Does Brand-to-Brand Competition Reduce Prices of Prescription Drugs?

By Drishti Baid[1]

Abstract

Competition is often expected to lower prices. However, there is scant empirical evidence on whether and to what extent brand-to-brand competition affects pricing in the pharmaceutical industry. This is in large part because it is challenging to identify competitors among imperfect therapeutic substitutes and to distinguish between multiple prices across the supply chain. I construct a novel panel dataset of new product entry events, list and net prices, and rebates across 244 therapeutic markets between 2010 Q1 and 2024 Q3 to estimate how incumbents' prices change with competition. Empirical results indicate that greater competition is associated with lower net prices and higher rebates. Average net prices of incumbent drugs are 15% to 29% lower in relatively more competitive markets, while average rebates 15% to 26% are higher. The entry of a competitor product is associated with 5% to 10% lower net prices and, for a subset of small-molecule products, 10% to 12% higher rebates. Analyses incorporating product quality suggest that the entry of a competitor with a one standard deviation higher relative quality score, measured in terms of safety and efficacy of drug delivery, can reduce incumbents' net prices by 39% and increase rebates by 25%. Changes in list price are much less common and significant only among a small subset of products. The findings suggest that greater competition generally reduces the financial rewards accruing to manufacturers without benefitting consumers via lower list prices. Standardized measures of delivery risk offer a more precise approach for identifying competitors in pharmaceutical markets. (*JEL* I11, L11, L65, O31)

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Section I: Introduction

Competition is commonly expected to lower prices. This is an important tenet of markets and a key premise underpinning present-day policymaking in the US (Food and Drug Administration 2025). In pharmaceutical markets, empirical studies find evidence consistent with this hypothesis in the context of generic competition (Center for Drug Evaluation and Research 2022; Berndt and Aitken 2011). However, the impact of brand-to-brand competition on prices is not well understood (Sarpatwari et al. 2019). Brand-to-brand competition, unlike generic competition, involves competition between imperfect therapeutic substitutes and often begins prior to an incumbent products' loss of market exclusivity. Empirical research in this area is challenging, due to the twofold difficulty of identifying competitors and distinguishing between multiple prices accruing to various agents in the complex supply chain (Sood et al. 2017). The pursuit of empirical evidence of the relationship between brand-to-brand competition and price remains challenging yet timely and important to inform health policy and antitrust enforcement in pharmaceutical markets today.

In theory, market entry of competitor products can exert downward pressure on incumbents' prices by introducing therapeutic substitutes to consumers. However, the active role of profit-seeking intermediaries in the supply chain, whose revenue is tied to the difference between net prices (i.e. prices retained by manufacturers) and list prices (i.e. retail prices) complicates this dynamic. When therapeutic substitutes for an incumbent drug become available, manufacturers' ability to increase net prices may become constrained due to anticipated loss in revenue from payors and consumers who can switch to competitor products.[2] Preliminary evidence suggests that the impact of market competition may be masked by the presence of Pharmacy Benefit Managers (PBMs), the intermediaries negotiating prices and formulary placement of drugs between manufacturers and insurers (Lakdawalla and Li 2021). The presence of competitors can strengthen PBM's ability to exclude incumbent drugs from preferred tiers for insurance coverage, and thus, shift bargaining power from the manufacturer to the PBM. Overall, greater market competition can reduce net price growth and increase rebate growth.

Antitrust law considers the magnitude of consumer harm associated with changes in product prices when evaluating the effects of competition. List prices, which are directly linked to uninsured consumer's out-of-pocket payments and insured consumers' coinsurance rates, offer important but incomplete insight into the impact of competition on end-consumers. An exclusive focus on list prices can obfuscate the impact of competition on manufacturers and intermediaries. Given the complex pharmaceutical supply chain, regulators and antitrust economists are increasingly paying careful attention to distinct trends in net and list prices to understand the source of anticompetitive distortions (Federal Trade Commission 2024).[3]

[2] A systematic review of the empirical literature on competition between pharmaceutical drugs suggests that competition does not lower list prices (i.e. the retail price) in select therapeutic markets (Sarpatwari et al. 2019). The impact of competition on net prices is not examined.

[3] The wide-ranging FTC investigation into rebate growth in the insulin market, followed by enforcement actions against major PBMs and GPOs, is a recent and significant example of analyses distinguishing between net, list price and rebates can reveal anticompetitive behavior associated with multiple agents in the supply chain (Rao and Federal Trade Commission 2024).

Technological complexity, a high degree of innovation, and the negative consequences of economic incentives on long-term innovation, make competitiveness of pharmaceutical markets a high-priority yet difficult area for antitrust enforcement. (Hovenkamp 2004) The effects of competition within a therapeutic market on the price of an incumbent drug can be limited despite the presence of a large number of innovator firms because of inelastic demand for products[4] and high degree of product differentiation. High prices of brand-name drugs are especially a concern prior to generic entry[5], a period during which competitor products are imperfect therapeutic substitutes at best. When examining the relationship between competition and prices in pharmaceutical markets, a foremost and significant challenge is market definition which involves precise identification of relevant competitor products.

This study addresses the issues outlined above by analyzing the impact of competition between branded pharmaceutical products on various prices, across a broad range of therapeutic markets. Using a novel panel dataset of product-level prices and competitor entry events across 244 therapeutic markets between the period of 2010 (quarter 1) to 2024 (quarter 3), I estimate the extent to which the net price, list price and rebates of incumbent products change with the availability of competitor products. I consider various measures of product-market competition. First, a simple market-level measure is considered: the number of distinct competitor products[6] in the same therapeutic market as the incumbent product. To examine whether average prices are lower in markets with greater competition, I estimate the differences in average prices of incumbent drugs in therapeutic markets with very few competitors relative to the markets with many competitors. Second, I consider new product entry ("competitor entry") during the active marketing period of an incumbent product. The impact of the first (and each subsequent) competitor entry event on the price of incumbent products is estimated relative to products which do not experience any entry events using a difference-in-differences framework.

The impact of changes in the quality of competitor products on incumbents' prices' is also considered. For a sub-sample of small-molecule drugs, I incorporate rich data pertaining to the chemical properties of active ingredients within products. Chemical characteristics of products are used to compare the extent to which a drug can be delivered safely relative to its competitors, a key dimension of product quality relevant to consumers and regulators in the pharmaceutical market (Hodgson 2001; Ferreira and Andricopulo 2019). Delivery risk profiles of drugs are used to develop a novel approach to product market definition which is more precise than widely-used standard therapeutic area classifications. Using the novel approach to market definition, I re-estimate the impact of competitor entry events to examine whether the quality (rather than quantity) of competitor products have an impact on price.

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[4] Another related issue is that consumers demand for drugs depends on preferences over two products: an insurance plan and the drugs covered by them. Insurance plans are differentiated products as they vary in terms of financial characteristics (e.g. associated copays, coinsurance, out of pocket costs) and formularies (i.e. the drugs covered by the plan) (Olssen and Demirer 2019). Many insurance plans involve selective contracting, such that insurance coverage is effective only among a preferred group of pharmacies. This makes consumer demand for drugs more inelastic (Starc and Swanson 2021).

[5] On average, prices of brand-name drugs fall by about 60% typically after three generic manufacturers have entered the market (Center for Drug Evaluation and Research 2022).

[6] A unique product in this analysis refers to a unique set of active ingredients.

Empirical results indicate that competition is associated with significant and economically meaningful effects on prices of incumbent drugs. Average net prices of incumbent drugs are lower in more competitive markets, while average rebates are higher. Average list prices do not vary significantly with market-level competition. The effects of competition on net price and rebates are greater in magnitude among large-molecule products, relative to small-molecule products. Competitor entry has similar effects on prices. Market entry of new competitors result in lower net prices. These changes are significant during the period between the second and third entry event experienced by an incumbent product. Rebates are higher during the period after the first competitor entry event for a subset of small-molecule incumbent products, but these differences are not significant after the third entry event. Changes in the quality of competitors impacts price of incumbent products. Entry events involving competitor products that have fewer delivery risks associated with drug delivery results in lower net and list prices for incumbents, relative to incumbents which do not experience entry of higher-quality competitors. Overall, these findings are consistent with the hypotheses that competition can result in lower prices to paid to manufacturers and higher prices paid to intermediaries in the supply chain.

This study addresses an important gap in the health policy and economics literature. A growing number of studies recognize the divergent trends in net and list prices of prescription drugs in the US (Kakani et al. 2020; Garthwaite 2025; Dickson et al. 2023). Competition has been recognized as a potential driver of rebate growth (Lakdawalla and Li 2021; Kakani et al. 2020). However, empirical studies considering the impact of competition on rebates have been limited to short time periods (i.e. four years or less) (Lakdawalla and Li 2021) or narrow therapeutic markets (e.g. the market for insulin products) (Dickson et al. 2023). Prior research on the impact of competition on prices in the pharmaceutical market has been either focused on generic competition in the economics literature (Dalen et al. 2006; Saha et al. 2006; Grabowski and Kyle 2007) or focused on list prices in the health policy literature (Sarpatwari et al. 2019). While economic theory has long recognized the association between product quality and competition (Motta 1993; Spence 1975; Kranton 2003), empirical research[7] has been limited (Reed and Watts 2018). To the best of my knowledge, this is the first study to investigate the effect of brand-to-brand competition on net prices and how competitor quality mediates that effect. In doing so, this study introduces a measure of quality for pharmaceutical products that is novel to the economics literature.

The rest of this paper proceeds as follows: Section II provides a brief background on price trends in pharmaceutical markets and intermediaries in the pharmaceutical supply chain. Section III describes the econometric framework used to examine the relationship between prices and competition in this study. Section IV describes the sources of data and the protocol for the construction of the panel dataset in detail. Section V provides a descriptive summary of prices and competitor entry events captured in the estimation panel and presents results from the empirical

[7] While measures of product quality in the context of pharmaceutical products have emerged in the context of the pharmaceutical market in the recent economics literature, these studies do not consider the association with competition. (Krieger, Nanda, et al. 2022; Dranove et al. 2022; Kyle and Williams 2017)

analysis. Section VI discusses the findings, including implications for antitrust enforcement, and concludes.

Section II: Background

Price Growth Among Pharmaceutical Products

Growth in list prices of brand-name prescription drugs in the US have attracted much attention from policymakers, payors and patient advocates over the past decade (Bosworth et al. 2022). High prices can incentivize innovators to take on large and uncertain R&D investments in drug development that yield important medical innovations (Acemoglu and Linn 2004; Dubois et al. 2015; Blume-Kohout and Sood 2013; Krieger, Li, et al. 2022) and increase welfare in the long-term albeit the negative short-term implications on access and affordability for consumers (Feldstein and Melnick 2007; Hemel and Ouellette 2013). However, a growing evidence base suggests that a large portion of the high list prices for prescription drugs are not retained by innovators.

