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Jorge Tamayo

Harvard Business School

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Tomomichi Amano† Jorge Tamayo‡

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Abstract

Retailers are key intermediaries through which consumers encounter innovation in the form of new products. How are these products rolled out within retailers? We observe significant variation in the availability of new products across stores in a large retail chain in Colombia—even within the same supplier and product category—despite centralized decision-making and standardized processes. This variation is consistent with known rollout frictions, including geographic frictions. We find that managerial quality, which varies significantly across store managers, affects rollout in two ways. First, high-quality managers enhance the performance of products in their stores, with the result that new products initially allocated to high-quality managers reach 28.5 percent more stores within 11 months. Second, high-quality managers seek out new products for their stores, reducing rollout frictions by an amount equivalent to 9.2 percent of geographic frictions. Variation in middle management quality thus significantly influences the diffusion of new products within retail chains.

JEL Codes: L25, L81, D22, M31
Keywords: Managerial quality, firm performance, diffusion of innovation, new product rollout, retailing

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†Harvard Business School. Email: tamano@hbs.edu.

‡Harvard Business School; Digital Reskilling Lab, The Digital, Data, and Design Institute at Harvard. Email: jtamayo@hbs.edu.

1 Introduction

Industrial innovation often materializes in the form of new products, whose value is realized through their widespread adoption by consumers. Consumers are exposed to these innovations through the key intermediary of retail.[1] Retailers generate billions in revenue annually from the sales of new products, and the availability of new products on retailer shelves increases the variety of consumer purchases and enables a half-percent increase in welfare per year (Neiman and Vavra, 2023). New product adoption also has wider economic implications: it affects the cost of living (Broda and Weinstein, 2010; Jaravel, 2019) and drives creative destruction, firm growth, and competition (Argente et al., 2024; Garcia-Macia et al., 2019).[2]

Despite the role that retailers play in making new products available to consumers, little is known about the process by which products are rolled out within a retail chain. On the one hand, modern retail chains are centralized organizations with standardized processes and information technology across their stores (Bronnenberg and Ellickson, 2015; Guadalupe et al., 2014; Hortaçsu and Syverson, 2015; Hsieh and Rossi-Hansberg, 2023). On the other hand, retail chains are large organizations that serve a wide range of heterogeneous markets and have tens of thousands of employees. While large organizations make many centralized decisions, internal coordination costs arise because some decision-making is delegated to decentralized units (stores) and their managers, generating organizational frictions (Gibbons and Henderson, 2012).[3] Individual managers, rather than the organization's capital alone, play a critical role in explaining the within variation in store performance (Bandiera et al., 2020; Hoffman and Tadelis, 2021; Metcalfe et al., 2023). Thus, heterogeneity in managers' capability may hinder or facilitate the rollout of new products—despite a retailer's homogeneous processes and shared systems.

In this paper, we examine the impact of managerial quality on the rollout of new products. We study two ways in which managerial quality affects the rollout across a retail chain. First, high-quality managers significantly improve product performance in their stores. As a result, new products that are exposed to these managers reach 28.5 percent more stores within

[1] For instance, the average American household visits a supermarket six to seven times a month (Rudi and Çakır, 2017), a retail environment in which nearly 30,000 new products—enough to "fill the average grocery store"—are introduced annually (NielsenIQ, 2019)

[2] These studies focus on consumer packaged goods (CPGs). In 2022, "trendsetter" CPGs identified by Circana surpassed $6 billion in first-year sales. Incremental innovations, often from incumbents, drive growth (Garcia-Macia et al., 2019; Sorescu and Spanjol, 2008). Examples of these innovations include better packaging technology as well as product marketing (Deng and Srinivasan, 2013; Depecik et al., 2023).

[3] A distinguishing feature of the retail industry is the heterogeneity of the store environment, including a store's physical location and local demand and supply conditions. To accommodate this heterogeneity, the responsibility for adjusting inventory, enforcing prices and promotions, and managing store employees is delegated to store managers (Aguirregabiria and Guiton, 2023; Metcalfe et al., 2023; Thomas, 2011).

11 months. Second, high-quality managers actively seek out new products for their stores, reducing rollout frictions by an amount equivalent to 9.2 percent of geographic frictions. Therefore, variations in the quality of middle management have a considerable impact on the diffusion of new products within retail chains.

Empirically examining the impact of managers on the rollout of new products is challenging because new product rollout is confounded with differences in product quality, store environments, and local demand conditions. To address this challenge, we leverage granular data on product and store performance, inventories, and personnel records from a large retailer in Colombia. The retailer has more than 200 stores, overseen by more than 600 managers. Its stores share standardized modern operations and inventory processes, as well as employee and manager functions.

