order pharmacies constituted an unjustified restriction on the free movement of goods.[9] This decision introduced a period of regulatory arbitrage, allowing foreign entrants to offer (small) bonuses on Rx drugs while domestic incumbents remained bound by fixed prices.[10]

To restore regulatory parity, the German government enacted the *Vor-Ort-Apotheken-Stärkungsgesetz* (Local Pharmacy Support Act) in December 2020.[11] This legislation mandated that all pharmacies – including foreign mail-order – adhere to fixed co-payment prices for prescriptions covered by statutory health insurance, i.e., forbidding rebates that were previously exploited by foreign competitors. While rebates remain legal for private prescriptions and privately insured patients ($\approx$ 10 % of all insured persons), the Act effectively neutralized the price advantage of online competitors.[12]

This institutional shift, combined with the persistently low Rx market share of mail-order pharmacies ($\approx$ 1 %) throughout the sample period, underscores that B&M pharmacies successfully capture and retain consumers through the Rx segment. This structural captivity provides the foundation for the cross-subsidization discussion in the following sections. While the recent mandatory rollout of electronic prescriptions (E-Rezept)[13] in 2024 is expected to fundamentally alter these dynamics, the market structure during the sample period was defined by the high transaction costs of the analogue

[9] ECJ Case C-148/15 (Judgment of 19 October 2016), https://curia.europa.eu/juris/document/document.jsf?text=&docid=184671&pageIndex=0&doclang=EN&mode=lst&dir=&occ=first&part=1&cid=3568174.

[10] Foreign pharmacies typically structured these discounts as bonuses redeemable on future purchases of OTC or non-pharmaceutical goods.

[11] For details on the market impact, see (Gail et al., 2025).

[12] See German Federal Ministry of Health (https://www.bundesgesundheitsministerium.de/themen/krankenversicherung/zahlen-und-fakten-zur-krankenversicherung/mitglieder-und-versicherte). 73.3 million statutory health insured vs. 8.7 million privately insured patients in 2020.

[13] See the German Federal Ministry of Health's information on the e-prescription rollout: https://www.bundesgesundheitsministerium.de/e-rezept.html.

paper regime.[14] The electronic prescription removes this barrier, potentially reducing the switching cost to a digital transaction (Albrecht et al., 2020, p. 76). Consequently, the captive nature of the Rx consumer, proposed in this analysis to contextualize the findings, represents a structural feature of the paper-based system, which may face erosion as digitization decouples the Rx transaction from the physical point of sale.

3 Data, Descriptive Statistics and Stylized Facts

This section details the high-frequency transaction dataset. Section 3.1 outlines the data source and variable construction, followed by Section 3.2 detailing data handling and balancing procedures. Section 3.3 presents descriptive statistics characterizing market structure, price dynamics, and profitability, concluding with an analysis of joint purchasing patterns (bundle purchases).

3.1 Data Sources

The empirical analysis relies on a proprietary high-frequency dataset comprising transaction records for 9,231 B&M pharmacies from January 2018 to June 2022, including approximately 4 billion observations. The panel covers roughly 50 % of the German pharmacies, ensuring broad representativeness.[15] Data access was provided by the three leading suppliers of pharmacy merchandise information systems (MIS).[16]

Raw transaction records consist of individual line items captured at the point of sale. Table 1 provides an overview of the data structure and the relevant variables. Products are uniquely identified via the pharmaceutical central number (PCN), a standardized 8-digit code capturing the brand, manufacturer, package size, and dosage form.[17] This granularity allows for the precise segmentation of sales into non-pharmaceuticals (e.g., cosmetics, medical devices), OTC drugs, and price-regulated Rx pharmaceuticals. For each transaction, the dataset records the quantity sold, the wholesale price, and the retail price. The analysis exclusively utilizes net-of-VAT retail

[14] During this period, patients wishing to use online pharmacies were required to physically mail the original paper prescription, creating a significant friction that effectively shielded local pharmacies from digital competition.

[15] Germany had 18,461 pharmacies at the end of 2021; see https://www.abda.de/aktuelles-und-presse/zdf/.

[16] Providers include Awinta (https://www.awinta.de/), ADG (https://www.adg.de/), and Pharmatechnik (https://www.pharmatechnik.de/). An MIS manages a pharmacy's technological and informational infrastructure, including inventory management, automatically logging item-level data.

[17] The PCN (in German: *Pharmazentralnummer*) is the official German identification key for all pharmaceutical products and medical devices. See, https://www.bfarm.de/EN/Medical-devices/Tasks/DiGA-and-DiPA/Digital-Health-Applications/Interesting-facts/_node.html.

Variable/Indicator	Level	Description
Transaction Data Variables		
Sales Volume	Product/Pharmacy	Number of packages sold per transaction.
Net Retail Price	Product/Pharmacy	Daily Net Retail Price to the consumer (in €).
Wholesale Price	Product/Pharmacy	Daily Wholesale Price (Cost) paid by the pharmacy (in €).
Absolute Markup	Product/Pharmacy	Net retail price minus wholesale price.
Relative Markup (Lerner-Index)	Product/Pharmacy	Absolute Markup divided by Net retail price.
Product Characteristics		
PCN	Product	Unique 8-digit product identifier capturing brand, manufacturer, package size, and dosage form.
ATC1-5	Product	Hierarchical Anatomical Therapeutic Chemical classification; ATC4/5 denote the chemical substance level. Unique to each PCN.
Aggregated Pharmacy Statistics		
Total Sales Volume	Pharmacy	Total number of packages sold.
Revenue	Pharmacy	Total turnover generated (in €).
Total costs	Pharmacy	Total variable costs from sales (calculated as Wholesale Prices $\times$ Sales Volume).
Gross Profits	Pharmacy	Revenue minus total costs.
Spatial and Socio-Demographic Characteristics		
Location of Pharmacy	Two-digit zip code	Pharmacies are pseudonymized at the two-digit zip code level.
Degree of Urbanization	Two-digit zip code	Classification (Urban/Intermediate/Rural) based on the Eurostat definition; sourced from the Federal Statistical Office of Germany.
Socio-Demographics	Two-digit zip code	Includes population structure, household counts, and average purchasing power (sourced from Acxiom Deutschland GmbH, Frankfurt (2024)).

Table 1: Overview of Variables and Data Structure

prices.[18] This approach further allows for the calculation of the absolute markup and the relative markup (Lerner Index) at the transaction level (see Footnote 1). Aggregating these unit margins by sales volume yields the total gross profit per pharmacy, defined here as total net revenue minus the cost of goods sold, excluding fixed operating expenses such as labor or rent.[19]

To ensure strict data privacy, the MIS pseudonymized individual pharmacies using unique identifiers and restricted spatial resolution by truncating the standard five-digit postal code to the leading two digits. Consequently, identity and location of each pharmacy remain unobservable, with the two-digit region serving as the spatial unit for geographical market definition.

To control for product heterogeneity, transaction records are enriched with detailed attribute data via the PCN identifier. Key characteristics – including brand, manufacturer, dosage form, and active ingredient – are primarily sourced from the healthcare analytics provider IQVIA. This metadata facilitates the classification of substances according to the Anatomical Therapeutical Chemical (ATC) system (see next paragraph). To ensure comprehensive coverage across the entire portfolio, the dataset is supplemented with web-scraped data from major online pharmacies (DocMorris, Shop-Apotheke) and the *Gelbe Liste Pharmaindex*.[20]

In the empirical analyses, an average competitor price variable will be used, ensuring that the analyses capture price changes and responses among similar chemical substances from other pharmacies. To determine this, PCN identifiers are mapped to the ATC classification, a hierarchical framework based on standards maintained by World Health Organization (WHO) and the European Pharmaceutical Market Research Association (EPHMRA) that categorizes pharmaceuticals from broad anatomical groups (Level 1) to specific chemical substances (Level 4/5) (see, e.g., Hollingworth & Kairuz, 2021).[21] The analysis relies on the ATC4 or ATC5 level as the primary definition of the relevant product market. From a demand perspective, products sharing the same ATC4 or ATC5 code are functionally equivalent, sharing both the active ingredient and the route of administration, and are thus

[18] This is done to prevent the mechanical inflation of pass-through estimates by the value-added tax (VAT) rate.

[19] In the case of Rx drugs, the remuneration per drug is fixed for every German B&M pharmacy and follows a specific statutory scheme (see, e.g., Gail et al., 2025, Appendix A).

[20] See https://www.docmorris.de/, https://www.shop-apotheke.com/, and https://www.gelbe-liste.de/. The *Gelbe Liste* serves as a standard pharmaceutical reference for medical professionals.

[21] The dataset integrates the standard WHO version (https://www.whocc.no/atc/structure_and_principles/) with the EPHMRA (https://www.ephmra.org/anatomical-classification) adaptation to ensure comprehensive coverage. See https://www.who.int/tools/atc-ddd-toolkit/atc-classification.

treated as close substitutes.[22]

In addition, to facilitate a descriptive analysis of sales volume and profitability across different medical domains, the granular ATC codes are aggregated into broader therapeutic categories. This aggregation is utilized to highlight the distribution of pharmacy sales, revenues and profits across major health indications, and will be a part of the robustness analysis. As outlined in Appendix Table D.1, specific ATC2 codes are mapped to distinct therapeutic systems. This classification scheme groups related treatment areas – such as *Respiratory System* (ATC1 code: R) or *Musculoskeletal System and Pain Management* (comprising analgesics like N02 and anti-inflammatory drugs like M01) – into consolidated categories.

To analyze socio-demographic heterogeneity, the transaction records are augmented with external geographic and socio-economic data. Data on the degree of urbanisation are sourced from the Federal Statistical Office of Germany, utilizing Eurostat definitions to classify five-digit postal code areas into urban, intermediate, and rural zones based on population density and settlement patterns.[23] Additionally, socio-economic covariates – including population structure, household counts, and average purchasing power – are obtained from Acxiom at the same five-digit level.[24] A central constraint is the spatial resolution of the pharmacy data, which is restricted to the two-digit postal code level (comprising 95 distinct regions, versus 8,170 five-digit codes). To align the datasets, the high-resolution socio-demographic and urbanisation data are aggregated from the five-digit to the two-digit level. Consequently, all regional heterogeneity variables utilized in this part of the analysis are constructed at the two-digit postal-code level (refer to Section 5.4 for detailed aggregation procedures).

3.2 Data Handling

Prior to the estimations, raw transaction records are aggregated to the daily level for each pharmacy-product pair. While the majority of data points represent single transactions (as will be detailed in Table 2), multiple sales of the same product (PCN) within a single day are consolidated into one daily observation by summing quantities and computing the volume-weighted average price.

To ensure a stable market structure, the sample is restricted to a balanced panel of pharmacies that remain continuously active (each quarter)

[22]A single chemical substance may be assigned to multiple ATC4/5 codes if the route of administration differs (e.g., Ibuprofen is classified under M01AE01 for oral use but M02AA13 for topical application). Defining the market at the ATC5 level prevents the erroneous treatment of disparate forms (e.g., ointment vs. tablets) as substitutes.

[23]See https://www.destatis.de/DE/Themen/Laender-Regionen/Regionales/Gemeindeverzeichnis/_inhalt.html and https://ec.europa.eu/eurostat/web/degree-of-urbanisation/information-data.

[24]See Acxiom Deutschland GmbH, Frankfurt (2024).

throughout this window.[25] It is important to note that while the set of pharmacies is fixed, the panel remains unbalanced at the product level, as the specific set of PCNs transacted varies daily for each pharmacy based on local demand and inventory.

To mitigate distortions from data recording errors (e.g., implausible booking entries), the dataset undergoes an outlier cleaning procedure. Specifically, the distributions of prices, price changes, and sales are trimmed using a percentile-based cutoff corresponding to a five-sigma threshold.[26]

Following these procedures, the final balanced panel covers the period from the first quarter of 2018 through the second quarter of 2022 and comprises 6,338 unique pharmacies, representing approximately one-third of all German B&M pharmacies. This sample size ensures substantial depth and broad geographical representation. As illustrated in Figure 1, the dataset maintains wide spatial coverage even after balancing, demonstrating that the included pharmacies are geographically dispersed across all major two-digit postal-code regions.[27]

[25] Data were supplied in distinct batches, leading to potential attrition unrelated to market dynamics. As it is not feasible to definitively distinguish between genuine market exit and the discontinuation of data provider contracts, this balancing criterion ensures that all included entities are consistently observed over the entire sample duration.

[26] This is implemented by excluding observations that fall outside the theoretical quantiles associated with a standard deviation of five. For sales, the lower percentile cutoff implies a value below the minimum feasible transaction size (one unit). Consequently, the procedure effectively operates as a one-sided trim, removing only the extreme upper tail. While the broader literature often employs more restrictive techniques – such as trimming the top and bottom 0.5 % of the distribution (e.g., Fagereng et al., 2020, p. 122) – the conservative criterion adopted here prioritizes the retention of genuine market volatility. This approach effectively removes technical errors while preserving the integrity of the underlying data structure.

[27] Since official administrative data on the number of pharmacies by two-digit postal-code region are not publicly available, market coverage was approximated by scraping location data from https://www.apotheken-umschau.de/apothekenfinder/ on February 24, 2021.

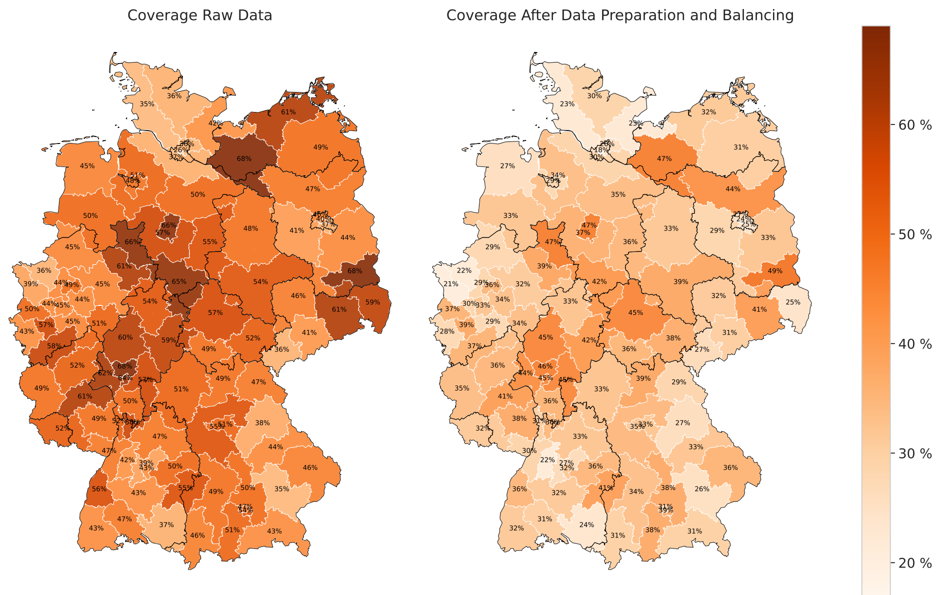


Figure 1: Coverage of Pharmacy Sales Data Across German two-digit zip-code regions. White (black) lines indicate the two-digit zip-code region (federal state) contours. Source: MIS suppliers and web page of *Apothekenumschau* (https://www.apotheken-umschau.de/apothekenfinder/), scraped on February 24, 2021.

The initial, unbalanced dataset comprises approximately 1.46 billion non-prescription packages, encompassing both OTC drugs and non-pharmaceuticals such as medical devices and cosmetics. Following the pharmacy balancing and outlier cleaning procedures, the final analytical sample retains 1.21 billion packages, representing 83.4 % of the initial non-prescription volume.[28] This volume corresponds to 913,035,552 distinct transaction line items. Notably, the outlier trimming procedure itself resulted in negligible attrition, with 99.87 % of observations in the balanced panel remaining intact.

Although the balanced panel is constructed primarily for the econometric analysis of OTC drugs and non-pharmaceutical competition, all available Rx drug transaction records are retained for the descriptive analysis in Section 3.3.[29] This retention allows for a comprehensive assessment of the pharmacies' overall economic performance – including total revenue, aggregate sales volume, and gross profit structure – before the analysis focuses exclusively on the non-prescription segment.

[28] In monetary terms, retention is similarly high: of the initial €11.98 billion in non-prescription revenue, €10.02 billion (83.65 %) is preserved in the balanced sample.

[29] For the balanced set of pharmacies, this segment accounts for an additional 1.36 billion Rx packages.

3.3 Descriptive Statistics and Stylized Facts

This section characterizes the dataset structure and market dynamics. First, summary statistics at the PCN level are presented to establish the central tendencies and distributional properties of the empirical sample. Second, the distribution of price adjustments is examined to characterize the frequency of price changes. Third, pharmacy sales, revenues and gross profits are decomposed into OTC, non-pharmaceutical, and Rx segments to quantify the relative economic contribution of each channel. Finally, the prevalence of joint purchases – the concurrent purchase of prescription and non-prescription items – is analyzed to provide descriptive evidence on potential cross-segment complementarities.

	Mean	SD	P001	P01	P05	P25	Median	P75	P95	P99	P999
Sales in Packages	1.38	1.75	1	1	1	1	1	1	3	6	15
(Net) Retail Price in € per Package	8.64	7.32	0.92	1.51	2.12	4.87	7.47	10.1	20.2	34	73.5
Wholesale Price in € per Package	4.95	5.29	0.38	0.58	0.91	2.48	3.99	5.62	12.8	23.8	53.2
Absolute Markup in € per Package	3.69	2.5	0.05	0.47	1	2.13	3.26	4.59	7.87	12.5	22.6
Ratio Retail Price to Wholesale Price	1.95	4.14	1.01	1.14	1.34	1.63	1.87	2.07	2.85	3.83	5.66
Relative Markup (Lerner-Index)	0.455	0.116	0.0119	0.121	0.256	0.385	0.466	0.516	0.649	0.739	0.823
Δ (Net) Retail Price in € per Package	0.0156	0.705	−5.9	−2.08	−0.26	0	0	0	0.42	2.22	6.17
Δ Wholesale Price in € per Package	0.00866	0.346	−2.89	−0.76	−0.04	0	0	0	0.12	0.91	3.2
Δ Between Sales in Days	22.8	69.8	1	1	1	2	5	16	90	314	951

	Count
Number of Observations	504,909,293
Unique Pharmacy IDs	6,338
Unique 2 digit zip codes	95
Unique Year-Days	1,642
Unique PCN	44,623
Unique PCN-Pharmacy Combinations	17,699,806

(a) Summary statistics for OTC drugs.

	Mean	SD	P001	P01	P05	P25	Median	P75	P95	P99	P999
Sales in Packages	1.27	4.45	1	1	1	1	1	1	2	5	16
(Net) Retail Price in € per Package	9.39	10	0.46	0.67	1.25	3.32	6.72	12.5	25.2	47	84
Wholesale Price in € per Package	6.35	7.28	0.18	0.44	0.79	2.07	4.26	8.36	17.7	35.1	64.5
Absolute Markup in € per Package	3.04	3.39	0.01	0.12	0.31	1.05	2.23	4.03	8.29	14.6	27.9
Ratio Retail Price to Wholesale Price	1.67	14.7	1	1.04	1.16	1.35	1.5	1.7	2.15	2.85	5.7
Relative Markup (Lerner-Index)	0.338	0.121	0.00228	0.0429	0.14	0.261	0.335	0.413	0.534	0.649	0.825
Δ (Net) Retail Price in € per Package	0.0181	0.919	−7.58	−2.77	−0.46	0	0	0	0.62	2.91	7.94
Δ Wholesale Price in € per Package	0.00863	0.527	−4.66	−1.31	−0.14	0	0	0	0.24	1.42	4.74
Δ Between Sales in Days	40.4	94.7	1	1	1	4	12	35	173	476	1,084

	Count
Number of Observations	408,126,138
Unique Pharmacy IDs	6,338
Unique 2 digit zip codes	95
Unique Year-Days	1,642
Unique PCN	168,493
Unique PCN-Pharmacy Combinations	31,199,825

(b) Summary statistics for Non-pharmaceuticals.

Table 2: Summary statistics. Note: P001 = 0.1th percentile, P01 = 1th percentile, P05 = 5th percentile, P25 = 25th percentile, P75 = 75th percentile, P99 = 99th percentile, and P999 = 99.9th percentile.

Table 2 presents detailed summary statistics for the (pharmacy) balanced panel. Panel (a) reports descriptive metrics for OTC drugs, while Panel (b) covers non-pharmaceutical products. The table summarizes the distributions of daily sales, wholesale and net retail prices. To capture the structure of profitability, it further reports the absolute markup, the relative markup (Lerner Index), and the retail-to-wholesale price ratio. Additionally, the magnitude of price adjustments is documented via the differenced variables (Δ Wholesale Price and Δ Retail Price). To characterize product turnover rates, the variable Δ *Between Sales in Days* records the time elapsed between consecutive transactions of the same product.[30] In addition to means and standard deviations, a broad range of percentiles (P001 to P999) is provided to document the substantial heterogeneity and extreme values in both segments.

The dataset's granularity is reflected in the substantial observation counts. The OTC segment comprises approximately 505 million product-pharmacy-day observations derived from 17.7 million unique product-pharmacy combinations. This segment covers 44,623 unique PCNs. As detailed in Appendix Tables D.2 and D.3, these products are not uniformly distributed; rather, the market is structurally dominated by acute care treatments. Specifically, products for the *Respiratory System* (e.g., cold remedies) and the *Musculoskeletal System* (e.g., pain management) act as the primary volume drivers, accounting for 32.3 % and 23.3 % of total OTC sales volume, respectively. The non-pharmaceutical segment of Table 2 is similarly extensive, containing 408 million observations across a more diverse range of 168,493 unique products and 31.2 million product-pharmacy pairs. However, this segment is heavily concentrated in general goods, with the *No ATC Code* category – representing diverse personal care and hygiene items – comprising 59.7 % of the segment's volume (see Tables D.2 and D.3). Pooling these three leading categories reveals a high degree of concentration as they collectively account for approximately 61 % of the entire sales volume in the sample.[31] Across both segments (OTC drugs and non-pharmaceuticals), the descriptive statistics track the same set of 6,338 balanced pharmacies distributed across 95 two-digit postal code regions over a 1,642-day time horizon.

Both segments exhibit distinct structural characteristics. Sales are highly right-skewed across both categories, anchored by a median of one package per transaction-day, indicating that bulk purchases are rare. While average net retail prices are broadly comparable (€8.64 for OTC versus €9.39 for non-pharmaceuticals), the underlying cost structures diverge significantly. Specifically, OTC drugs incur relative lower average wholesale costs (€4.95) than non-pharmaceuticals (€6.35). Consequently, the OTC segment exhibits superior profitability, commanding an average Lerner Index of 0.455 com-

[30] Example: If a specific product (identified by its PCN) is sold on March 1st and the next transaction for the same product occurs on March 5th, the variable takes a value of 4. Consequently, lower values indicate high-turnover, whereas high values characterize slow-moving niche items.

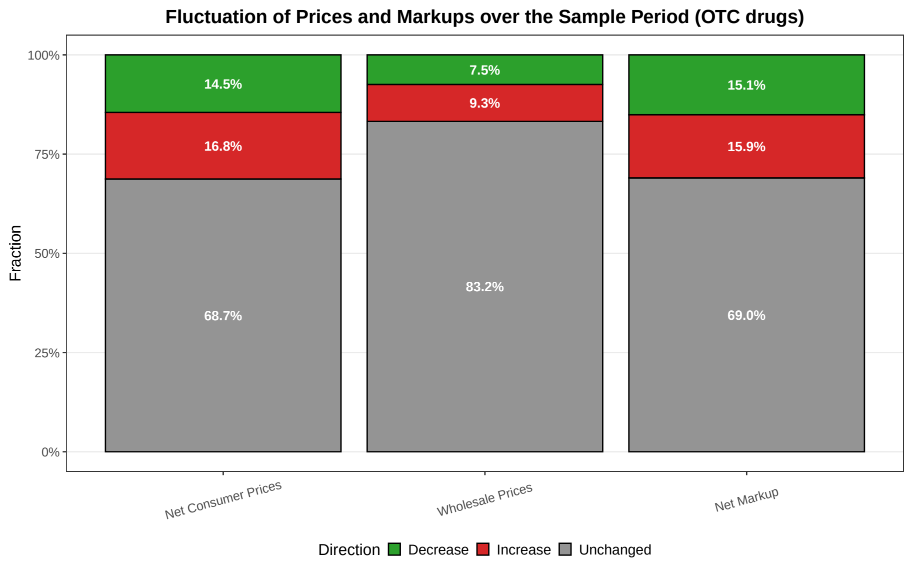
[31] In terms of revenue, the market structure is similarly concentrated, though slightly less pronounced due to price heterogeneity. Within the OTC segment, *Respiratory* and *Musculoskeletal* products generate 26.8 % and 19.2 % of revenue, respectively. In the non-pharmaceutical segment, *No ATC Code* category accounts for 53.3 % of revenue. Combined, these three categories represent 52.3 % of the total revenue in the balanced panel.

pared to 0.338 for non-pharmaceutical goods. Thus OTC drugs exhibit 35 % higher Lerner Indices than non-pharmaceuticals.

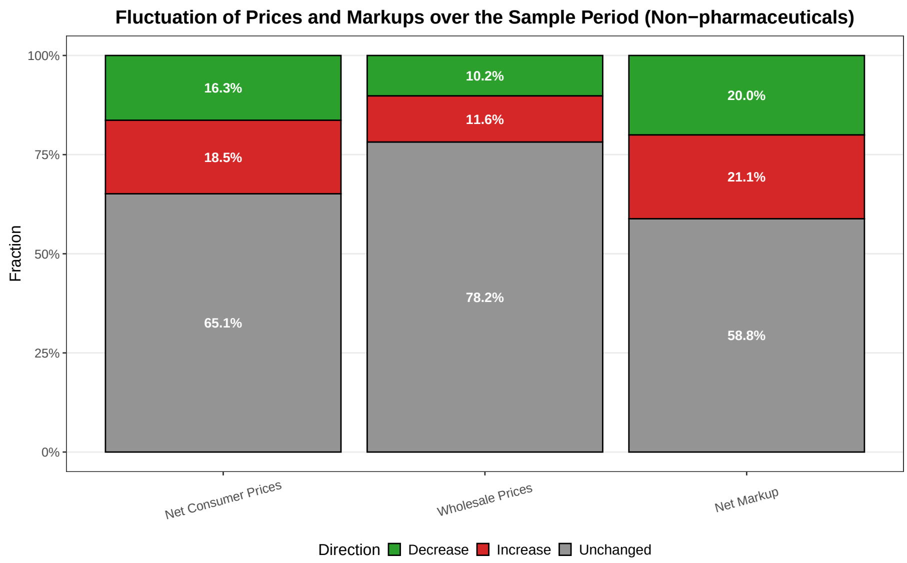
Beyond static levels, the table captures the dynamics of price adjustment through the differenced variables Δ Net Retail Price and Δ Wholesale Price. These metrics are fundamental for the analysis of asymmetric pass-through in Section 5.1. Crucially, these differentials are computed relative to the *last observed transaction* for each pharmacy-product pair, rather than the previous calendar day (e.g., the median interval between consecutive OTC drug transactions is five days). This approach ensures that price changes are accurately identified even for products with irregular sales frequencies, bridging periods of inactivity without generating spurious zero-price changes, which would occur if days without sales were artificially populated with the last known price. As indicated by the mean values (e.g., €0.0156 for OTC retail price changes), the average transaction-to-transaction adjustment is small, yet the wide range highlights the presence of substantial discrete price jumps.