Growth in the net prices of brand-name drugs, which represent the financial rewards to manufacturers per unit sold, has been much slower than growth in list prices. Since 2013, the spread between list and net prices has been steadily increasing. List prices grew four times as much as net prices (12% vs 3%) for drugs sold in retail pharmacies between 2012-2017 (Garthwaite 2025; Kakani et al. 2020). More recent estimates suggest that inflation-adjusted net prices for brand-name drugs in the US have declined for the seventh consecutive year as of 2024 while list prices have continued to increase (Fein 2025a).

Rebates, or the total discounts retained by intermediaries and payors in the pharmaceutical supply chain, have been growing in multiple therapeutic markets (Dickson et al. 2023; Kakani et al. 2020). Between 2012-2017, average rebate levels increased from 32% to 48% of list prices (Garthwaite 2025; Kakani et al. 2020). This suggests that large portions of list prices are being retained by payors and intermediaries in the pharmaceutical supply chain, rather than being passed on to innovators. In theory, the presence of intermediaries can improve consumer welfare by simultaneously rewarding innovators with high prices and improving the affordability of prescription drugs for consumers (Lakdawalla and Sood 2013). However, the growth in rebates suggests that list prices of prescription drugs continue to grow while neither of these benefits are being realized.

Intermediaries in the Pharmaceutical Supply Chain

Market power varies across different levels of the pharmaceutical supply chain (Sood et al. 2017). Due to the presence of distributors and fiscal intermediaries, retail prices of drugs may not accurately reflect the degree of market power or its impact on consumer welfare. Different prices, barriers to entry, and regulatory environments influence the degree of market power at each level of the supply chain.

At the top of the supply chain, upstream manufacturers are faced with decisions about how to invest in in drug development and to price new drugs that are successfully developed. The oft-cited "innovation-access" trade-off illustrates the tension between (1) incentivizing firms to innovate

by allowing large profit margins and (2) promoting competition for lower prices and wider access to existing innovations for consumers. Drug development is highly uncertain and demands large investments of capital and time from manufacturers. To increase profitability and incentivize innovative activity, the government grants limited-term monopoly power to drug manufacturers through patents. In theory, high prices for on-patent drugs reward innovators. (Feldstein and Melnick 2007; Hemel and Ouellette 2013) In heavily insured markets, the innovation-access trade-off may not apply to branded manufacturers because insurance premiums are used to capture profits rather than mark-ups on drug prices (Lakdawalla and Sood 2013).

Intermediaries play an active role in the supply chain. Drugs are sold from manufacturers to purchasers (i.e. wholesalers or pharmacies) at net prices. These purchasers impose a markup above the net prices for their distribution services. For consumers without insurance, drugs are sold at a marked-up list price in retail pharmacies. Consumers with insurance pay a fraction of the list price in the form of a copayment. The remaining portion of the list price is borne by fiscal intermediaries (i.e., the insurer or pharmacy benefit manager (PBM) acting on behalf on the insurer). PBMs also play an important role in negotiating the reimbursements to pharmacies and rebates form manufacturers in return for inclusion on formularies. The size of these reimbursements and rebates are typically not publicly available (Lyles 2017). Unlike the retail supply chain for pharmaceutical products sold in retail settings, there is no role for pharmacies in the context of physician administered drugs. Recently, PBMs have disrupted buy-and-bill systems by offering several physician-administered oncology drugs through their specialty pharmacies (Fein 2023).

Section II: Econometric framework

The main objective of the empirical analyses is to evaluate the impact of changes in competition within therapeutic markets to net prices, list prices and rebates. I do this is a variety of ways to account for the number of competitor products, new product entry and the quality of competitor products. Each regression relates changes in market-level competition to the prices of an incumbent product using two-way fixed effects regressions. The independent variable is defined in multiple ways to examine various measures of competition. The common elements of all regressions are described below, followed by detailed specifications.

Each product is defined by a unique set of active ingredients. Competitor products include all products which are actively marketed in each market-quarter. Let the subscript p represent unique products, m represent unique therapeutic markets and q represent time measured in calendar quarters. All regressions includes fixed effects for each product and quarter and a control variable for the time since market entry, following prior research (Dubois et al. 2015). Product fixed effects capture the unobserved, time-invariant differences between products such as demand across therapeutic areas or disease profiles, socioeconomic, demographic or health profiles of the patients targeted by each product, which can affect product prices. Quarter fixed effects absorb

annual growth in prices and seasonal factors which can affect the price estimates across quarters[8]. Time since market entry of the incumbent product is included as a control variable, because drug vintage may influence the rate of utilization by physicians and consumers, and could be associated with the prices of the incumbent product. Time since market entry for each product is specified using a categorical variable with six levels ranging from less than three years (least time on market) to more than 24 years (most time on market). Alternative definitions of the time since market entry variable are considered for robustness.

A generalized linear model with a log-link function and gamma distribution family is used to estimate all regression models, which is commonly used in prior literature to model highly-skewed health expenditures (Deb et al. 2024). All prices are inflation-adjusted to reflect real values in terms of USD 2024 (Bureau of Labor Statistics 2025). Three product-level prices are considered in each regression: Net prices, List prices (WAC) and Rebates (defined as the difference between Net and List prices).

Impact of Competition on Prices

The main empirical analyses relies on variation created by changes in the number of competitor products within a therapeutic market, hereafter "market-level competition", over time. The first specification is expressed below:

$$log(price_{pq}) = \alpha_p + \delta_q + \beta_1 \cdot I\{\text{moderate competition}\}_{pmq} + \beta_2 \cdot I\{\text{high competition}\}_{pmq} + \beta_3 \cdot I\{\text{very high competition}\}_{pmq} + \gamma_1 \cdot \{time\ on\ market\}_{pq} + \epsilon_{pq} \quad (1)$$

In equation 1, the levels of market competition are defined using quartiles of the number of competitors across all product-quarters in the estimation sample. Low competition (at or below the 25th percentile) corresponds to <=5 competitors (<=5, <=5) in the sample of all drugs (small molecules, large molecules). Moderate competition (between 25th percentile and median) corresponds to 5-10 competitors (5-11, 5-9) in the sample of all drugs (small molecules, large molecules). High competition (between the median and 75th percentile) corresponds to 10-17 competitors (11-18, 9-16) in the sample of all drugs (small molecules, large molecules). Very high competition (above the 75th percentile) corresponds to >17 competitors (>18, >16) in the sample of all drugs (small molecules, large molecules). Coefficients (β_i) can be interpreted as the difference in average product prices for products experiencing moderate, high, and very high competition relative to products experiencing low competition.

Impact of Competitor Entry on Prices

To estimate the impact of specific competitor entry events on drug prices, I employ a difference-in-difference (DD) framework. Competitor entry events that occur during the time after market entry are used to identify treatment status for an incumbent product. Products which never experience competitor entry after their market entry date are referred to as the pure control group ("never-

[8] Product-level prices are determined using manufacturer revenue estimates. Quarterly revenue estimates may vary due to seasonal variation in buying and selling stock between purchasers and manufacturers. (Ippolito and Levy 2022; SSR Health 2025)

treated"). Products which experience at least one competitor entry event after their market entry date are identified as treated drugs. The key regression specification used to estimate the impact of competitor entry on prices is described below:

$$\begin{aligned} log(price_{pq}) = \alpha_p + \delta_q + \beta_1 \cdot I\{first\ entry\ event\}_{pq} + \beta_2 \cdot I\{second\ entry\ event\}_{pq} \\ + \beta_3 \cdot I\{third\ entry\ event\}_{pq} + \cdots + \beta_n \cdot I\{n^{th}\ entry\ event\}_{dq} \\ + \gamma_1 \cdot \{time\ on\ market\}_{pq} + \epsilon_{pq} \end{aligned} \quad (2)$$

The treatment period is defined to include every quarter after which at least one competitor enters the market. In many cases, an incumbent product experiences multiple competitor entry events after its' market entry date. Variation in treatment intensity across treated products are captured using multiple treatment indicators. The treatment indicators are defined to switch on (i.e. take on the value of 1) for every quarter after the n^{th} competitor has entered the market.[9] Note that the indictor for the n^{th} entry event will always be switched on when the indicator for the $(n+1)^{th}$ entry event is switched on, by construction. The impact of competitor entry on product prices is captured by the coefficients, (β_i) can be interpreted as the average treatment effect of the n^{th} entry event in quarters between $(n-1)^{th}$ entry event and the $(n+1)^{th}$ entry event.

Impact of Competitor Quality on Prices

Two approaches to analyzing the effects of competitor quality are considered. First, the DD regression in equation (2) is re-estimated using various definitions of treatment. For the sub-sample of incumbent small-molecule products, I consider an additional definition of what constitutes a competitor using chemical properties of the competitor product. The alternative approaches is a more precise approach to identifying competitors that are likely to be substitutes of the incumbent product, and thus, are likely to have greater impacts on the prices of incumbent products. I assign treatment status using the entry of a competitor product with lower delivery risk scores than the competitor product. This specification estimates the impact of entry events on incumbents' prices which involve competitor products which have a more favorable ADMET profile (i.e. may be regarded as of higher quality) relative to all other incumbent products.

In a secondary analyses, I examine the impact of changes in the quality of the closest competitor in a given quarter is considered. When evaluating claims of monopolization and related antitrust issues, the assessment of an incumbent drug is often conducted relative to a narrowly defined product market often including one or two products. These cases implicitly compare the incumbent product to a single, closest competitor in the therapeutic market. I evaluate the impact of changes in the quality of the closest competitor product on an incumbent products' price using the following specification:

$$log(price_{pq}) = \alpha_p + \delta_q + \beta_1 \cdot \max\{relative\ delivery\ risk_{pq}\} + \gamma_1 \cdot \{time\ on\ market_{pq}\} + \epsilon_{pq} \quad (3)$$

[9] Ibid

In equation 3, the independent variable which captures the quality of the closest competitor is defined as the maximum difference in product-level delivery risk scores in a given quarter. The maximum similarity score captures the chemical similarity between the incumbent product and it's most chemically similar competitor. The maximum difference in delivery risk captures the difference in delivery risks relative to the competitor product with the most favorable ADMET profile in a given quarter. The quality of the closest competitor changes only when competitor entry events involve a competitor product that has a better ADMET profile than any existing competitor to an incumbent product. Thus, changes in quality of the closest competitors occur much less frequently that the changes in the number of competitors.

Section III: Data

The main empirical analyses relies on a novel panel dataset of product-level prices and therapeutic market-level competition. Branded prescription drugs, hereafter "incumbent products", are observed on a quarterly basis between the first quarter of 2010 and the third quarter of 2024. Each product is classified into a therapeutic market using the standardized definitions from the Anatomical Therapeutic Chemical classification system. (World Health Organization 2025) Within each therapeutic market, every actively marketed product is identified from a dataset encompassing the universe of FDA-approved drugs up to the third quarter of 2024. For each unique combination of therapeutic market and calendar quarter ("market-quarters"), all branded prescription drugs that were actively marketed in the same market-quarter are identified as competitors (hereafter "competitor products"). The full set of competitor products comprises the sample of incumbent products as well as new entrants in each market-quarter of interest. Product-level characteristics including market entry dates and therapeutic market classifications are extracted primarily from three data sources, as detailed below. The approach for constructing the panel dataset is illustrated in Figure 1.