Despite this homogeneity, we observe substantial variation in the extent to which individual new products reach stores, consistent with patterns documented in other retailers (Bronnenberg and Mela, 2004). Although a new product reaches 44.4 additional stores (19.4 percent of stores) on average over an 11-month period—the median observed lifespan in our data—the standard deviation across products, controlling for product category and supplier, is a substantial 36.7 stores (16.0 percent). The heterogeneous rollout patterns align with what we would expect to observe in the presence of external frictions (Morales et al., 2019): a new product is 19.0 percentage points more likely to enter a focal store if it is already available in a geographically close market. Similarly, a new product is 1.1 percentage points more likely to enter a store if it is already available in a market that shares similar local demand features, as proxied by per capita income.

Store managers have strong incentives to pay close attention to new products, given their outsize contribution to store growth and the uncertainty surrounding their performance. New products drive store revenue: they add 3.7 percentage points to the overall 2.9 percent growth in revenue for the average store quarter, offsetting a 0.8 percentage point decline from existing products—patterns that align with Argente et al. (2024). At the same time, new products differ markedly from existing ones in ways that reflect the retail challenges posed by uncertainty about their performance (Aguiar and Waldfogel, 2018; Hitsch, 2006; Sudhir and Rao, 2006). Compared to existing products, new products undergo 44 percent fewer price changes per month (2.4 on average), have 11 percent lower inventory turnover, and experience 9 percent more stockout events. These differences are even more pronounced for the most innovative products. These incentives are corroborated by the concern for new products that store managers shared with us in structured interviews.

Motivated by managers' concern for new products, we examine two mechanisms through which local managerial quality affects rollout frictions. First, we identify a "push" mechanism:

effective managers improve the in-store performance of new products, thus demonstrating their commercial viability to the retailer's centralized decision-makers and facilitating their wider adoption across stores. Second, we highlight a "pull" mechanism: effective managers proactively seek out new products, reducing the geographic and demand-driven frictions widely prevalent in retail. The pull mechanism reflects the direct efforts of managers to bring new products into their stores.

Focusing first on the push mechanism, we find that the in-store performance of new products strongly predicts their subsequent adoption. Products with revenue above the category median have a 12.7 percent higher one-year survival rate and expand to 7.18 more stores. To determine whether managerial quality drives these outcomes, we obtain a measure of managerial quality by exploiting manager mobility (Abowd et al., 1999). Managers move between stores frequently: 50 percent of managers move between stores, and over 86 percent of stores see a change of manager during the study period. The variation in individual managers' impact on store revenue is substantial—the standard deviation of managerial impact is 70 percent of that of the store environment itself.

We observe individual managers' decisions—such as updating prices and managing inventory—over time and across hundreds of new product rollouts. Effective managers improve the performance of new products by improving inventory management: using an event study design, we find that within half a year of the arrival of a high-quality manager (one with above-mean productivity), the revenue per product of new products increases by nearly 20 percent, coupled with a nearly five-day (5 percent) decrease in inventory age. These in-store improvements translate into a broader subsequent rollout for new products: using the quasi-random allocation of managerial quality at product launch across product cohorts, we find that products initially allocated to an above-median number of high-quality managers reach 7.3 more stores within 11 months (a 28.5 percent increase). This effect corresponds to 20.0 percent of the aforementioned standard deviation of the 11-month reach of new products across stores. Our estimates are robust to alternative sources of variation and hold across different product types and suppliers.

Turning to the pull mechanism, we adopt a stylized gravity model of product rollout (Morales et al., 2019) to formalize the economic impact of managers directly seeking out new products for their stores. This model reflects the fact that stores incur entry costs for products not yet on their shelves. These costs are moderated by gravity effects—decreases in rollout frictions for products that are already available in stores that are geographically close or similar in local demand conditions. We capture the role of managerial practices in this model by allowing the quality of a manager to affect the magnitude of the entry costs.

We find that the presence of a high-quality manager is associated with a significant decrease in rollout frictions, corresponding to 9.2 percent of geographic frictions. This effect remains robust when focusing on products with higher survival rates, suggesting that the gravity model captures actual rollout frictions rather than reflecting variation in product types. The influence of managerial quality is especially pronounced for products from larger suppliers and those in categories that represent a relatively greater share of store revenue. These findings suggest that managers allocate their limited attention to products that they are most incentivized to promote.

Finally, to corroborate our measure of managerial quality and the two mechanisms by which high-quality managers enable new product rollout, we gathered self-reported data on middle manager traits and management practices. These data were collected through an online survey designed and implemented in partnership with the retailer. Traits such as locus of control and positive adaptation strongly correlate with managers' ability. Likewise, when included as alternative measures of managerial quality, these traits replicate our empirical results. These findings reinforce the validity of our measures of managerial quality and the mechanisms by which it affects new product rollout.