To visualize the frequency and direction of these adjustments, Figure 2 decomposes the daily fluctuations of net retail and wholesale prices, and net markups. Because raw transactions are aggregated to the daily level for each pharmacy-product pair, a single observation may encompass multiple individual sales. Therefore, the distribution separates *observations* into three distinct states: decreases (green), increases (red), and periods of rigidity where values remain unchanged (grey). Because the absolute net markup is defined as the spread between retail and wholesale prices, its volatility (Δmarkup) is mechanically determined by the interplay between retail price adjustments and wholesale price shocks. Consequently, a change in the absolute markup occurs whenever the pass-through of a wholesale cost shock deviates from unity (e.g., is incomplete, delayed, or overshifted), or when retail prices are adjusted independently of cost shifts.

Panel (a) illustrates the dynamics for OTC drugs. Wholesale prices remain unchanged in 83.2% of observations, though exhibiting decreases in 7.5% and increases in 9.3% of cases. Retail prices, however, are adjusted more frequently, changing in 31.3% of observations (14.5% decreases, 16.8% increases). Consequently, net markups are not constant; they fluctuate in 31.0% of cases. This discrepancy in the frequency of adjustments – where retail prices change nearly twice as often as wholesale prices – indicates that price updates do not perfectly synchronize with cost shocks in the cross-section. Panel (b) depicts the corresponding patterns for non-pharmaceutical products, which exhibit higher volatility across all dimensions. Wholesale prices change in 21.8 % of observations, while retail prices adjust in 34.9 % of cases. Consequently, net markups fluctuate more often, changing in 41.2 % of observations. Collectively, these descriptive statistics establish that markup volatility is a pervasive feature of the pharmacy market. The extent to which these retail adjustments are driven by wholesale price shocks is the central



(a) Distribution of daily changes for OTC drugs.



(b) Distribution of daily changes for non-pharmaceuticals.

Figure 2: Overall daily changes. (a) Prices and markups for OTC drugs. (b) Prices and markups for non-pharmaceuticals. Note: Fractions represent the share of total daily observations (pharmacy-product pairs) exhibiting a change, independent of sales volume.

focus of the ECM-based pass-through estimation presented in Section 5.

To provide a broader economic context, the following analysis focuses on stylized aggregates of the transaction data at the year level, distinguishing between the regulated Rx-drug sector and the unregulated segment (OTC drugs and non-pharmaceuticals). Figure 3 provides aggregate evidence of the evolution of sales, revenue, and gross profits from 2018 through 2021.[32]

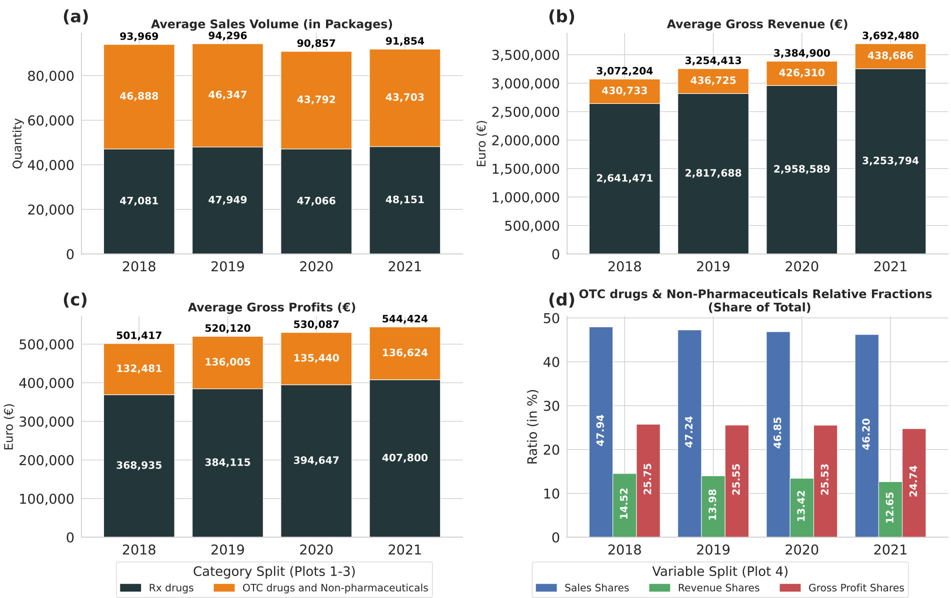


Figure 3: Evolution of average sales, revenue and gross profits per year. For further descriptive statistics highlighting the distribution across pharmacies, see Table D.4.

Panel (a) and Panel (b) of Figure 3 reveal a distinct contrast between the physical volume of trade and the financial revenue it generates. In terms of packages sold (Panel (a)), the pharmacy business is split almost evenly: on average, a pharmacy dispenses approximately 47,000 to 48,000 Rx packages annually, which is very similar to the volume of unregulated products sold (ranging from roughly 44,000 to 47,000 packages). However, when looking at revenue (Panel (b)), Rx drugs dominate. For instance, in 2021, the average pharmacy generated €3.25 million from Rx drugs compared to just €0.44 million from the unregulated segment. This huge gap exists because prescription drugs are, on average, much more expensive per package than OTC or non-pharmaceutical items.

Crucially, Panel (c) and Panel (d) highlight a shift in the composition of pharmacy profitability. Rx drugs drove the overall growth in gross profits, increasing from an average of €368,935 in 2018 to €407,800 in 2021.

32 Detailed evidence is provided in Appendix D Table D.4. Figures illustrating the distribution of gross profits, revenue, and sales are provided in Figures D.2 through D.6. Note: The year 2022 is not exhibited as only the first half of 2022 is available.

In contrast, gross profits from the unregulated segment remained virtually stagnant in nominal terms, rising only marginally from €132,481 to €136,624 over the four-year period. This nominal increase of approximately 3.1% lags behind the inflation rate of roughly 5.1% recorded in Germany between 2018 and 2021.[33] Consequently, the unregulated segment has experienced a decline in real profitability. This trend is mirrored in Panel (d), where the segment's share of total gross profits falls from 25.75% to 24.74%. Concurrently, the average revenue share of the unregulated segment consistently remains below the gross profit share, falling from 14.52 % to 12.65 % over the sample period. Thus, OTC drugs and non-pharmaceutical products act as disproportionately strong profit drivers despite their smaller revenue share. This relative decline in profits likely reflects the growing competitive pressure from online pharmacies, which have increasingly captured market share in the non-prescription sector, leaving B&M pharmacies more dependent on the regulated prescription business (see Section 2).

Another crucial determinant of pharmacy profitability is the composition of the consumer's shopping basket. Specifically, consumers frequently purchase OTC drugs and non-pharmaceuticals in conjunction with prescription medications – a transaction referred to in the sector as a *bundle purchase* (see Section 2.2 and Albrecht et al., 2020, p. 24).[34] Analyzing these joint purchasing patterns provides insights into cross-selling potential and consumer convenience. The dataset allows to use the unique *order number* to identify the combination of purchases made by a single customer. It is important to note that this method establishes a conservative *lower bound* for the true frequency of joint purchasing.[35]

Figure 4 illustrates this relationship on an aggregate scale for the years 2018 through 2021. The figure decomposes the total volume of non-prescription sales into three mutually exclusive categories: (1) sales occurring in single-product orders (orange bars), (2) sales occurring in multi-product orders containing only non-prescription products (black bars), and (3) sales occurring in joint-purchases containing at least one Rx-drug (teal bars).

[33] Based on the Consumer Price Index (CPI) data from the Federal Statistical Office of Germany, the inflation for this period is approximately 5.1%. See, https://www-genesis.destatis.de/datenbank/online/url/1481501c.

[34] In this context, the term "bundle" is used descriptively to denote joint purchasing behavior rather than a strategic supply-side constraint (such as tying, pure bundling, or mixed price bundling) as rigorously defined in the industrial organization and marketing literature (Adams & Yellen, 1976; Stremersch & Tellis, 2002).

[35] Operational realities in pharmacy practice may cause a single patient visit to be split into multiple transactions. First, if a prescribed medication is out of stock, the patient must undertake a further physical visit, separating purchases temporally. Second, patients or staff may separate insurance-reimbursed items from private purchases due to distinct workflow requirements at the point of sale. Consequently, the observed share of sales in bundles represents a conservative lower bound of this joint purchasing behavior.

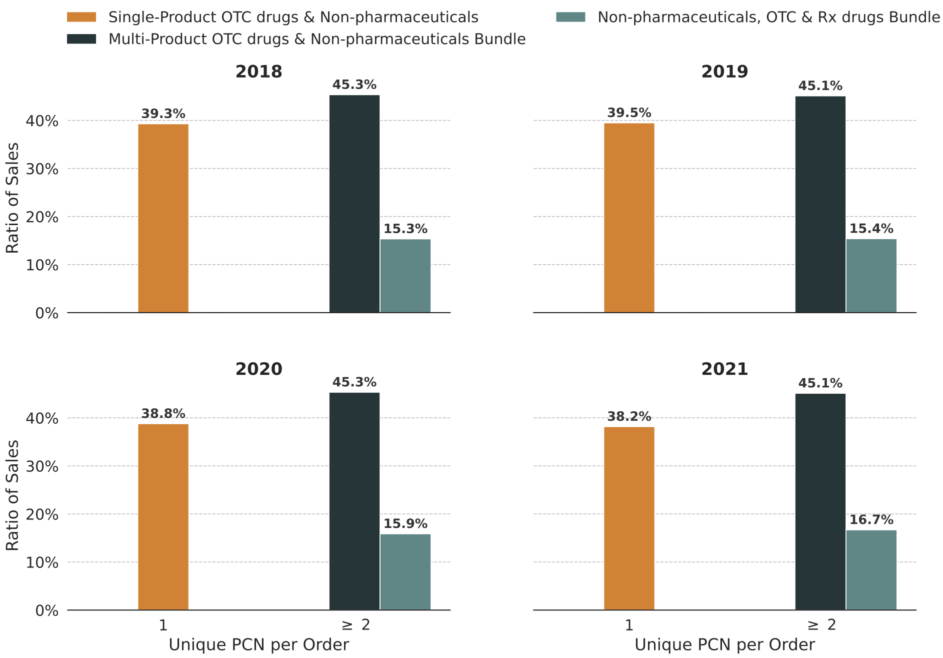


Figure 4: Sales ratio according to order size and bundle type, focusing on sales containing at least one unique PCN of OTC drugs or non-pharmaceuticals. By definition, multi-product and Rx-bundles require an order size of ≥ 2; therefore, single-item orders consist exclusively of standalone OTC or non-pharmaceutical purchases.

The data reveal an evolving pattern in consumer behavior. The majority of non-prescription volume is generated through pure OTC or non-pharmaceutical transactions. Specifically, single-product purchases account for approximately 38.2% to 39.5% of the volume per year, while multi-product OTC and non-pharmaceutical orders constitute the largest share, fluctuating narrowly around 45.1% to 45.3%. The Rx-bundle purchases represent a smaller portion of the market. In 2018, these mixed bundles accounted for 15.3 % of non-prescription sales. Notably, this share exhibits a gradual upward trend, reaching 16.7 % by 2021.

Viewed through the lens of the institutional background from Section 2, this descriptive finding provides an interesting context for the subsequent analysis. It suggests a potential dynamic where, as online competitors exert pressure on the market for OTC and non-pharmaceuticals, the physical Rx visit might serve as an increasingly important anchor for secondary sales in these unregulated segment. The plausibility of this relationship will be discussed extensively in Section 6 in light of the empirical estimations presented in Section 5.

4 Empirical Strategy

This section outlines the identification strategy used to estimate cost pass-through (CPT) rates.[36] The identification strategy relies on an error correction model (ECM), which is chosen to structurally match the economic dynamics of cost transmission. While fluctuations in wholesale prices act as exogenous cost shocks, pharmacies do not respond to them instantaneously (see Section 3.3); rather, they seem to adjust their retail prices over a dynamic path. The ECM framework is explicitly designed to capture this temporal and dynamic structure, distinguishing between the immediate short-run response to such shocks and the gradual convergence to a long-run equilibrium (see, e.g., Borenstein et al., 1997; Peltzman, 2000). Furthermore, from an econometric perspective, this framework addresses the non-stationarity and cointegrating relationship between retail and wholesale prices, thereby mitigating the risk of spurious regression bias inherent in static level specifications (Engle & Granger, 1987; Granger & Newbold, 1974).[37]

Section 4.1 details the ECM approach. By distinguishing between short-run dynamics and the long-run equilibrium, this model allows to formally test for pricing asymmetries – referred to as the *rockets and feathers* phenomenon. The cost changes (changes in wholesale prices) are decomposed into positive and negative shocks to identify whether pharmacies adjust prices symmetrically or exhibit downward rigidity. Specifically, the bounds testing approach (Pesaran et al., 2001) is employed to test for the existence of a long-run cointegrating relationship.

Section 4.2 describes the heterogeneity analysis, which permits pass-through rates to vary across pharmacies, revenue deciles, and product segments. This step is crucial not only for identifying idiosyncratic pricing behaviors but also for addressing the heterogeneity bias described by Pesaran and Smith (1995), who demonstrate that pooling dynamic panels with heterogeneous slope coefficients can yield inconsistent estimates.

Finally, Section 4.3 outlines the strategy for the spatial and socio-demographic analysis. This framework exploits the recovered heterogeneity in pharmacy-level parameters by regressing economic outcomes – including prices, markups, and the estimated pass-through coefficients – on the degree of urbanization and local socio-demographic controls. By isolating the variation attributable to spatial structure, this specification allows for a formal test of whether rural markets exhibit distinct pricing differences, such as a structural differences between lower transaction volumes and higher unit margins, driven by local market power. Testing this mechanism is empirically straightforward because the transaction records contain exact wholesale and retail prices, allowing absolute and relative markups (the Lerner Index)

[36] All CPT estimations and subsequent analyses are estimated separately for non-pharmaceuticals and OTC drugs.

[37] For comparison, results from static level models are reported in Appendix A.

to be computed directly (detailed in Section 3.1).

4.1 Dynamic & Asymmetric Strategy

To investigate potential asymmetries in pricing behavior (see, e.g., Borenstein et al., 1997; Heim, 2021), the analysis employs an asymmetric ECM (Engle & Granger, 1987; Granger & Lee, 1989; Stock, 1987). Departing from early two-step estimation procedures (e.g., Balaguer & Ripollés, 2012; Galeotti et al., 2003; Peltzman, 2000), the study leans on the strategy of Balaguer and Ripollés (2016), by specifying a single-equation conditional unrestricted ECM in the style of a non-linear autoregressive distributed lag (NARDL) model (see, e.g., Greenwood-Nimmo & Shin, 2013; Pesaran & Shin, 1999; Pesaran et al., 2001; Salisu & Isah, 2017; Shin et al., 2014). This unified framework provides superior power properties and estimation efficiency (Banerjee et al., 1998), while allowing for the identification of long-run level relationships irrespective of whether the underlying variables are $I(0)$, $I(1)$, or mutually cointegrated (Pesaran et al., 2001).[38] To account for unobserved heterogeneity, the model is estimated using a high-dimensional fixed effects estimator.[39] Furthermore, while the specification is estimated in first differences to ensure stationarity, it explicitly retains lagged levels to capture both the immediate price adjustments to cost shocks and the gradual correction toward the long-run equilibrium – a dynamic distinction shown to be critical in pharmaceutical markets, where Granlund and Bergman (2018) demonstrate that prices exhibit substantial inertia, requiring multi-period adjustments to fully reflect structural market changes.[40] This enables the simultaneous recovery of short-run impact parameters and long-run equilibrium targets in a unified framework.

The estimation specification is defined such that the subscripts denote product j (identified by PCN), pharmacy f (uniquely located in two-digit zip code g), calendar day t and calendar month m. Therefore, the unit of observation is defined at the granular product-pharmacy-day level (jf, t). The following specification is estimated:

[38] Given the high dimensionality of the data, standard panel cointegration tests (e.g., Westerlund, 2007) are computationally infeasible. Instead, the long-run relationship is confirmed via the significant negative coefficient of the error correction term (t-test) and the joint significance of all lagged level variables (Wald test). Furthermore, panel unit root tests confirm a mixture of $I(0)$ and $I(1)$ series, see Appendix Table E.1.

[39] Given the high-frequency nature of our data ($T = 1,642$ and the inclusion of numerous fixed effects), the dynamic panel bias (Nickell, 1981) is of order $O(1/T)$ and therefore negligible.

[40] The finding of non-stationarity and co-integration between retail and wholesale prices is common in the literature (Loy et al., 2016).

$$
\begin{aligned}
\Delta p_{jf,t} = \mathcal{I}^{+}_{jf,t} \Bigg\{ & \underbrace{\rho^{+} \Delta w_{jf,t} + \sum_{k=1}^{K} \beta_k^{+} \Delta w_{jf,t-k} + \sum_{k=1}^{K} \phi_k^{+} \Delta p_{jf,t-k}}_{\text{Short-Run Dynamics (+)}} \\
& + \underbrace{\gamma^{+} p_{jf,t-\tau} + \lambda^{+} w_{jf,t-\tau}}_{\text{Long-Run Adjustment (+)}} \Bigg\} \\
+ \mathcal{I}^{-}_{jf,t} \Bigg\{ & \underbrace{\rho^{-} \Delta w_{jf,t} + \sum_{k=1}^{K} \beta_k^{-} \Delta w_{jf,t-k} + \sum_{k=1}^{K} \phi_k^{-} \Delta p_{jf,t-k}}_{\text{Short-Run Dynamics (-)}} \\
& + \underbrace{\gamma^{-} p_{jf,t-\tau} + \lambda^{-} w_{jf,t-\tau}}_{\text{Long-Run Adjustment (-)}} \Bigg\} \\
+ \, & \omega \Delta \text{Days}_{jf,t} + \sigma^{\Delta} \Delta \bar{w}_{-f,ag,t} + \sigma^{\tau} \bar{w}_{-f,ag,t-\tau} \\
+ \, & \alpha_{jf} + \eta_t + \delta_{fm} + \mu_{jf,t},
\end{aligned} \tag{1}
$$

where $\Delta p_{jft} = p_{jft} - p_{jf\tau}$ and $\Delta w_{jft} = w_{jft} - w_{jf\tau}$ represent the change in retail and wholesale prices, respectively, between the current transaction t and the previous transaction τ.[41] To capture the temporary dynamics of the adjustment path, the model can include up to K lags of the cost changes ($\Delta w_{jf,t-k}$) and the autoregressive price changes ($\Delta p_{jf,t-k}$). The asymmetry is captured by the indicator variables $\mathcal{I}^{+}_{jft}$ and $\mathcal{I}^{-}_{jft}$, which partition the cost shocks based on their direction. Specifically, $\mathcal{I}^{+}_{jft}$ takes the value of 1 if $\Delta w_{jft} > 0$ (Cost Increase) and 0 otherwise, while $\mathcal{I}^{-}_{jft}$ takes the value of 1 if $\Delta w_{jft} < 0$ (Cost Decrease) and 0 otherwise.

As specified, the model explicitly controls for the lagged retail price level, $p_{jf\tau}$, to capture mean-reversion dynamics (Borenstein et al., 1997). Retaining the lagged wholesale cost level ($w_{jf\tau}$) allows to recover the long-run equilibrium target (see next paragraph). As stated, the single-equation conditional ECM is adapted for the high-dimensional fixed effects structure. The term α_{jf} denotes combined pharmacy-product fixed effects, which absorb all time-invariant heterogeneity specific to each drug within each pharmacy (e.g., baseline price levels and time-invariant local markups). Additionally, η_t controls for common daily shocks, δ_{fm} absorbs pharmacy-specific monthly trends (e.g., drifts) and μ_{jft} denotes the idiosyncratic error term. Finally, to account for the irregular time structure of the panel, the variable $\Delta\text{Days}_{jf,t}$ (calculated as $t-\tau$) controls for the time elapsed between observations. This

[41] Due to irregular transaction records the difference operator Δ must be defined relative to the last observed transaction τ.

ensures that price changes occurring over longer intervals (e.g., over weekends or due to infrequent transactions) are measured accurately and remain directly comparable to overnight adjustments.

Since individual pharmacies act as short-run price-takers in the wholesale market, their local retail pricing decisions cannot influence the upstream wholesale price. This structurally rules out reverse causality. Furthermore, the inclusion of high-dimensional fixed effects mitigates omitted variable bias: day fixed effects η_t absorb aggregate demand or supply shocks; pharmacy-month fixed effects δ_{fm} capture time-varying pharmacy heterogeneity (such as intra-year bargaining dynamics); and pharmacy-product fixed effects α_{jf} control for time-invariant heterogeneity. Collectively, these features isolate the exogenous variation in costs, permitting the interpretation of the estimated coefficients as the pass-through of wholesale cost shocks on retail prices. While pharmacies may negotiate volume-based discounts, these contracts typically are fixed over longer horizons (e.g., annually, see Footnote 8). Consequently, the high-frequency daily variation in wholesale costs ($\Delta w_{jf,t}$) exploited here reflects exogenous updates to the wholesale price rather than endogenous daily or monthly renegotiations.

Most importantly, this flexible specification permits to decompose the adjustment dynamics into three distinct mechanisms: (i) *Short-Run Asymmetry:* The coefficients ρ^+ and ρ^- estimate the immediate pass-through rate on the day of the shock, while the lag coefficients $\beta_k^\pm$ and $\phi_k^\pm$ capture the persistence and momentum of the short-run adjustment path. A finding of $\rho^+ > \rho^-$ (or a strictly larger cumulative short-run effect) provides evidence of *rockets and feathers*, indicating that prices adjust upward more sharply in response to cost increases than they adjust downward for cost declines. (ii) *Asymmetric Speed of Adjustment:* The coefficients γ^+ and γ^- measure the rate at which the pharmacy corrects towards the long-run equilibrium. If $|\gamma^+| > |\gamma^-|$, it implies that pharmacies close the gap to the new equilibrium faster when prices are below the target (after a cost increase) than when prices are above the target (after a cost drop). (iii) *Long-Run Equilibrium Asymmetry:* The coefficients λ^+ and λ^- capture the direct response to the lagged cost level, which, combined with the adjustment speeds γ^+ and γ^-, define the long-run attractor of the system. The long-run pass-through target θ is recovered non-linearly as the ratio of the lagged cost and price coefficients (see, e.g., Greenwood-Nimmo & Shin, 2013):

$$\theta^k = -\frac{\lambda^k}{\gamma^k}, \quad \text{for } k \in \{+, -\}. \tag{2}$$

This relationship is derived by imposing the steady-state condition where all short-run fluctuations have ceased ($\Delta p_{jf,t} = \Delta w_{jf,t} = 0$).[42] Consequently, θ^k represents the permanent transmission rate of a cost shock to retail prices, i.e., the long-run equilibrium pass-through rate, once the adjustment process is complete. This enables to test for long-term asymmetry where the final equilibrium price depends on the direction of the shock (Galeotti et al., 2003; Meyer & von Cramon-Taubadel, 2004).

Model validity is confirmed via Bounds Tests for cointegration (Pesaran et al., 2001), while coefficient equality and long-run symmetries are evaluated using standard Wald tests and the Delta method.[43]

Drawing on the dynamic panel framework of Pesaran et al. (1999), the long-run speed of adjustment is restricted to be homogeneous across pharmacies to exploit the efficiency gains of a pooled estimation. This assumption is relaxed in the next Section 4.2, where cross-sectional variation in pricing dynamics of pharmacies and their products is investigated.

Last, competitors' wholesale prices are included (the short-run effect $\Delta\bar{w}_{-f,agt}$ and the lagged component $\bar{w}_{-f,ag\tau}$), motivated by standard oligopoly theory. In a simple Nash-Bertrand framework, a firm's (equilibrium) pricing depends on the costs of its rivals. As noted by MacKay et al. (2014), omitting competitors' costs can severely bias pass-through estimates if cost shocks are correlated across firms. Due to the dimensionality of the product space, including the individual costs of all rival products is infeasible. Following the literature (e.g., Miller et al., 2017; Muehlegger & Sweeney, 2022), controlling for competitors' average wholesale prices serves as a tractable alternative. The average competitor wholesale price is calculated at the broader chemical substance level (ATC4 or ATC5) within the same geographical market g (two-digit postal code). This aggregation acknowledges that consumer substitution primarily occurs between products sharing the same active ingredient, such as Ibuprofen (M01AE01). Defining the market at this level ensures that disparate forms of the same chemical (e.g., tablets vs. topical creams) are correctly treated as distinct product markets. The coefficient σ^Δ captures the immediate strategic response to concurrent changes in

[42] Under this condition, the error correction mechanism implies that $0 = \gamma^k p_{jf\tau} + \lambda^k w_{jf\tau}$. Rearranging this equation yields the steady-state relationship $p_{jf,\tau} = (-\lambda^k/\gamma^k)w_{jf,\tau}$, where $\theta^k = (-\lambda^k/\gamma^k)$ represents the long-run coefficient.

[43] In detail, a series of Wald tests are performed to formally evaluate the model validity and the presence of asymmetry (see, e.g., Cameron & Trivedi, 2005, Chapter 7.2). Furthermore, following Pesaran et al. (2001), a Bounds Test is performed by testing the joint significance of the lagged level coefficients ($\gamma^\pm, \lambda^\pm$) to confirm the existence of a valid cointegrating relationship. Conditional on this relationship, the specifics tests for equality and nullity are conducted by the following program: (1) tests on equality of short-run coefficients ($\rho^+ = \rho^-$) using a standard F-test; (2) tests on equality of the adjustment speeds ($\gamma^+ = \gamma^-$); (3) tests on the equality of the lagged wholesale prices ($\lambda^+ = \lambda^-$); (4) tests on the joint nullity of all four parameters ($\gamma^+ = \gamma^- = \lambda^+ = \lambda^- = 0$); and (5) the Delta Method is employed to approximate the standard errors of the non-linear long-run targets (Oehlert, 1992; Cameron and Trivedi, 2005, Chapter 7.2.8) and test the null hypothesis of symmetry in the long-run equilibrium ($\theta^+ = \theta^-$).

rivals' costs, while σ^τ governs the long-run equilibrium relationship. If prices exhibit strategic complementarity (Bulow et al., 1985; Vives, 1990), both coefficients are expected to be positive, indicating that pharmacies raise prices when their competitors face higher costs, reflecting a strategic response to the resulting price increases initiated by those competitors.

4.2 Heterogeneity Strategy

The dynamic specification in Section 4.1 yields estimates of aggregate market-wide pricing dynamics. To capture structural differences across pharmacies and time, this framework is generalized by relaxing the assumption of constant parameters. Specifically, the ECM of Equation (1) is extended by allowing the pass-through and speed-of-adjustment coefficients to vary at the pharmacy-year level. This disaggregated specification serves as the foundation for the socio-demographic analysis (see Section 5.4), which exploits the resulting heterogeneity to examine pricing disparities between urban and rural markets. The heterogeneous specification is given by:

$$\begin{aligned}
\Delta p_{jf,t} = {} & \mathcal{I}^{+}_{jf,t}\left\{\rho^{+}_{fy}\Delta w_{jf,t} + \gamma^{+}_{fy} p_{jf,t-\tau} + \lambda^{+}_{fy} w_{jf,t-\tau}\right\} \\
& + \mathcal{I}^{-}_{jf,t}\left\{\rho^{-}_{fy}\Delta w_{jf,t} + \gamma^{-}_{fy} p_{jf,t-\tau} + \lambda^{-}_{fy} w_{jf,t-\tau}\right\} \\
& + \omega \Delta Days_{jf,t} + \eta_t + \delta_{fm} + \mu_{jf,t}
\end{aligned} \tag{3}$$

where the subscript fy denotes that the parameters ρ_{fy}, γ_{fy}, and θ_{fy} are estimated specifically for each pharmacy-year pair. Estimating this equation is computationally intensive, as it requires interacting every price and cost variable with thousands of pharmacy-year indicators. This results in a high-dimensional problem, necessitating the use of the specialized variable-slope algorithms provided by the *fixest* package (Bergé, 2018).[44]

In contrast to the pooled baseline, this specification omits autoregressive lags and product fixed effects (α_{jf}) for two critical reasons. First, the inclusion of lags would drastically inflate the parameter space, reducing the degrees of freedom available for identifying the coefficients in years with lower transaction volumes. Second, and economically more significant, the omission of product fixed effects is necessitated by the limited within-product variance available in the data (see Figure 2). Since wholesale costs for many products remain stable within a single year, a fixed-effects specification would fail to identify the cost parameters for a large subset of the portfolio. By relaxing the fixed effects, the equilibrium parameters are identified using both

[44] All computations were conducted on the following hardware: AMD Ryzen Threadripper PRO 7965WX 24 Cores (48 Threads) with 256 GB of system memory running Ubuntu 24.04.

temporal and cross-sectional variation which effectively assumes that the pharmacy applies a consistent pricing strategy across its assortment, rather than relying solely on time-series volatility.