Prices

Product-level prices reported on a quarterly basis from the first quarter of 2010 to the third quarter of 2024, were obtained via the US Brand Rx Net Pricing Tool from SSR Health (SSR Health 2025; Ippolito and Levy 2022) Product-level prices are standardized to reflect utilization over one year or one course of therapy by multiplying estimated price per unit at the product/strength/form level by the maximum representative annual/course dosage on the product's package insert.[10] Three product-level prices are considered: Net cost, Wholesale Acquisition Cost (WAC), and rebates observed in nominal dollar values. Net costs refer to the average product-level net price that is retained by the manufacturer after all discounts have been accounted for. The Wholesale Acquisition Cost (WAC) refers to the product-level list prices set by the manufacturer prior to any discounts. Rebates refer the difference between WAC and Net costs, representing the product-level mark-up that is potentially retained by middlemen in the pharmaceutical supply chain. There are various components of rebates such as: discounts and fees paid to commercial payers and plans,

[10] Dosage is measured by the product of units per dose, doses per days, and days per year or course. Dosage also reflects standard published values for representative body weight and/or body surface area (SSR Health 2025; Ippolito and Levy 2022).

rebates and coverage gap discounts in Medicare Part D, rebates to Medicaid, discounts under the 340B Drug Pricing Program, manufacturer payments to drug channel participants including administrative fees and discounts to wholesalers, pharmacies, PBMs, and patient assistance and copayment support funds. (Fein 2020) Prices are reported in nominal terms and were inflation-adjusted using the quarterly average of monthly CPI-U data obtained from BLS for all of the analyses (Bureau of Labor Statistics 2025).

Therapeutic market classification

The Anatomical Therapeutic Chemical 4th level (ATC4) classification assigned to actively marketed products is used to define therapeutic markets.[11] Products were classified into therapeutic markets using ATC4 codes associated with every 11-digit National Drug Code (NDC) associated with a product between 2010 and 2024, via the First DataBank Drug Database (First Databank 2025). Products may be assigned to multiple ATC4 codes across NDCs. For incumbent drugs, a single therapeutic market was assigned using the modal ATC4 value across all NDCs associated with the product. For competitor products, every ATC4 value identified across associated NDCs were considered. Thus, competitor products may appear in more than one therapeutic market.[12] Therapeutic market definitions using ATC4 codes have been used in prior literature examining the economics of the pharmaceutical markets. (Feng et al. 2023)

Product definition

Products are defined by a single unique set of active ingredients via a standardized numeric identifier in the First DataBank Drug Database (First Databank 2025).[13] For every competitor product identified via FDB, each product is associated with exactly one unique set of active ingredients. For products identified in the SSR data, the brand name provided in the raw data was mapped to a unique set of active ingredients in FDB. For a minority of incumbent drugs (N=51, 6.25% of the sample), a brand name was associated with multiple unique sets of active ingredients. For these cases, multiple unique identifier values were assigned to the incumbent product in order to capture the full set of active ingredients that are associated with the product.[14] For every incumbent drug that appears in the pricing dataset, all products which are actively marketed between 2010 (quarter 1) and 2024 (quarter 3) in the same therapeutic market are identified from the universe of NDCs associated with drugs approved by the FDA, via the FDB Drug Database.

Market entry and exit dates

Product-level market entry and exit dates are derived using NDC-level data from First DataBank Drug Database (First Databank 2025). Market entry dates for each product are assigned using either the (i) earliest non-missing market launch date, (ii) earliest non-missing approval date, or (iii) date on which a related NDC first appears in the database, in the specified order based on data availability. Market

[11] ATC codes are structured in five levels. The ATC-4 level code, which provides the most narrow market definition, is used to define therapeutic markets for all subsequent analyses.
[12] Incumbent products appear in exactly one (N=765, 93.75%), two (N=49, 6%) or three (N=2, <1%) ATC4 markets. The modal ATC4 is considered when assigning an incumbent product to a therapeutic market.
[13] The unique identifier is a six-character numeric column that identifies a unique combination of active ingredients, irrespective of the manufacturer, package size, dosage form, route of administration, or strength.
[14] All unique ingredient identifiers listed across NDCs (FDB) associated with the given brand name in the raw SSR data, were considered.

launch dates indicate the date a manufacturer releases the drug product to the marketplace, as supplied on the Centers for Medicare and Medicaid Services' quarterly update. Approval dates are determined using dates on all NDA applications associated with an NDC.

If products exit the market during the period of analyses, a market exit date is assigned using either (i) the date on which a related NDC becomes obsolete or (ii) the date on which an NDC is terminated on the market, in that order. Product obsolescence refers to products that are discontinued, no longer marketed, no longer produced, or otherwise made unavailable to the marketplace.[15]

Market termination dates represent the shelf-life expiration date of the last batch of product produced, as supplied on the Centers for Medicare and Medicaid Services' quarterly update. For each quarter in the panel dataset, the number of quarters for which a product has been actively marketed is calculated using the market entry and exit dates.

Chemical properties

Each active ingredient encompassed in each unique product is identified via the FDB database. Using the active ingredient names, molecule types and molecular structures are extracted via an API to two comprehensive, publicly-available repositories of data on chemical substances in approved drugs and drug candidates: ChEMBL and PubChem. (PubChem 2025b; ChEMBL 2025) PubChem is a large-scale chemical database maintained by the US National Institutes of Health which relies on over 800 of sources for bioactivity data, including U.S. government agencies, international organizations, academic institutions, pharmaceutical companies, chemical vendors, and other chemical biology databases. (Kim and Bolton 2024; PubChem 2025a) ChEMBL is a widely recognized and manually-curated database which primarily relies on published bioactivity data, from a set of seven Medicinal Chemistry journals. (Zdrazil et al. 2024) For the active ingredients identified to be small molecules, the molecular structure was retrieved in a standardized format known as the Simplified Molecular Input Line Entry System (SMILES). (Öztürk et al. 2016) SMILES strings were used to retrieve images of the chemical structure for each unique active ingredient in our sample and extract additional chemical properties related to risks associated with the delivery of a drug, as described below.

Delivery Risk Scores: The quality of a drug includes an assessment of efficacy and safety associated with the use of the drug. Four dimensions of drug efficacy and safety for a drug pertain to the absorption, distribution, metabolism, elimination and toxicity (ADMET) of the drug. The ADMET profile of a drug, together with pharmacological characteristics, is commonly considered when evaluating the effectiveness of a drug that can be achieved while causing no harm. (Hodgson 2001) Using the SMILES strings, an overall measure of ADMET profiles at the ingredient-level are extracted via the proprietary ADMET Predictor 12.0 software (Simulations Plus 2025). A comprehensive measure of ADMET properties is captured by the ADMET risk score, hereafter "delivery risk": a score

[15] Obsolescence date is a date or estimated date provided by the manufacturer or via FDA notification. FDB also applies an obsolete date to products that provide an insufficient basis for an assessment of their safety and efficacy or otherwise present regulatory compliance issues. The obsolete date is unrelated to the expiration date present on a product's label. (First Databank 2023)

in the 0-22 range[16] indicating the number of potential ADMET problems a compound might have. The overall score involves four key component risk scores: absorption contributes up to 8 points, distribution up to 2 points, CYP metabolism up to 6 points, and toxicity up to 6. For each product, a product-level delivery risk score is calculated as the average of ADMET risk scores across all constituent active ingredients. Differences in product-level ADMET risk scores are calculated for each pair of competitor products.

Differences in delivery risk scores capture whether a competitor product has a more favorable ADMET profile relative to the incumbent product. Relative delivery risk scores are calculated as the difference in ADMET risk scores for each unique pair of incumbent products and their competitors. Positive values of the relative delivery risk score indicates instances in which the competitor product is of better quality (i.e. is associated with fewer ADMET risks) than the incumbent and vice versa. The distribution of product-level relative delivery risk score scores in described in Figure 2.

Section IV: Results

Characteristics of incumbent products are summarized in Tables 1 and 2. The analytic sample consists of 816 incumbent marketed during the period of 2010 (quarter 1) and 2024 (quarter 3)[17], including 514 incumbent products which entered the market during the period of analysis. Most incumbents are small-molecule products throughout the analytic period, although the share of small-molecule products becomes smaller over time (78% in 2010 quarter 1 to 56% in 2024 quarter 3). Less than one fourth of the sample of products are combinations involving more than one active ingredient.

On average, the magnitude and variation in net and list prices of incumbent products increase substantially over time (Table 1). Average net prices (list prices) increase substantially from USD 19,581 (USD 25,494) in 2010 quarter 1 to USD 130,368 (USD 171,344) in 2024 quarter 3. Incumbent products span 244 therapeutic markets. More than two-thirds of small-molecule products (83%, N=470) and large-molecule products (91%, N=227) experience at least one competitor entry event after their market entry date (Table 2). Among products experiencing at least one competitor entry event, small-molecule products experience fewer competitor entry events after being launched on the market (4-5 events) than large-molecule products (6-7 events) on average.

Figure 2 illustrates the variation in the quality of competitors relative to incumbent products. Among incumbent small-molecule products experiencing new competitor entry, incumbents experience an average of 3-4 competitor entry events involving competitor products with fewer delivery risks. Most competitor-incumbent pairs in the analytic sample involve competitors with weakly more favorable risk profiles than incumbent products (mean difference in delivery scores =

[16] Exceeds 7 for 10% of a focused World Drug Index (WDI) subset when all component risks are included. (Simulations Plus 2025)
[17] The sample of products for which at least one price datapoint between the period of 2010 (quarter 1) and 2024 (quarter 3) could be observed.

0.034, median = 0) (Figure 2).[18] When a more precise definition of competitor products is adopted, the number of competitor entry events in the same therapeutic market as an incumbent product is smaller in magnitude as expected (see Appendix Figure 2, right panel).

Impact of Competition on Prices

The estimated impact of changes in market-level competition on product-level prices is described in Table 3. Average net prices decrease as the level of market competition increases (Table 3, Panel A, column 1). Relative to the least competitive markets, average net prices in moderately competitive markets are almost 15% lower (since exp(0.139)-1 = 0.149)[19] after controlling for product-specific characteristics including the time since market entry. The magnitude of differences in mean net prices become larger as the level of market competition increases. Relative to the least competitive markets, average net prices in therapeutic markets with high and very high competition are 22% and 29% lower after controlling product-specific characteristics and time since market entry.

Competition has a greater impact on average net prices in the sub-sample of large molecule products (Table 3, Panel A, columns 7-9). For small-molecule products, lower average net prices are lower in moderately competitive markets relative to the least competitive markets. However, differences in average net prices are not statistically significant at greater levels of competition. On the other hand, the magnitude of differences in average net prices are larger and consistently increase with market-level competition in the sub-sample of large-molecule incumbent products. Relative to the least competitive markets, average net prices for markets with moderate, high, and very high competition are 15%, 42% and 59% lower after controlling for product-specific characteristics, respectively.