The question of how new products diffuse widely and enable consumers to benefit from innovations has been a focal point for academics and policymakers alike (Bryan and Williams, 2021; Schumpeter, 1942). Our research speaks to the role of organizational frictions and individual managers within a common form of organization: retail chains. Although the impact of managers on firm productivity has been widely documented (Adhvaryu et al., 2023; Best et al., 2023; Bloom et al., 2013; Cai and Wang, 2022; Lazear et al., 2015; Metcalfe et al., 2023), less is known about the impact of good management on other economic outcomes (Friebel et al., 2022; Minni, 2023; Neyra-Nazarrett et al., 2024). To the best of our knowledge, this is the first paper to demonstrate the causal impact of middle management in the rollout and success of new products in retail. Our results suggest that general managerial skills are likely conducive to the management of new products as well.

By demonstrating the roles of managerial quality and rollout frictions, our research unpacks the black box of new product diffusion. Previous research has focused primarily on how the relationship between retailers and suppliers affects the availability of new products. There is a growing literature on the drivers of product availability, such as category captaincy arrangements (Zhu, 2021), vendor allowances (Hristakeva, 2022), and trade arrangements between manufacturers and retailers (Ailawadi et al., 2010; Luo, 2023). Likewise, the relationship between retailers, as a whole, and suppliers is a focal point in the United States Federal Trade Commission's (FTC) investigations of slotting fees (Federal Trade Commission, 2001) and supply shortages (Federal Trade Commission, 2021). Yet little is known about the specific practices that determine product availability *within* a retailer. We demonstrate that managers can generate dispersion in product availability along the intensive margin among the stores of a retail chain. Managers' impact also contributes to differences in product availability between smaller and larger suppliers, adding to the role that supplier-size heterogeneity in retail plays in economic outcomes (Faber and Fally, 2022). Our approach thus diverges from the recurrent investigations of policymakers, who have focused on the extensive margin of how retailer–supplier relations affect availability.

The paper is structured as follows. Section 2 describes key institutional features and the data. Section 3 presents motivating evidence. Sections 4 and 5 demonstrate the push and pull mechanisms, respectively. Section 6 presents the results of our survey. Section 7 concludes.

2 Empirical Context and Data

2.1 Institutional Details

The $51 billion grocery market in Colombia, the fourth-largest economy in Latin America, comprises a few formal players that maintain large chains, alongside many non-chain retailers.[4] Our focal retailer, one of the large chains, has 229 stores in 109 cities across all of Colombia's administrative divisions. The local per capita GDP level in these divisions ranges widely (Appendix Tables A.1 and A.2). This wide variation in per capita GDP reflects a common characteristic of many large retail chains: their stores operate in vastly different environments.

2.1.1 Store Managers

Each store in the retail chain has at least one general manager and several shift and section managers. [5] Managers are in charge of the overall functioning of each store, leading teams of approximately 116.75 employees on average, spanning multiple shifts and sections of the store. Managers oversee all operations, ensuring efficient daily operations. They are responsible for personnel management (employee schedules, recruitment, training, and promotions). At the product level, managers are responsible for ensuring that the price and promotion schedules laid out by the retailer's headquarters are implemented. Managers oversee inventory levels and inspect product displays and layouts, and they also monitor local competitors' prices.

Managers are trained in most sections of a store. They generally spend their time supporting section leaders with their operations, reviewing inventory (e.g., to prevent stockouts

[4]In 2018, non-chain retailers held 73 percent of the market share, and the remaining market share was distributed among other formal players. The five largest players held roughly 20 percent of the market.

[5]We use the term "manager" to refer to all these types of managers in the stores in our sample. While it can be useful in some contexts to acknowledge differences in the duties of each type of manager, the responsibilities we study in this paper are common to most or all levels of management.

and ensure high sell-through), and analyzing store and product performance. Managers receive a base salary comparable to what they could earn elsewhere in the retail industry, and 30–50 percent of their salary is tied to the relative performance of their store.

We conducted structured interviews with store managers to understand their daily responsibilities, task loads, and processes. Typically, managers start their day early with a team meeting that includes section leaders. In the meeting, the team members review the previous day's performance and set weekly or monthly goals. They examine a dashboard that shows key performance metrics, sales, inventory, absenteeism, and product loss. They also strategically analyze important categories and products and discuss strategies to address poor product performance, which may include reviewing product quality (e.g., defects), pricing appropriateness, and product placement. Managers communicate pricing and inventory issues to headquarters and to regional managers, with whom they maintain working relationships.

2.1.2 New Products

New products are a substantial part of the focal retailer's business due to their frequent launches and significant presence on store shelves, as we document in this section.