This flexible specification allows to recover the full distribution of short-run asymmetries and adjustment speeds across the market, as well as derive heterogeneous pharmacy-specific long-run targets. The resulting distributions of the estimated short-run coefficients ($\hat{\rho}^{+}_{fy}, \hat{\rho}^{-}_{fy}$) and the derived long-run targets ($\hat{\theta}^{+}_{fy}, \hat{\theta}^{-}_{fy}$) are visualized in Section 5.3.

Finally, to assess whether pricing dynamics for the most economically significant items differ from the full sample, Equation (1) is re-estimated using restricted samples of top-ranked products.[45] Specifically, the analysis is stratified by the top 10, 100, and 1,000 products according to three distinct metrics: sales, total revenue, and gross profit. This approach yields nine distinct estimation specifications, allowing for a granular examination of whether pass-through rates and asymmetric adjustments in the most important segments diverge from the dynamics observed in the aggregate market.

4.3 Socio-Demographic Analysis

To analyze whether the aggregate pricing dynamics mask heterogeneity across market types, pharmacy-level outcomes – specifically prices, markups, sales, and the CPT rates estimated in Section 5 – are related to the degree of urbanization and local population characteristics (see Section 3.1). This estimation determines if market structure, particularly the distinction between urban and rural environments, drives systematic differences in these economic parameters. The following specification is estimated:

$$\begin{aligned} O_{fgdy} = \alpha + \nu \mathrm{OTC}_d &+ \sum_{k \in \{I,R\}} D_g^k \left(\beta_k + \gamma_k \mathrm{OTC}_d\right) \\ &+ \sum_{\tau=2019}^{2022} \phi_\tau \mathbf{1}\{y = \tau\} \\ &+ X'_{gy}\delta + \varepsilon_{fgdy}, \end{aligned} \tag{4}$$

where O_{fgdy} represents the outcome of interest for pharmacy f, in two-digit zip code region g, for drug type d, in year y. The intercept α captures the estimated outcome for the reference category: non-pharmaceutical products sold in *Urban* pharmacies during the base year 2018. Accordingly, the coefficients ϕ_τ measure the aggregate temporal deviations for each subsequent year τ relative to this baseline. The dummy variables D_g^k indicate whether a region is *Intermediate* or *Rural*. The coefficients within the first summation distinguish between general and product-specific regional effects: β_k captures the baseline level difference for region k, while γ_k measures the

[45] For simplicity, autoregressive lags are omitted from the regression.

additional difference for OTC drugs ($\text{OTC}_d = 1$) in that region. The vector X'_{gy} controls for regional income and demographics to ensure the results capture underlying differences in spatial market concentration, rather than merely reflecting variations in local purchasing power.

As explained at the end of Section 3.1, all socio-demographic variables and the degree of urbanization are originally defined at the five-digit postal-code level and are aggregated to the two-digit level to match the geographical definition of markets (see Figure D.8). Because the degree of urbanization is a categorical measure describing spatial land structure and population density,[46] it is aggregated using two distinct methods to ensure robustness: (i) the mode (assigning the most frequently occurring category within each spatial unit) and (ii) area-weighting (see Figure D.9). These two schemes account for different spatial aggregation dynamics: the mode reflects the most frequent category among sub-units, which heavily captures the high count of small rural municipalities, whereas area-weighting naturally emphasizes physically more expansive regions, revealing that intermediate regions (towns and suburbs) actually constitute the largest land area within many two-digit zones. In contrast, because socio-demographic variables represent continuous aggregate population metrics (such as total income), they are aggregated using population-weighted averages to ensure representativeness on a per capita basis.

The dependent variable O_{fgdy} comprises a set of pharmacy-level performance metrics aggregated by year and drug category. Consequently, variables such as net retail or wholesale prices do not refer to individual products but represent volume-weighted averages reflecting the specific composition of goods sold by pharmacy f within category d. For the empirical estimation, the natural logarithm is applied to wholesale and retail prices, absolute markups, sales volumes, and gross profits.[47] In contrast, the Lerner Index and the estimated pass-through coefficients are modeled in levels, as the Lerner Index represents a dimensionless ratio and pass-through rates measure the absolute Euro-for-Euro transmission of cost shocks.

5 Cost Pass-Through Results

The analysis proceeds in four stages. First, Section 5.1 applies the ECM to investigate pooled pass-through asymmetries by distinguishing between short-run shock effects and the speed of adjustment toward the long-run equilibrium. Then, Section 5.2 validates these baseline findings by extending the lag structure to account for delayed cost transmission. Section 5.3 analyzes structural heterogeneity by relaxing parameter pooling assumptions,

[46] See, https://ec.europa.eu/eurostat/web/degree-of-urbanisation/methodology.

[47] This transformation handles the right-skewed nature of the data and allows the coefficients to be interpreted as semi-elasticities (approximate percentage changes).

examining pricing dynamics across pharmacy and year, by revenue deciles and top-ranked products. Finally, Section 5.4 details the results for the spatial and socio-demographic analysis. Throughout this section, the focus remains on reporting the empirical estimates, while the theoretical mechanisms and broader economic implications of these findings are discussed comprehensively in Section 6.

5.1 Dynamic & Asymmetric Results

Table 3 reports the estimation results of Equation (1) with $K = 0$ (without additional lags),[48] while Figure 5 visualizes the adjustment paths through cumulative impulse-response functions (CIRFs).[49]

The analysis distinguishes between the transmission of positive wholesale cost shocks (Δw^+) and negative shocks (Δw^-) across OTC drugs (Columns (1)–(4)) and non-pharmaceuticals (Columns (5)–(8)). To highlight the robustness of the findings across different specifications, the results are presented sequentially. Columns (1) and (5) establish the baseline asymmetric response without fixed effects on the product level, capturing immediate pass-through ($\rho^\pm$) and direction-specific mean-reversion adjustment speeds ($\gamma^\pm$ and $\lambda^\pm$) and long-run coefficients ($\theta^\pm$); Columns (2) and (6) include competitor effects; and Columns (3) and (7) include PCN fixed effects. Finally, the fully flexible specifications in Columns (4) and (8) includes fixed effects at the pharmacy-PCN level, accounting for detailed cross-sectional unobservable heterogeneity.

The results provide compelling empirical evidence of *rockets and feathers* across both segments. In all specifications, the immediate pass-through of cost increases (ρ^+) is significantly larger than that of cost decreases (ρ^-). For OTC-drugs (Column (4)), the immediate response to a cost increase is 0.263, while the response to a cost decrease is only 0.123. This implies that pharmacies pass on approximately 26 % of a cost increase of €1 on the

48 *Significance Codes and Interpretation:* Throughout this paper, reported statistical significance follows the scheme: $^+p < 0.1$, $^*p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$ (see, e.g., Engelmann et al., 2024; Hoagland & Wang, 2025; Kim & Riegel, 2025). Consistent with the granularity of the dataset, which comprises nearly a billion of observations, emphasis will be placed on the *economic significance* – the magnitude and direction of the estimates – over the pure reliance on statistical thresholds. As noted by Lin et al. (2013) and Lucas, Shmueli, et al. (2013), in large samples, point estimates can be statistically distinguishable from zero even when economically negligible. Therefore, following recommendations (Imbens, 2021; McCloskey & Ziliak, 1996; Wasserstein & Lazar, 2016), the analysis focuses on the substantive implications of the coefficient sizes (e.g., the extent of overshifting) to determine relevance. Furthermore, in this high-power setting, non-significant results are interpreted as highly informative: given the massive sample size, a failure to reject the null hypothesis indicates the precise absence of an effect rather than a lack of statistical power (Abadie, 2020).

49 The cumulative impulse-response functions are derived in line with (Borenstein et al., 1997, p. 337), but adjusted to fit Equations (1) and (3), respectively.

Dependent Variable:	Δp_{jft}							
	OTC-drugs				Non-Pharmaceuticals			
Coefficients & Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\rho^- \Delta w_{jft}$	0.1062***	0.1077***	0.1170***	0.1227***	0.2332***	0.2312***	0.2329***	0.2270***
	(0.0097)	(0.0105)	(0.0102)	(0.0113)	(0.0151)	(0.0155)	(0.0128)	(0.0144)
$\rho^+ \Delta w_{jft}$	0.3172***	0.2896***	0.2806***	0.2629***	0.3951***	0.3987***	0.4025***	0.4075***
	(0.0163)	(0.0101)	(0.0093)	(0.0092)	(0.0326)	(0.0356)	(0.0335)	(0.0398)
$\gamma^- p_{jf,t-\tau}$	-0.0869***	-0.0876***	-0.0966***	-0.1155***	-0.1000***	-0.1030***	-0.1186***	-0.1557***
	(0.0031)	(0.0031)	(0.0032)	(0.0038)	(0.0091)	(0.0096)	(0.0091)	(0.0132)
$\gamma^+ p_{jf,t-\tau}$	-0.1278***	-0.1331***	-0.1388***	-0.1498***	-0.1518***	-0.1516***	-0.1678***	-0.1953***
	(0.0061)	(0.0041)	(0.0042)	(0.0049)	(0.0142)	(0.0148)	(0.0147)	(0.0201)
$\lambda^- w_{jf,t-\tau}$	0.1299***	0.1323***	0.1472***	0.1775***	0.1403***	0.1442***	0.1659***	0.2176***
	(0.0049)	(0.0049)	(0.0051)	(0.0061)	(0.0129)	(0.0136)	(0.0131)	(0.0188)
$\lambda^+ w_{jf,t-\tau}$	0.1882***	0.2011***	0.2101***	0.2286***	0.2051***	0.2043***	0.2259***	0.2648***
	(0.0098)	(0.0063)	(0.0064)	(0.0075)	(0.0191)	(0.0199)	(0.0197)	(0.0273)
$\omega \Delta Days_{jft}$	0.0007***	0.0007***	0.0007***	0.0006***	0.0004***	0.0004***	0.0004***	0.0004***
	(1.68×10^{-5})	(1.6×10^{-5})	(1.43×10^{-5})	(1.5×10^{-5})	(1.49×10^{-5})	(1.55×10^{-5})	(1.24×10^{-5})	(1.39×10^{-5})
Δ Avg. Price of Competitors (σ^Δ)		8.3×10^{-5}	0.0010***	0.0011***		0.0003	0.0007**	0.0005*
		(0.0002)	(0.0003)	(0.0002)		(0.0003)	(0.0002)	(0.0002)
Lag Avg. Price of Competitors (σ^τ)		-0.0016***	0.0005*	0.0004		-0.0017**	-0.0008**	-0.0010**
		(0.0002)	(0.0002)	(0.0002)		(0.0006)	(0.0003)	(0.0003)
Fit statistics								
# Year-Days	1,641	1,641	1,641	1,641	1,641	1,641	1,641	1,641
# Pharmacy ID × Year-Month	341,968	341,966	341,966	341,958	341,960	341,950	341,950	341,935
# PCN	–	–	28,724	–	–	–	109,087	–
# Pharmacy ID × PCN	–	–	–	8,772,672	–	–	–	15,174,353
Observations	487,209,481	471,465,749	471,462,173	469,293,937	376,934,836	366,362,066	366,347,873	361,946,441
Adjusted R^2	0.03556	0.03221	0.03633	0.04499	0.06426	0.06375	0.08434	0.11475
Within Adjusted R^2	0.02829	0.02502	0.02343	0.02134	0.04042	0.03925	0.04006	0.04132
Long-run Pass-Through θ^+	1.473	1.510	1.514	1.526	1.351	1.348	1.347	1.355
Long-run Pass-Through θ^-	1.495	1.510	1.523	1.537	1.403	1.400	1.398	1.398
Z-test $\theta^+ = \theta^-$	−1.964*	−0.007	−1.928+	−2.887**	−4.788***	−4.429***	−5.591***	−5.038***
Wald test $\rho^+ = \rho^-$	158.302***	236.677***	279.839***	239.834***	19.607***	17.947***	21.419***	16.966***
Wald test $\gamma^+ = \gamma^-$	71.381***	344.504***	329.714***	212.992***	17.842***	14.562***	17.555***	10.327**
Wald test $\lambda^+ = \lambda^-$	53.224***	355.548***	346.697***	218.311***	14.858***	11.886***	14.184***	7.813**
Wald test $\gamma^+ = \gamma^- = \lambda^+ = \lambda^- = 0$	204.810***	331.575***	335.293***	292.597***	39.408***	36.504***	48.115***	36.564***
Fixed Effects (FEs)								
Year-Days FEs	✓	✓	✓	✓	✓	✓	✓	✓
Pharmacy ID × Year-Month FEs	✓	✓	✓	✓	✓	✓	✓	✓
PCN FEs			✓				✓	
Pharmacy ID × PCN FEs				✓				✓

Standard errors (in parentheses) are clustered on the pharmacy ID and PCN. Wald tests show F-statistics and z-test the standard z-score. Differences in the number of observations across models stem from perfect fits and singletons.
Signif. Codes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3: Baseline asymmetric estimation results (Equation (1) with $K = 0$): Pass-through of positive and negative wholesale cost shocks to retail prices for the aggregate OTC drugs and non-pharmaceuticals segments.

day of the shock, but only about 12 % of a corresponding cost reduction. For non-pharmaceuticals (Column (8)), the asymmetry follows a similar pattern, with coefficients of 0.408 and 0.227, respectively. Formal Wald tests reported in Table 3 provide substantial support for this asymmetry. The null hypothesis of short-run symmetry ($\rho^+ = \rho^-$) is rejected at the 0.1 % level across all specifications, with F-statistics of 239.8 for OTC-drugs and 17.0 for non-pharmaceuticals (Columns (4) and (8)). Both OTC-drug and non-pharmaceutical estimates closely align with the 2-to-1 ratio observed in the literature (Benzarti et al., 2020; Peltzman, 2000).

The dynamic parameters of the ECM provide further insight into the adjustment process. As shown in Columns (4) and (8), the joint significance of the lagged level coefficients is evaluated, and the resulting F-statistics ($F = 292.6$ and $F = 36.6$, respectively) reject the null hypothesis of no level relationship, confirming a stable long-run cointegration.[50] Crucially, the speed of adjustment itself is asymmetric. For OTC drugs (Column (4)), the adjustment speed following a cost increase ($|\gamma^+| = 0.150$) is significantly faster than that following a cost decline ($|\gamma^-| = 0.116$). This implies that pharmacies converge toward the long-run equilibrium target more rapidly when prices are below the target (following a cost increase) than when they are above it. However, the fact that these adjustments are strictly partial suggests the presence of retail frictions; rather than (nearly) instantaneously jumping to the new long-run level, pharmacies seem to smooth price increases and decreases over time, potentially due to the presence of frictions, e.g., menu costs and/or the strategic smoothing of price changes to avoid alienating price-sensitive consumers (which will be discussed further in Section 6).

The analysis of the long-run equilibrium targets (θ) reveals a persistent overshifting behavior. In the OTC segment (Column (4)), the long-run pass-through rates for both cost increases ($\theta^+ = 1.526$) and decreases ($\theta^- = 1.537$) significantly exceed unity, indicating that pharmacies eventually recover more than 150 % of the original cost shock of one Euro. Although the z-test indicates a statistical difference ($p < 0.01$), the economic magnitudes are remarkably similar. In the non-pharmaceutical segment (Column (8)), a similar pattern emerges, though with lower absolute magnitudes ($\theta^+ = 1.355$, $\theta^- = 1.398$). This indicates that while short-run adjustments are characterized by significant rigidity, the long-run outcome in both segments involves a systematic expansion or contraction of absolute markups. For non-pharmaceuticals, the rejection of equilibrium symmetry ($\theta^+ = \theta^-$) provides evidence of a more pronounced long-term asymmetry (confirmed by

[50]The test statistics are computed as a standard Wald F-statistic testing the joint significance of the lagged level terms. However, usually inference relies on the non-standard critical value bounds provided by Pesaran et al. (2001) to account for the uncertain order of integration of the regressors (upper-bound critical values approximately 5.0 at the 1 % level) which are decisively smaller than the provided results.

the Wald test: $F = -5.04$).

Rather than merely reflecting transitory pricing frictions, this persistent overshifting may be an outcome of pricing under imperfect competition, including local monopolies. Specifically, if pharmacies face a log-convex demand curve, such as an iso-elastic or log-linear demand structure (Miller et al., 2013), the profit-maximizing strategy inherently yields a pass-through rate strictly greater than one (see, e.g., Mrázová & Neary, 2017; Ritz, 2024; Weyl & Fabinger, 2013). From the current analysis, comparing the two segments already reveals a clear distinction in market power. The consistently higher long-run pass-through target for OTC drugs compared to non-pharmaceuticals (≈ 1.53 vs. 1.38) implies that pharmacies possess significantly greater pricing power for OTC drugs. This structural difference is likely driven by the captive nature of the OTC consumer, resulting in a more inelastic demand, as high search costs and the necessity of acute care allow pharmacies to extract larger rents. In contrast, the lower coefficient for non-pharmaceuticals reflects a more competitive environment, where substitution to standard drugstores or supermarkets is easier, thereby constraining the pharmacy's ability to extend margins (for the extended discussion including the spatial dimension see Section 6).

To quantify the temporal dynamics of these adjustments, Figure 5 presents the CIRFs.[51] The visual contrast in the top panel underscores the severity of the asymmetry for OTC-drugs. Following a €1 cost increase (solid red line), retail prices jump by €0.26 immediately. The more steep curvature of the subsequent adjustment reflects the high speed of correction ($|\gamma^+| \approx 0.15$), allowing prices to converge faster toward the long-run pass-through target of €1.53. Conversely, a cost decrease (solid blue line) triggers an initial drop of only €0.12. The flatter trajectory of the blue line – driven by the significantly lower adjustment speed ($|\gamma^-| \approx 0.12$) – indicates a slightly more sluggish descent that requires longer (≈ 2 days) to fully absorb the shock and finally reach the long-run target of €1.54.

For non-pharmaceuticals (bottom panel), the initial gap is smaller, with short-run effects of €0.41 and €0.23 for increases and decreases, respectively. However, the simulation explicitly visualizes the (small) structural asymmetry discussed above: the adjustment path for cost decreases (solid blue line) eventually crosses and settles at a higher long-run level (€1.40) than the path for cost increases (€1.36). This indicates that while downward adjustments suffer from short-run inertia, the long-run transmission for cost

[51] These trajectories are derived by iterating the estimated results of the ECM (Equation 1) to track the propagation of an initial positive or negative, one-time wholesale cost shock of €1. At the moment of the shock ($t = 0$), the price adjusts by the estimated short-run coefficient (ρ^k). In subsequent periods, the price evolves to close the gap between the current level and the long-run equilibrium (θ^k), with the convergence rate governed by the estimated speed of adjustment parameters (γ^k) from Columns (5) and (10) of Table 3.

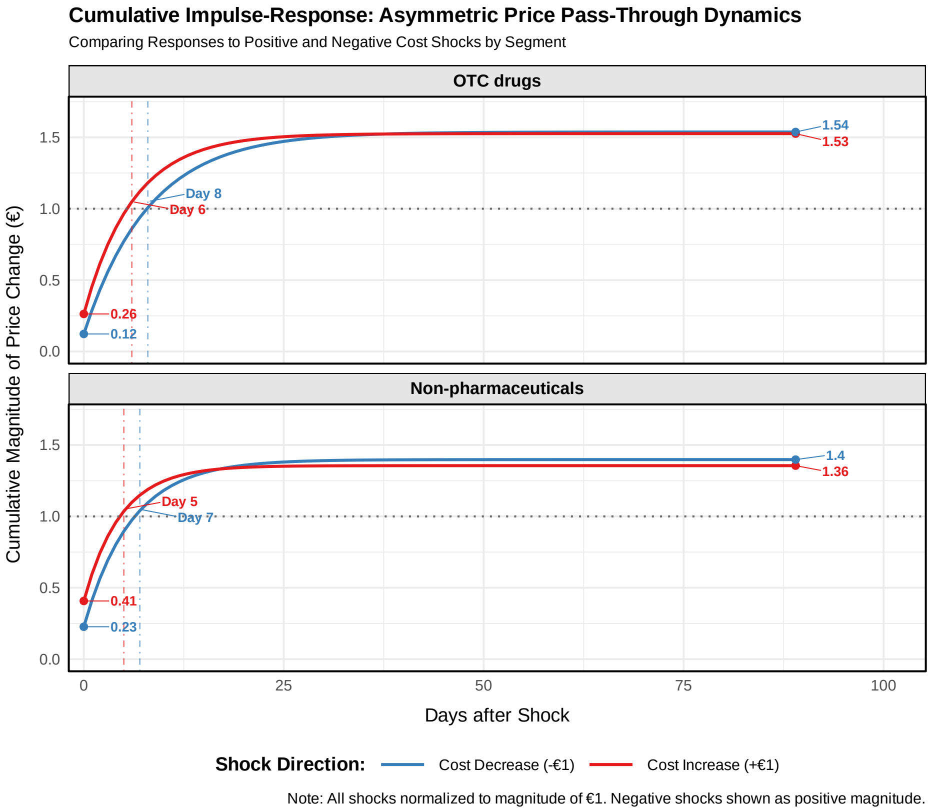


Figure 5: Asymmetric Cumulative Impulse-Response Functions ($K = 0$): Cumulative Price Adjustment to €1 Cost Shocks. The figure illustrates the dynamic path of retail price adjustments for OTC-drugs (top panel) and non-pharmaceuticals (bottom panel) following a normalized €1 wholesale cost increase (solid red curves) and decrease (solid blue curves). Negative shocks are shown in absolute magnitude for comparability. The estimated immediate short-run effects and long-run equilibrium targets are explicitly annotated at the beginning and end of each path. The horizontal dotted line represents the complete pass-through threshold (€1), while the vertical lines denote the exact number of days required for the cumulative adjustment to reach this level. Effects are derived from Columns (4) and (8) from Table 3.

savings is statistically stronger. In both regimes, the adjustment process exhibits rapid decay, with the price fully converging to its new equilibrium level within approximately one to two months. Taken in its entirety, these findings represent the standard rockets and feathers phenomenon. By passing on wholesale price increases more strongly than decreases, pharmacies effectively protect their margins in the short-run. As touched upon before, this asymmetry may be driven by pharmacies exploiting local market power, but it is also consistent with consumer search frictions.

Finally, the analysis incorporates competitor pricing behavior to test for strategic responses, i.e., strategic complementarity. The results, reported in Table 4, point to a dichotomy between statistical significance and economic magnitude. For OTC drugs (Column (4)), a statistically significant positive short-run response is observed ($\sigma^{\Delta} \approx 0.001$), suggesting a weak tendency of a pharmacy to respond immediately to market-wide price changes. However, the coefficient on the lagged competitor price level (σ^{τ}) is statistically indistinguishable from zero, implying no stable long-run relationship. Thus, pharmacies do not align their long-run equilibrium prices with those of their competitors. This finding indicates an absence of strategic complementarity; from a broader perspective, B&M pharmacies do not appear to actively compete against each other on price.

In the non-pharmaceutical segment (Column (8)), the competitor sensitivity is even more attenuated. In the short run, the estimated response to competitor price changes (σ^{Δ}) is positive but economically negligible (0.0005). Similarly, while the lagged level coefficient (σ^{τ}) is statistically significant, its magnitude (-0.0010) implies a vanishingly small long-run pass-through of approximately 0.006 (calculated as $-\sigma^{\tau}/\gamma$). These findings imply that while competitor prices are statistically detectable, they are economically irrelevant compared to the magnitude of the own-cost pass-throughs.

This lack of competitor response can be interpreted in two ways: either that pharmacies operate in an environment characterized by strong spatial differentiation and monopolistic competition, where local market power renders them largely indifferent to broader market pricing, or that the utilized geographic market definition is too broad. Because the product market is already defined at the narrowest possible level (the chemical substance), it is more probable that relying on two-digit postal codes dilutes the measurement of true localized, city-level competition, capturing a broader non-competitive aggregate instead. Yet, most importantly, the inclusion of the competitor variables does not alter the other coefficient magnitudes.

5.2 Robustness Analysis

To validate the baseline findings and account for potential delayed transmission of cost shocks, Table 4 presents the results of the full ECM (Equation (1)) including up to $K = 4$ lags. For the complete set of estimates, including results for all intermediate lag specifications and full coefficient reports, see Appendix E Table E.2. Due to the computational intensity of estimating this high-dimensional fixed-effects model on the full dataset, this robustness check restricts the sample to the highest-turnover product categories:[52] *Respiratory System* and *Musculoskeletal System/Pain Management* for OTC drugs (32 % and 23 % of sales within OTC drugs), alongside *No ATC Code*

[52]See, Table D.2 and D.3.

for non-pharmaceuticals (60 % of sales within non-pharmaceuticals).[53]

A key distinction from the baseline results from Section 5.1 is the magnitude of the immediate impact coefficient ($\rho^{\pm}$). In the most dynamic specification (Table 4 Column (3)), the day-zero pass-through for OTC drugs cost increases is $\rho^{+} \approx 0.133$, roughly half the magnitude of the baseline estimate (Table 3). However, this does not imply lower responsiveness. Rather, the impact is distributed across the subsequent days, as evidenced by the statistically significant positive coefficients on the lagged cost terms ($\beta^{+}_{t-1}, \beta^{+}_{t-2}, \ldots$, see Table E.2). The cumulative short-run response, visualized in Figure 6, mirrors the trajectory observed in the baseline specification (Figure 5): a sharp instantaneous impulse followed by a monotonic adjustment. However, the temporal structure differs in duration. The extended lag specification reveals substantial persistence, lengthening the convergence horizon to over a quarter even up to more than half a year before the new steady-state equilibrium is fully established.

Crucially, the inclusion of lags refines the understanding of the long-run equilibrium. Unlike the baseline model, which often detects statistical differences in long-run targets for OTC-drugs, the dynamic specification (Column (4)) shows that pass-through rates for cost increases ($\theta^{+} = 1.572$) and decreases ($\theta^{-} = 1.550$) converge to statistically indistinguishable levels ($p = 0.177$). This reinforces the finding that while the *speed* of adjustment is asymmetric (confirming rockets and feathers), the long-run equilibrium is symmetric. Conversely, in the non-pharmaceutical segment (Column (6)), the dynamic model confirms the presence of a long-term asymmetry: the long-run pass-through of cost decreases ($\theta^{-} \approx 1.395$) remains higher than that of increases ($\theta^{+} \approx 1.254$), a difference that remains statistically significant ($p < 0.01$).

Figure 6 visually corroborates these dynamics. The solid red lines (cost increases) exhibit a steep initial slope, capturing the rapid accumulation of the immediate and lagged coefficients. The solid blue lines (cost decreases) follow a distinctively concave, sluggish path. Yet, for OTC-drugs (top panel), the lines clearly converge to a similar asymptote, demonstrating that the observed asymmetry is purely a phenomenon of delay rather than permanent retention. In contrast, the bottom panel illustrates the long-run asymmetry in the non-pharmaceutical segment, where the slow-moving downward adjustment eventually surpasses the upward response, settling at a higher equilibrium level of 1.4. Regarding duration asymmetries, convergence toward the long-run equilibrium takes distinctly longer for decreases than for increases. For example, it takes 27 and 24 days for non-pharmaceuticals and

[53] The selection of $K = 4$ is empirically supported by the model fit statistics reported in Tables 4. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) exhibit a monotonic decrease as lags are added (comparing Columns (1) through (3) and (4) through (6)), indicating that the fully specified model with four lags provides the superior fit by capturing the distributed nature of the price adjustment process.