Average list prices do not consistently decline with increasing levels of market competition (Table 3, Panel A, column 2). Average list prices of products in markets with very high levels of competition are almost 10% lower relative to incumbents in the least competitive markets. This effect appears to be largely attributable to the impact of competition among the subset of the large molecule products. While average list prices across levels of market competition are not statistically significant in the sample of small-molecules, list prices of large molecule incumbent products are 25% lower in markets with very high levels of competition are almost 10% lower than incumbents in the least competitive markets.

Unsurprisingly, average rebates increase with greater levels of competition (Table 3, Panel A, column 3), especially in the sample of large-molecule products (Table 3, Panel A, column 8).[20] Relative to the least competitive markets, average rebates for incumbents in moderately and highly competitive markets are almost 15% and 26% higher after controlling for product characteristics,

[18] Variation in relative delivery risk scores is correlated with the degree of chemical similarity, an alternative metric used to assess product quality in the recent economics literature (Krieger, Li, et al. 2022; Dranove et al. 2022), within pairs of competitor products (Appendix Figure 2, left panel). While differences in delivery risk are highly varied among dissimilar competitors, these differences become much smaller as the similarity between competitor products increases. The empirical distribution of quality indicators confirms that the two alternative approaches to competitor identification employed capture related but distinct dimensions of competitor quality.

[19] Regression coefficients from the GLM (log-link) specifications can be expressed as a percentage change using this approach for ease of interpretation in the rest of the paper.

[20] Recall that, by definition, differences in mean rebates of incumbent products are a result of changes in list prices relative to net prices across levels of market competition.

respectively. The magnitude of these effects are larger among the subset of large molecule products. Relative to the least competitive markets, rebates for large-molecule products in markets with moderate and high levels of competition are almost 20% and 34% higher, respectively. However, when comparing the most and least competitive markets, differences in mean rebates are not statistically significant due to the significant declines in average list prices in the most competitive markets.

The impacts of changes in levels of market competition on incumbent prices' are qualitatively similar in the sub-sample of incumbent products which were launched during the period of analyses (Table 3, Panel B). These findings suggest that the price effects of changes in market-level competition are not restricted to either the initial or later phases of the incumbent products' active marketing period.

Impact of Competitor Entry on Prices

Given the differences in price effects across levels of market competition in the prior analyses, the impact of competitor entry events is estimated separately for the sub-samples of small molecule and large molecule drugs (Table 4, Panel A). In both sub-samples, net prices of incumbent products fall between the entry of the 2nd competitor and the 3rd competitor (Table 4, Panel A, columns 1 and 4). Declines in net prices are larger in magnitude for the sample of large molecule products relative to the sample of small molecule drugs (5% vs 10%, respectively). While the entry of competitors beyond the 3rd competitor does not have any statistically significant impact on net prices for small-molecule products, the net price of large-molecule products is approximately 10% lower after the entry of the 5th competitor. Estimates of competitor entry events on net prices are qualitatively similar in the sample of drugs which were launched during the period of analyses (Table 4, Panel B, column 1 and column 4).

List prices do not significantly change after competitor entry events in the sample of small-molecule products (Table 4, Panel A, column 2 and 5). In the sample of large molecule products, declines in list prices ranging from approximately 3-7% are observed after the third competitor entry event (Table 4, Panel A, column 5). In the sample of newly launched large-molecule products, declines in mean list prices are small but statistically significant only between the 2nd and 3rd competitor entry events and after the 5th competitor entry event (Table 4, Panel B, column 5).

Mean rebates are higher after the first competitor event for small-molecule drugs sample (Panel A and B, column 3), but this effect is statistically significant only in the sample of newly launched small-molecule products (Panel B, column 3). For newly launched small-molecule products, mean rebates are 10% and 12% higher between the first and second competitor entry event and between second and third competitor entry event, respectively. Among large molecule incumbent products (Panel A, column 6), changes in mean rebates are significant only in the two cases where declines in list prices are observed. First, mean rebates are significantly lower (8%) during the period between the 4th and 5th competitor entry event in the sample of large-molecule drugs (Panel A, column 6). Second, mean rebates are significantly higher (10%) during the period after the 5th competitor entry event in the sample of newly launched large molecule products (Panel

B, column 6) due to the larger decline in net relative to list prices. Given the lack of consistent effects between the full sample and sub-sample of newly launched products (Panel A vs. Panel B) of large-molecule products, these effects of competitor entry on rebates should be generalized with caution.

Impact of the Quality of Competitors on Prices

For the sample of small-molecule drugs, the impact of competitor entry is estimated using an alternative approach to competitor identification using delivery risks associated with the product (Table 5 and Table 6). Entry of competitors which have lower delivery risk than incumbents have significant effects on incumbent prices (Table 5, columns 4-6). The first competitor entry event is associated with 9% and 7% lower mean net and list prices, respectively (Table 5, Panel A, column 4 and 5). After the 3rd competitor entry event, subsequent entry events may change the net and/or list prices by 10% or less. Changes in net prices, list prices and rebates are qualitatively similar but not statistically significant in the sub-sample of newly launched drugs (Table 5, Panel B, columns 4-6). This may be because the entry of competitors with lower delivery risk typically happens later in the active product life cycle and is, thus, less frequent in the sample of newly-launched small-molecule products. Subsequent analyses reaffirms that the entry of a close competitor with lower delivery risk results in lower net prices. Specifically, a unit increase in the relative delivery risk of an incumbent product relative to the next best competitor is associated with 12% lower net prices (Table 6). An additional approach for the identification of competitors, using a measure of chemical similarity considered in the recent economics literature (Krieger, Li, et al. 2022; Dranove et al. 2022), is considered in the Appendix (refer to Appendix Tables 1-3, Figures 1-3).

Section V: Discussion and Conclusion

Price growth among newly launched and existing branded pharmaceutical products has been an important driver of rising pharmaceutical spending in the US over the past decade (BioPharma Dive 2018; US Department of Health and Human Services 2018; Bosworth et al. 2022). Competition, especially from imperfect therapeutic substitutes that enter the market much before a branded drug loses market exclusivity, may benefit consumers through lower prices. However, it is challenging to empirically examine the relationship between price and brand-to-brand competition given the difficulty of identifying competitors among imperfect therapeutic substitutes and distinguishing between multiple prices which accrue to different agents in the supply chain. Using a novel dataset, this study provides comprehensive empirical evidence of the impact of competition on the prices of branded pharmaceutical products.

Empirical results indicate that competition is associated with lower net prices and higher rebates in two ways. First, market-level competition lowers the average financial rewards retained by manufacturers per unit sold (i.e. net prices) and increases the average rebate per unit that can be retained by middlemen in the supply chain. The magnitude of these effects are meaningful. Average net prices of incumbent drugs are 15% to 29% lower in relatively more competitive markets, whereas average rebates 15% to 26% are higher. For the average incumbent product in the estimation sample as of 2024 quarter 3, these estimates translate to $19,555 to $37,807 lower unit prices paid to

manufacturers and USD 6,146 to 10,654 rebate per unit potentially retained by middlemen as a result of greater therapeutic market competition.

Second, increases in competition due to new product entry is associated with lower net prices and larger rebates for incumbent products after controlling for product-level characteristics. The entry of a competitor product is associated with 5% to 10% lower net prices and, for a subset of small-molecule products, 10% to 12% higher rebates. The marginal decrease in net prices of incumbent products is significant after the entry of the second competitor. Analyses incorporating the product quality, measured as delivery risks associated with competitors, suggest that the entry entry of higher-quality competitors can reduce incumbents' net prices by 9% to 12% and increase rebates by 9%. As opposed to measures related to molecular similarity used in related literature despite being poorly associated with therapeutic function (Krieger, Li, et al. 2022; Martin et al. 2002), supplementary analyses indicate that delivery risk scores better capture a dimension of product quality that affects price. Overall, these findings suggest that product-market competition reduce the financial rewards accruing to manufacturers without benefitting consumers via lower list prices. Moreover, greater competition can increase revenue-generating rebates accruing to middlemen that is consistent with accounts of significant bargaining power held by these payors when negotiating with manufacturers (Healthcare Dive 2015; Fein 2025b).

Competition has heterogeneous impacts across different product groups. Across a broad range of therapeutic areas, empirical results indicate that the impacts of competition on net prices and rebates are larger and more consistently increasing with levels of market competition among large-molecule products, relative to small-molecule products. Moreover, average list prices of incumbent products are also lower in more competitive markets. These findings may be a result of differences in the nature of scientific progress between these product groups. While follow-on competitors of small-molecule drugs are often cast as incremental improvements over the initial first-in-class product, innovation amongst close competitors of large molecule products is often described to be more radical or discontinuous (DiMasi et al. 2016; Cockburn and Henderson 2001; Dranove et al. 2022). If competitor entry involves therapeutic substitutes which are more novel and if novelty is associated with clinical value (Krieger, Li, et al. 2022), new competitor entry may be more likely to suppress the prices of incumbents in large-molecule markets. Understanding the quality of competitors in the large-molecule product market can shed light on this hypothesis and remains a promising area for further research.

For the sample of small-molecule products, this study provides evidence that the quality of competitors has a significant effect on net prices and rebates. While measures of chemical similarity used in recent literature examining the economic returns to scientific novelty (Krieger, Li, et al. 2022; Dranove et al. 2022) did not have a significant effect on incumbent prices, the risk profile of a competitor relative to incumbents impacts net prices and rebates. These findings suggest that the standardized and widely available measures of delivery risk, which capture multiple risks related to the safety and efficacy of a drug, offers a more precise approach for identifying competitors that is demonstrated to be associated with prices. This alternative, and more precise, approach to competitor identification can be useful when evaluating claims of monopolization involving branded

drugs during their market exclusivity period. Assessments for such antitrust cases are often for incumbent drugs relative to the closest therapeutic equivalents of the drug being evaluated (Federal Trade Commission 2023; Pierson 2023).

The findings offer important insights for antitrust economists and policymakers seeking to simultaneously preserve consumer welfare and incentives to innovate in pharmaceutical markets. Antitrust enforcement relies on real-world evidence of consumers' sensitivity to prices when defining product markets, evaluating the potential for monopolization and assessing the magnitude of consumer harm. This study provides valuable empirical evidence pertaining to the impacts of competition in a large sample of branded pharmaceutical products spanning over two hundred therapeutic markets over a fifteen-year period. Results pertaining to list prices are directly related to out-of-pocket burden on consumers[21] and relevant to conventional analyses undertaken by the FTC and state attorney generals (Salt Lake County Third Judicial District Court 2023; California Department of Justice, Office of the Attorney General 2023; Federal Trade Commission 2024). The wide-ranging evidence of growth in list prices despite greater competition reinforces regulators' concerns of anticompetitive distortions in the supply chain which exist despite the availability of therapeutic substitutes (Rao and Federal Trade Commission 2024).