According to our conversations with the retailer's headquarters, the initial decision about how to launch a new product—that is, which stores initially receive it—is centralized. This decision is based on the perceived potential of the product and the relationship with the supplier.[6] Headquarters also monitors the performance of newly launched products to decide on their subsequent rollout trajectory. Therefore, the new product rollout process is also, in principle, centralized.

However, in the context of this centralized process, institutional features suggest that individual store managers can have an impact on new product rollout in two ways. First, since headquarters monitors the performance of a new product to decide about its subsequent rollout, products that perform well due to the efforts of store managers may be rolled out more extensively. Once a new product arrives in their store, managers can employ various tactics to increase its sales. For instance, managers can place "new product" tags on a product to emphasize it or advertise a product in various parts of the store. They can also decide how much to implement the prices and promotions set by headquarters. Although managers cannot affect the layout of fixed store shelves, they can control product displays (e.g., which products to display on shelves at the edge of aisles or near checkout). These management strategies motivate one mechanism by which store managers can influence rollout: improvements in the in-store performance of new products, due to better management, may increase the extent of

[6] Manufacturers may introduce new products to maintain retailer and consumer interest and to expand shelf space (Rao and McLaughlin, 1989).

their subsequent rollout. We call this mechanism the "push" mechanism.

Second, managers can directly influence the centralized decision-making process by requesting particular new products for their stores. Managers are aware of products that are performing well in other stores: they carefully monitor the leaderboards that display product and store performance in their dashboards. Attentive store managers can leverage their relationships with regional managers and headquarters to request that particular new products be rolled out to their stores. We call this mechanism the "pull" mechanism.

In summary, while the initial launch decision for a new product is centralized, store-level managerial decisions and incentives can affect its subsequent performance and rollout. Now that we have described these push and pull mechanisms, we turn to the data we use to empirically examine them.

2.2 Data

We obtain transaction-level data from the focal retailer. These data incorporate 608 million transactions for 229 stores, covering the period from 2017 to 2019. We exclude data from 2020 due to COVID-19-related supply chain issues and demand abnormalities affecting our results. We compile the transaction data at the product-store-month or product-store-quarter level, depending on the analysis.

2.2.1 Products and Suppliers

We define a "product" as a distinct item offered for sale, characterized by a unique combination of observables provided by the brand, primarily a detailed brand description and size.[7] We observe the daily sales, price, and inventory levels of products. We define "new products" as those for which sales and inventory did not exist in all previous months.

We focus on products in 16 product categories, such as beer, chips, and yogurt. Some of these categories include products that are highly differentiated. For example, products in the cookies and chips category are commonly consumed, and new products in this category are introduced frequently (as in the general salty snacks category in the US). Other categories include products that take up valuable freezer shelf space or are highly perishable. These characteristics may affect the amount of attention that managers allocate to products in these categories.[8] Together, the 16 categories represent 8.5 percent of total revenue.

We calculate product-store-month revenue and standard industry performance metrics. A "price change" is any variation in price relative to the previous transaction. Store managers are

[7] This is a coarser measure of a product than stock-keeping units.

[8] Similar considerations led the FTC to focus on similar product categories in their study of slotting fees (Federal Trade Commission, 2021).

Table 1: Numbers of Products, Suppliers, and New Products by Category

Category	Overall total				Average month			
	Products	Suppliers	New products	Share of new products (%)	Products	Suppliers	New products	Share of new products (%)
Beer	328	37	178	54.3	158.42	23.19	5.56	3.5
Breads and desserts	1724	205	768	44.5	905.92	130.75	21.94	2.4
Canned products	244	58	119	48.8	142.03	42.67	3.50	2.5
Cereal	332	42	155	46.7	187.53	27.39	4.70	2.5
Cheese	735	102	307	41.8	424.69	69.75	8.77	2.1
Chips	388	55	172	44.3	200.17	36.58	5.38	2.7
Cookies	710	96	388	54.6	350.44	58.28	11.09	3.2
Energy and hydration drinks	79	24	32	40.5	36.28	14.06	1.60	4.4
Grains	706	147	319	45.2	392.94	102.58	9.11	2.3
Ice cream	306	39	142	46.4	166.75	19.86	4.18	2.5
Liquor	2247	174	797	35.5	1282.36	118.25	22.77	1.8
Milk	498	77	168	33.7	284.25	51.89	4.80	1.7
Cooking oils and vinegars	497	114	218	43.9	297.94	78.97	6.41	2.2
Soda	262	22	122	46.6	123.86	12.31	4.21	3.4
Sugars	280	80	99	35.4	190.89	59.00	3.41	1.8
Yogurt	608	40	270	44.4	312.89	29.69	7.94	2.5
Total	9944	829	4254	42.8	5457.36	593.08	121.54	2.2

Note: The table presents the number of unique products, suppliers, and new products for the data period overall (left panel) and for the average month (right panel). The final column in each panel presents the share of products in each category that were new.

responsible for ensuring that posted prices, discounts, and promotions align with headquarters' recommendations.