Dependent Variable:	Δp_{jft}					
	OTC-drugs			Non-Pharmaceuticals		
Coefficients & Variables	(1)	(2)	(3)	(4)	(5)	(6)
$\rho^{-}\Delta w_{jft}$	0.0772***	0.0656***	0.0645***	0.2226***	0.1948***	0.1976***
	(0.0092)	(0.0067)	(0.0062)	(0.0300)	(0.0203)	(0.0167)
$\rho^{+}\Delta w_{jft}$	0.1882***	0.1405***	0.1333***	0.4481***	0.4176***	0.4044***
	(0.0088)	(0.0081)	(0.0076)	(0.0749)	(0.0748)	(0.0689)
$\gamma^{-}p_{jf,t-\tau}$	-0.0930***	-0.0529***	-0.0440***	-0.1298***	-0.0703***	-0.0476***
	(0.0062)	(0.0039)	(0.0033)	(0.0218)	(0.0140)	(0.0109)
$\gamma^{+}p_{jf,t-\tau}$	-0.1151***	-0.0728***	-0.0628***	-0.1622***	-0.1057***	-0.0810**
	(0.0057)	(0.0036)	(0.0030)	(0.0363)	(0.0290)	(0.0262)
$\lambda^{-}w_{jf,t-\tau}$	0.1470***	0.0825***	0.0682***	0.1830***	0.0984***	0.0664***
	(0.0110)	(0.0065)	(0.0055)	(0.0315)	(0.0201)	(0.0156)
$\lambda^{+}w_{jf,t-\tau}$	0.1819***	0.1142***	0.0988***	0.2158***	0.1361***	0.1015**
	(0.0101)	(0.0061)	(0.0052)	(0.0494)	(0.0391)	(0.0355)
Fit statistics						
# PCN-Pharmacy ID	2,491,778	2,491,778	2,491,778	6,078,232	6,078,232	6,078,232
# Year-Days	1,637	1,637	1,637	1,637	1,637	1,637
# Pharmacy-ID × Year-Month	341,772	341,772	341,772	341,307	341,307	341,307
Observations	231,400,516	231,400,516	231,400,516	172,288,976	172,288,976	172,288,976
Adjusted R^2	0.03062	0.23224	0.25603	0.13450	0.31951	0.36392
Within Adjusted R^2	0.01031	0.21615	0.24044	0.03726	0.24306	0.29245
Long-run Pass-Through θ^+	1.580	1.569	1.572	1.330	1.287	1.254
Long-run Pass-Through θ^-	1.581	1.560	1.550	1.410	1.401	1.395
Z-test $\theta^+ = \theta^-$	-0.119	0.630	1.350	-3.386***	-3.096**	-2.729**
K Lags	0	1	4	0	1	4
AIC	377,566,880.9	314,690,484.8	306,142,571.7	429,071,416.9	387,977,778.5	374,094,333.3
BIC	426,501,332.6	363,625,005.6	355,077,299.6	538,004,721.7	496,911,151.1	483,027,909.5
LogLik	-185,948,248.5	-154,510,046.4	-150,236,077.9	-208,114,527.4	-187,567,704.2	-180,625,969.7
Fixed Effects (FEs)						
PCN-Pharmacy ID FEs	✓	✓	✓	✓	✓	✓
Year-Days FEs	✓	✓	✓	✓	✓	✓
Pharmacy-ID × Year-Month FEs	✓	✓	✓	✓	✓	✓

Standard errors (in parentheses) are clustered on the pharmacy ID and PCN. Wald tests show F-statistics.
Signif. Codes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4: Dynamic asymmetric estimation results (Equation (1) with up to $K = 4$ lags): Short-run and long-run pass-through estimates for high-turnover OTC drugs (*Respiratory System*, *Musculoskeletal System and Pain Management*) and non-pharmaceuticals (*No ATC Code*). For brevity, only specifications with $K \in \{0, 1, 4\}$ are displayed. The complete set of results, including all intermediate lag specifications, is provided in Appendix E Table E.2.

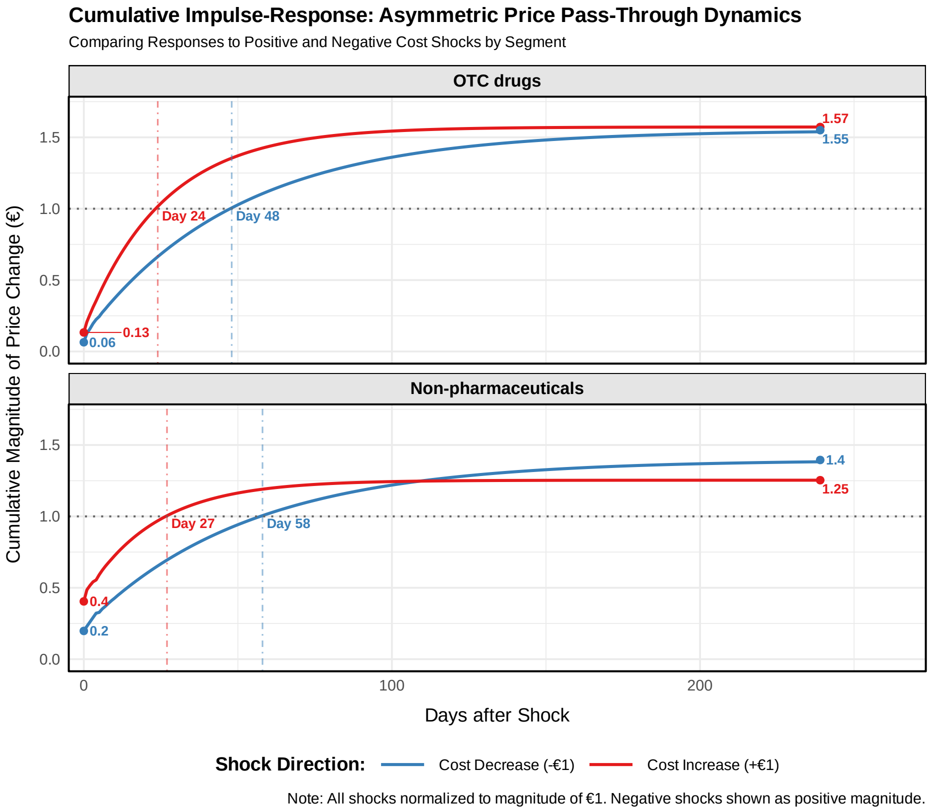


Figure 6: Asymmetric Cumulative Impulse-Response Functions utilizing Table 4, Column (4) and (8): Cumulative Price Adjustment to €1 Cost Shocks. The figure illustrates the dynamic path of retail price adjustments for OTC-drugs (top panel) and non-pharmaceuticals (bottom panel) following a normalized €1 wholesale cost increase (solid red curves) and decrease (solid blue curves). Negative shocks are shown in absolute magnitude for comparability. The estimated immediate short-run effects and long-run equilibrium targets are explicitly annotated at the beginning and end of each path. The horizontal dotted line represents the complete pass-through threshold (€1), while the vertical lines denote the exact number of days required for the cumulative adjustment to reach this level.

OTC drugs, respectively, to reach complete pass-through following a cost increase (vertical colored lines). In contrast, cost decreases require 58 and 48 days, respectively. Thus, pharmacies are approximately twice as fast to pass through cost increases as they are to pass through decreases. Furthermore, the duration until the long-run equilibrium is reached is approximately one quarter for cost increases, but extends to over more than half a year for decreases.

This structural asymmetry in the non-pharmaceutical segment – where long-run price cuts exceed price hikes ($\theta^{-} > \theta^{+}$) – potentially reflects the strategic role of these products as another traffic builder (compared to Rx drugs). Unlike medicinal OTC drugs, which are sold exclusively in pharmacies, non-pharmaceutical products (e.g., cosmetics, supplements) face direct external competition from mass-market drugstores and supermarkets. Consequently, pricing dynamics could be driven by the incentive to defend and expand market share against rivals. When wholesale prices rise, pharmacies are constrained by the high demand elasticity of discretionary shoppers; to avoid customer switch to cheaper competitors, pharmacies are forced to absorb a larger part of the cost increase (limiting θ^+). Conversely, periods of falling wholesale prices offer a strategic opportunity to aggressively improve price competitiveness. Thus, pharmacies might utilize these episodes to overshift the cost reduction stronger than an increase ($\theta^- > \theta^+$), effectively subsidizing lower prices to stimulate footfall that can subsequently be monetized through cross-sales in the higher-margin OTC-drug segment (or even to attract customers with prescriptions).

In summary, the analysis confirms that pricing dynamics in the pharmacy market are universally characterized by short-run downward rigidity (rockets and feathers). However, the long-run equilibrium outcomes reveal a fundamental structural divergence between segments. For OTC drugs, the asymmetry is temporary: pharmacies delay price reductions but eventually converge to a symmetric, high-markup equilibrium ($\theta^+ \approx \theta^-$). Conversely, the non-pharmaceutical segment exhibits a more competitive reverse asymmetry where long-run price cuts exceed price increases ($\theta^- > \theta^+$). This behavior would be consistent with the strategic use of unregulated products as traffic builders, where pharmacies aggressively overshift cost savings to defend market share against external competition. The full discussion will be adjourned to Section 6.

5.3 Heterogeneity Analysis

The pooled estimates presented in Section 5.1 provide a robust baseline for market-wide pricing dynamics. However, these average effects may mask significant structural heterogeneity across pharmacies. To investigate this, Equation (3) is estimated, yielding a distribution of approximately 60,000 unique short-run and adjustment parameters, respectively.[54]

[54] For a detailed structural analysis regressing these estimated pharmacy-level pass-through coefficients on revenue deciles to test for size-dependent effects, see Appendix B.1.

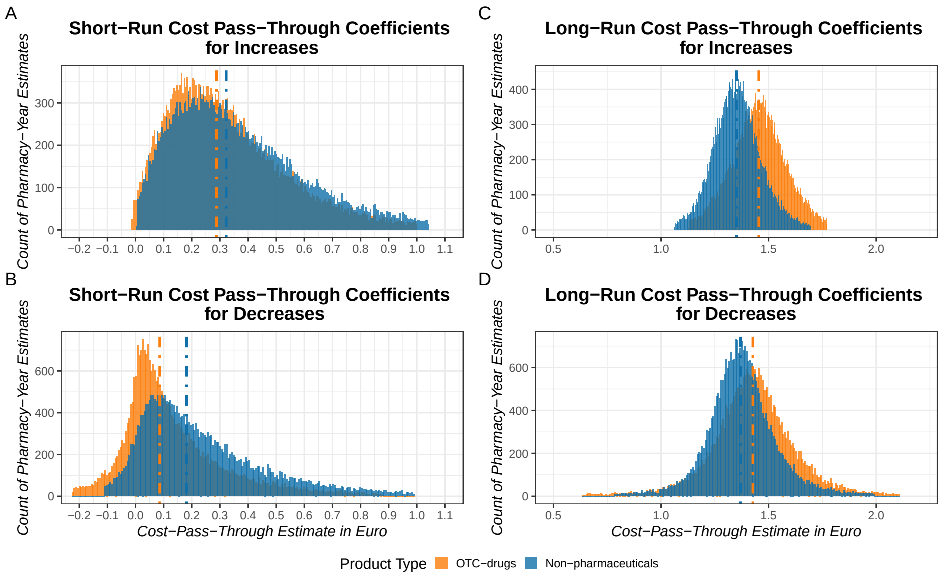


Figure 7: Distribution of Pharmacy-Level CPT Coefficients. The figure displays the histograms of estimated short-run (ρ_{fy}) and long-run (θ_{fy}) coefficients for OTC drugs (orange) and non-pharmaceuticals (blue). Panels A and B show the immediate response to cost increases and decreases, respectively. Panels C and D show the derived long-run equilibrium targets. Note: The distributions have been truncated by 2.5 % at both the lower and upper ends. Dashed lines represent the median of each distribution.

Figure 7 plots the histograms of the estimated short-run ($\hat{\rho}_{fy}$) and long-run ($\hat{\theta}_{fy}$) coefficients, distinguishing between OTC drugs (orange) and non-pharmaceuticals (blue).

Three key patterns emerge from these distributions. First, there is substantial variation in pricing behavior. CPT rates exhibit substantial dispersion, revealing heterogeneous pricing responses to identical cost shocks. Second, *rockets and feathers* are clearly visible in the distributions. While both short-run distributions (Panels A and B) exhibit right-skewness, there is a sharp contrast between their respective medians. For cost increases (Panel A), the mass is centered around 0.30–0.40; in contrast, for cost decreases (Panel B), the distribution shifts toward zero, particularly for OTC drugs, confirming that a large subset of pharmacies exhibits stark rigidity to cost savings in the short run. Third, while long-run overshifting is pervasive (distributions in Panels C and D are above unity), the structural distinction between segments remains. In both long-run panels, the OTC distributions are positioned to the right of the non-pharmaceutical distributions. This visual gap corroborates the econometric evidence that pharmacies consistently enforce higher long-run pass-through targets in the OTC market compared to the competitive non-pharmaceutical sector.[55]

[55]For a detailed analysis of heterogeneous pass-through dynamics across pharmacies, see Appendix B.2.

Dependent Variable:	Δp_{jft}					
	(1)	(2)	(3)	(4)	(5)	(6)
$\rho^- \Delta w_{jft}$	0.0659**	0.1054***	0.1219***	0.1403***	0.0915***	0.1208***
	(0.0138)	(0.0108)	(0.0186)	(0.0279)	(0.0138)	(0.0142)
$\rho^+ \Delta w_{jft}$	0.0689*	0.1156***	0.2135***	0.0963**	0.1423***	0.2205***
	(0.0226)	(0.0088)	(0.0146)	(0.0206)	(0.0116)	(0.0121)
Fit statistics						
Observations	37,531,035	180,112,138	422,089,152	30,265,844	167,176,855	409,592,325
Adjusted R^2	0.03715	0.03413	0.02923	0.04239	0.02919	0.03591
Within Adjusted R^2	0.00405	0.00672	0.01524	0.00753	0.00959	0.01793
# Top PCN	10	100	1000	10	100	1000
Top PZN by	Sales	Sales	Sales	Revenue	Revenue	Revenue
Fraction of Total in %	13.1520	44.2220	87.3466	9.2187	37.9892	83.1285
Wald test $\rho^+ = \rho^-$	0.025	0.621	107.109***	3.521+	9.813**	140.860***
Long-run Pass-Through θ^+	1.672	1.633	1.580	1.558	1.556	1.535
Long-run Pass-Through θ^-	1.715	1.636	1.581	1.557	1.534	1.536
Z-test $\theta^+ = \theta^-$	−1.794+	−0.435	−0.100	0.131	2.613**	−0.233

Standard errors (in parentheses) are clustered on the pharmacy ID and PCN. Wald tests show F-statistics.
Signif. Codes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

(a) OTC drugs: Top 10, 100, and 1000.

Dependent Variable:	Δp_{jft}					
	(1)	(2)	(3)	(4)	(5)	(6)
$\rho^- \Delta w_{jft}$	0.1235***	0.1275***	0.1824***	0.1593**	0.1792***	0.2098***
	(0.0109)	(0.0127)	(0.0124)	(0.0352)	(0.0184)	(0.0110)
$\rho^+ \Delta w_{jft}$	0.1317***	0.2356***	0.2704***	0.2348***	0.2629***	0.2789***
	(0.0226)	(0.0236)	(0.0132)	(0.0267)	(0.0118)	(0.0077)
Fit statistics						
Observations	14,012,783	65,992,694	207,336,289	10,709,504	52,381,667	177,019,976
Adjusted R^2	0.04635	0.05226	0.07846	0.05001	0.07388	0.07572
Within Adjusted R^2	0.01014	0.01699	0.02665	0.02277	0.02815	0.03322
# Top PCN	10	100	1000	10	100	1000
Top PZN by	Sales	Sales	Sales	Revenue	Revenue	Revenue
Fraction of Total in %	3.8819	16.8351	52.5124	4.2602	18.1514	50.9730
Wald test $\rho^+ = \rho^-$	0.184	16.972***	28.569***	3.121+	33.704***	36.934***
Long-run Pass-Through θ^+	1.482	1.348	1.385	1.290	1.342	1.373
Long-run Pass-Through θ^-	1.470	1.347	1.397	1.287	1.334	1.375
Z-test $\theta^+ = \theta^-$	2.755**	0.155	−2.505*	0.298	1.443	−0.471

Standard errors (in parentheses) are clustered on the pharmacy ID and PCN. Wald tests show F-statistics.
Signif. Codes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

(b) Non-pharmaceuticals: Top 10, 100 and 1000.

Table 5: Estimation results for top-ranked products by sales and revenue. Note: The complete tables can be found in the Appendix E, Tables E.3 and E.4.

To examine how the aggregate pricing dynamics reported in Section 5.1 are affected by the long-tail of many low-volume products, Equation (1) is estimated with subsets of top-ranked PCNs (with $K = 0$). Table 5 presents the results for the top 10, top 100, and top 1,000 products, ranked by sales volume and revenue (total turnover in Euro).[56] These subsets capture the majority of market activity. For instance, the top 1,000 OTC products (non-pharmaceuticals), account for approximately 83 % (52 %) of total segment revenue.[57]

[56] Top-ranked products are identified by aggregate sales volume or revenue over the full sample period of all pharmacies.

[57] See Appendix Tables E.3 and E.4 for a full table including the lagged coefficients, detailed statistics on fixed effects, and the ranking by gross profits exhibiting similar results.

The estimates in Table 5 reveal distinct heterogeneity in pricing strategies across the assortment depth. Concerning Table 5a, for the high-frequency bestsellers (Top 10 and Top 100 by sales, Columns (1)–(2)), pricing is symmetric in both the short and long run. In Column (2), the short-run response to cost decreases ($\rho^- = 0.105$) and increases ($\rho^+ = 0.116$) is statistically indistinguishable, leading to symmetric long-run pass-through ($\theta^+ \approx \theta^- \approx 1.63$; $p = 0.664$). Interestingly, while the Top 1,000 sales products (Column (3)) exhibit significant short-run asymmetry ($\rho^+ > \rho^-$), this difference dissipates completely in the long run. In contrast, the revenue-generating assortment exhibits sustained asymmetry only in Column (5), which focuses on the Top 100 revenue products. In the short run, the short-run response to cost increases ($\rho^+ = 0.142$) significantly exceeds that for decreases ($\rho^- = 0.092$). This divergence persists into the long run, where pass-through for increases ($\theta^+ = 1.556$) remains significantly higher than for decreases ($\theta^- = 1.534$), yielding a rejection of symmetry. However, this long-run asymmetry vanishes for the broader Top 1,000 revenue products.

Table 5b presents the results for non-pharmaceuticals. For the Top 100 revenue products (Column (5)), a strong short-run asymmetry is observed ($\rho^+ = 0.263$ vs. $\rho^- = 0.179$) , but this does not translate into statistically significant long-run asymmetry ($\theta^+ = 1.342$ vs. $\theta^- = 1.334$). This convergence is equally evident in the broader Top 1,000 sample (Column (6)): despite highly significant short-run asymmetry, the long-run pass-through coefficients are statistically indistinguishable ($\theta^+ \approx 1.37$ vs. $\theta^- \approx 1.38$). Thus, while non-pharmaceuticals exhibit transient asymmetric dynamics, they do not sustain the permanent asymmetric deviations observed in the high-revenue OTC drug assortment.

In summary, the heterogeneity analysis reveals that the aggregate rockets and feathers phenomenon does not appear uniformly across a pharmacy's inventory. For bestsellers, pricing remains symmetric, potentially because consumers are highly attentive to the prices of these everyday items. However, these top-selling products simultaneously exhibit higher absolute long-run pass-through magnitudes (e.g., up to 1.715) compared to the market average of approximately 1.54. This indicates that pharmacies extract greater permanent margins on high-demand goods, even while abstaining from asymmetric pricing. Furthermore, persistent long-run asymmetry is highly concentrated, emerging exclusively within the narrowest segment of high-revenue OTC products. In contrast, for non-pharmaceuticals, asymmetry remains strictly transient across all top-ranked specifications, completely dissipating in the long run. Given that the aggregate results from Tables 3 and 4 showed long-run asymmetry for the full non-pharmaceutical sample, this effect must be driven by the long tail of low-volume products. Together, these findings suggest that pharmacies seem to employ targeted pricing strategies, maximizing absolute margins symmetrically on visible bestsellers, while isolating permanent asymmetric deviations to specific high-revenue OTC items and the less-visible long tail of the non-pharmaceutical assortment.

5.4 Socio-Demographic Analysis

Table 6 presents results of the estimation of Equation (4) for several outcome variables and the mode aggregation function (see Section 4.3). The constant captures the baseline conditional mean for the reference group (urban pharmacies, non-pharmaceuticals, 2018). The remaining coefficients quantify the marginal effects of socio-demographics, urbanization, product type, interaction terms, and year fixed effects. The estimates indicate that rural pharmacies exhibit significantly lower sales for OTC drugs. As shown in Column (5), the interaction term for sales volume (*Rural* $\times$ *OTC drugs*) is -0.076, implying approximately 7.6 % lower sales. However, pharmacies compensate via raising absolute markups by 8.3 % (Column (3)).[58] Consequently, the net effect on gross profits (Column (6)) is statistically insignificant, highlighting that higher unit margins fully offset the volume deficit. In this context, rural pharmacies seem to leverage their spatial differentiation to sustain higher markups, effectively compensating for the lower demand density inherent to rural locations.[59]

Furthermore, rural markets exhibit lower retail prices of 4.2 % for non-pharmaceuticals. However, this effect reverses for OTC drugs: the positive interaction term (0.083) offsets the negative value, resulting in a net rural price premium of approximately 4.1 % ($-0.042 + 0.083$). These structural differences persist even after controlling for a comprehensive set of socio-demographic covariates, such as income per capita, where a €10,000 increase in local purchasing power is associated with an 18.4 % price premium (0.184).

Crucially, the higher retail prices in rural markets are accompanied by higher wholesale prices. Column (1) indicates that while rural pharmacies purchase non-pharmaceuticals at a significantly lower wholesale price than urban pharmacies (-0.054), they face significantly higher wholesale prices for OTC drugs. The interaction term for wholesale prices is positive and statistically significant (0.082). Consequently, higher retail prices observed for OTC drugs in rural areas parallel the higher procurement costs for these products.

The analysis of the Lerner Index (Column (4)) confirms that the markup increase is proportional to the price level. Although absolute markups (in Euros) are significantly higher for rural OTC products, the interaction term for the Lerner Index, which measures the markup relative to the price, is statistically insignificant. This implies that while rural pharmacies charge

[58] The baseline estimates for rural pharmacies concerning sales and markups are statistically insignificant. Thus, the total spatial effect for OTC drugs is driven entirely by the interaction term.

[59] Similar results arise when the area-weighted aggregation is utilized (see Table C.3).

Dependent Variable:	log(Wholesale Price)	log(Retail Price)	log(Markup)	Lerner Index	log(Sales)	log(Gross Profits)
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	2.955***	3.303***	2.141***	0.3037***	6.034***	8.176***
	(0.2015)	(0.2321)	(0.3723)	(0.0666)	(0.7148)	(0.8065)
Intermediate	-0.0095	-0.0023	0.0105	0.0044	-0.0762	-0.0657
	(0.0107)	(0.0108)	(0.0173)	(0.0034)	(0.0505)	(0.0538)
Rural	-0.0544***	-0.0422***	-0.0184	0.0078*	0.0272	0.0088
	(0.0092)	(0.0097)	(0.0174)	(0.0035)	(0.0448)	(0.0478)
Intermediate × OTC drugs	0.0266*	0.0265*	0.0286*	0.0003	0.0318	0.0605+
	(0.0113)	(0.0116)	(0.0142)	(0.0024)	(0.0324)	(0.0324)
Rural × OTC drugs	0.0819***	0.0833***	0.0830***	0.0007	-0.0759*	0.0071
	(0.0122)	(0.0129)	(0.0152)	(0.0021)	(0.0325)	(0.0305)
OTC drugs	-0.2752***	-0.1014***	0.1878***	0.1072***	0.3416***	0.5294***
	(0.0081)	(0.0090)	(0.0115)	(0.0017)	(0.0276)	(0.0277)
year = 2019	0.0214***	0.0279***	0.0407***	0.0042***	-0.0418***	-0.0010
	(0.0032)	(0.0030)	(0.0045)	(0.0010)	(0.0115)	(0.0123)
year = 2020	0.0420***	0.0562***	0.0838***	0.0092***	-0.1347***	-0.0510***
	(0.0028)	(0.0024)	(0.0030)	(0.0007)	(0.0076)	(0.0081)
year = 2021	0.0542***	0.0636***	0.0808***	0.0060***	-0.0806***	0.0002
	(0.0042)	(0.0037)	(0.0055)	(0.0014)	(0.0155)	(0.0170)
year = 2022(H1)	0.0173**	0.0312***	0.0555***	0.0087***	-0.7632***	-0.7077***
	(0.0051)	(0.0043)	(0.0065)	(0.0017)	(0.0192)	(0.0212)
Income per Person (in 10T)	0.1748***	0.1837***	0.2021***	0.0061	0.1695*	0.3716***
	(0.0134)	(0.0126)	(0.0213)	(0.0050)	(0.0653)	(0.0725)
Fraction of Population ≥ 65	0.0061**	0.0042+	0.0012	-0.0011	-0.0170+	-0.0158
	(0.0022)	(0.0023)	(0.0036)	(0.0008)	(0.0095)	(0.0104)
Fraction of Population < 18	-0.0164***	-0.0179***	-0.0214**	-0.0011	0.0783***	0.0569***
	(0.0041)	(0.0047)	(0.0073)	(0.0013)	(0.0160)	(0.0163)
Fraction of 1-Person-Households	-0.0146***	-0.0135***	-0.0121***	0.0006	0.0273***	0.0152*
	(0.0016)	(0.0019)	(0.0030)	(0.0005)	(0.0055)	(0.0060)
Fraction of 2-Person-Households	-0.0266***	-0.0258***	-0.0256***	0.0003	0.0347**	0.0091
	(0.0030)	(0.0034)	(0.0054)	(0.0010)	(0.0120)	(0.0132)
Fit statistics						
Observations	63,380	63,380	63,380	63,380	63,380	63,380
Adjusted R^2	0.51786	0.28857	0.35409	0.60792	0.22006	0.26870

Standard errors (in parenthesis) are clustered on the two-digit zip code.
Signif. Codes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6: Estimation results from Equation (4) for the outcome variables: wholesale and retail prices, markups, Lerner Indices, sales and gross profits. *Note:* The degree of urbanization is aggregated using the mode method (assigning the most frequently occurring category). For results using area-weighted aggregation, see Table C.2.

higher absolute markups, their relative profit margin per unit remains statistically indistinguishable from that of urban pharmacies.

Finally, the year fixed effects reveal significant temporal dynamics during the observation period.[60] Relative to the 2018 baseline, retail prices and absolute markups exhibited a steady upward trend from 2019 through 2021. This price growth coincided with a persistent contraction in sales volumes, which reached its trough in 2020 (-0.135), likely reflecting pandemic-related demand and supply shocks. Despite this volatility in sales activity, nominal gross profits remained statistically stable in 2019 and 2021, with a significant but moderate decline observed only in 2020 (-0.051).