Regulators have also considered whether rebate growth is attributed to growth in list prices or declines in net prices, in efforts to target enforcement actions at specific actors in the supply chain (Rao and Federal Trade Commission 2024). I find that rebate growth in increasingly competitive markets are driven by declines in net prices. These results lend more weight to regulators' concerns about anticompetitive conduct among intermediaries who profit from the gap between net and list prices. Estimates of the expected, negative effect of declines in product quality on net prices lends further support to the hypothesis that competition yields lowers prices in various therapeutic markets but the declines in price get absorbed by intermediaries. Further research on the heterogeneous impacts of competition across actors in the supply chain is timely and essential in order to address related regulatory concerns of exclusionary conduct and foreclosure of low-list price rivals in pharmaceutical markets (Federal Trade Commission 2024).

Three limitations of this study should be noted. First, the sample of branded incumbent drugs in the US considered in these analyses do not capture the universe of branded prescription drugs that were actively marketed globally between 2010 and 2024. As noted in prior literature using the same data source, the dataset of prices captures branded drugs sold by publicly owned companies prior to the entry of a generic product. Notably, even within the US market, high-priced drugs which are sold by private companies are not captured in the sample. (Kakani et al. 2020; Ippolito and Levy 2022) Second, delivery risk scores do not fully capture the clinical value of products. While our analyses introduce a new measure of competitor quality for assessing the impact of competition on prices, many dimensions of quality that are relevant for assessing the value of a drug to patients, such as the selectivity of a drug and notable drug-drug interactions, are not captured by ADMET profiles. (Hodgson 2001) Despite its limitations, ADMET risk scores are predictive of efficacy, are

[21] Coinsurance rates faced by insured consumers are tied to list prices. List prices are paid in full in absence of insurance.

widely available and can be feasibly used by regulators when comparing competitors in pharmaceutical markets (Ferreira and Andricopulo 2019). Finally, while this study provides useful insights pertaining to product-level rebates, it should be reiterated that rebates are calculated as the differences between list and net prices. The total value, or portions of the rebates, cannot be attributed to any specific payor in the supply chain with certainty.

Tables and Figures

Table 1. Summary of product-level characteristics (N=816 products)

	2010q1			2024q3			All quarters (2010q1 to 2024q3)		
	N	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**
Net price	184	19,581.82	52,156.18	369	130,368.50	270,662.50	18616	74,460.68	164,086.10
List price	184	25,493.55	69,668.76	369	171,344.40	333,267.80	18616	97,279.01	199,748.40
Rebate	184	5,911.73	21,301.78	369	40,975.87	68,840.94	18616	22,818.33	46,094.09
Time since market entry (years)	183	9.39	6.37	369	9.17	7.55	18611	9.04	7.63
	N	**%**		**N**	**%**		**N**	**%**	
Small molecule products	143	78.14		206	55.83		12416	66.71	
Large molecule products	40	21.86		163	44.17		6195	33.29	
Combination products	45	24.59		80	21.68		4414	23.72	

Note: All prices are expressed as inflation-adjusted real dollars (USD 2024 quarter 3) using the quarterly average of monthly CPI-U indices. (Bureau of Labor Statistics 2025) Large molecule products are defined to include products with active ingredients classified as genes, cells, proteins, antibodies, antibody drug conjugates, enzymes, peptides, oligonucleotides, oligosaccharides and with no active ingredients that have a molecule structure which can be captured by a standardized SMILES notation. Combination products are products with more than one distinct active ingredient.

Table 2. Competitor Entry Events (N=816 products)

	N	Mean	SD	25th Pct	Median	75th Pct
Panel A: Large molecule products						
Number of competitors	227	6.66	5.65	3	5	9
Panel B: Small molecule products						
Number of competitors	470	4.77	4.46	2	3	6
Number of competitors with lower delivery risk	314	3.33	3.15	1	2	4

Note: Competitors refer to all products with a distinct set of active ingredients relative to the incumbent that are actively marketed within the same therapeutic market (ATC4). Competitors with lower risk refer to products with lower overall ADMET risk. Product-level ADMET risk scores are derived using the mean of ingredient-level ADMET risk scores within each product.

Table 3. Impact of Market-level Competition on Product-level Prices (USD, 2024)

	All products			Small molecules			Large molecules		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Net	WAC	Rebate	Net	WAC	Rebate	Net	WAC	Rebate
Panel A: Full Sample of Products									
Market-level competition (Omitted reference: Low)									
Moderate	-0.139***	-0.0294	0.139***	-0.129***	-0.0184	0.0810	-0.139**	-0.0257	0.179**
	(0.0439)	(0.0281)	(0.0494)	(0.0468)	(0.0311)	(0.0533)	(0.0703)	(0.0441)	(0.0777)
High	-0.202***	-0.0162	0.227***	-0.0715	0.0461	0.144*	-0.352***	-0.0529	0.296***
	(0.0616)	(0.0402)	(0.0679)	(0.0674)	(0.0510)	(0.0853)	(0.0939)	(0.0592)	(0.0966)
Very high	-0.261***	-0.0913*	0.139	-0.100	0.0310	0.111	-0.464***	-0.224***	0.147
	(0.0801)	(0.0540)	(0.0855)	(0.0988)	(0.0615)	(0.106)	(0.119)	(0.0853)	(0.130)
Unique products	816	816	816	567	567	567	249	249	249
Unique therapeutic markets	244	244	244	201	201	201	68	68	68
Observations	18,611	18,611	18,611	12,416	12,416	12,416	6,195	6,195	6,195
Panel B: Products launched between 2010q1 and 2024q3									
Market-level competition (Omitted reference: Low)									
Moderate	-0.103**	-0.0190	0.120**	-0.123**	-0.0135	0.102	-0.0895	-0.0147	0.160*
	(0.0406)	(0.0330)	(0.0571)	(0.0510)	(0.0320)	(0.0662)	(0.0552)	(0.0748)	(0.0901)
High	-0.220***	-0.0197	0.207***	-0.111	0.0280	0.167	-0.252***	-0.0249	0.245**
	(0.0663)	(0.0481)	(0.0767)	(0.112)	(0.0662)	(0.121)	(0.0701)	(0.0848)	(0.111)
Very high	-0.309***	-0.119*	0.111	-0.137	0.0266	0.154	-0.494***	-0.229*	0.124
	(0.0905)	(0.0655)	(0.0950)	(0.126)	(0.0756)	(0.134)	(0.138)	(0.123)	(0.168)
Unique products	514	514	514	342	342	342	172	172	172
Unique therapeutic markets	192	192	192	156	156	156	54	54	54
Observations	9,924	9,924	9,924	6,738	6,738	6,738	3,186	3,186	3,186

Notes: All regression models include a control for the time on market, product and quarter fixed effects. All prices are expressed as inflation-adjusted real dollars (USD 2024 quarter 3) using the quarterly average of monthly CPI-U indices. (Bureau of Labor Statistics 2025) Levels of market competition are defined using quartiles of the number of competitors across all product-quarters in the estimation sample. Low competition (at or below the 25th percentile) corresponds to <=5 competitors (<=5, <=5) in the full sample and the sample of newly launched products (small molecules, large molecules). Moderate competition (between 25th percentile and median) corresponds to 5-10 competitors (5-11, 5-9) in the full sample and the sample of newly launched products (small molecules, large molecules). High competition (between the median and 75th percentile) corresponds to 10-17 [10-19] competitors (11-18, 9-16) [11-19, 9-17] in the full sample (small molecules, large molecules) and the sample of newly launched products [small molecules, large molecules]. Very high competition (above the 75th percentile) corresponds to >17 [>19] competitors (>18, >16) [>19, >17] in the sample of all products (small molecules, large molecules) and the sample of newly launched products [small molecules, large molecules]. Robust standard errors in parentheses. Standard errors are clustered at the product-level. Statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Impact of competitor entry events

	Small molecules			Large molecules		
	(1)	(2)	(3)	(4)	(5)	(6)
	Net	WAC	Rebate	Net	WAC	Rebate
Panel A: Full sample of products						
Treatment indicator						
After 1st entry event	-0.00786	0.00301	0.0477	0.0249	0.0257	-0.00761
	(0.0253)	(0.0206)	(0.0419)	(0.0395)	(0.0232)	(0.0593)
After 2nd entry event	-0.0462**	0.0112	0.0512	-0.0962***	-0.00899	0.0360
	(0.0227)	(0.0161)	(0.0318)	(0.0319)	(0.0223)	(0.0502)
After 3rd entry event	0.0151	0.00914	0.0109	-0.0423	-0.0279*	-0.0422
	(0.0259)	(0.0145)	(0.0354)	(0.0292)	(0.0161)	(0.0408)
After 4th entry event	0.0215	0.0164	0.0362	-0.0611	-0.0375***	-0.0757*
	(0.0304)	(0.0198)	(0.0352)	(0.0406)	(0.0127)	(0.0443)
After 5th entry event	0.0489	-0.0143	-0.00413	-0.0980**	-0.0629***	0.0545
	(0.0338)	(0.0203)	(0.0424)	(0.0422)	(0.0174)	(0.0575)
Unique products	567	567	567	249	249	249
Unique therapeutic markets	201	201	201	68	68	68
Observations	12,416	12,416	12,416	6,195	6,195	6,195
Panel B: Products launched between 2010q1 and 2024q3						
Treatment indicator						
After 1st entry event	0.0120	0.0359	0.115**	-0.0527	-0.0347	0.0497
	(0.0267)	(0.0236)	(0.0524)	(0.0417)	(0.0259)	(0.0631)
After 2nd entry event	-0.0631**	0.0213	0.0932**	-0.0941**	-0.0370*	-0.0501
	(0.0265)	(0.0158)	(0.0382)	(0.0393)	(0.0221)	(0.0540)
After 3rd entry event	0.00501	0.00317	0.0118	-0.0240	-0.00802	-0.0529
	(0.0322)	(0.0130)	(0.0442)	(0.0312)	(0.0138)	(0.0419)
After 4th entry event	-0.0424	-0.0165	0.0477	-0.0173	-0.0126	-0.00606
	(0.0361)	(0.0163)	(0.0442)	(0.0340)	(0.0121)	(0.0443)
After 5th entry event	0.0629	-0.0120	-0.0520	-0.0659**	-0.0302**	0.0993*
	(0.0405)	(0.0183)	(0.0416)	(0.0334)	(0.0136)	(0.0533)
Unique products	342	342	342	172	172	172
Unique therapeutic markets	156	156	156	54	54	54
Observations	6,738	6,738	6,738	3,186	3,186	3,186

Note: All regression models include a control for the time on market, product and quarter fixed effects. All regression models include a control for the time on market, product and quarter fixed effects. All prices are inflation-adjusted real dollars (USD 2024 quarter 3) using the quarterly average of monthly CPI-U indices. (Bureau of Labor Statistics 2025) Treatment indicators are defined as binary indicator variables which take on the value of 1 for every product-quarter after the specified competitor entry event occurs. Robust standard errors in parentheses. Standard errors are clustered at the product-level. Statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Impact of competitor entry in small-molecule sample using alternative competitor definitions