Inventory metrics measure sales efficiency, reflecting the appeal of the product and the effectiveness of the sales environment. Inventory turnover, which is calculated by dividing the quantity sold in the month by the average inventory during that period, indicates how frequently the inventory is renewed. Inventory age, which is calculated by dividing 30 by the inventory turnover, represents the average number of days that products remain in inventory before sale. We estimate stockout events by counting how often inventory levels reach zero.

New products account for a sizable share of sales in the focal retailer's stores. Table 1 shows the number of products, suppliers, and new products by category. Throughout the data period, 4254 out of 9944 products, or 42.8 percent, were new products. Overall, new products accounted for more than 50 percent of products in the beer and cookies categories, while they only accounted for 33.7 percent in the milk category. In the average month, across categories, 2.2 percent of products were new. This figure ranged from 1.7 percent for milk to 4.4 percent for energy and hydration drinks. The median product is launched in a small fraction of stores (Table 2). For instance, cheeses are launched in a median of seven stores, or 3.1 percent of all stores.

We observe each product's supplier. There are 829 unique suppliers. The average supplier introduced 5.1 new products and had 12.0 products on the retailer's shelves (Table A.3). The breads and desserts category had the highest number of suppliers (205), while soda had the lowest (22). The average supplier introduced between 1.2 and 6.8 new products.

Big suppliers introduced more new products on average than small ones. We define "big

Table 2: Number of Stores New Products Enter at Launch

Category	Mean	SD	P25	Median	P75
Beer	25.74	39.10	1	3.5	38
Breads and desserts	21.32	36.18	1	5	22
Canned products	44.92	53.48	1	16	89
Cereal	39.59	44.81	1	23	64
Cheese	23.91	39.05	1	7	25
Chips	59.81	61.28	4	36	111.5
Cookies	35.63	45.30	1	14	57.5
Energy and hydration drinks	54.91	61.22	1.5	24	106.5
Grains	23.46	37.36	1	3	28
Ice cream	39.73	42.78	2	20	71
Liquor	6.45	15.84	1	1	3
Milk	51.15	58.89	2	15	111
Cooking oils and vinegars	26.17	43.21	1	3	31
Soda	69.61	61.62	12	46.5	132
Sugars	33.46	40.60	1	14	62
Yogurt	56.10	56.95	4	34	109

Note: The table presents the number of stores, out of the total of 229 in the retail chain, that carry new products at launch (i.e., within the first month a product is observed).
SD = standard deviation; P25 = 25th percentile; P75 = 75th percentile.

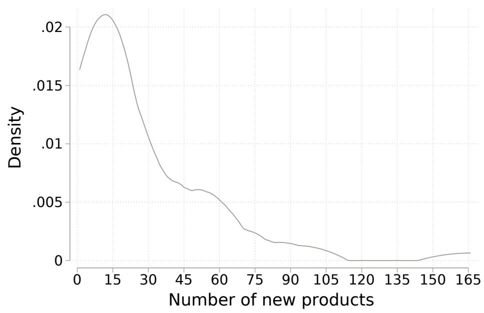
suppliers" as those whose average revenue per month is above the 96th percentile for suppliers within the same category. On average, big suppliers introduced 26.5 products during the data period, while small ones introduced 3.6 (Figure 1). The products introduced by big suppliers were also available in more stores at launch (Figure 2). Products introduced by big suppliers were available in 43.5 stores, on average, while those introduced by small ones were available in 22.6 stores.[9]

2.2.2 Stores

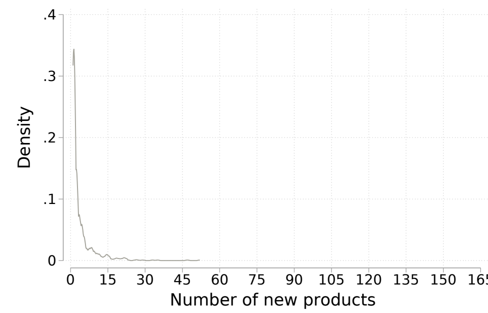
Our data cover the focal retailer's 229 stores. The average store has 116.8 employees (standard deviation of 127.2 across stores) and 45,771 unique products (standard deviation of 42,185.1). The retailer operates four types of stores: small (64 out of 229 stores), medium (30), medium-large (43), and large (92). These different types of stores range in selling area from a small convenience-store format (under 2,200 square feet) to medium-large and large stores (greater than 37,000 square feet), which are comparable in size to American supermarkets and

[9]Big suppliers maintain a more rapid product introduction and withdrawal cycle in the market. Consistent with this theorizing, big suppliers retract more existing products when they launch new ones. We analyze instances in which the introduction of a new product in a store coincides with the withdrawal of an older product from the same supplier, suggesting a replacement strategy. Table A.4 shows that when big suppliers introduce a new product into a store, it replaces an older product 44.8 percent of the time. In contrast, for small suppliers, this only happens 13.3 percent of the time. Figure A.1 shows that new products from small suppliers are also more likely to exit the market: approximately 46.55 percent of products from small suppliers persist until the end of the period, in contrast to about 42.87 percent from big suppliers.