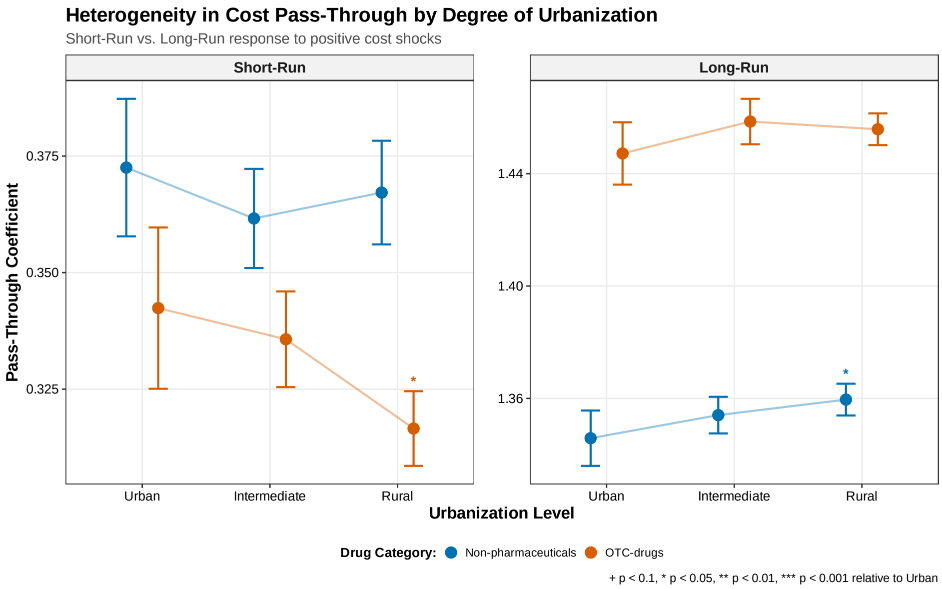
Next the short- and long-run CPT are regressed via Equation (4) on the set of regional and socio-demographic variables (see Appendix C and Tables (C.1) and (C.3) for details). To translate the regression estimates into more intuitive magnitudes, Figure 8 illustrates comparative statics for positive cost shocks utilizing *predicted marginal means* for both aggregation functions (Panel (a) and (b) correspond to the aggregation by mode and area, respectively).[61]

As explained in Section 4.3, presenting both spatial aggregation schemes is important because they account for different geographical biases. Aggregating by the mode treats all five-digit zip codes equally, which systematically overrepresents the high count of small rural municipalities, whereas area-weighting emphasizes more expansive intermediate regions. This distinction is relevant here: the underlying spatial classifications differ so strongly that the statistical significance of the estimates hinges on the chosen aggregation scheme, even though the directional trends remain consistent.

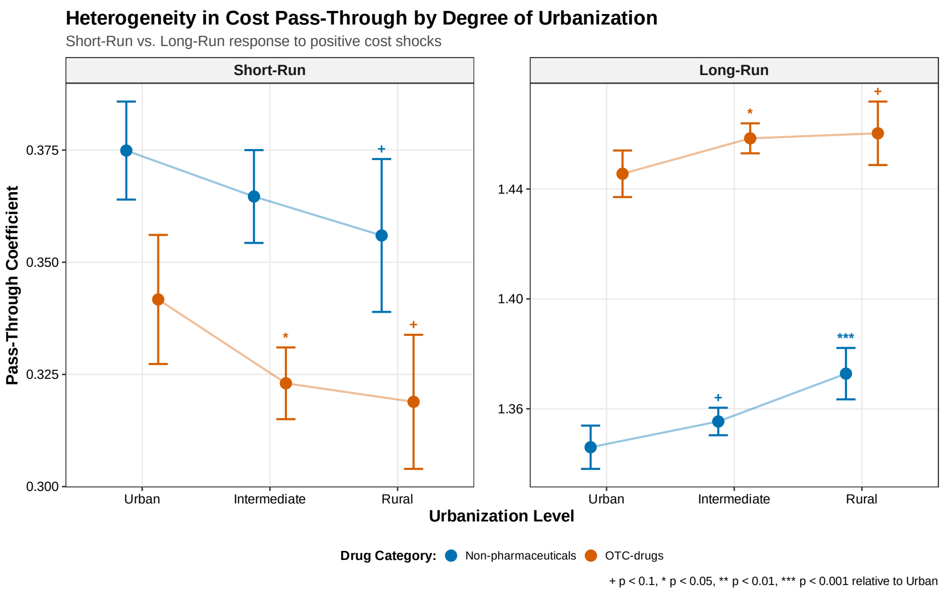
In the short run (left columns), the analysis reveals a distinct pricing inertia in rural markets. Panel (a) shows that for OTC drugs (orange line), the short-run pass-through effect declines significantly as urbanization decreases. While urban pharmacies pass through a substantial portion of cost shocks immediately, rural incumbents exhibit a statistically significant reduction in responsiveness ($p < 0.05$), with magnitudes decreasing to approximately 0.315. Crucially, this rigidity is present across the assortment: non-pharmaceuticals (blue line) exhibit consistently higher short-run pass-through rates than OTC drugs across all spatial categories, indicating that pricing inertia is most acute for health-related products where consumer sensitivity is probably lower. This pattern of stickiness is reinforced in Panel

[60] The coefficients for the year 2022 (H1) are included in the regression to control for the final period of the sample. However, as this indicator covers only the first half of the year, the coefficients are not directly comparable to the full-year estimates of 2018–2021 and are therefore excluded from the interpretation.

[61] *Predicted marginal means* are calculated at the average value of all control variables. These values differ from the regression coefficients reported in Table C.1 and C.3, which represent the estimated pass-through for a hypothetical pharmacy with zero income and zero population (marginal effects). By evaluating the model at the sample means, the figure provides a representative estimate for a typical pharmacy within that region.



(a) Aggregation by mode.



(b) Aggregation by area.

Figure 8: Heterogeneity in CPT by degree of urbanization using the aggregation function: Panel (a) mode and by area Panel (b). Note: The points represent predicted marginal means evaluated at the sample average of all control variables (income and demographics). Error bars indicate 95 % confidence intervals. Significance levels relative to Urban: $^{+}p < 0.1, ^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$.

(b) using the area-weighted aggregation, where rural pass-through for OTC drugs remains significantly lower than in urban areas ($p < 0.05$), and non-pharmaceuticals exhibit a similar albeit marginally significant drop ($p < 0.1$). This systematic delay suggests that rural pharmacies, shielded by spatial isolation, face less competitive pressure to adjust prices compared to urban ones.

In the long run (right columns), this inertia dissipates and is replaced by substantial markup expansion. Panel (a) demonstrates that for OTC drugs, rural pass-through rates converge to levels significantly exceeding unity (approximately 1.46). Structurally, however, the order reverses compared to the short run: long-run pass-through is consistently higher for OTC drugs than for non-pharmaceuticals across all regions, indicating that the capacity for an overshifting is greatest for OTC drugs. This pattern is reinforced in Panel (b), which further reveals a statistically significant overshifting for non-pharmaceuticals in rural areas relative to urban ones ($p < 0.001$). This stark contrast – low short-run responsiveness followed by aggressive long-run price increases – indicates that rural incumbents possess sufficient spatial market power to smooth short-term volatility while securing permanently expanded margins on their entire assortment.

Finally, it is important to acknowledge that these effects likely constitute conservative lower bounds of the true structural divergence between rural, intermediate and urban markets, as the degree of urbanization is aggregated from the five-digit to the two-digit postal code level to match the definition of regional markets.

6 Discussion

The preceding empirical analyses indicate that B&M pharmacies exercise pricing power in the OTC and non-pharmaceutical segments. Specifically, the ECM estimates reveal a structural dichotomy in cost pass-through: short-run adjustments exhibit rockets & feathers pricing dynamics, whereas the long-run equilibrium is characterized by systematic cost overshifting. Combined with spatial evidence – where structurally lower transaction volumes in rural markets are offset by higher unit markups – and descriptive data on joint purchasing, these dynamics suggest that pharmacies may leverage the regulated Rx segment to exert pricing power over OTC and non-pharmaceuticals. The remainder of this section contextualizes these findings within the broader theoretical literature.

Beginning with the long run CPT rates ($\approx$ 1-10 months depending on the model, products and pharmacies), the general persistence of overshifting CPT rates indicates that market power in the pharmacy market is not merely transitory but a structural feature of the market. As established by the literature (see e.g., Gabaix et al., 2016; Miravete et al., 2023; Ritz, 2024; Weyl & Fabinger, 2013) such overshifting may be a result of several components such as imperfect competition, log-convexity of demand, the convexity of costs or spatial frictions. Nevertheless, the pervasive finding of overshifting allows to conclude that pharmacies leverage consumer insensitivity to maintain constant percentage markups, effectively amplifying cost shocks to preserve or expand profit margins. Furthermore, the systematic overshifting suggests that competitive pressure in the OTC segment is insufficient to discipline price setting, allowing pharmacies to keep or expand markups beyond the level for non-pharmaceuticals (see next paragraph) and far above a complete pass-through. This contrasts with the interpretation, but not the findings of previous surveys of the German market (Heinsohn & Flessa, 2013). They documented low perceived competitive pressure and argue a lack of price-based strategies. The results presented here highlight that this apparent stability masks a more structural segmentation, where high long-run pass-through may serves as a mechanism for profitability, but price changes are sticky in the short-run.

The analysis further reveals a strategic divergence between OTC drugs and non-pharmaceuticals. While OTC drugs exhibit rockets and feathers in the short-run, non-pharmaceuticals display a reverse asymmetry in the long run, where long-run pass-through rates of cost decreases exceed those of cost increases (see Sections 5.1 and 5.2). This behavior is consistent with a *traffic-builder* strategy; because non-pharmaceuticals face direct external competition from drugstores and supermarkets, pharmacies may be compelled to pass on savings aggressively to defend market share and generate footfall. In contrast, the OTC segment, protected by pharmacy-only dispensing regulations, serves as a profit center. Here, pharmacies exhibit short-run rockets and feathers pricing by swiftly passing on cost increases while delaying price reductions. This asymmetry is likely driven by the urgent nature of acute-care purchases, which inherently depresses consumer search intensity and exacerbates informational frictions – well-established theoretical determinants of asymmetric pass-through (e.g., Tappata, 2009, based on Varian, 1980).

Crucially, pricing power is heterogeneous across products. While bestsellers exhibit lower short-run pass-through rates and symmetric adjustments, their long-run pass-through rates are the highest (see Section 5.3 and Table 5). For instance, the long-run pass-through for cost increases for OTC bestsellers ($\theta^+ \approx 1.67$) exceeds that of niche products ($\theta^+ \approx 1.58$), indicating that pharmacies leverage the high demand for top-selling items to aggressively overshift cost shocks and systematically expand their absolute profit margins. This sustained overshifting could imply that consumers exhibit stronger preferences for leading brands, translating into a more inelastic or log-convex demand curve relative to niche products (see e.g., Gabaix et al., 2016; Ritz, 2024; Weyl & Fabinger, 2013).

In the short run, the empirical findings appear inconsistent with the long-run equilibrium, as pharmacies exhibit greater pricing inertia among bestsellers. However, this makes sense from a behavioral perspective: because prices for top sellers are probably well known and highly visible, pharmacies may be disciplined by the fear of customer anger (Rotemberg, 2005), employing symmetric competitive pricing strategies to signal a favorable price image to consumers (Lal & Matutes, 1994). Consequently, short-run price adjustments remain small. Furthermore, this short-run behavior may also be consistent with *add-on pricing* strategies, where firms keep prices stable on the visible products (bestsellers) but aggressively manage the margins on the products a consumer does not keep track (niche products) (e.g., Ellison, 2005). This mirrors the findings of Granlund and Bergman (2018), who document that original brand-name drugs exhibit significantly higher price stickiness than generics, with only 20% of price adjustments occurring within three months, whereas generics exhibit 70% of the price adjustment in the same window of time. Consistent with the results of this study, this suggests that for bestselling OTC drugs, the reputational cost of frequent price fluctuations may outweigh the benefits from an immediate price adjustment, whereas for niche products, it allows for a more aggressive and asymmetric margin management. Nevertheless, this dynamic reverses in the long run, where bestsellers exhibit the highest pass-through rates. Ultimately, while strategic arguments and behavioral models provide a rationale for this temporal discrepancy between short-run and long-run pass-through rates, definitively isolating the exact mechanisms remains beyond the scope of the current data.

The overall pricing dynamics are underpinned by spatial differentiation and *one-stop shopping* frictions. Since approximately 75 % to 90 % of new prescriptions are filled within 7 days of a physician visit (Franklin et al., 2018; May et al., 2017 as cited in Albrecht et al., 2020, p. 27) and descriptive evidence indicates that nearly 20 % of OTC and non-pharmaceutical volumes are purchased jointly with Rx drugs (see Section 3.3), this gives rise to the argument that the demand for the unregulated assortment could be anchored to the regulated Rx transaction. This idea is motivated by the hypothesis, that consumers, which have already incurred search and travel costs to fulfill a prescription, exhibit inelastic demand for complementary OTC purchases. This would allow pharmacies to leverage a lock-in and joint search effect (which arise when consumers minimize the total transaction costs of the shopping basket (Florez-Acosta & Herrera-Araujo, 2020) and the marginal search cost for a second product become negligible once the consumer is committed to the store (Zhou, 2014)). Whether stemming from ex-ante planning or in-store convenience, this joint purchasing enables the pharmacy to exercise market power in for OTC drugs and non-pharmaceuticals. In a sense, the consumer is effectively *captive* due to the prescription visit (building on the dichotomy of shoppers versus captive consumers, see, e.g., Baye et al., 2006; Ronayne and Taylor, 2022; Tappata, 2009; Varian, 1980), what allows the pharmacy to increase margins on unregulated items, without facing the competitive pressure of a planned or standalone transaction. The absolute primacy of the medical or prescription transaction in driving pharmacy footfall is corroborated by recent evidence from Canada. Hoagland and Wang (2025) demonstrate that when Ontario expanded pharmacists' scope of practice to allow prescribing for minor ailments, foot traffic to pharmacies increased by 16%. This confirms that regulatory authority over prescribing and medical treatment is an important catalyst for store visits, creating the captive audience necessary for OTC cross-selling.

Furthermore, interpreting the analyses through the lens of a lock-in effect highlights that rural pharmacies may exploit this on a broader scope: despite facing 7.6% lower transaction volumes than urban competitors, rural incumbents maintain equivalent profitability by setting OTC markups 8.3% higher. In addition, rural pharmacies overshift wholesale prices more strongly than urban ones, and exhibit more inertia in their short-run pass-through behavior. Combined with the previous described findings, this corroborates that the fixed-price Rx segment may serve as an anchor, allowing geographically more isolated pharmacies to cross-subsidize their operations through higher margins on the unregulated segment. However, it is important to note, that due to the aggregation of five-digit zip-codes to two-digit zip codes, these findings likely understate the true market power of rural incumbents.

Moreover, since rural locations typically benefit from lower land and labor costs compared to urban centers, the observation of equivalent *gross* profitability implies that rural pharmacies may generate superior *net* margins (net of fixed costs). This suggests that the elevated rural markups serve not only as a solvency mechanism but also as a vehicle for extracting rents derived from local market power. This pricing behavior aligns with the structural findings of Schaumans and Verboven (2008), who demonstrate that substantial fixed costs in low-density markets compel pharmacies to rely on high unit margins to ensure firm viability. While their analysis focuses on a regime of regulated pricing, the empirical evidence presented in this paper confirms a functional equivalent in the unregulated segment: rural incumbents, shielded from the profit-eroding effects of competition typical in denser markets, leverage local market power to extract rents (potentially necessary to cover fixed costs and pharmacists remuneration). This competition effect is empirically mirrored in the Swedish pharmacy market, where Granlund and Bergman (2018) find that increasing the number of competitors from one to ten reduces generic prices by 81% in the long run. The absence of such competitive pressure in rural German markets may allow incumbent pharmacies to sustain the high-markup equilibrium required to maintain geographic coverage.

These findings have significant implications for the digitization of the healthcare market. The current financial viability of the rural pharmacy network relies partially on this implicit cross-subsidization. However, the introduction of electronic prescriptions (*E-Rezept*) and the potential liberalization of Rx mail-order bonuses (see Section 2.3) threaten to decouple the Rx transaction from the physical point of sale. Such a decoupling has the potential to systematically favor foreign mail-order and internet pharmacies (see Section 2), thereby eroding the captive footfall required to sustain high-margins on OTC drugs and non-pharmaceutical sales. Consequently, these findings can be interpreted in light of the discussion on the provision of a nationwide dense pharmacy network that is part of public service provision.

To be concrete, the shift towards electronic prescriptions is already well advanced; by early 2025, approximately 90% of all statutory prescriptions were issued digitally.[62] If digitization reduces the necessity of physical visits for prescriptions, the captive footfall that upholds high OTC margins may erode. This shift may represent a fundamental breakdown of the strategic complementarity traditionally observed between medical practitioners and B&M pharmacies. While Schaumans and Verboven (2008) establish that pharmacy and physician presence are mutually reinforcing due to geographic proximity (strategic complements), the E-Rezept effectuates a digital decoupling. By removing the requirement for a physical stop at a nearby pharmacy immediately following a physician visit, digitization dissolves the primary catalyst for the one-stop shopping mechanism, potentially rendering the current rural financing model unsustainable. The severity of this threat is empirically validated by Anderes (2026), who demonstrates that when Swiss pharmacies lost their local Rx monopoly to dispensing physicians, they suffered a substantial drop in Rx revenue and profit decline, driven by a collapse in acute care sales. Reconciling this with the presented findings: without the ability to cross-subsidize via the one-stop shopping mechanism, the OTC and non-pharmaceutical profits sustaining rural pharmacies may collapse, necessitating a reassessment of how rural pharmaceutical access is financed.

The interpretation of these results is subject to constraints imposed by data privacy. First, the absence of detailed consumer-level panel data and the non-disclosure of pharmacy locations preclude the estimation of a structural demand model. However, the analysis leverages high-frequency transaction data that permits the direct measurement of absolute margins and Lerner Indices, in addition facilitating an ECM estimation at the product-pharmacy level. Although this reduced-form approach abstracts from potential intra-firm portfolio pricing strategies, such as cross-subsidizing cost shocks across complementary goods (Bliss, 1988; Chevalier et al., 2003), it cleanly isolates the pass-through dynamics of products and successfully captures key dimensions of pharmacy pricing behavior directly from the observed transaction data. Second, the pseudonymization of pharmacy identifiers necessitates the

[62] See https://www.abda.de/fileadmin/user_upload/assets/ZDF/Jahrbuch-ZDF-2025/ZDF_2025_76_77_Eingeloeste_E_Rezepte.pdf.

aggregation of spatial data to the two-digit postal code level. To the extent that this spatial coarsening introduces measurement error by grouping heterogeneous local markets, standard econometric theory implies attenuation bias, driving the coefficients toward zero (Wooldridge, 2010, Chapter 4.4.2). Therefore, the actual differences in pricing power, cost pass-through and volume contraction experienced by isolated rural pharmacies are likely even more pronounced than the aggregated estimates suggest (Section 5.4). Furthermore, the strategic responses to rival costs (Section 5.1) likely represent conservative lower bounds of the true competitive effects.

7 Conclusion

This study provides granular empirical evidence on the competitive conduct of B&M pharmacies, documenting substantial pricing inertia and asymmetric CPT dynamics. The analysis reveals that the market is characterized by the *rockets and feathers* phenomenon, where pharmacies adjust prices upward significantly faster than downward. This asymmetry is structurally distinct across product segments: non-pharmaceuticals and OTC drugs exhibit adjustment dynamics aligning with a 2-to-1 ratio. Crucially, this aggregate rigidity masks significant heterogeneity within the assortment as best-selling products exhibit higher pass-through inertia in the short-run and the observed overall asymmetries are driven by the long-tail of more niche products. In the long run, however, inertia dissipates, and pass-through rates for OTC drugs and non-pharmaceuticals converge to levels significantly exceeding unity. While pass-through rates for OTC drugs converge to higher levels, effectively permanently expanding absolute margins, the non-pharmaceutical segment exhibits minor reverse asymmetry, with higher-long run pass-through rates for cost decreases. Here, pharmacies pass on savings more aggressively, likely to defend market share, consistent with a traffic-builder' strategy.

A spatial analysis highlights regional differences in transaction volumes and markups. Rural pharmacies exhibit transaction volumes approximately 7.6 % lower than their urban counterparts but compensate for this by setting unit markups on OTC drugs and non-pharmaceuticals roughly 8.3 % higher. This pricing strategy effectively offsets the volume shortfall, generating gross profits that are statistically indistinguishable from high-volume urban locations. This suggests that B&M pharmacies may exercise local market power to neutralize the structural volume disadvantage of rural locations with higher markups. Furthermore, rural pharmacies exhibit more pronounced long-run cost overshifting than their urban counterparts. This market power is likely underpinned by the sector's structural reliance on the Rx segment, where prices are legally fixed. The urgency and necessity of filling prescriptions could incentivize consumers to choose the nearest provider to minimize opportunity costs. Consequently, pharmacies may leverage these Rx visits to extract rents from captive consumers via high-margin cross-selling of OTC drugs and non-pharmaceuticals. Whether driven by acute urgency, complementarity (purchasing OTC drugs alongside prescriptions), or informational frictions, such *one-stop shopping* behavior could create a lock-in effect. This may enable pharmacies to exert significant market power over selling OTC drugs and non-pharmaceuticals.

From a health-policy perspective, these findings imply that the stability of pharmaceutical provision, particularly in rural areas, relies partially on this implicit cross-subsidization mechanism. Despite the secondary role of OTC drugs and non-pharmaceuticals in a pharmacy's overall gross profits, these products constitute a critical financial pillar, effectively financing the infrastructure required for prescription drug provision where Rx volumes alone might be insufficient to cover fixed costs. Consequently, the high degree of cost transmission and markup expansion observed in this sector may not merely be a result of market power, but a structural necessity for maintaining a dense pharmacy network, and thus a part of public service provision.

Looking forward, these dynamics necessitate further investigation at the micro-geographic level to fully verify the relationship between local competitive density and pricing strategies from B&M pharmacies. More critically, future research must monitor the impact of digitization, particularly the introduction of mandatory electronic prescriptions (*E-Rezept*). By reducing the transaction costs associated with forwarding prescriptions to remote providers (e.g., online pharmacies), electronic prescriptions have the potential to erode the transaction volume of Rx-drugs for B&M pharmacies. This, in turn, jeopardizes the revenue stream from OTC drugs and non-pharmaceuticals, as the observed market power in these unregulated segments could be structurally dependent on the footfall generated by Rx-drugs. If this digital decoupling breaks the *one-stop shopping* advantage, the cross-subsidization mechanism may collapse. As recent evidence from Switzerland demonstrates, losing the Rx anchor can disrupt this cross-subsidization mechanism and permanently erodes pharmacy profitability (Anderes, 2026). Consequently, this may force policy makers to reassess how (rural) pharmaceutical access is financed to guarantee an appropriately dense pharmacy network, fulfilling the state's responsibility for adequate public service provision.

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During the preparation of this work the authors used Google's Gemini in order to improve language. After using this service, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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A Empirical Strategy in Levels

A.1 Strategy

This section outlines the baseline level specification, which serves as a structural precursor to the ECM presented in the main text. While the ECM is preferred for handling non-stationarity and asymmetries, estimating the relationship in levels provides a benchmark for the average pass-through and validates the effectiveness of the high-dimensional fixed effects structure. The specification is defined as follows:

$$p_{jf,t} = \alpha_{jf} + \eta_t + \delta_{fm} + \rho w_{jf,t} + \phi p_{jf,\tau} + \beta w_{jf,\tau} + \sigma \bar{w}_{-f,ag,t} + \epsilon_{jf,t}, \quad \text{(A.1)}$$

where p_{jft} and w_{jft} denote the retail and wholesale prices, respectively, of product j (identified by PCN) sold by pharmacy f at calendar day t and calendar month m. The unit of observation is the granular product-pharmacy level (jf, t), which inherently avoids composition biases arising from shifts in product mix. The coefficients ρ and β estimate the contemporaneous and lagged direct pass-through of wholesale costs. To account for irregular transaction records, lagged values are defined relative to the last observed transaction τ. The long-run CPT rate can be recovered as $\theta_{level} = (\rho+\beta)/(1-\phi)$.

The model employs a high-dimensional fixed effects structure to isolate idiosyncratic shocks. α_{jf} (product $\times$ pharmacy fixed effects) absorbs time-invariant characteristics and pharmacy-specific markups; η_t captures common daily market shocks; and δ_{fm} (pharmacy $\times$ month fixed effects) controls for time-varying local demand or labor cost fluctuations. Following standard oligopoly theory (MacKay et al., 2014), the specification controls for strategic interactions using the average competitor wholesale price, $\bar{w}_{-f,ag,t}$, calculated at the chemical substance level within the same two-digit postal code. A positive coefficient σ indicates strategic complementarity (Bulow et al., 1985; Vives, 1990).

Three econometric limitations motivate the use of the ECM in the main text over this level specification. First, including a lagged dependent variable ($p_{jf,t-\tau}$) with fixed effects introduces Nickell bias (Nickell, 1981), though this is mitigated by the large time dimension ($T > 1,600$). Second, and more critically, retail and wholesale prices may exhibit $I(1)$ non-stationarity. While time fixed effects absorb common trends, they cannot fully correct for idiosyncratic stochastic trends, rendering level regressions susceptible to spurious correlation. Thus, these results should be interpreted as average baseline estimates before accounting for cointegration and asymmetry. Third, the ECM with autoregressive distributed lags can handle dynamics, especially, if parts of the data exhibits non-stationarity (see Table E.1).

A.2 Results

Table A.1 presents the baseline estimates. Columns (1)–(5) report results for OTC drugs, and Columns (6)–(10) for non-pharmaceuticals. The specification is saturated sequentially to demonstrate the necessity of granular controls. Columns (1) and (6) include only time fixed effects (η_t); Columns (2) and (7) introduce separate product and pharmacy fixed effects; Columns (3) and (8) add granular product $\times$ pharmacy interactions; and Columns (4) and (9) incorporate the full set of time-varying pharmacy controls. Finally, Columns (5) and (10) – the preferred specifications within this framework – extend the model dynamically by including the lagged dependent variable to capture price persistence.

The results highlight the severity of composition bias in the naive specifications. A model including only time fixed effects (Columns 1 and 6) yields pass-through coefficients exceeding unity (1.337 and 1.339), suggesting price overshifting.[A1] However, this finding can be an artifact of composition bias, whereby high-markup pharmacies systematically stock higher-cost product variants. The estimate declines sharply upon the inclusion of separate product and pharmacy fixed effects (Column (2)) and stabilizes at approximately 0.30 once granular pharmacy $\times$ product interactions are introduced (Columns (3) and (4)). This confirms that the α_{jf} term effectively isolates idiosyncratic cost shocks from unobserved, pharmacy-specific pricing strategies.

In the preferred dynamic specifications (Columns (5) and (10)), still evidence of an incomplete pass-through appears. For OTC drugs, the immediate short-run pass-through (ρ) is 0.147. Due to significant price persistence ($\phi = 0.597$), the implied long-run pass-through is $\theta \approx 0.31$, indicating that pharmacies absorb nearly 70% of a (€1) cost shock even in the long run. Non-pharmaceuticals exhibit higher sensitivity, with a short-run coefficient of 0.290 and a long-run pass-through of approximately 0.50. The coefficient on competitors' wholesale prices (σ) is positive and statistically significant across preferred specifications (0.0061 for OTC), supporting the theoretical prediction of strategic complementarity. For non-pharmaceuticals the effect is not significant. This discrepancy could appear due to measurement precision: OTC-drugs are precisely matched via granular ATC5 codes, whereas the non-pharmaceutical segment contains more heterogeneous products. This measurement error introduces attenuation bias, driving the estimated competitive effect toward zero (Wooldridge, 2010, Chapter 4.4.2).

Comparing these baseline estimates with the asymmetric error correc-

[A1] Simple pooled OLS estimations (see Table A.2, Columns 1 and 4) yield results nearly identical to the time-fixed effects specifications. This composition bias remains evident even when the data are aggregated at coarser unit levels (e.g., by ATC5, brand, or manufacturer) or along coarser temporal dimensions (e.g., quarterly), as detailed in Table A.4.