	Small molecule competitor			Lower risk competitor		
	(1)	(2)	(3)	(4)	(5)	(6)
	Net	WAC	Rebate	Net	WAC	Rebate
Panel A: Full sample of small-molecule products (N=567 products)						
Treatment indicator						
After 1st entry event	-0.00786	0.00301	0.0477	-0.0820***	-0.0701***	-0.0713
	(0.0253)	(0.0206)	(0.0419)	(0.0285)	(0.0225)	(0.0505)
After 2nd entry event	-0.0462**	0.0112	0.0512	0.0331	0.0511**	0.0594
	(0.0227)	(0.0161)	(0.0318)	(0.0295)	(0.0201)	(0.0422)
After 3rd entry event	0.0151	0.00914	0.0109	0.0423	0.0240	0.0263
	(0.0259)	(0.0145)	(0.0354)	(0.0327)	(0.0209)	(0.0351)
After 4th entry event	0.0215	0.0164	0.0362	0.0841**	0.0407	-0.00355
	(0.0304)	(0.0198)	(0.0352)	(0.0337)	(0.0295)	(0.0418)
After 5th entry event	0.0489	-0.0143	-0.00413	-0.0963*	-0.0610**	-0.0591
	(0.0338)	(0.0203)	(0.0424)	(0.0502)	(0.0272)	(0.0569)
Unique products	567	567	567	567	567	567
Unique therapeutic markets	201	201	201	201	201	201
Observations	12,416	12,416	12,416	12,416	12,416	12,416
Panel B: Small-molecule products launched between 2010q1 and 2024q3 (N=342)						
Treatment indicator						
After 1st entry event	0.0120	0.0359	0.115**	-0.0541	-0.0191	-0.0281
	(0.0267)	(0.0236)	(0.0524)	(0.0362)	(0.0229)	(0.0521)
After 2nd entry event	-0.0631**	0.0213	0.0932**	-0.00481	0.00720	0.0210
	(0.0265)	(0.0158)	(0.0382)	(0.0330)	(0.0210)	(0.0446)
After 3rd entry event	0.00501	0.00317	0.0118	0.00915	0.0104	0.0159
	(0.0322)	(0.0130)	(0.0442)	(0.0335)	(0.0196)	(0.0434)
After 4th entry event	-0.0424	-0.0165	0.0477	0.0330	-0.00406	-0.0376
	(0.0361)	(0.0163)	(0.0442)	(0.0393)	(0.0296)	(0.0509)
After 5th entry event	0.0629	-0.0120	-0.0520	-0.00613	-0.0239	-0.105*
	(0.0405)	(0.0183)	(0.0416)	(0.0517)	(0.0300)	(0.0567)
Unique products	342	342	342	342	342	342
Unique therapeutic markets	156	156	156	156	156	156
Observations	6,738	6,738	6,738	6,738	6,738	6,738

Note: All regression models include a control for the time on market, product and quarter fixed effects. All prices are expressed as inflation-adjusted real dollars (USD 2024 quarter 3) using the quarterly average of monthly CPI-U indices. (Bureau of Labor Statistics 2025) Treatment indicators are defined as binary indicator variables which take on the value of 1 for every product-quarter after the specified competitor entry event occurs. Lower risk competitors refer to products with lower overall ADMET risk scores. Product-level ADMET risk scores are derived using the mean of ingredient-level ADMET risk scores within each product. Robust standard errors in parentheses. Standard errors are clustered at the product-level. Statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Impact of changes in the quality of the closest competitor

	(1) Net	(2) WAC	(3) Rebate
Panel A: Full sample of small-molecule products (N=567 products)			
Relative delivery risk	-0.112***	-0.00825	0.0846**
	(0.0300)	(0.0152)	(0.0413)
Unique products	561	561	561
Unique therapeutic markets	199	199	199
Observations	12,343	12,343	12,343
Panel B: Small-molecule products launched between 2010q1 and 2024q3 (N=342)			
Relative delivery risk	-0.0810***	-0.0245	0.0281
	(0.0265)	(0.0162)	(0.0349)
Unique products	342	342	342
Unique therapeutic markets	156	156	156
Observations	6,560	6,560	6,560

Note: All regression models include a control for the time on market, product and quarter fixed effects. All prices are expressed as inflation-adjusted real dollars (USD 2024 quarter 3) using the quarterly average of monthly CPI-U indices. (Bureau of Labor Statistics 2025) Relative delivery risk (i.e. the difference in ADMET risk) is calculated using the product-level ADMET risk scores on a scale of 0 (no risk) to 22 (maximum risk). Product-level ADMET risk scores are derived using the mean of all ingredient level ADMET risk scores associated with a product. Robust standard errors in parentheses. Standard errors are clustered at the product-level. Statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Figure 1: Panel data construction

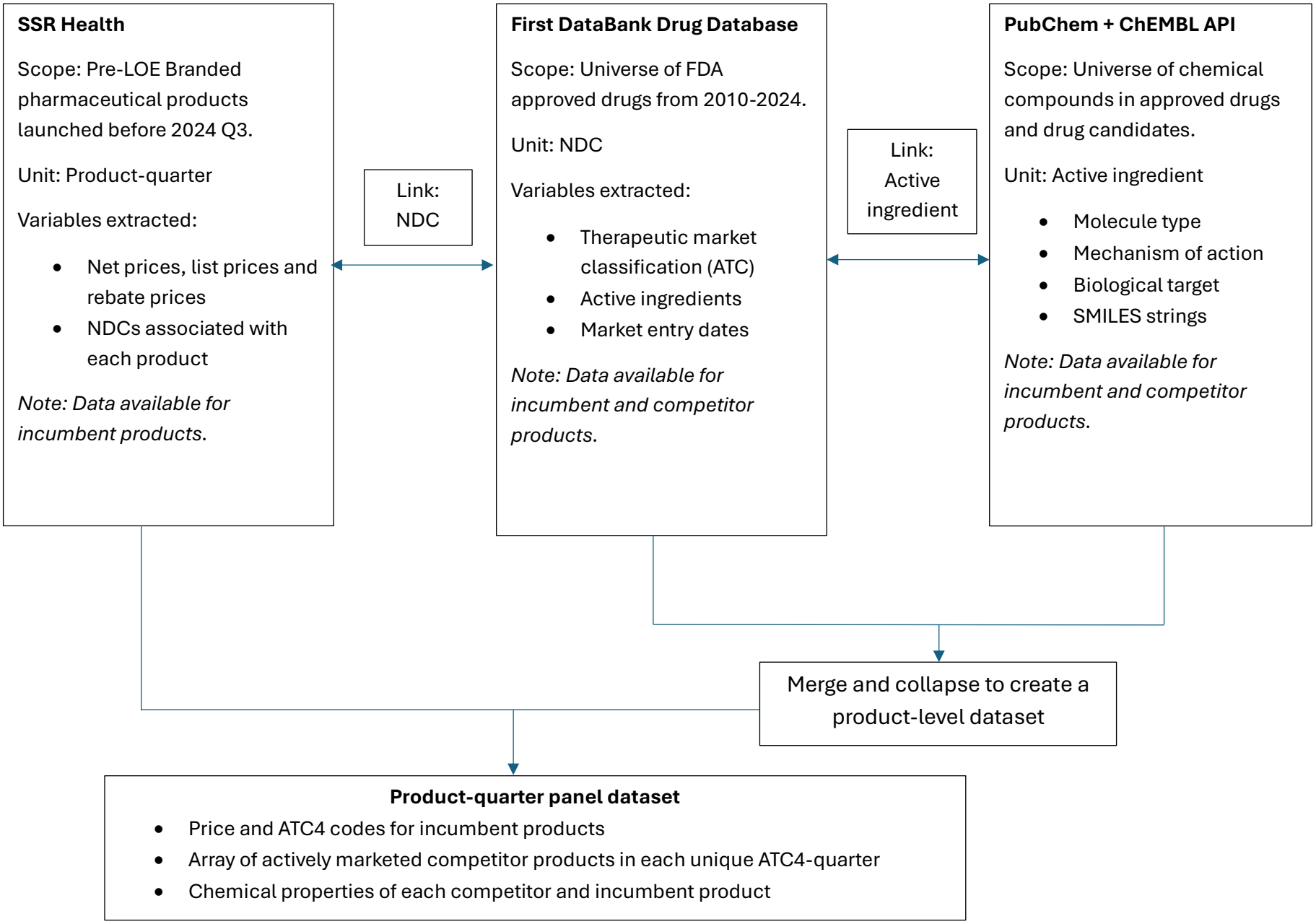
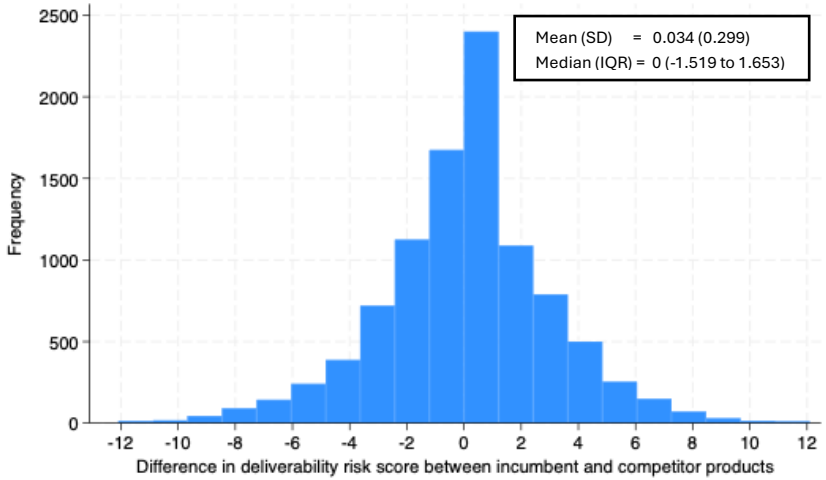
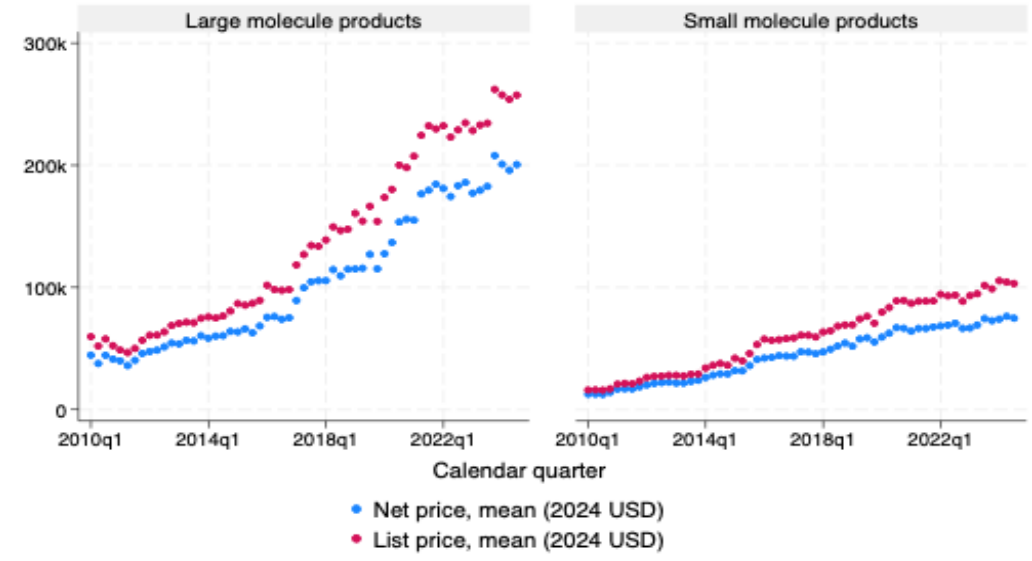