Figure 1: Number of New Products Introduced by Supplier Size



(a) Big suppliers



(b) Small suppliers

Note: The figure shows the distribution of the number of new products introduced by the suppliers. "Big suppliers" are suppliers whose average revenue per month is above the 96th percentile for suppliers within the same category.

hypermarkets.[10] Given these differences, we include controls for store type in our analysis.

2.2.3 Managers

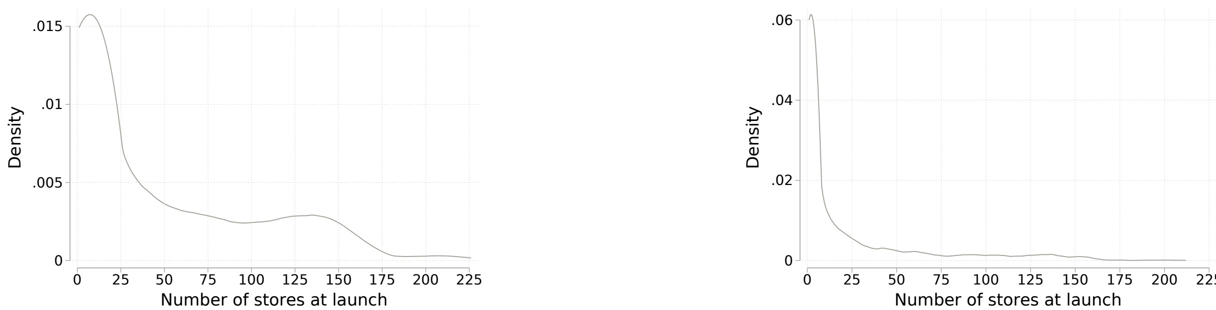
We observe the managers' identities in each store and period, allowing us to track the associated performance of the stores they manage over time. Managers are assigned to stores by headquarters and are moved across stores primarily for professional development. Headquarters believes that exposing managers to diverse environments improves their skills. These movements occur only when a suitable position becomes available and the manager is ready to transition. Consequently, the specific identity of the incoming manager and the timing of their appointment are largely independent of store and product performance, as well as new product availability. Alternatively, employees are promoted to managers, primarily based on their tenure, to fill positions due to personnel changes and turnover.

It is therefore plausible that the movement of managers is not confounded with other drivers of individual store and product performance; we elaborate on our empirical examination of this assumption below.[11] We leverage the mobility of managers across different stores to decompose sales productivity into store and manager fixed effects. Of the 616 unique managers, we observe that 50.5 percent worked in more than one store; we classify them as *movers*. More than 86 percent of the stores changed their managers at least once during our

[10]The average selling area for a supermarket in the US was 33,360 square feet in 2016 ("Average Per-Store Supermarket Performance Measures: Selling Area," *Progressive Grocer Magazine*, April 2017, 50).

[11]The departments responsible for human resources and for allocating new products are separate within the retailer's organizational structure. This observation adds further credence to our argument.

Figure 2: Number of Stores New Products Enter at Launch by Supplier Size



(a) Big suppliers

(b) Small suppliers

Note: The figure shows the distribution of the number of stores a new product enters at launch (i.e., within the first month a product is observed). "Big suppliers" are suppliers whose average revenue per month is above the 96th percentile for suppliers within the same category.

data period, and about 72 percent changed managers 1 to 5 times. A smaller fraction, 14.6 percent, changed managers 6 to 10 times, and two stores changed managers 11 to 20 times. We observe managers move across 16 connected sets of stores.

To characterize the performance of individual managers, we estimate a two-way fixed effects model following Abowd et al. (1999) (henceforth AKM) using store-level revenue data:

$$ln(y_{kt}) = \theta_k + \psi_{j(k,t)} + x'_{kt}\beta + \nu_{kt}. \tag{1}$$

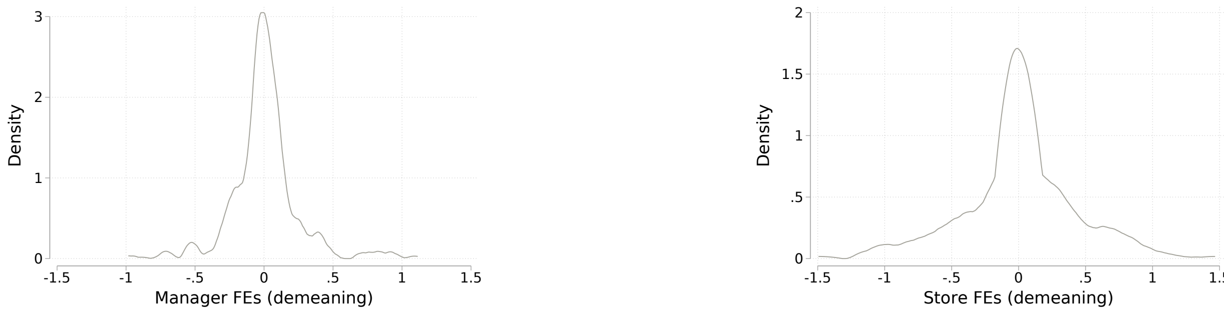
The dependent variable, $ln(y_{kt})$, is the log revenue of the store at which manager k works at time t. θ_k is a manager fixed effect, our key variable of interest. $\psi_{j(k,t)}$ is a store fixed effect for the store $j(k,t)$ that the manager oversees. x'_{kt} are time-varying controls, such as the number of transactions in the store.

Following Card et al. (2013, 2018), the error term in (1), ν_{kt}, can be decomposed into a match-specific component ($\eta_{k,j(k,t)}$), a unit root component (ξ_{kt}), and a transitory error (ϵ_{kt}):

$$\nu_{kt} = \eta_{k,j(k,t)} + \xi_{kt} + \epsilon_{kt}. \tag{2}$$

To identify the manager and store fixed effects, the assignment of managers to workers must be conditionally mean-independent of past, present, and future values of ν_{it}. These conditions permit managers to be assigned to stores on the basis of the permanent component of managerial ability (θ_k) and store productivity ($\psi_{j(k,t)}$). In appendix B, we demonstrate that there is no evidence of sorting of managers to stores based on the match-specific component

Figure 3: Distribution of Estimated Manager and Store Fixed Effects in AKM Model



(a) Manager fixed effect

(b) Store fixed effect

Note: This figure presents distributions of the estimated fixed effects of managers (a) and stores (b). The fixed effects presented here are normalized by subtracting the average fixed effects of the connected set for managers and the average fixed effects of the connected set and store type for stores.

and that there are no pretrends in the error terms leading up to, or following, manager movements. We also describe formal econometric assumptions and additional checks of endogenous mobility.

Figure 3 shows the standardized distribution of the estimated manager and store fixed effects.[12] The standard deviation of the manager fixed effect is 0.31, which is 72.1 percent of the standard deviation of the store fixed effect, controlling for store type. This suggests that a manager's identity has a meaningful relationship with store performance.

We refer to "high-quality" managers as managers whose estimated fixed effect is above the mean.[13]

3 New Products and Frictions in their Rollout Process

In this section, we show the data patterns that motivate our investigation into the mechanisms by which store managers impact the rollout of new products. First, we show why store managers are attentive to new products within their stores, as new products require differentiated price and inventory management. Second, we show that new products face rollout frictions as they are rolled out to stores. Finally, we show exploratory evidence

[12]We standardize the store and manager fixed effects by subtracting the average value of each variable within their respective connected sets.

[13]While high-quality managers are likely to be slightly older, managerial quality is not strongly associated with managers' tenure, gender, or the training they have received (Table A.5 and Figure A.2). We further examine the managerial traits of high-quality managers in Section 6.

highlighting how high-quality managers impact new product rollout by affecting internal performance ("push") and proactively seeking them out ("pull") for their store.

3.1 The Role of New Products for Store Managers

Two pieces of evidence support the claim that managers pay close attention to new products. First, new products significantly contribute to store growth. Second, new products differ markedly from existing products along key metrics, reflecting the uncertainty and additional challenges managers face in overseeing them.

Much of the growth of in-store revenue comes from new products. Following Argente et al. (2024), we evaluate the contribution of new products to the average store's growth in sales. The growth in store j's sales, $\Delta S_{j,t}$, can be decomposed as

$$\Delta S_{j,t} = \underbrace{n_{j,t}^{new} \times \bar{s}_{j,t}^{new}}_{\text{new products}} + \underbrace{\Delta S_{j,t}^{old,survive} + \bar{S}_{j,t-1}^{old,exit}}_{\text{product life cycle}}, \tag{3}$$

where the contribution of new products to sales growth is a product of the entry rate of new products ($n_{j,t}^{new}$) and the sales of new products relative to the average sales of products in the store ($s_{j,t}^{new}$). The contribution of existing products can be decomposed as the sales growth of existing products conditional on survival ($S_{j,t}^{old,survive}$) and the sales share of non-surviving products ($\bar{S}_{j,t-1}^{old,exit}$).