Dependent Variable:	p_{jft}									
	OTC-drugs					Non-Pharmaceuticals				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ρw_{jft}	1.337***	0.4775***	0.2934***	0.3004***	0.1469***	1.339***	0.6706***	0.4679***	0.4472***	0.2896***
	(0.0102)	(0.0288)	(0.0143)	(0.0145)	(0.0070)	(0.0106)	(0.0431)	(0.0544)	(0.0424)	(0.0203)
Avg. Price of Competitors (σ)	0.0790***	0.0079*	0.0127***	0.0126***	0.0061***	0.0093	0.0039**	0.0087***	0.0088***	0.0047***
	(0.0122)	(0.0037)	(0.0027)	(0.0026)	(0.0012)	(0.0158)	(0.0014)	(0.0015)	(0.0015)	(0.0008)
$\phi p_{jf\tau}$					0.5969***					0.4611***
					(0.0128)					(0.0175)
$\beta w_{jf\tau}$					-0.0217***					-0.0182
					(0.0052)					(0.0120)
Fit statistics										
# Year-Days	1,642	1,642	1,642	1,642	1,641	1,642	1,642	1,642	1,642	1,641
# PCN	–	38,100	–	–	–	–	140,367	–	–	–
# Pharmacy ID	–	6,338	–	–	–	–	6,338	–	–	–
# Pharmacy ID × PCN	–	–	11,083,124	11,083,120	9,025,825	–	–	19,669,497	19,669,489	15,320,263
# Pharmacy ID × Year-Month	–	–	–	341,995	341,959	–	–	–	341,971	341,942
Observations	493,055,951	493,050,598	487,657,495	487,657,458	474,947,837	400,185,218	400,158,602	389,388,666	389,388,604	365,635,572
Adjusted R^2	0.93955	0.97173	0.98636	0.98681	0.99111	0.93790	0.97449	0.98876	0.98972	0.99281
Within Adjusted R^2	0.93944	0.08881	0.03517	0.03648	0.37069	0.93773	0.20491	0.09806	0.09053	0.29538
Fixed Effects (FEs)										
Year-Days FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
PCN FEs		✓					✓			
Pharmacy ID FEs		✓					✓			
Pharmacy ID × PCN FEs			✓	✓	✓			✓	✓	✓
Pharmacy ID × Year-Month FEs				✓	✓				✓	✓

Standard errors (in parenthesis) are clustered on the pharmacy id & PCN.
Differences in the number of observations across models stem from perfect fits and singletons.
Signif. Codes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.1: Baseline estimation results from Equation (A.1): Average pass-through of wholesale costs to retail prices for OTC drugs and non-pharmaceuticals.

tion model (Table 3 in the main text) reveals that the level specification captures a weighted average of the underlying short-run pricing dynamics. For OTC drugs, the baseline short-run coefficient of 0.147 masks significant heterogeneity: the asymmetric model decomposes this average into a rapid response to cost increases ($\rho^+ \approx 0.26$) and a sluggish response to cost decreases ($\rho^- \approx 0.12$). A similar pattern emerges for non-pharmaceuticals, where the baseline estimate of 0.290 falls strictly between the estimated upward ($\rho^+ \approx 0.41$) and downward ($\rho^- \approx 0.23$) adjustment parameters.

However, the disparity is most pronounced regarding the long-run equilibrium. While the baseline model implies substantial incomplete pass-through ($\theta_{level} \approx 0.31$ for OTC-drugs), the error correction framework recovers long-run targets exceeding unity ($\theta^+ \approx 1.53, \theta^- \approx 1.54$). This stark contrast indicates that the level specification suffers from severe attenuation bias due to the non-stationarity of the price series. By failing to explicitly model the cointegrating relationship, the level model conflates short-run adjustment frictions with the long-run equilibrium, erroneously suggesting that pharmacies permanently absorb cost shocks when, in reality, they overshift them. A similar pattern is observed for non-pharmaceuticals, where the long-run pass-through estimate rises from approximately 0.50 in the level model to approximately 1.36—1.40 in the error correction specification.

Overall, while these baseline results establish a robust finding of incomplete pass-through, the high persistence of prices and theoretical concerns regarding non-stationarity suggest that the adjustment process is better modeled within the error correction framework presented in Section 4.1.

Dependent Variable:	p_{jft}					
	OTC-drugs			Non-Pharmaceuticals		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	1.587***			0.7722***		
	(0.0679)			(0.0681)		
ρw_{jft}	1.337***	0.5121***	0.3709***	1.339***	0.6783***	0.4881***
	(0.0102)	(0.0269)	(0.0183)	(0.0106)	(0.0422)	(0.0517)
Avg. Price of Competitors (σ)	0.0790***	0.0137**	0.0221***	0.0101	0.0164***	0.0225***
	(0.0121)	(0.0047)	(0.0046)	(0.0157)	(0.0019)	(0.0021)
Fit statistics						
# PCN	–	38,100	–	–	140,367	–
# Pharmacy ID	–	6,338	–	–	6,338	–
# Pharmacy ID × PCN	–	–	11,083,124	–	–	19,669,497
Observations	493,055,951	493,050,598	487,657,495	400,185,218	400,158,602	389,388,666
Adjusted R^2	0.93942	0.97111	0.98562	0.93781	0.97434	0.98858
Within Adjusted R^2		0.10166	0.05622		0.20915	0.10645
Fixed Effects (FEs)						
PCN FEs		✓			✓	
Pharmacy ID FEs		✓			✓	
Pharmacy ID × PCN FEs			✓			✓

Standard errors (in parenthesis) are clustered on the pharmacy id & PCN.
Differences in the number of observations across models stem from perfect fits and singletons.
Signif. Codes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.2: Stepwise estimation results for Equation (A.1). The table reports the average pass-through of wholesale costs to retail prices for OTC drugs and non-pharmaceuticals, sequentially introducing more granular fixed effects to illustrate the magnitude of composition bias.

Dependent Variable:	p_{jft}					
	OTC-drugs			Non-Pharmaceuticals		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	1.788***			0.8248***		
	(0.0835)			(0.0519)		
ρw_{jft}	1.356***	0.5302***	0.3649***	1.339***	0.6755***	0.4870***
	(0.0132)	(0.0258)	(0.0183)	(0.0094)	(0.0408)	(0.0501)
Fit statistics						
# PCN	–	39,286	–	–	141,633	–
# Pharmacy ID	–	6,338	–	–	6,338	–
# Pharmacy ID × PCN	–	–	11,888,023	–	–	20,139,641
Observations	504,909,293	504,903,956	499,097,510	408,126,138	408,099,278	397,065,954
Adjusted R^2	0.94210	0.97359	0.98722	0.93829	0.97428	0.98867
Within Adjusted R^2		0.11292	0.05343		0.20722	0.10644
Fixed Effects (FEs)						
PCN FEs		✓			✓	
Pharmacy ID FEs		✓			✓	
Pharmacy ID × PCN FEs			✓			✓

Standard errors (in parenthesis) are clustered on the pharmacy id & PCN.
Differences in the number of observations across models stem from perfect fits and singletons.
Signif. Codes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.3: Stepwise estimation results for Equation (A.1) excluding competitor effects. The table reports the average pass-through of wholesale costs to retail prices for OTC drugs and non-pharmaceuticals, sequentially introducing more granular fixed effects to illustrate the magnitude of composition bias.

Dependent Variable:	p_{jft}							
	OTC-drugs				Non-Pharmaceuticals			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ρw_{jft}	1.173***	1.186***	0.5536***	0.3614***	1.293***	1.288***	0.7256***	0.6233***
	(0.0279)	(0.0257)	(0.0287)	(0.0164)	(0.0216)	(0.0195)	(0.0400)	(0.0526)
Avg. Price of Competitors (σ)	-0.0003	0.0186*	0.0005	0.0452***	-0.0117	0.0038	0.0029	0.0388***
	(0.0084)	(0.0088)	(0.0110)	(0.0130)	(0.0080)	(0.0067)	(0.0048)	(0.0074)
Fit statistics								
# ABFM	4,829	–	–	–	10,645	–	–	–
# Year-Quarter	18	18	18	18	18	18	18	18
# Pharmacy ID	6,338	–	6,338	–	6,338	–	6,338	–
# ABFM × Pharmacy ID	–	6,525,189	–	–	–	8,885,314	–	–
# PCN	–	–	38,667	–	–	–	139,021	–
# PCN-Pharmacy ID	–	–	–	10,868,768	–	–	–	18,015,070
Standard-Errors	Pharmacy ID & ATC5		Pharmacy ID & PCN		Pharmacy ID & ATC5		Pharmacy ID & PCN	
Observations	64,397,221	62,071,446	97,267,243	90,487,665	73,991,934	69,720,862	132,387,355	119,198,530
Adjusted R^2	0.97523	0.98890	0.98085	0.99266	0.95809	0.97429	0.97863	0.99257
Within Adjusted R^2	0.91252	0.85921	0.13112	0.06971	0.80091	0.76061	0.25461	0.22207
Fixed Effects (FEs)								
ABFM FEs	✓				✓			
Year-Quarter FEs	✓	✓	✓	✓	✓	✓	✓	✓
Pharmacy ID FEs	✓		✓		✓		✓	
ABFM × Pharmacy ID FEs		✓				✓		
PCN FEs			✓				✓	
PCN-Pharmacy ID FEs				✓				✓

Standard errors (in parenthesis) are clustered on the pharmacy id & ATC5 or PCN.
Differences in the number of observations across models stem from perfect fits and singletons.
Signif. Codes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.4: Sensitivity of pass-through estimates to aggregation levels. This table presents estimation results for Equation (A.1) where the time dimension t is aggregated to the quarterly level across all specifications. For columns (1), (2), (5) and (6) the product dimension j is aggregated at the ATC5, format, brand name, and manufacturer.

B Heterogeneity Analysis

B.1 Pharmacy Size

Since the magnitude of CPT can serve as a proxy for market power, using the estimated CPT from Equation (3) allows to test whether firm size plays a relevant role in long-run pricing outcomes. To formally quantify these systematic differences, pharmacies are stratified into deciles based on their total annual revenue. Total annual revenue is calculated as the aggregate of all revenue sources, including OTC-drugs, Rx-drugs, and non-pharmaceutical products. The derived long-run pass-through targets ($\hat{\theta}^{+}_{fy}$ and $\hat{\theta}^{-}_{fy}$) are subsequently regressed on these decile indicators using the following specification:

$$\hat{\Psi}^{k}_{fy} = \sum_{d=2}^{10} \psi_d \mathbf{1}\{\text{Decile}_{fy} = d\} + \kappa_y + \nu_{fy}, \tag{B.1}$$

where the dependent variable $\hat{\Psi}^{k}_{fy} \in \{\hat{\rho}^{k}_{fy}, \hat{\theta}^{k}_{fy}\}$ represents the structural pricing parameter for pharmacy f in year y corresponding to shock direction $k \in \{+, -\}$. Specifically, the model is estimated separately for the long-run equilibrium targets ($\hat{\theta}^{+}_{fy}, \hat{\theta}^{-}_{fy}$) and by OTC drugs and non-pharmaceuticals. The term $\mathbf{1}\{\text{Decile}_{fy} = d\}$ is an indicator variable equal to 1 if the pharmacy falls into the d-th revenue decile in that year. The summation starts at

$d = 2$ as the first decile serves as the reference category. Consequently, the coefficient ψ_d captures the systematic deviation in pricing power for larger pharmacies relative to the smallest market participants. The term κ_y denotes year fixed effects, absorbing common temporal shifts in the distribution of coefficients, and ν_{fy} is the error term.

Table B.1 reports the results of regressing the pharmacy-specific long-run pass-through estimates ($\hat{\theta}_{fy}$) on revenue decile indicators. The constant term captures the baseline pass-through for the smallest pharmacies (Decile 1) in the reference year (2018).

The results reveal a clear inverse relationship between pharmacy size and pass-through magnitude. For OTC drugs (Columns (3) and (4)), the baseline pass-through for the smallest pharmacies is estimated at 1.474 for cost increases and 1.438 for decreases. In contrast, the coefficients for the upper revenue deciles are consistently negative and statistically significant. The largest pharmacies (Decile 10) exhibit a pass-through rate approximately 0.033 points lower for positive shocks ($p < 0.001$) and 0.038 points lower for negative shocks. This indicates that small pharmacies are the most aggressive in expanding markups, passing on roughly €1.47 of a €1 cost shock in the long run. This systematic difference suggests that scale is associated with differentiated pricing dynamics. While cost overshifting remains a universal feature of the market (with even the largest pharmacies staying well above unity at ≈ 1.44), the statistically distinct reduction for high-revenue pharmacies indicates that they operate with slightly tighter markup constraints.

The year fixed effects reveal distinct reactions to macroeconomic shocks. In the pre-pandemic year of 2019, pricing remained largely comparable to the 2018 baseline, with only minor deviations observed (most notably a slight increase in pass-through for OTC cost decreases, 0.015). The onset of the pandemic in 2020, however, triggered a significant and uniform increase in pass-through rates across all categories (e.g., 0.034 for non-pharmaceutical decreases). Although pharmacies were classified as essential infrastructure and remained open during the national lockdowns,[B1] the market was characterized by severe volatility, supply chain disruptions, and shifting demand patterns. This uniformity dissipated in 2021. While non-pharmaceuticals remained highly sensitive to cost reductions (+0.032), OTC pass-through rates re-anchored to pre-pandemic levels (−0.006 for increases). Finally, while estimates for 2022 suggest a resurgence in sensitivity for non-pharmaceuticals, conclusive interpretation is constrained as the dataset covers only the first half of the year.

Economically, the finding that smaller pharmacies pass on costs more intensely suggests a link to spatial market power. Small-revenue pharmacies

[B1] See, https://www.politikwissenschaft.tu-darmstadt.de/media/politikwissenschaft/ifp_dokumente/arbeitsbereiche_dokumente/oeffentliche_verwaltung__public_policy/forschung_2/corona_projekt/2020_03_16_BLK.pdf.

Dependent Variable:	Long-Run CPT Estimate (+)	Long-Run CPT Estimate (-)	Long-Run CPT Estimate (+)	Long-Run CPT Estimate (-)
	Non-Pharmaceuticals		OTC-drugs	
	(1)	(2)	(3)	(4)
Constant	1.359***	1.366***	1.474***	1.438***
	(0.0038)	(0.0051)	(0.0040)	(0.0066)
Decile = D02	-0.0023	-0.0047	-0.0085*	-0.0177**
	(0.0036)	(0.0049)	(0.0040)	(0.0066)
Decile = D03	-0.0113**	-0.0204***	-0.0164***	-0.0197**
	(0.0039)	(0.0049)	(0.0046)	(0.0072)
Decile = D04	-0.0106**	-0.0149**	-0.0219***	-0.0194**
	(0.0039)	(0.0052)	(0.0046)	(0.0066)
Decile = D05	-0.0027	-0.0091+	-0.0144**	-0.0261***
	(0.0038)	(0.0051)	(0.0048)	(0.0067)
Decile = D06	-0.0085*	-0.0198**	-0.0251***	-0.0277***
	(0.0039)	(0.0058)	(0.0046)	(0.0063)
Decile = D07	-0.0079+	-0.0158**	-0.0243***	-0.0319***
	(0.0040)	(0.0055)	(0.0048)	(0.0072)
Decile = D08	-0.0103*	-0.0173**	-0.0272***	-0.0351***
	(0.0040)	(0.0057)	(0.0041)	(0.0070)
Decile = D09	-0.0058	-0.0220***	-0.0242***	-0.0352***
	(0.0044)	(0.0063)	(0.0052)	(0.0069)
Decile = D10	-0.0079+	-0.0225***	-0.0326***	-0.0378***
	(0.0044)	(0.0056)	(0.0057)	(0.0074)
Year = 2019	0.0033+	0.0018	-0.0021	0.0152***
	(0.0017)	(0.0027)	(0.0022)	(0.0034)
Year = 2020	0.0069***	0.0338***	0.0087***	0.0277***
	(0.0018)	(0.0028)	(0.0022)	(0.0037)
Year = 2021	-0.0083***	0.0321***	-0.0062**	-0.0070+
	(0.0019)	(0.0028)	(0.0022)	(0.0038)
Year = 2022(H1)	0.0138***	0.0442***	-0.0004	0.0277***
	(0.0021)	(0.0033)	(0.0023)	(0.0041)
Fit statistics				
Observations	26,398	26,398	26,317	26,317
Adjusted R^2	0.00533	0.01536	0.00671	0.00836

Standard errors (in parenthesis) are clustered on the two-digit zip code level.
Signif. Codes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.1: Estimation results from Equation (B.1): Variation in long-run pass-through rates ($\hat{\theta}^{+}_{fy}$ and $\hat{\theta}^{-}_{fy}$) by pharmacy revenue decile.

are frequently located in rural or less densely populated areas, where geographical isolation grants them a degree of local market power. This position likely enables them to overshift cost shocks to captive consumers who face high search and travel costs. Conversely, high-revenue pharmacies are typically situated in competitive urban centers where rival pressure constrains their ability to expand markups, forcing them to absorb a marginally larger share of cost fluctuations. The extent to which these pricing dynamics are explicitly driven by local socio-demographic factors is formally examined in the Section 5.4.

B.2 Pass-Through Dynamics

To quantify how this parameter heterogeneity translates into dynamic pricing outcomes, Figure B.1 visualizes the distribution of CIRFs. The colored lines represent the median adjustment path, while the shaded regions (interquartile range (25th–75th), 10th–90th and 2.5th–97.5th percentiles) capture the spread of responses across the market.

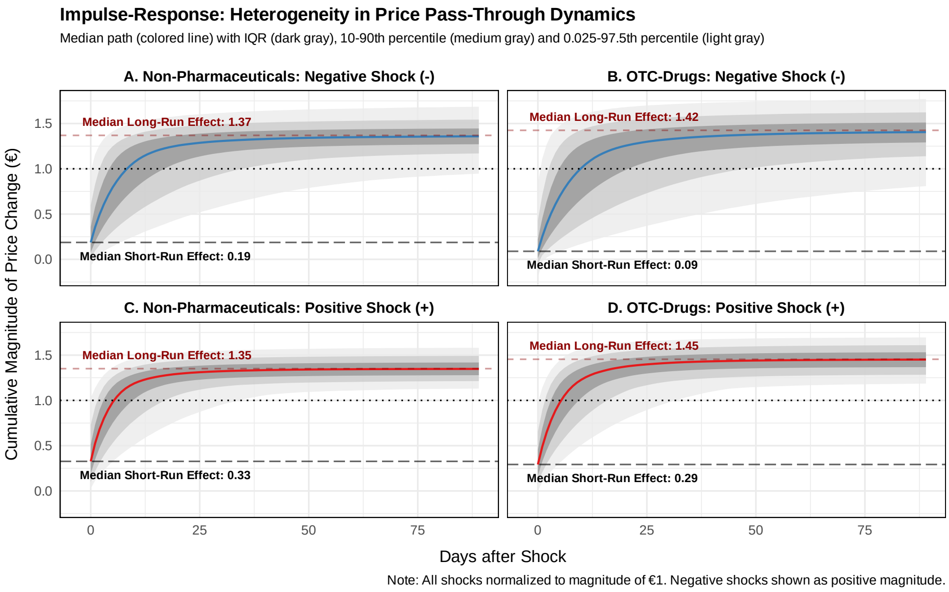

Figure B.1: Heterogeneity in Dynamic Adjustment Paths. The figure plots the median cumulative impulse response (colored line) along with the interquartile range (dark gray), 10th–90th percentile range (medium gray), and 2.5th–97.5th percentile range (light gray). Panels illustrate the dispersion in adjustment dynamics for negative and positive shocks across product segments.

The results exhibit large dispersion in adjustment dynamics, particularly for OTC cost decreases (Panel B). While the median short-run effect is €0.09, the lower tail of the distribution reveals severe rigidity. The bottom 10th percentile shows negligible price adjustments for the first week, and the most rigid 2.5 % of pharmacies do not pass on any portion of the cost saving for nearly two weeks following the shock. Conversely, for cost increases (Panel D), the entire distribution shifts upward; even the least responsive pharmacies (bottom 10th percentile) implement price increases almost immediately. Furthermore, the widening confidence bands in the long run highlights the diversity in equilibrium strategies. While the median long-run pass-through converges to approximately 1.45, the upper 90th and 97.5th percentile bands extend significantly higher. This suggests that a subset of pharmacies overshifts cost shocks well beyond the average.

Finally, comparing the paths across segments reveals differences in pricing asymmetry. For OTC drugs, the rockets and feathers effect is strictly a short-run phenomenon driven by extreme stickiness: the median short-run response to a cost increase (€0.29) is more than three times larger than for a decrease (€0.09). However, this asymmetry vanishes after approximately one month in the long run (approx. €1.45 vs. €1.42). In the non-pharmaceutical segment, the short-run asymmetry is less pronounced as increases (€0.33) outpace decreases (€0.19). Uniquely, this segment exhibits a long-run inversion: the cumulative pass-through for cost decreases (€1.37) slightly exceeds that of cost increase (€1.35).

C Socio-Demographic Analysis

Table C.1 examines whether the structural differences in market power identified above translate into differential CPT behavior. The estimated short-run and long-run CPT coefficients from Table 7 are regressed via Equation (4) on the set of regional and socio-demographic variables to test for inertia, asymmetry and differences in magnitudes.

The results reveal that rural markets exhibit pricing inertia, particularly for OTC drugs. In the short run (Columns (1) and (2)), the interaction terms for OTC drugs in rural areas are consistently negative for both cost increases (-0.0178) and decreases (-0.0205). This indicates that rural pharmacies are generally slower to adjust prices in response to immediate shocks compared to their urban counterparts, consistent with lower competitive pressure necessitating less frequent price adjustments.

However, the long-run estimates (Columns (3) and (4)) uncover an asymmetry regarding cost savings. For the baseline non-pharmaceutical category, rural markets are more responsive to cost reductions (0.0218) than they are to cost increases (0.0137). However, this finding vanishes for OTC drugs: the negative interaction term (-0.0278) fully offsets the rural baseline, indicating that rural pharmacies do not pass on OTC cost savings, and the effect is the same for positive pass-through rates from OTC drugs and non-pharmaceuticals (0.0137). In contrast, for cost increases, the interaction is statistically insignificant; consequently, rural pharmacies exhibit a uniform pass-through rate of 0.0137 across both product types.

Dependent Variable:	Negative CPT	Positive CPT	Negative CPT	Positive CPT
	Short-Run		Long-Run	
	(1)	(2)	(3)	(4)
Constant	0.1213	0.4946***	1.252***	1.391***
	(0.1435)	(0.1377)	(0.1526)	(0.1191)
Intermediate	-0.0018	-0.0109	0.0089	0.0082
	(0.0086)	(0.0100)	(0.0084)	(0.0063)
Rural	-0.0040	-0.0054	0.0218**	0.0137*
	(0.0081)	(0.0101)	(0.0081)	(0.0063)
Intermediate × OTC drugs	-0.0074	0.0042	-0.0011	0.0031
	(0.0068)	(0.0092)	(0.0067)	(0.0055)
Rural × OTC drugs	-0.0173**	-0.0205*	-0.0278***	-0.0051
	(0.0061)	(0.0093)	(0.0067)	(0.0048)
OTC drugs	-0.0909***	-0.0301***	0.0654***	0.1013***
	(0.0040)	(0.0066)	(0.0055)	(0.0039)
year = 2019	0.0150***	0.0372***	0.0062*	-0.0003
	(0.0034)	(0.0034)	(0.0027)	(0.0021)
year = 2020	0.0203***	0.1101***	0.0310***	0.0081***
	(0.0026)	(0.0029)	(0.0025)	(0.0017)
year = 2021	0.0345***	0.1450***	0.0116***	-0.0076**
	(0.0037)	(0.0043)	(0.0033)	(0.0028)
year = 2022(H1)	0.0469***	0.1405***	0.0343***	0.0061+
	(0.0044)	(0.0045)	(0.0036)	(0.0032)
Income per Person (in 10T)	-0.0357**	-0.0275*	0.0270*	0.0225*
	(0.0111)	(0.0126)	(0.0121)	(0.0089)
Fraction of Population ≥ 65	0.0020	0.0016	-0.0040**	-0.0024
	(0.0013)	(0.0016)	(0.0015)	(0.0015)
Fraction of Population < 18	0.0014	-0.0051*	-0.0002	-0.0033
	(0.0028)	(0.0025)	(0.0026)	(0.0024)
Fraction of 1-Person-Households	0.0006	-0.0019+	0.0012	0.0002
	(0.0012)	(0.0011)	(0.0011)	(0.0009)
Fraction of 2-Person-Households	0.0026	-0.0005	0.0021	-9.42×10^{-5}
	(0.0023)	(0.0024)	(0.0024)	(0.0019)
Fit statistics				
Observations	57,245	57,380	57,245	57,380
Adjusted R^2	0.06984	0.07815	0.03170	0.16380

Standard errors (in parenthesis) are clustered on the two-digit zip code.
Signif. Codes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C.1: Estimation results from Equation (4): Determinants of CPT. *Note:* Outcome variables include short-run positive (ρ^+_{fy}) and negative (ρ^-_{fy}) pass-through coefficients, and the long-run pass-through rate (θ^-_{fy} and θ^+_{fy}). The degree of urbanization is aggregated using the mode method. For results using area-weighted aggregation, see Table C.3.

These results reveal a distinct pricing strategy in rural areas depending on the product type. For non-pharmaceuticals, rural pharmacies actually pass on cost savings more aggressively than the urban baseline. However, this pattern reverses for OTC drugs. Instead of passing on these savings, rural pharmacies retain a larger share of the cost reduction. By shielding OTC drug margins in this way, they might compensate for lower transaction volumes.