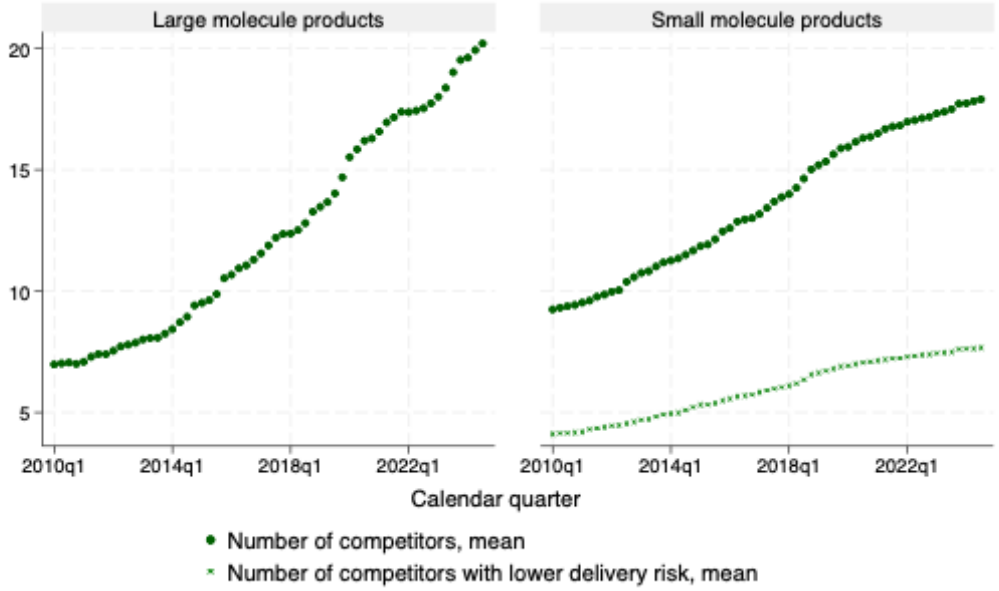
Figure 2: Distribution of Delivery Risk Scores across pairs of competitors (N=9800)



Note: The distribution of relative delivery risk scores across all unique pairs of competitors is illustrated above. The analytic sample consists of 567 small-molecule products with pricing data and 9800 unique competitor-pairs. The distribution of relative delivery risk scores across all unique pairs of competitors is illustrated above. Relative Delivery Risk scores are calculated as the overall product-level ADMET risk score for the incumbent products (i.e. SSR products) minus the score of the competitor product. Thus, positive scores indicate more favorable profiles for competitor products (i.e. lower ADMET risk). Among pairs of small-molecule competitor products, ADMET risk could not be obtained for 40/9800 unique competitor pairs.

Figure 3. Growth in Average Prices (Upper) and Number of Competitors (Lower) over time, 2010 Q1 to 2024 Q3





Note: All prices are expressed as inflation-adjusted real values using the quarterly average of monthly CPI-U indices. (Bureau of Labor Statistics 2025) Competitors refer to all products with a distinct set of active ingredients relative to the incumbent that are actively marketed within the same therapeutic market (ATC4). Competitors with lower delivery risk refer to products with lower overall ADMET risk scores. Product-level ADMET risk scores are derived using the mean of ingredient-level ADMET risk scores within each product. Measures of similarity and risk are only defined for small-molecule products.

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Appendix

Appendix 1: Overview of Chemical Similarity Scores

As supplementary analyses, we consider an alternative measure of product quality: the similarity of the molecular structure of molecules among competitor products. Chemical similarity scores were computed for each product relative to each of its' competitors using SMILES strings in two steps. First, similarity was assessed at the ingredient-level. For each pair of active ingredients, a Tanimoto distance indicating the structural similarity of a pair of active ingredients is computed on a scale of 0 (completely novel) to 1 (completely identical), using SMILES strings. Tanimoto distances capture structural similarity of molecules which has been found to be correlated with the functional properties of molecules. (Wawer et al. 2014; Bickerton et al. 2012) While the correlation between structural and functional similarity is not perfect, Tanimoto scores have been used to assess the scientific novelty of pharmaceutical drugs in recent literature. (Krieger, Li, et al. 2022; Baldi and Nasr 2010) Pairwise chemical similarity scores represent the chemical similarity between a product and a competitor product in each therapeutic market and quarter on a scale of 0 (chemically novel) to 1 (chemically identical).

Tanimoto distances at the ingredient-level are then used to obtain a product-level similarity score for pairs of competitor products in each therapeutic market and quarter on an analogous scale of 0 (chemically novel) to 1 (chemically identical). The product-level similarity score is evaluated as the Tanimoto distance between an active ingredient in a drug and the chemically most similar active ingredient present in a competitor drug. For a drug that comprises more than one active ingredient, only newly introduced component active ingredients in the drug are considered for the calculation.[22] Chemical similarity scores of a drug can go up due to competitor entry, but only when competitor entry introduces an active ingredient to the market which is more similar to an active ingredient in a drug than any other active ingredient present in existing products within the same therapeutic market. Chemical similarity scores can decline in instances where a competitor exits the market. The distribution of product-level similarity scores in described in Appendix Figure 2.

Appendix Table 1. Number of competitors for small-molecule incumbents (N=567 products)

	N	Mean	SD	25th Pct	Median	75th Pct
Number of competitors	470	4.77	4.46	2	3	6
Number of chemically similar competitors	369	3.01	2.77	1	2	4
Number of competitors with lower delivery risk	314	3.33	3.15	1	2	4

Note: Competitors refer to all products with a distinct set of active ingredients relative to the incumbent that are actively marketed within the same therapeutic market (ATC4). Chemically similar competitors refer to competitor products which have a similarity score >= 0.176 (median value in the distribution of all competitors). Product-level similarity scores are constructed using all pairwise Tanimoto scores between ingredients in each pair of competitor products. Competitors with lower risk refer to products with lower overall ADMET risk. Product-level ADMET risk scores are derived using the mean of ingredient-level ADMET risk scores within each product.

[22] A combination drug will have a similarity score = 1 if all active ingredients included exist in one or more competitor products. That is, a "novel combination" of existing active ingredients will not be captured in the similarity score.

Appendix Table 2: Impact of competitor entry in small-molecule sample using alternative competitor definitions

	Small molecule competitor			Chemically similar competitor			Lower risk competitor		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Net	WAC	Rebate	Net	WAC	Rebate	Net	WAC	Rebate
Panel A: Full sample of small-molecule products (N=567 products)									
Treatment indicator									
After 1st entry event	-0.00786	0.00301	0.0477	0.00470	-0.0116	-0.00103	-0.0820***	-0.0701***	-0.0713
	(0.0253)	(0.0206)	(0.0419)	(0.0273)	(0.0212)	(0.0425)	(0.0285)	(0.0225)	(0.0505)
After 2nd entry event	-0.0462**	0.0112	0.0512	-0.0477	-0.00847	-0.00821	0.0331	0.0511**	0.0594
	(0.0227)	(0.0161)	(0.0318)	(0.0292)	(0.0203)	(0.0404)	(0.0295)	(0.0201)	(0.0422)
After 3rd entry event	0.0151	0.00914	0.0109	0.0519*	0.0247	0.0387	0.0423	0.0240	0.0263
	(0.0259)	(0.0145)	(0.0354)	(0.0295)	(0.0180)	(0.0481)	(0.0327)	(0.0209)	(0.0351)
After 4th entry event	0.0215	0.0164	0.0362	0.0274	-0.0220	-0.0852	0.0841**	0.0407	-0.00355
	(0.0304)	(0.0198)	(0.0352)	(0.0585)	(0.0277)	(0.0750)	(0.0337)	(0.0295)	(0.0418)
After 5th entry event	0.0489	-0.0143	-0.00413	0.0360	-0.0269	-0.0303	-0.0963*	-0.0610**	-0.0591
	(0.0338)	(0.0203)	(0.0424)	(0.0663)	(0.0311)	(0.0878)	(0.0502)	(0.0272)	(0.0569)
Unique products	567	567	567	567	567	567	567	567	567
Unique therapeutic markets	201	201	201	201	201	201	201	201	201
Observations	12,416	12,416	12,416	12,416	12,416	12,416	12,416	12,416	12,416
Panel B: Small-molecule products launched between 2010q1 and 2024q3 (N=342)									
Treatment indicator									
After 1st entry event	0.0120	0.0359	0.115**	0.0472*	0.0501**	0.0702	-0.0541	-0.0191	-0.0281
	(0.0267)	(0.0236)	(0.0524)	(0.0282)	(0.0249)	(0.0521)	(0.0362)	(0.0229)	(0.0521)
After 2nd entry event	-0.0631**	0.0213	0.0932**	-0.0253	0.0227	0.0276	-0.00481	0.00720	0.0210
	(0.0265)	(0.0158)	(0.0382)	(0.0334)	(0.0266)	(0.0515)	(0.0330)	(0.0210)	(0.0446)
After 3rd entry event	0.00501	0.00317	0.0118	0.0647	0.0486**	0.0717	0.00915	0.0104	0.0159
	(0.0322)	(0.0130)	(0.0442)	(0.0442)	(0.0210)	(0.0632)	(0.0335)	(0.0196)	(0.0434)
After 4th entry event	-0.0424	-0.0165	0.0477	-0.106	-0.0766***	-0.104	0.0330	-0.00406	-0.0376
	(0.0361)	(0.0163)	(0.0442)	(0.0732)	(0.0288)	(0.0710)	(0.0393)	(0.0296)	(0.0509)
After 5th entry event	0.0629	-0.0120	-0.0520	0.145*	0.00403	-0.137*	-0.00613	-0.0239	-0.105*
	(0.0405)	(0.0183)	(0.0416)	(0.0821)	(0.0296)	(0.0797)	(0.0517)	(0.0300)	(0.0567)
Unique products	342	342	342	342	342	342	342	342	342
Unique therapeutic markets	156	156	156	156	156	156	156	156	156
Observations	6,738	6,738	6,738	6,738	6,738	6,738	6,738	6,738	6,738