Dependent Variable:	log(Wholesale Price)	log(Consumer Price)	log(Markup)	Lerner Index	log(Sales)	log(Gross Profits)
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	2.941***	3.184***	1.834***	0.2379***	5.485***	7.319***
	(0.2016)	(0.2050)	(0.3142)	(0.0641)	(0.8169)	(0.8656)
Intermediate	-0.0243*	-0.0168	-0.0035	0.0046	0.0216	0.0181
	(0.0113)	(0.0103)	(0.0135)	(0.0028)	(0.0366)	(0.0390)
Rural	-0.0295*	-0.0068	0.0378*	0.0147***	0.0753	0.1130*
	(0.0125)	(0.0125)	(0.0181)	(0.0035)	(0.0501)	(0.0557)
Intermediate × OTC drugs	0.0366*	0.0382*	0.0419*	0.0013	-0.0046	0.0373
	(0.0163)	(0.0168)	(0.0181)	(0.0019)	(0.0323)	(0.0251)
Rural × OTC drugs	0.0595***	0.0570**	0.0460*	-0.0023	-0.0749*	-0.0289
	(0.0169)	(0.0174)	(0.0194)	(0.0024)	(0.0356)	(0.0321)
OTC drugs	-0.2571***	-0.0833***	0.2058***	0.1072***	0.3286***	0.5344***
	(0.0143)	(0.0150)	(0.0161)	(0.0014)	(0.0284)	(0.0219)
year = 2019	0.0212***	0.0269***	0.0383***	0.0037***	-0.0436***	-0.0053
	(0.0031)	(0.0028)	(0.0039)	(0.0009)	(0.0117)	(0.0120)
year = 2020	0.0425***	0.0564***	0.0834***	0.0090***	-0.1354***	-0.0520***
	(0.0028)	(0.0023)	(0.0028)	(0.0007)	(0.0077)	(0.0080)
year = 2021	0.0552***	0.0642***	0.0806***	0.0057***	-0.0817***	-0.0011
	(0.0042)	(0.0035)	(0.0050)	(0.0013)	(0.0155)	(0.0162)
year = 2022(H1)	0.0178***	0.0312***	0.0544***	0.0083***	-0.7621***	-0.7077***
	(0.0052)	(0.0041)	(0.0060)	(0.0017)	(0.0192)	(0.0205)
Income per Person (in 10T)	0.1742***	0.1831***	0.2014***	0.0061	0.1691*	0.3705***
	(0.0131)	(0.0117)	(0.0201)	(0.0051)	(0.0666)	(0.0706)
Fraction of Population ≥ 65	0.0048*	0.0030	-0.0001	-0.0011	-0.0188+	-0.0189+
	(0.0021)	(0.0020)	(0.0032)	(0.0007)	(0.0097)	(0.0101)
Fraction of Population < 18	-0.0156***	-0.0154***	-0.0156*	2.14×10^{-5}	0.0842***	0.0686***
	(0.0043)	(0.0044)	(0.0067)	(0.0013)	(0.0186)	(0.0191)
Fraction of 1-Person-Households	-0.0146***	-0.0126***	-0.0097***	0.0011*	0.0340***	0.0244***
	(0.0016)	(0.0016)	(0.0023)	(0.0005)	(0.0061)	(0.0064)
Fraction of 2-Person-Households	-0.0260***	-0.0241***	-0.0217***	0.0011	0.0401**	0.0184
	(0.0029)	(0.0030)	(0.0044)	(0.0009)	(0.0128)	(0.0130)
Fit statistics						
Observations	63,380	63,380	63,380	63,380	63,380	63,380
Adjusted R^2	0.51105	0.27980	0.35351	0.60877	0.21835	0.26893

Standard errors (in parenthesis) are clustered on the two-digit zip code.
Signif. Codes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C.2: Estimation results from Equation (4) for the outcome variables: wholesale and retail prices, markups, Lerner Indices, sales and gross profits. *Note:* The degree of urbanization is aggregated by area-weights

Dependent Variable:	Negative CPT	Positive CPT	Negative CPT	Positive CPT
	Short-Run		Long-Run	
	(1)	(2)	(3)	(4)
Constant	0.2212	0.6181***	1.091***	1.276***
	(0.1466)	(0.1587)	(0.1635)	(0.1196)
Intermediate	-0.0021	-0.0102	0.0180*	0.0094+
	(0.0078)	(0.0085)	(0.0072)	(0.0052)
Rural	-0.0126	-0.0189+	0.0347***	0.0268***
	(0.0097)	(0.0111)	(0.0093)	(0.0068)
Intermediate × OTC drugs	-0.0143*	-0.0084	-0.0081	0.0035
	(0.0057)	(0.0085)	(0.0072)	(0.0045)
Rural × OTC drugs	-0.0117	-0.0039	-0.0226**	-0.0120*
	(0.0076)	(0.0122)	(0.0080)	(0.0055)
OTC drugs	-0.0917***	-0.0332***	0.0596***	0.0996***
	(0.0035)	(0.0058)	(0.0062)	(0.0037)
year = 2019	0.0157***	0.0380***	0.0051+	-0.0011
	(0.0034)	(0.0034)	(0.0027)	(0.0021)
year = 2020	0.0206***	0.1105***	0.0307***	0.0078***
	(0.0027)	(0.0029)	(0.0025)	(0.0017)
year = 2021	0.0350***	0.1457***	0.0113***	-0.0080**
	(0.0038)	(0.0042)	(0.0032)	(0.0027)
year = 2022(H1)	0.0475***	0.1413***	0.0338***	0.0055+
	(0.0046)	(0.0044)	(0.0035)	(0.0030)
Income per Person (in 10T)	-0.0359**	-0.0277*	0.0268*	0.0225*
	(0.0113)	(0.0125)	(0.0110)	(0.0086)
Fraction of Population ≥ 65	0.0019	0.0016	-0.0048**	-0.0027+
	(0.0013)	(0.0016)	(0.0014)	(0.0014)
Fraction of Population < 18	-0.0002	-0.0072*	0.0028	-0.0011
	(0.0032)	(0.0030)	(0.0026)	(0.0023)
Fraction of 1-Person-Households	-0.0002	-0.0030*	0.0027*	0.0012
	(0.0012)	(0.0013)	(0.0013)	(0.0009)
Fraction of 2-Person-Households	0.0016	-0.0017	0.0040	0.0013
	(0.0020)	(0.0025)	(0.0025)	(0.0019)
Fit statistics				
Observations	57,245	57,380	57,245	57,380
Adjusted R^2	0.06981	0.07758	0.03135	0.16475

Standard errors (in parenthesis) are clustered on the two-digit zip code.
Signif. Codes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C.3: Estimation results from Equation (4): Determinants of CPT. *Note:* Outcome variables include short-run positive (ρ^+_{fy}) and negative (ρ^-_{fy}) pass-through coefficients, and the long-run pass-through rate ($\theta^+_{fy}-$ and θ^+_{fy}). The degree of urbanization is aggregated by area-weights.

D Additional Descriptive Statistics

This appendix complements the empirical analysis by providing granular descriptive evidence on market structure (e.g., Figure D.1) and data composition. It details the classification of therapeutic categories (ATC mappings, Table D.1) and reports the aggregate distribution of sales volume and revenue across these segments (Tables D.2 and D.3). Furthermore, it presents supplementary visualizations of pharmacy profitability, transaction patterns (including bundle purchases), and the spatial distribution of urbanization used to define local markets (Table D.4 and Figures D.2 to D.9).

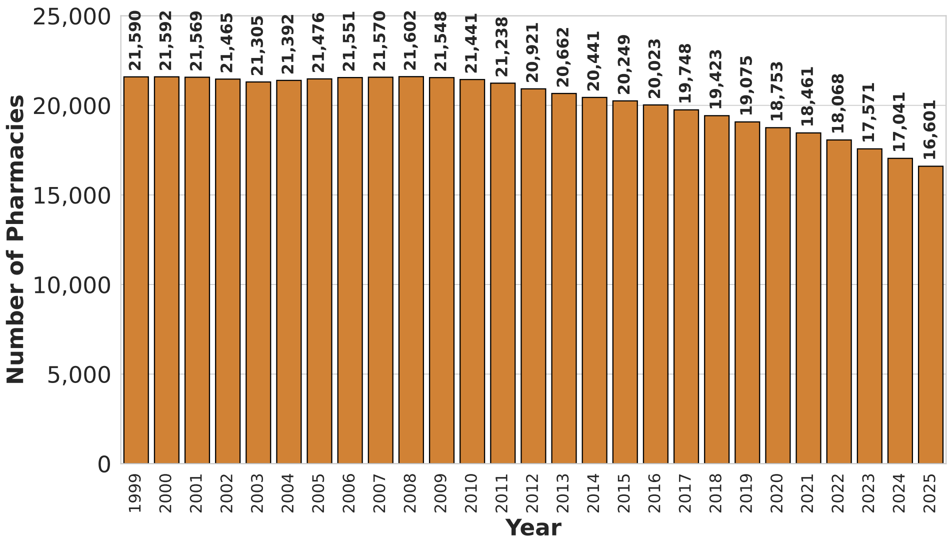

Figure D.1: Evolution of the number of pharmacies in Germany from 1999 to 2025. Sources: ABDA (2024) and Statista (2024b) and https://www.abda.de/aktuelles-und-presse/pressemitteilungen/detail/2025-apothekenzahl-sinkt-auf-16601-betriebsstaetten/.

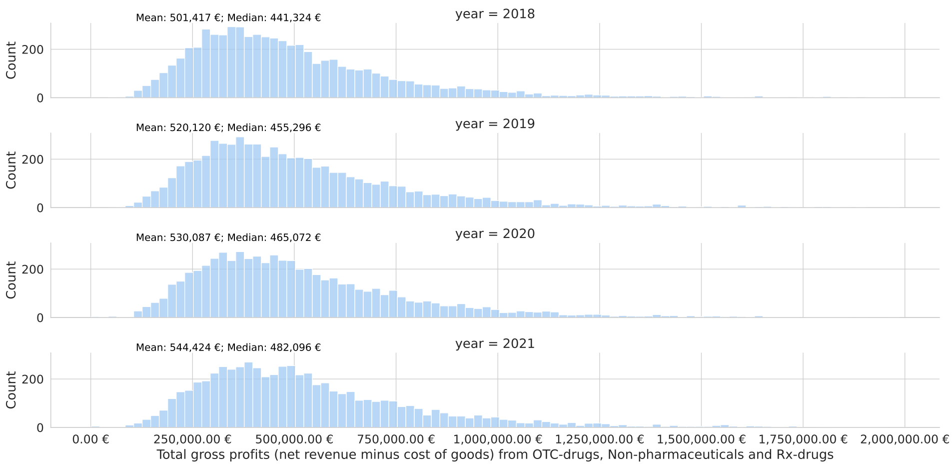

Figure D.2: Distribution of total pharmacy remuneration (gross profit). Note: The distribution represents the aggregated gross profit across all segments.

Therapeutic System Category	**ATC2 Codes**
Alimentary Tract and Metabolism	A01—A10, A13—A16
Vitamins and Minerals	A11, A12
Cardiovascular and Blood System	B01—B06, C01—C10
Dermatological Preparations	D01—D11
Genito-Urinary System and Sex Hormones	G01—G04
Systemic Hormonal Preparations	H01—H05
Hospital Solutions	K01, K04, K05, K07
Antineoplastics and Immunomodulating Agents	L01—L04
Musculoskeletal System and Pain Management	M01—M05, M09, N02
Nervous System	N01, N03—N07
Antiparasitics, Insecticides and Repellents	P01—P03
Respiratory System	R01—R07
Sensory Organs	S01—S03
Diagnostic Agents	T02, T03, V04, V08, V09
Other Therapeutic Products	V03
Antiseptics for Non-Human Use	V05
General and Nutritional Products	V06
Other Non-Therapeutic Products	V07
Therapeutic Radiopharmaceuticals	V10
Surgical Products	V20
Homeopathic and Anthroposophic Preparations	V60

Table D.1: Mapping of ATC2 codes to broad therapeutic system categories used in the analysis.

Product Type	Drug Market	Sales in Packages in Mio.	Fraction of Sales Within in %	Overall in %
OTC-drugs	Alimentary Tract and Metabolism	98.763	14.231	8.203
	Antineoplastics and Immmunomodulating Agents	1.149	0.166	0.095
	Antiparasitics, Insecticides and Repellents	1.032	0.149	0.086
	Cardiovascular and Blood System	29.500	4.251	2.450
	Dermatological Preparations	71.661	10.325	5.952
	Diagnostic Agents	0.092	0.013	0.008
	General and Nutritional Products	0.138	0.020	0.011
	Genito-Urinary System and Sex Hormones	14.394	2.074	1.196
	Homeopathic and Anthroposophic Preparations	21.954	3.163	1.823
	Hospital Solutions	0.080	0.012	0.007
	Musculoskeletal System and Pain Management	161.476	23.267	13.412
	Nervous System	23.587	3.399	1.959
	No ATC Code	1.264	0.182	0.105
	Other Non-Therapeutic Products	1.948	0.281	0.162
	Other Therapeutic Products	0.126	0.018	0.010
	Respiratory System	224.386	32.331	18.637
	Sensory Organs	23.487	3.384	1.951
	Systemic Hormonal Preparations	1.602	0.231	0.133
	Vitamins and Minerals	17.385	2.505	1.444
Non-pharmaceuticals	Alimentary Tract and Metabolism	21.111	4.140	1.753
	Antineoplastics and Immmunomodulating Agents	0.003	0.001	0.000
	Antiparasitics, Insecticides and Repellents	1.131	0.222	0.094
	Antiseptics for Non-Human Use	0.126	0.025	0.010
	Cardiovascular and Blood System	5.462	1.071	0.454
	Dermatological Preparations	30.328	5.947	2.519
	Diagnostic Agents	7.055	1.383	0.586
	General and Nutritional Products	27.334	5.360	2.270
	Genito-Urinary System and Sex Hormones	7.527	1.476	0.625
	Homeopathic and Anthroposophic Preparations	0.013	0.003	0.001
	Hospital Solutions	0.004	0.001	0.000
	Musculoskeletal System and Pain Management	6.846	1.342	0.569
	Nervous System	5.359	1.051	0.445
	No ATC Code	304.387	59.689	25.282
	Other Non-Therapeutic Products	33.292	6.528	2.765
	Other Therapeutic Products	0.781	0.153	0.065
	Respiratory System	35.812	7.023	2.974
	Sensory Organs	21.767	4.268	1.808
	Surgical Products	0.020	0.004	0.002
	Systemic Hormonal Preparations	0.000	0.000	0.000
	Vitamins and Minerals	1.599	0.314	0.133

Table D.2: Aggregate market composition by therapeutic category. The table reports the total accumulated sales volume (in millions of packages) for each mapped category (see Table D.1) over the full sample period (2018–2021). The rightmost columns display the relative market share of each category within the total unregulated market.

Product Type	Drug Market	Revenue in Euro in Mio.	Fraction of Revenue Within in %	Overall in %
OTC-drugs	Alimentary Tract and Metabolism	848.991	15.516	8.536
	Antineoplastics and Immmunomodulating Agents	18.581	0.340	0.187
	Antiparasitics, Insecticides and Repellents	18.599	0.340	0.187
	Cardiovascular and Blood System	230.665	4.215	2.319
	Dermatological Preparations	621.685	11.362	6.250
	Diagnostic Agents	4.811	0.088	0.048
	General and Nutritional Products	4.976	0.091	0.050
	Genito-Urinary System and Sex Hormones	206.323	3.771	2.074
	Homeopathic and Anthroposophic Preparations	207.271	3.788	2.084
	Hospital Solutions	0.367	0.007	0.004
	Musculoskeletal System and Pain Management	1,049.568	19.181	10.552
	Nervous System	388.029	7.091	3.901
	No ATC Code	27.603	0.504	0.278
	Other Non-Therapeutic Products	12.181	0.223	0.122
	Other Therapeutic Products	1.939	0.035	0.019
	Respiratory System	1,467.562	26.820	14.755
	Sensory Organs	163.641	2.991	1.645
	Systemic Hormonal Preparations	9.367	0.171	0.094
	Vitamins and Minerals	189.672	3.466	1.907
Non-pharmaceuticals	Alimentary Tract and Metabolism	187.946	4.200	1.890
	Antineoplastics and Immmunomodulating Agents	0.031	0.001	0.000
	Antiparasitics, Insecticides and Repellents	16.294	0.364	0.164
	Antiseptics for Non-Human Use	1.191	0.027	0.012
	Cardiovascular and Blood System	93.464	2.089	0.940
	Dermatological Preparations	204.164	4.563	2.053
	Diagnostic Agents	102.192	2.284	1.027
	General and Nutritional Products	518.248	11.582	5.210
	Genito-Urinary System and Sex Hormones	79.632	1.780	0.801
	Homeopathic and Anthroposophic Preparations	0.082	0.002	0.001
	Hospital Solutions	0.092	0.002	0.001
	Musculoskeletal System and Pain Management	58.893	1.316	0.592
	Nervous System	47.147	1.054	0.474
	No ATC Code	2,383.972	53.279	23.968
	Other Non-Therapeutic Products	301.650	6.742	3.033
	Other Therapeutic Products	6.038	0.135	0.061
	Respiratory System	214.450	4.793	2.156
	Sensory Organs	243.438	5.441	2.448
	Surgical Products	1.189	0.027	0.012
	Systemic Hormonal Preparations	0.002	0.000	0.000
	Vitamins and Minerals	14.383	0.321	0.145

Table D.3: Aggregate market composition by therapeutic category. The table reports the total accumulated revenue (in millions of Euro) for each mapped category (see Table D.1) over the full sample period (2018–2021). The rightmost columns display the relative market share of each category within the total unregulated market.

	Sales Rx-drugs			Sales OTC-drugs & Non-pharmaceuticals			Total Sales		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
year									
2018	47,081.03	42,081	23,911.47	46,888.10	37,397	36,070.82	93,969.13	81,827	53,370.04
2019	47,948.88	42,730	24,534.82	46,347.30	36,841	35,711.38	94,296.17	81,893	53,438.76
2020	47,065.53	42,149	23,846.30	43,791.96	36,029	30,430.21	90,857.49	80,354	48,433.17
2021	48,150.86	43,401	24,025.71	43,702.82	36,067	30,201.34	91,853.68	81,806	48,562.57

(a) Rx- vs. OTC-drug & non-pharmaceutical sales

	Revenue Rx-drugs			Revenue OTC-drugs & Non-pharmaceuticals			Total Revenue		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
year									
2018	2,641,471.18 €	2,268,976 €	1,670,603.45 €	430,733.16 €	338,304 €	349,899.24 €	3,072,204.34 €	2,657,181 €	1,850,619.18 €
2019	2,817,688.19 €	2,397,699 €	1,810,110.22 €	436,725.19 €	340,879 €	357,250.92 €	3,254,413.38 €	2,794,304 €	1,989,201.52 €
2020	2,958,589.17 €	2,508,114 €	2,041,277.60 €	426,310.39 €	343,027 €	318,571.84 €	3,384,899.57 €	2,893,897 €	2,192,510.82 €
2021	3,253,794.31 €	2,763,038 €	2,425,588.67 €	438,685.79 €	354,983 €	331,880.57 €	3,692,480.10 €	3,156,138 €	2,572,515.15 €

(b) Rx- vs. OTC-drug & non-pharmaceutical revenue

	Gross Profits Rx-drugs			Gross Profits OTC-drugs & Non-pharmaceuticals			Total Gross Profits		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
year									
2018	368,935.48 €	325,200 €	199,211.51 €	132,481.31 €	103,848 €	108,223.74 €	501,416.79 €	441,324 €	270,792.97 €
2019	384,114.85 €	336,351 €	212,572.20 €	136,005.15 €	106,204 €	111,277.58 €	520,120.00 €	455,296 €	284,697.91 €
2020	394,646.85 €	344,672 €	302,601.62 €	135,439.84 €	108,950 €	114,994.23 €	530,086.68 €	465,072 €	356,220.90 €
2021	407,800.05 €	360,392 €	251,196.59 €	136,624.16 €	109,703 €	135,778.06 €	544,424.21 €	482,096 €	324,405.50 €

(c) Rx- vs. OTC-drug & non-pharmaceutical gross profits

	Fraction OTC-drug & Non-pharmaceutical								
	Sales to Total Sales			Revenue to Total Revenue			Gross Profits to Total Gross Profits		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
year									
2018	47.94 %	46.60 %	10.62 %	14.52 %	12.83 %	7.62 %	25.75 %	23.83 %	10.25 %
2019	47.24 %	45.93 %	10.64 %	13.98 %	12.32 %	7.53 %	25.55 %	23.65 %	10.25 %
2020	46.85 %	45.59 %	10.33 %	13.42 %	11.98 %	7.12 %	25.53 %	23.87 %	9.88 %
2021	46.20 %	44.91 %	10.03 %	12.65 %	11.30 %	6.70 %	24.74 %	22.98 %	9.57 %

(d) Fraction of OTC drug & non-pharmaceutical sales, revenues and gross profits compared to their total values (including Rx drugs), respectively.

Table D.4: Descriptive statistics for the evolution of sales, revenue and gross profits per year.

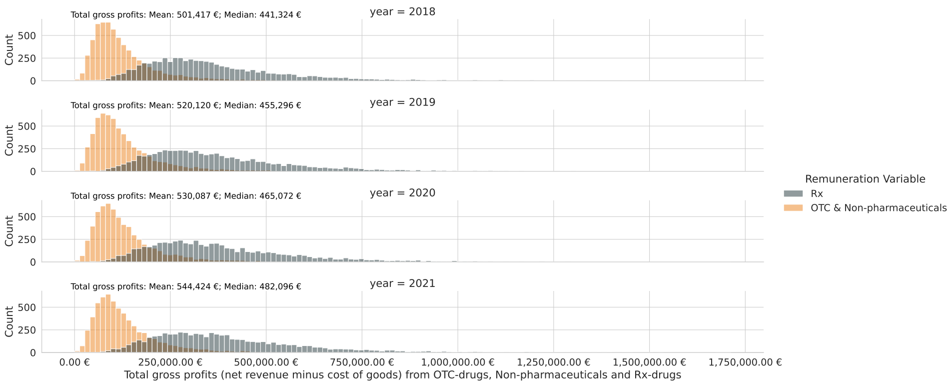

Figure D.3: Distribution of total gross profits by Rx drugs, OTC drugs and non-pharmaceuticals.

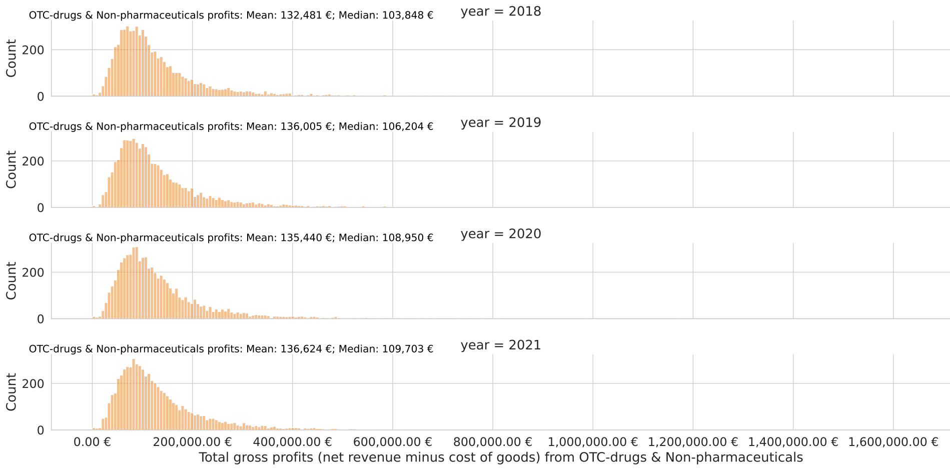

Figure D.4: Distribution of gross profits from OTC drug and non-pharmaceuticals.

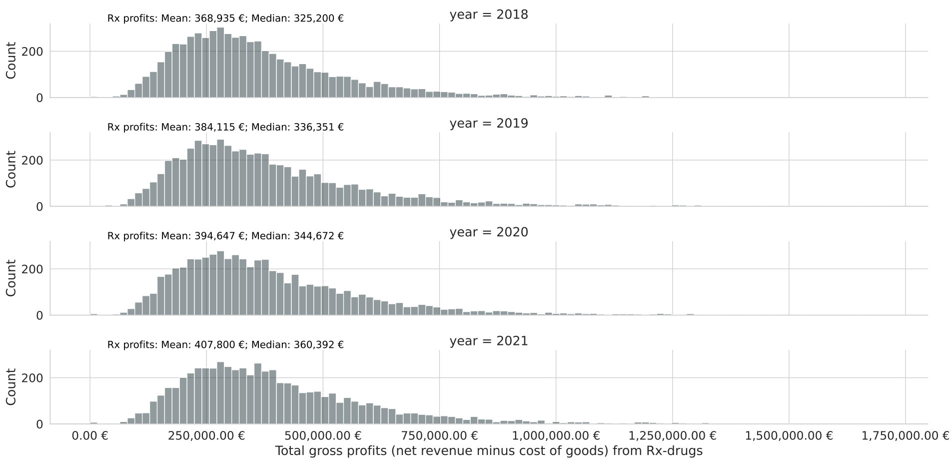

Figure D.5: Distribution of gross profits fromRx drugs.

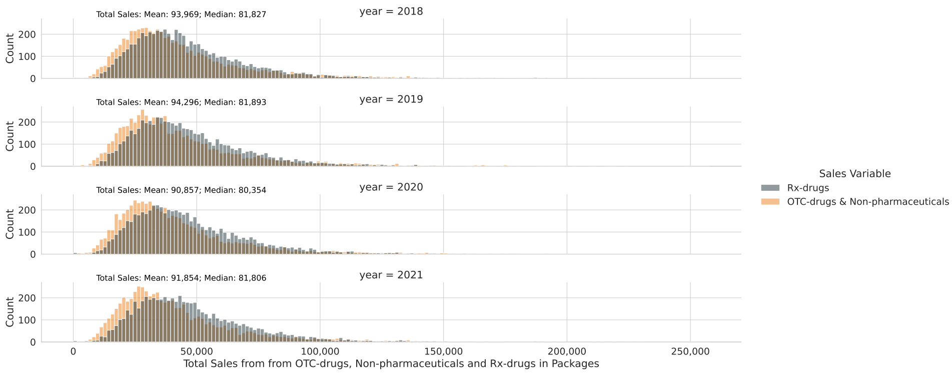

Figure D.6: Distribution of total pharmacy sales by Rx drugs, OTC drugs and non-pharmaceuticals.

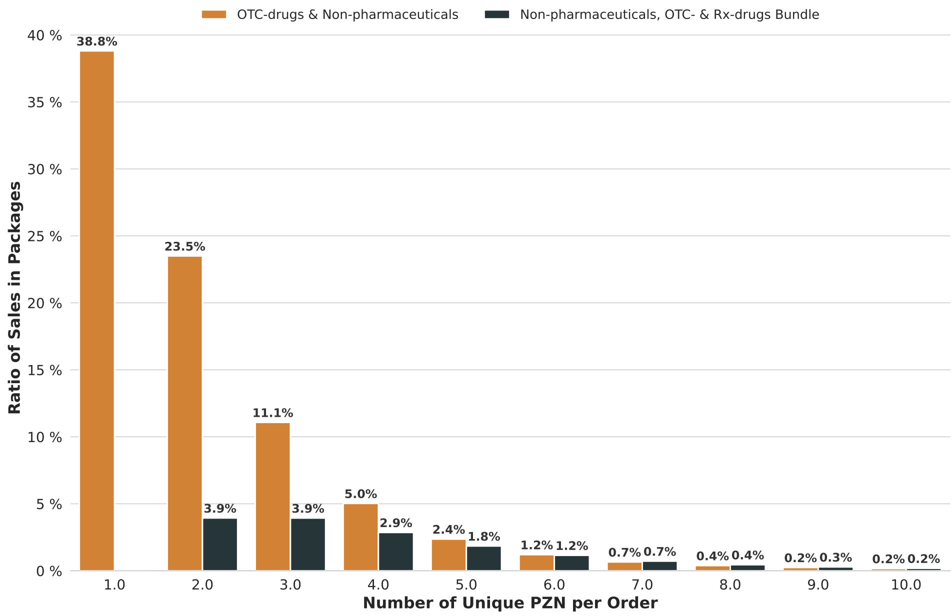

Figure D.7: Sales ratio according to order size and bundle type, focusing on sales containing at least one unique PCN of OTC drugs or non-pharmaceuticals.