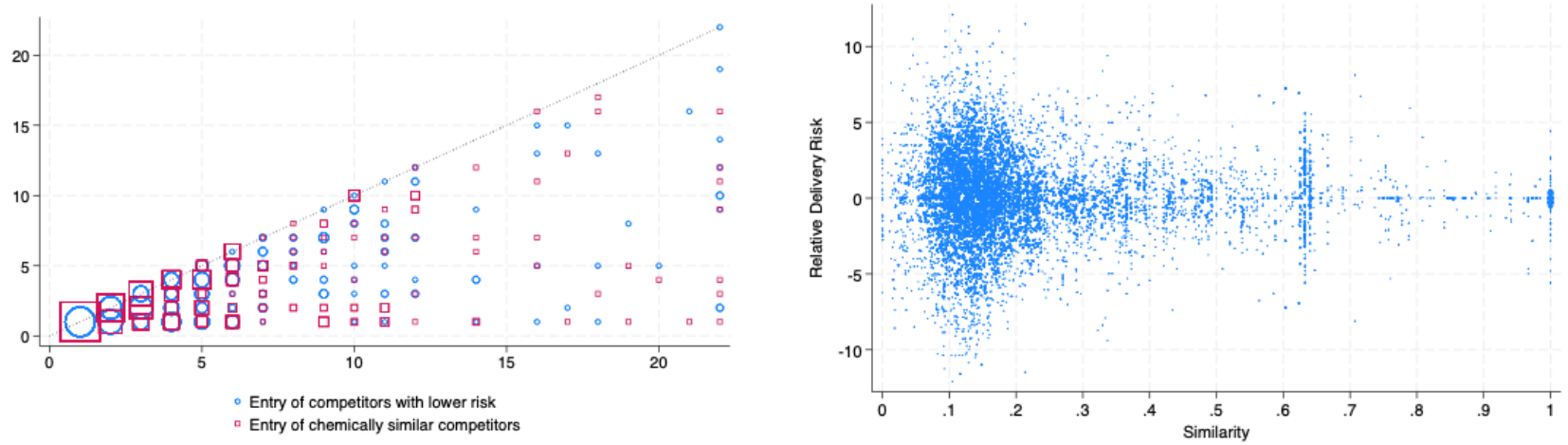
Note: All regression models include a control for the time on market, product and quarter fixed effects. All prices are expressed as inflation-adjusted real dollars (USD 2024 quarter 3) using the quarterly average of monthly CPI-U indices. (Bureau of Labor Statistics 2025) Treatment indicators are defined as binary indicator variables which take on the value of 1 for every product-quarter after the specified competitor entry event occurs. Chemically similar competitors refer to competitor products which have a similarity score >= 0.176 (median value in the distribution of all competitors). Product-level similarity scores are constructed using all pairwise Tanimoto scores between ingredients in each pair of competitor products. Lower risk competitors refer to products with lower overall ADMET risk. Product-level ADMET risk scores are derived using the mean of ingredient-level ADMET risk scores within each product. Robust standard errors in parentheses. Standard errors are clustered at the product-level. Statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 3: Impact of changes in the quality of the closest competitor

	(1) Net	(2) WAC	(3) Rebate	(4) Net	(5) WAC	(6) Rebate
Quality relative to closest competitor						
Similarity	-0.00720	-0.000619	0.0942			
	(0.0752)	(0.0487)	(0.140)			
Relative delivery risk				-0.112***	-0.00825	0.0846**
				(0.0300)	(0.0152)	(0.0413)
Unique products	561	561	561	561	561	561
Unique therapeutic markets	199	199	199	199	199	199
Observations	12,347	12,347	12,347	12,343	12,343	12,343

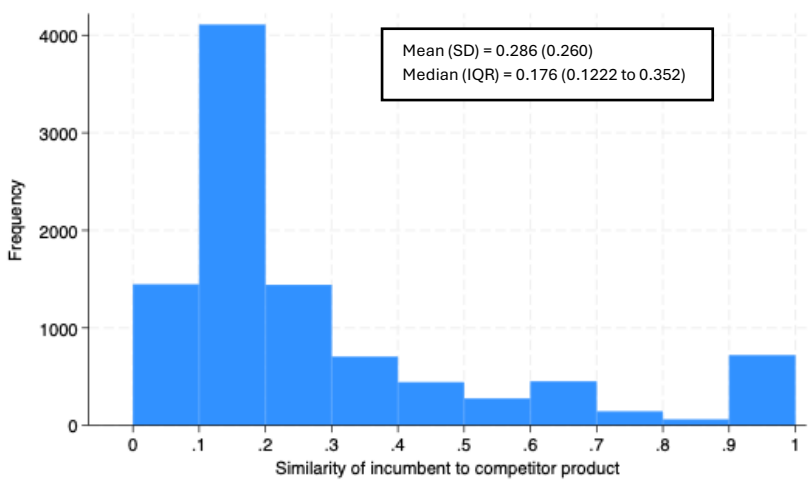
Note: All regression models include a control for the time on market, product and quarter fixed effects. All prices are expressed as inflation-adjusted real dollars (USD 2024 quarter 3) using the quarterly average of monthly CPI-U indices. (Bureau of Labor Statistics 2025) Chemically similarity capture product-level similarity in the chemical structure of two competitor products in the range of 0=completely dissimilar and 1=perfectly identical. Product-level similarity is calculated using all pairwise Tanimoto scores between ingredients in each pair of competitor products. Difference in ADMET risk is calculated using the product-level ADMET risk scores on a scale of 0 (no risk) to 22 (maximum risk). Product-level ADMET risk scores are derived using the mean of all ingredient level ADMET risk scores associated with a product. Robust standard errors in parentheses. Standard errors are clustered at the product-level. Statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1.

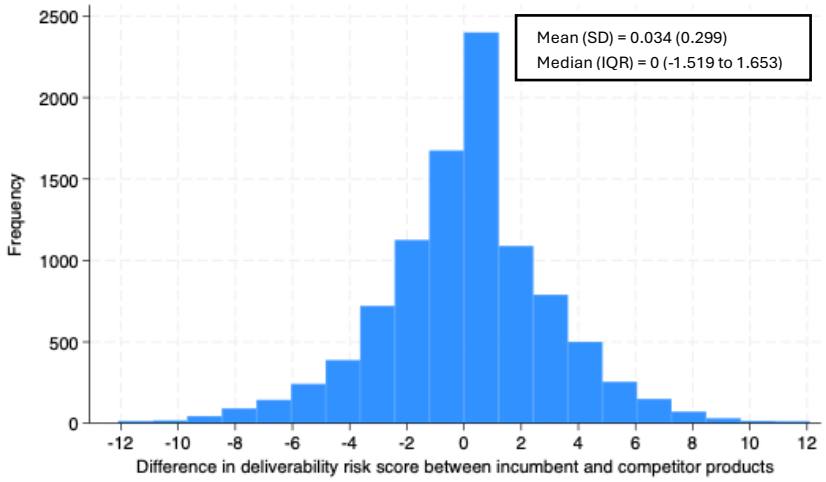
Appendix Figure 1. Comparison of Competitor Definitions for Small Molecule Products in terms of New Competitor Entry Events (Left) and All Competitor Product-Pairs (Right)



Note: Competitors refer to all products with a distinct set of active ingredients relative to the incumbent that are actively marketed within the same therapeutic market (ATC4). Chemically similar competitors refer to competitor products which have a similarity score >= 0.176 (median value in the distribution of all competitors). Product-level similarity scores are constructed using all pairwise Tanimoto scores between ingredients in each pair of competitor products. Competitors with lower risk refer to products with lower overall ADMET risk. Product-level ADMET risk scores are derived using the mean of ingredient-level ADMET risk scores within each product. The analytic sample comprises N=567 small-molecule products and N=9800 unique competitor-pairs.

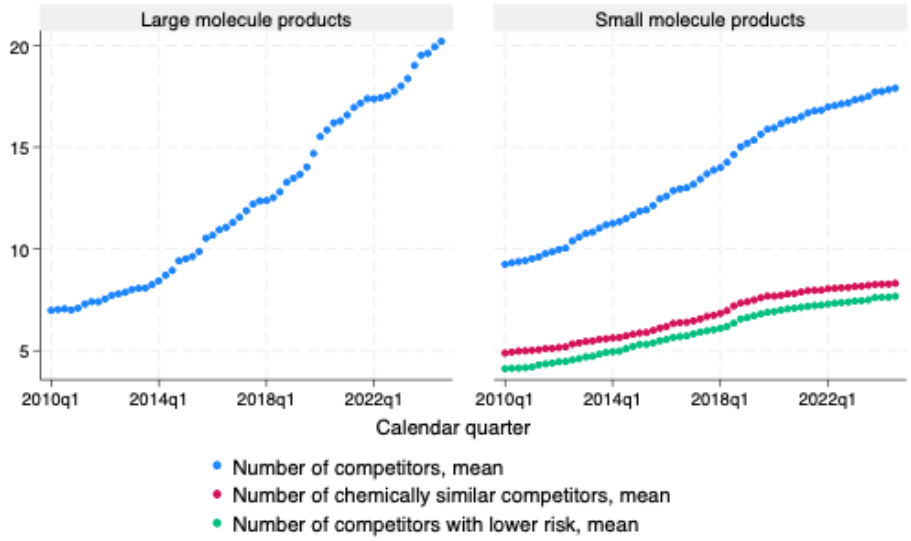
Appendix Figure 2: Distribution of Product-level Similarity and Delivery Risk Scores across pairs of competitors (N=9800)





Note: The distribution of product-level similarity scores (derived from ingredient-level Tanimoto distances) and relative delivery risk scores across all unique pairs of competitors is described below. The analytic sample consists of 567 small-molecule products with pricing data and 9800 unique competitor-pairs. Among pairs of small-molecule competitor products, ADMET risk could not be obtained for 40/9800 unique competitor pairs. Product-level similarity scores are constructed using all pairwise Tanimoto scores between ingredients in each pair of competitor products. Relative Deliverability Risk scores are calculated as the overall product-level ADMET risk score for the incumbent products (i.e. SSR products) minus the score of the competitor product. Thus, positive scores indicate more favorable profiles for competitor products (i.e. lower ADMET risk).

Appendix Figure 3. Number of Competitors over time, 2010 Q1 to 2024 Q3



Note: All prices are expressed as inflation-adjusted real values using the quarterly average of monthly CPI-U indices. (Bureau of Labor Statistics 2025) Competitors refer to all products with a distinct set of active ingredients relative to the incumbent that are actively marketed within the same therapeutic market (ATC4). Chemically similar competitors refer to competitor products which have a similarity score >= 0.176 (median value in the distribution of all competitors). Product-level similarity scores are constructed using all pairwise Tanimoto scores between ingredients in each pair of competitor products. Less risky competitors refer to products with lower overall ADMET risk. Product-level ADMET risk scores are derived using the mean of ingredient-level ADMET risk scores within each product. Measures of similarity and risk are only defined for small-molecule products.