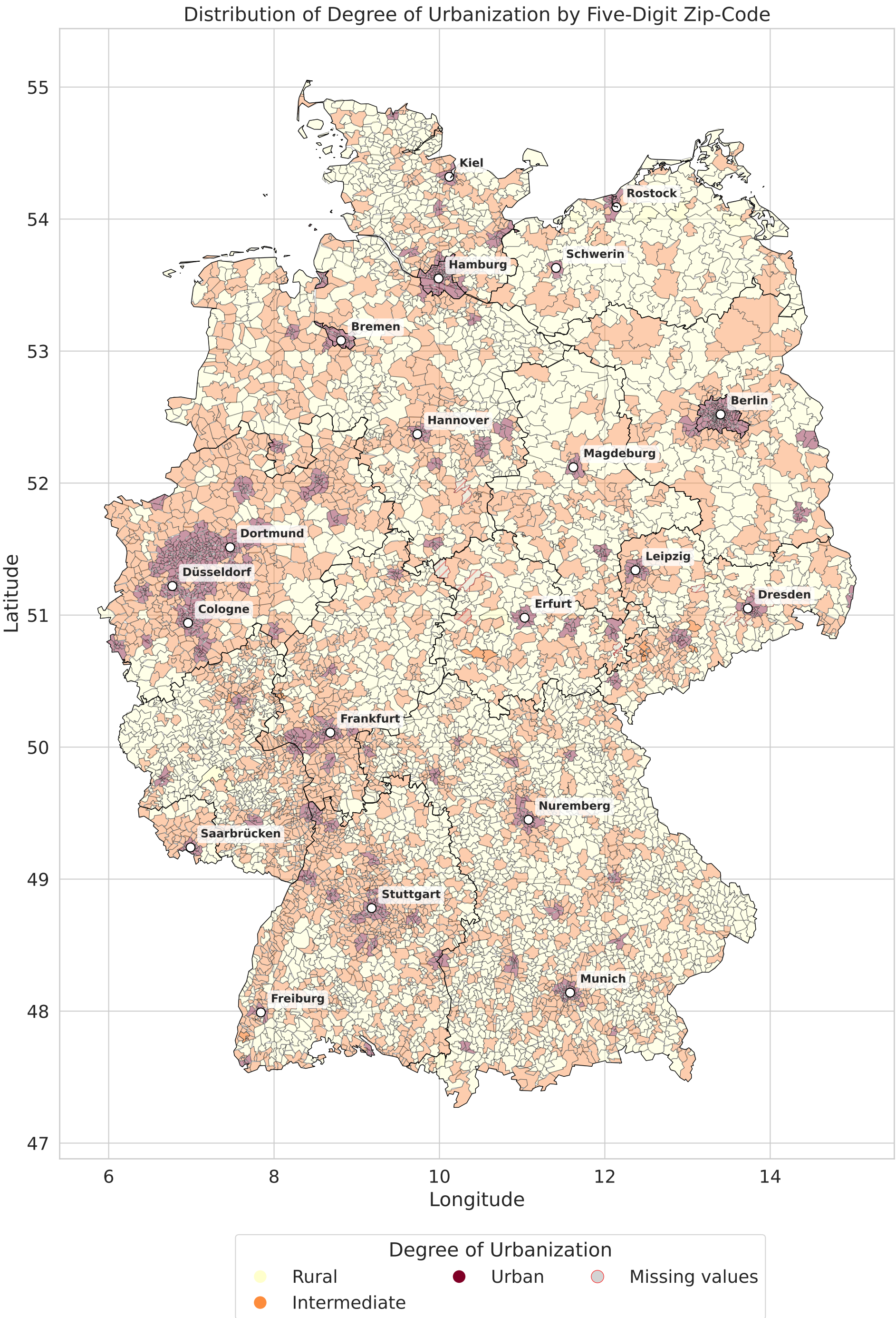

Figure D.8: Degree of urbanization by five-digit zip-code.

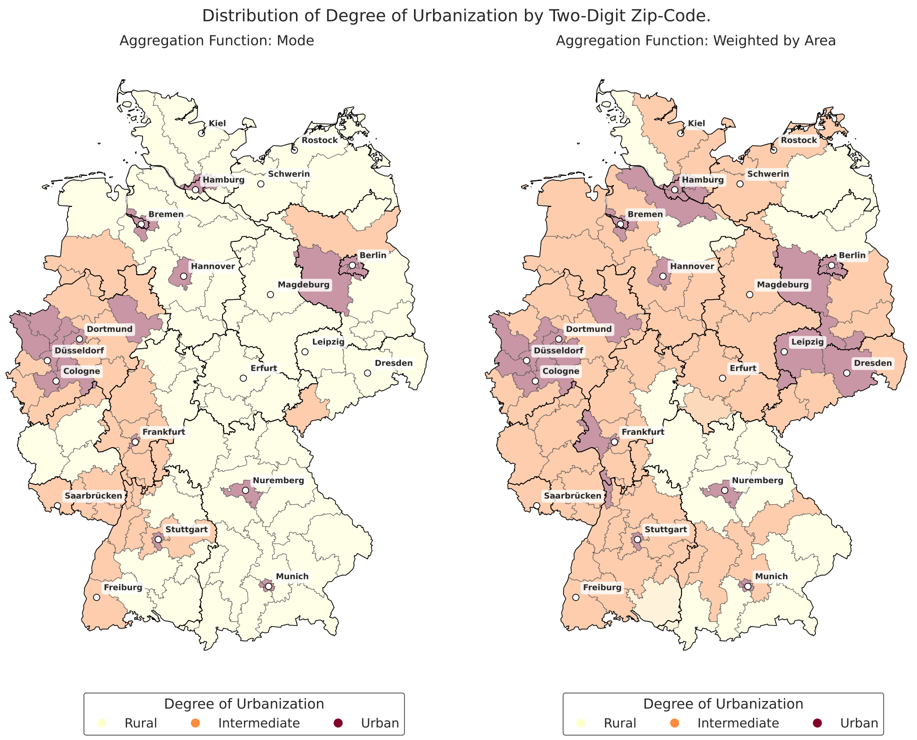

Figure D.9: Degree of urbanization aggregated at the two-digit zip-code. Left panel: Aggregation by mode. Right panel: Aggregation by area.

E Additional Regression Outputs

This appendix presents the full suite of econometric results and robustness checks supporting the main findings. It includes panel unit root tests (Figure E.1) validating the model's stationarity assumptions (i.e., a part is $I(0)$, but all are at least $I(1)$) and reports the complete estimation outputs for the dynamic ECM with extended lag structures (Table E.2). Additionally, it provides disaggregated pass-through estimates for top-ranked product hierarchies (bestsellers vs. niche products, Tables E.3 and E.4).

Test	Integration Order	Global Stat	Total Units	Units p-value below 1%	% Stationary
Consumer Net Price					
IPS (W_{tbar})	Levels - I(0)	-573.7	8859	6225	70.27%
Maddala-Wu (χ^2)	Levels - I(0)	384434.6	8859	6225	70.27%
modified P test (P_m)	Levels - I(0)	1948.1	8859	6225	70.27%
inverse normal test (z-value)	Levels - I(0)	-451.9	8859	6225	70.27%
Logit (L^*)	Levels - I(0)	-1117.6	8859	6225	70.27%
IPS (W_{tbar})	First Diff. - I(1)	1672327.1	8859	8859	100%
Maddala-Wu (χ^2)	First Diff. - I(1)	-3347.6	8859	8859	100%
modified P test (P_m)	First Diff - I(1)	8789.7	8859	8859	100%
inverse normal test (z-value)	First Diff - I(1)	-1258.1	8859	8859	100%
Logit (L^*)	First Diff - I(1)	-4898.0	8859	8859	100%
Wholesale Price (AEP)					
IPS (W_{tbar})	Levels - I(0)	-258.7	8859	4720	53.28%
Maddala-Wu (χ^2)	Levels - I(0)	145841.5	8859	4720	53.28%
modified P test (P_m)	Levels - I(0)	680.6	8859	4720	53.28%
inverse normal test (z-value)	Levels - I(0)	-256.5	8859	4720	53.28%
Logit (L^*)	Levels - I(0)	-413.8	8859	4720	53.28%
IPS (W_{tbar})	First Diff. - I(1)	-2946.6	8859	8859	100%
Maddala-Wu (χ^2)	First Diff. - I(1)	1847641.9	8859	8859	100%
modified P test (P_m)	First Diff - I(1)	9721.0	8859	8859	100%
inverse normal test (z-value)	First Diff - I(1)	-1330.0	8859	8859	100%
Logit (L^*)	First Diff - I(1)	-5411.5	8859	8859	100%

Table E.1: This table reports the results of the panel unit root tests proposed by Im et al. (2003) (IPS), Maddala and Wu (1999) (Maddala-Wu) and Choi (2001) (modified P test, inverse normal test and logit) on units (pharmacy-product ids) of the data that exhibit more than 3 years of observations. The tests are performed on both levels and first-differences of the variables to determine their order of integration. The *Global Stat* represents the W_{tbar} for the IPS test, the χ^2 statistic for the Maddala-Wu test, the P_m, z and L^* statistic for three tests from Choi, all of which strongly reject the null hypothesis of a unit root across the overall panel ($p < 0.01$). To address potential panel heterogeneity, the number and percentage of individual pharmacy-product time series are reported that independently reject the null hypothesis of a unit root at the strict 1 % significance level. The results confirm that while the panel exhibits mixed $I(0)$ and $I(1)$ behavior in levels, all series are stationary in first-differences ($I(1)$), thereby ruling out $I(2)$ non-stationarity.

Dependent Variable:	Δp_{jft}									
	OTC-drugs					Non-Pharmaceuticals				
Coefficients & Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\rho^{-}\Delta w_{jft}$	0.0772***	0.0656***	0.0643***	0.0645***	0.0645***	0.2226***	0.1948***	0.1935***	0.1980***	0.1976***
	(0.0092)	(0.0067)	(0.0064)	(0.0063)	(0.0062)	(0.0300)	(0.0203)	(0.0162)	(0.0167)	(0.0167)
$\rho^{+}\Delta w_{jft}$	0.1882***	0.1405***	0.1359***	0.1343***	0.1333***	0.4481***	0.4176***	0.4137***	0.4088***	0.4044***
	(0.0088)	(0.0081)	(0.0078)	(0.0077)	(0.0076)	(0.0749)	(0.0748)	(0.0736)	(0.0714)	(0.0689)
$\gamma^{-}p_{jf,t-\tau}$	-0.0930***	-0.0529***	-0.0474***	-0.0452***	-0.0440***	-0.1298***	-0.0703***	-0.0571***	-0.0514***	-0.0476***
	(0.0062)	(0.0039)	(0.0035)	(0.0034)	(0.0033)	(0.0218)	(0.0140)	(0.0123)	(0.0114)	(0.0109)
$\gamma^{+}p_{jf,t-\tau}$	-0.1151***	-0.0728***	-0.0668***	-0.0643***	-0.0628***	-0.1622***	-0.1057***	-0.0920***	-0.0850**	-0.0810**
	(0.0057)	(0.0036)	(0.0033)	(0.0031)	(0.0030)	(0.0363)	(0.0290)	(0.0277)	(0.0268)	(0.0262)
$\lambda^{-}w_{jf,t-\tau}$	0.1470***	0.0825***	0.0737***	0.0701***	0.0682***	0.1830***	0.0984***	0.0798***	0.0717***	0.0664***
	(0.0110)	(0.0065)	(0.0059)	(0.0057)	(0.0055)	(0.0315)	(0.0201)	(0.0175)	(0.0164)	(0.0156)
$\lambda^{+}w_{jf,t-\tau}$	0.1819***	0.1142***	0.1050***	0.1010***	0.0988***	0.2158***	0.1361***	0.1168**	0.1070**	0.1015**
	(0.0101)	(0.0061)	(0.0056)	(0.0054)	(0.0052)	(0.0494)	(0.0391)	(0.0374)	(0.0362)	(0.0355)
$\omega\Delta \text{Days}_{jft}$	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***
	(2.41×10^{-5})	(2.32×10^{-5})	(2.36×10^{-5})	(2.39×10^{-5})	(2.41×10^{-5})	(2.41×10^{-5})	(2.08×10^{-5})	(1.97×10^{-5})	(1.91×10^{-5})	(1.86×10^{-5})
$\beta_1^{-}\Delta w_{jf,t-1}$		0.0386***	0.0392***	0.0406***	0.0414***		0.0955***	0.1067***	0.1192***	0.1261***
		(0.0030)	(0.0031)	(0.0031)	(0.0031)		(0.0089)	(0.0105)	(0.0124)	(0.0136)
$\beta_1^{+}\Delta w_{jf,t-1}$		0.0026	0.0150***	0.0196***	0.0215***		0.0982***	0.1470***	0.1609***	0.1635***
		(0.0019)	(0.0021)	(0.0022)	(0.0023)		(0.0235)	(0.0309)	(0.0305)	(0.0294)
$\beta_2^{-}\Delta w_{jf,t-2}$			0.0255***	0.0275***	0.0286***			0.0514***	0.0651***	0.0748***
			(0.0021)	(0.0022)	(0.0023)			(0.0066)	(0.0078)	(0.0107)
$\beta_2^{+}\Delta w_{jf,t-2}$			0.0007	0.0080***	0.0111***			0.0364*	0.0727**	0.0830**
			(0.0022)	(0.0020)	(0.0021)			(0.0165)	(0.0223)	(0.0261)
$\beta_3^{-}\Delta w_{jf,t-3}$				0.0205***	0.0218***				0.0467***	0.0550***
				(0.0019)	(0.0020)				(0.0064)	(0.0096)
$\beta_3^{+}\Delta w_{jf,t-3}$				0.0041**	0.0088***				0.0301*	0.0551**
				(0.0013)	(0.0014)				(0.0131)	(0.0169)
$\beta_4^{-}\Delta w_{jf,t-4}$					0.0157***					0.0455***
					(0.0017)					(0.0066)
$\beta_4^{+}\Delta w_{jf,t-4}$					0.0014					0.0096
					(0.0013)					(0.0250)
$\phi_1^{-}\Delta p_{jf,t-1}$		-0.6667***	-0.6795***	-0.6876***	-0.6905***		-0.6886***	-0.7353***	-0.7543***	-0.7633***
		(0.0146)	(0.0140)	(0.0140)	(0.0139)		(0.0187)	(0.0182)	(0.0182)	(0.0180)
$\phi_1^{+}\Delta p_{jf,t-1}$		-0.1173***	-0.2560***	-0.2765***	-0.2843***		-0.1877***	-0.3198***	-0.3551***	-0.3741***
		(0.0078)	(0.0095)	(0.0108)	(0.0114)		(0.0165)	(0.0195)	(0.0220)	(0.0238)
$\phi_2^{-}\Delta p_{jf,t-2}$			-0.2184***	-0.2382***	-0.2482***			-0.2985***	-0.3526***	-0.3787***
			(0.0080)	(0.0094)	(0.0102)			(0.0139)	(0.0139)	(0.0154)
$\phi_2^{+}\Delta p_{jf,t-2}$			-0.0815***	-0.1608***	-0.1757***			-0.0940**	-0.1790***	-0.2086***
			(0.0048)	(0.0067)	(0.0078)			(0.0304)	(0.0387)	(0.0429)
$\phi_3^{-}\Delta p_{jf,t-3}$				-0.1217***	-0.1366***				-0.1733***	-0.2148***
				(0.0059)	(0.0070)				(0.0166)	(0.0202)
$\phi_3^{+}\Delta p_{jf,t-3}$				-0.0471***	-0.0976***				-0.0872***	-0.1501***
				(0.0035)	(0.0050)				(0.0072)	(0.0121)
$\phi_4^{-}\Delta p_{jf,t-4}$					-0.0755***					-0.1282***
					(0.0046)					(0.0114)
$\phi_4^{+}\Delta p_{jf,t-4}$					-0.0378***					-0.0647***
					(0.0027)					(0.0072)
Fit statistics										
# PCN-Pharmacy ID	2,491,778	2,491,778	2,491,778	2,491,778	2,491,778	6,078,232	6,078,232	6,078,232	6,078,232	6,078,232
# Year-Days	1,637	1,637	1,637	1,637	1,637	1,637	1,637	1,637	1,637	1,637
# Pharmacy-ID × Year-Month	341,772	341,772	341,772	341,772	341,772	341,307	341,307	341,307	341,307	341,307
Observations	231,400,516	231,400,516	231,400,516	231,400,516	231,400,516	172,288,976	172,288,976	172,288,976	172,288,976	172,288,976
Adjusted R^2	0.03062	0.23224	0.24879	0.25385	0.25603	0.13450	0.31951	0.34682	0.35781	0.36392
Within Adjusted R^2	0.01031	0.21615	0.23305	0.23821	0.24044	0.03726	0.24306	0.27343	0.28566	0.29245
Long-run Pass-Through θ^{+}	1.580	1.569	1.572	1.572	1.572	1.330	1.287	1.270	1.259	1.254
Long-run Pass-Through θ^{-}	1.581	1.560	1.554	1.552	1.550	1.410	1.401	1.398	1.396	1.395
Z-test $\theta^{+}=\theta^{-}$	−0.119	0.630	1.151	1.288	1.350	−3.386***	−3.096**	−2.791**	−2.754**	−2.729**
K Lags	0	1	2	3	4	0	1	2	3	4
AIC	377,566,880.9	314,690,484.8	308,763,817.1	306,907,315.1	306,142,571.7	429,071,416.9	387,977,778.5	379,255,256.0	375,814,942.5	374,094,333.3
BIC	426,501,332.6	363,625,005.6	357,698,406.8	355,841,973.8	355,077,299.6	538,004,721.7	496,911,151.1	488,188,696.5	484,748,450.8	483,027,909.5
LogLik	-185,948,248.5	-154,510,046.4	-151,546,708.5	-150,618,453.5	-150,236,077.9	-208,114,527.4	-187,567,704.2	-183,206,439.0	-181,486,278.2	-180,625,969.7
Wald test $\rho^{+}=\rho^{-}$	114.768***	69.185***	69.116***	68.646***	68.589***	6.796**	7.670**	8.517**	8.476**	8.880**
Wald test $\gamma^{+}=\gamma^{-}$	83.788***	108.474***	107.367***	110.624***	109.617***	1.754	2.758+	2.943+	2.867+	3.049+
Wald test $\lambda^{+}=\lambda^{-}$	70.682***	70.682***	70.682***	70.682***	70.682***	70.682***	70.682***	70.682***	70.682***	70.682***
Wald test $\gamma^{+}=\gamma^{-}=\lambda^{+}=\lambda^{-}=0$	140.523***	129.992***	130.068***	132.341***	134.152***	10.738***	9.343***	8.532***	9.243***	9.191***
Fixed Effects (FEs)										
PCN-Pharmacy ID FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Days FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Pharmacy-ID × Year-Month FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Standard errors (in parenthesis) are clustered on the pharmacy id & PCN. Wald tests show F-statistics
Signif. Codes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table E.2: Dynamic asymmetric estimation results (Equation (1) with up to $K = 4$ lags): Short-run and long-run pass-through estimates for high-turnover OTC drugs (*Respiratory System*, *Musculoskeletal System and Pain Management*) and non-pharmaceuticals (*No ATC Code*).

Dependent Variable:					Δp_{jft}				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\rho^{-}\Delta w_{jft}$	0.0659**	0.1054***	0.1219***	0.1403***	0.0915***	0.1208***	0.1265**	0.0994***	0.1209***
	(0.0138)	(0.0108)	(0.0186)	(0.0279)	(0.0138)	(0.0142)	(0.0313)	(0.0120)	(0.0144)
$\rho^{+}\Delta w_{jft}$	0.0689*	0.1156***	0.2135***	0.0963**	0.1423***	0.2205***	0.1034**	0.1367***	0.2222***
	(0.0226)	(0.0088)	(0.0146)	(0.0206)	(0.0116)	(0.0121)	(0.0219)	(0.0088)	(0.0123)
$\omega\Delta Days_{jft}$	0.0002	0.0003***	0.0006***	5.19×10^{-5}	0.0006***	0.0007***	6.2×10^{-5}	0.0006***	0.0007***
	(0.0001)	(4.06×10^{-5})	(2.28×10^{-5})	(0.0002)	(7.67×10^{-5})	(2.75×10^{-5})	(0.0002)	(5.79×10^{-5})	(2.75×10^{-5})
$\gamma^{-}p_{jf,t-\tau}$	-0.0756***	-0.0989***	-0.1136***	-0.1143***	-0.1066***	-0.1162***	-0.1101***	-0.1113***	-0.1152***
	(0.0155)	(0.0051)	(0.0052)	(0.0114)	(0.0086)	(0.0044)	(0.0134)	(0.0056)	(0.0045)
$\gamma^{+}p_{jf,t-\tau}$	-0.0879***	-0.1076***	-0.1408***	-0.1209***	-0.1205***	-0.1441***	-0.1172***	-0.1209***	-0.1432***
	(0.0146)	(0.0047)	(0.0072)	(0.0115)	(0.0077)	(0.0059)	(0.0128)	(0.0055)	(0.0060)
$\lambda^{-}w_{jf,t-\tau}$	0.1296***	0.1619***	0.1796***	0.1781***	0.1636***	0.1785***	0.1697***	0.1771***	0.1777***
	(0.0258)	(0.0096)	(0.0092)	(0.0151)	(0.0143)	(0.0072)	(0.0180)	(0.0086)	(0.0073)
$\lambda^{+}w_{jf,t-\tau}$	0.1470***	0.1757***	0.2226***	0.1884***	0.1875***	0.2211***	0.1814***	0.1931***	0.2205***
	(0.0239)	(0.0085)	(0.0116)	(0.0152)	(0.0126)	(0.0089)	(0.0169)	(0.0085)	(0.0092)
Fit statistics									
# Pharmacy ID × PCN	62,652	604,653	4,586,395	62,564	616,835	4,557,057	62,496	615,238	4,583,496
# Year-Days	1,641	1,641	1,641	1,641	1,641	1,641	1,641	1,641	1,641
# Pharmacy ID × Year-Month	341,660	341,820	341,940	341,653	341,820	341,951	341,681	341,815	341,951
Observations	37,531,035	180,112,138	422,089,152	30,265,844	167,176,855	409,592,325	32,517,007	171,686,780	413,605,018
Adjusted R^2	0.03715	0.03413	0.02923	0.04239	0.02919	0.03591	0.04085	0.03031	0.03414
Within Adjusted R^2	0.00405	0.00672	0.01524	0.00753	0.00959	0.01793	0.00724	0.00869	0.01756
# Top PCN	10	100	1000	10	100	1000	10	100	1000
Top PZN by	Sales	Sales	Sales	Revenue	Revenue	Revenue	Profits	Profits	Profits
Fraction of Total in %	13.1520	44.2220	87.3466	9.2187	37.9892	83.1285	9.0191	38.7750	84.4188
Long-run Pass-Through θ^{+}	1.672	1.633	1.580	1.558	1.556	1.535	1.547	1.597	1.540
Long-run Pass-Through θ^{-}	1.715	1.636	1.581	1.557	1.534	1.536	1.542	1.591	1.542
Z-test $\theta^{+}=\theta^{-}$	-1.794^{+}	-0.435	-0.100	0.131	2.613**	-0.233	0.485	0.815	-0.417
Wald test $\rho^{+}=\rho^{-}$	0.025	0.621	107.109***	3.521^{+}	9.813**	140.860***	0.763	5.532*	139.894***
Wald test $\gamma^{+}=\gamma^{-}$	20.606***	15.735***	43.765***	4.767*	32.525***	102.880***	4.015*	21.213***	95.340***
Wald test $\lambda^{+}=\lambda^{-}$	21.404***	14.278***	49.337***	4.476*	34.539***	121.419***	4.235*	21.971***	110.915***
Wald test $\gamma^{+}=\gamma^{-}=\lambda^{+}=\lambda^{-}=0$	31.039***	138.006***	195.660***	56.118***	91.221***	269.226***	49.640***	128.911***	248.821***
Fixed Effects (FEs)									
Pharmacy ID × PCN FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Days FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Pharmacy ID × Year-Month FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓

Standard errors (in parenthesis) are clustered on the pharmacy id & PCN. Wald tests show F-statistics.
Signif. Codes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table E.3: OTC drugs: Top 10 vs. Top 100 and Top 1000. Full table of estimation results for top-ranked products by sales, revenue and gross profits.

Dependent Variable:	Δp_{jft}								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\rho^- \Delta w_{jft}$	0.1235***	0.1275***	0.1824***	0.1593**	0.1792***	0.2098***	0.1272**	0.1718***	0.1982***
	(0.0109)	(0.0127)	(0.0124)	(0.0352)	(0.0184)	(0.0110)	(0.0270)	(0.0193)	(0.0126)
$\rho^+ \Delta w_{jft}$	0.1317***	0.2356***	0.2704***	0.2348***	0.2629***	0.2789***	0.2364***	0.2554***	0.2500***
	(0.0226)	(0.0236)	(0.0132)	(0.0267)	(0.0118)	(0.0077)	(0.0263)	(0.0110)	(0.0213)
$\omega \Delta Days_{jft}$	0.0002*	0.0004***	0.0004***	0.0014*	0.0010***	0.0006***	0.0014**	0.0010***	0.0006***
	(7.48×10^{-5})	(6.59×10^{-5})	(2.38×10^{-5})	(0.0005)	(0.0001)	(3.02×10^{-5})	(0.0004)	(0.0001)	(3.16×10^{-5})
$\gamma^- p_{jf,t-\tau}$	-0.1105***	-0.1053***	-0.1483***	-0.1429***	-0.1498***	-0.1720***	-0.1694***	-0.1339***	-0.1503***
	(0.0155)	(0.0090)	(0.0093)	(0.0260)	(0.0153)	(0.0108)	(0.0174)	(0.0142)	(0.0154)
$\gamma^+ p_{jf,t-\tau}$	-0.1233***	-0.1283***	-0.1784***	-0.1674***	-0.1962***	-0.2087***	-0.1882***	-0.1812***	-0.1686***
	(0.0197)	(0.0080)	(0.0095)	(0.0288)	(0.0138)	(0.0070)	(0.0196)	(0.0135)	(0.0257)
$\lambda^- w_{jf,t-\tau}$	0.1624***	0.1418***	0.2071***	0.1839***	0.1999***	0.2365***	0.2490***	0.1795***	0.2080***
	(0.0231)	(0.0159)	(0.0146)	(0.0356)	(0.0227)	(0.0163)	(0.0256)	(0.0214)	(0.0220)
$\lambda^+ w_{jf,t-\tau}$	0.1828***	0.1730***	0.2471***	0.2159***	0.2633***	0.2866***	0.2777***	0.2443***	0.2328***
	(0.0297)	(0.0146)	(0.0150)	(0.0382)	(0.0195)	(0.0108)	(0.0301)	(0.0191)	(0.0353)
Fit statistics									
# Pharmacy ID × PCN	61,419	561,720	3,771,609	61,190	564,193	3,709,785	61,973	569,763	3,712,649
# Year-Days	1,641	1,641	1,641	1,641	1,641	1,641	1,641	1,641	1,641
# Pharmacy ID × Year-Month	341,462	341,685	341,808	341,227	341,681	341,798	341,242	341,681	341,809
Observations	14,012,783	65,992,694	207,336,289	10,709,504	52,381,667	177,019,976	11,482,192	54,224,648	180,881,482
Adjusted R^2	0.04635	0.05226	0.07846	0.05001	0.07388	0.07572	0.04365	0.07525	0.09061
Within Adjusted R^2	0.01014	0.01699	0.02665	0.02277	0.02815	0.03322	0.02043	0.02578	0.02683
# Top PCN	10	100	1000	10	100	1000	10	100	1000
Top PZN by	Sales	Sales	Sales	Revenue	Revenue	Revenue	Profits	Profits	Profits
Fraction of Total in %	3.8819	16.8351	52.5124	4.2602	18.1514	50.9730	3.9915	51.2765	51.2765
Long-run Pass-Through θ^+	1.482	1.348	1.385	1.290	1.342	1.373	1.475	1.348	1.381
Long-run Pass-Through θ^-	1.470	1.347	1.397	1.287	1.334	1.375	1.470	1.341	1.384
Z-test $\theta^+ = \theta^-$	2.755**	0.155	−2.505*	0.298	1.443	−0.471	1.442	1.103	−0.601
Wald test $\rho^+ = \rho^-$	0.184	16.972***	28.569***	3.121+	33.704***	36.934***	7.360**	27.826***	8.534**
Wald test $\gamma^+ = \gamma^-$	6.140*	53.663***	164.596***	25.788***	9.381**	18.306***	9.673**	10.432**	1.310
Wald test $\lambda^+ = \lambda^-$	6.618*	62.560***	156.984***	31.610***	9.660**	17.095***	9.469**	10.525**	1.253
Wald test $\gamma^+ = \gamma^- = \lambda^+ = \lambda^- = 0$	19.062***	137.082***	139.536***	39.520***	69.139***	264.872***	40.470***	59.679***	36.030***
Fixed Effects (FEs)									
Pharmacy ID × PCN FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Days FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Pharmacy ID × Year-Month FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓

Standard errors (in parentheses) are clustered on the pharmacy ID and PCN. Wald tests show F-statistics.
Signif. Codes: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table E.4: Non-pharmaceuticals: Top 10 vs. Top 100 and Top 1000. Full table of estimation results for top-ranked products by sales, revenue and gross profits.