Table 3, column (1), shows that the average store sees 2.9 percent growth in sales in the average quarter. Of this growth, the contribution of new products is 3.7 percent. This contribution, in turn, is the product of an 8.9 percent entry rate of new products and average sales of new products relative to existing products of 41.5 percent. The positive contribution of new products helps make up for the 0.8 percent decrease in growth from existing products, and, in particular, the 2.8 percent decrease in growth stemming from exiting (discontinued) products. The results of this decomposition using a balanced panel of stores, rather than all observed stores, are very similar (Table 3, column 2).[14]

The role of new products in driving store growth is consistent with the regular introduction of new products we observe throughout our data period (figure A.3). Both the contribution of new products to store growth and the regularity with which new products are introduced may be reasons why store managers may need to be particularly attentive to new products.

Store managers may also need to be attentive to new products because they may face more challenges and uncertainty when selling these items (Aguiar and Waldfogel, 2018; Hitsch,

[14]Compared to Argente et al. (2024), who study the life cycle of firms, in our study new products have a smaller impact on growth, both in absolute magnitude and in relative contribution. Our focus on growth at the individual store level may be one factor that contributes to this difference.

Table 3: Decomposition of Stores' Sales Growth

	(1) All stores	(2) Balanced panel
Sales growth	0.029	0.027
Product life cycle component	−0.008	−0.009
Growth of surviving	0.02	0.019
Sales share of exit	−0.028	−0.028
New products component	0.037	0.036
Entry rate	0.089	0.088
Entrants' relative sales	0.415	0.413

Note: The table presents a decomposition of the average sales growth at the store-quarter level (equation 3) across all store-quarters (column 1) and for stores that were open throughout the data period (column 2). For this decomposition, "new products" are those that were introduced in a given quarter.

2006; Sudhir and Rao, 2006). Without established sales patterns, managers may struggle to optimize inventory levels and to move inventory stock. Our data support this notion: new products differ substantially from existing ones along key product metrics.

Table 4 shows product-store-level statistics, as defined in Section 2.2. A comparison between columns (1) and (2) shows that new products are systematically different from existing products: they show significantly fewer price changes (2.44 for new products versus 4.32 for existing ones in the average month), higher inventory age (94.42 days for new products versus 78.11 days for existing ones), lower turnover (2.12 for new products versus 2.39 for existing ones), and more stockouts (0.12 for new products versus 0.11 for existing ones). These differences are statistically significant (column 5).

Using product descriptions, we can further classify new products as "innovative" (i.e., not closely matching an existing product description) or "non-innovative" (i.e., likely to be extensions of existing products, such as a new package size or flavor variant). Innovative products (column 3) are particularly distinct in their store metrics, which aligns with our theory that products with more uncertain potential pose greater challenges for managers.

These statistics are consistent with managers' reports (in structured interviews) that they pay increased attention to new products. Before discussing how managers affect the rollout of new products, we discuss patterns that suggest the existence of substantial rollout frictions.

3.2 New Product Rollout Frictions

We observe vast heterogeneity in how broadly new products are rolled out. We show data patterns to characterize this heterogeneity and to demonstrate that it is consistent with how products would reach new stores in the presence of well-known rollout frictions.

The median observed lifetime of new products is 11 months. During that period, while

Table 4: Summary Statistics of Retail Metrics for Existing Versus New Products

	(1) **Existing products** 5,690 products ($n = 149,416$)	(2) **New products** 4,254 products ($n = 47,049$)	(3) **Innovative** 1,454 products ($n = 15,568$)	(4) **Non-Innovative** 2,800 products ($n = 31,481$)	(5) ***t*-value** (1)–(2)	(6) ***t*-value** (3)–(4)
Avg. number of price changes per month	4.32	2.44	1.83	2.74	14.67***	−11.78***
	(27.45)	(7.88)	(4.30)	(9.14)		
Avg. inventory age (days)	78.11	94.42	104.21	89.58	−33.64***	13.88***
	(85.97)	(107.80)	(115.76)	(103.30)		
Avg. inventory turnover	2.39	2.12	2.00	2.18	16.99***	−6.39***
	(3.07)	(2.89)	(2.86)	(2.91)		
Avg. number of stockout events per month	0.11	0.12	0.14	0.12	−3.36***	4.90***
	(0.46)	(0.48)	(0.51)	(0.46)		
Avg. time in store (months)	14.48	8.08	7.54	8.35	135.53***	−12.37***
	(9.52)	(6.71)	(6.26)	(6.91)		

Note: This table presents retail metrics for existing products (column 1) and new products (column 2). New products are further classified into those that are presumed to be innovative (i.e., those with product descriptions not previously observed) (column 3) and those that are non-innovative (column 4). The metrics are defined in section 2.2. Average values are calculated across product-months, with standard deviations given in parentheses.

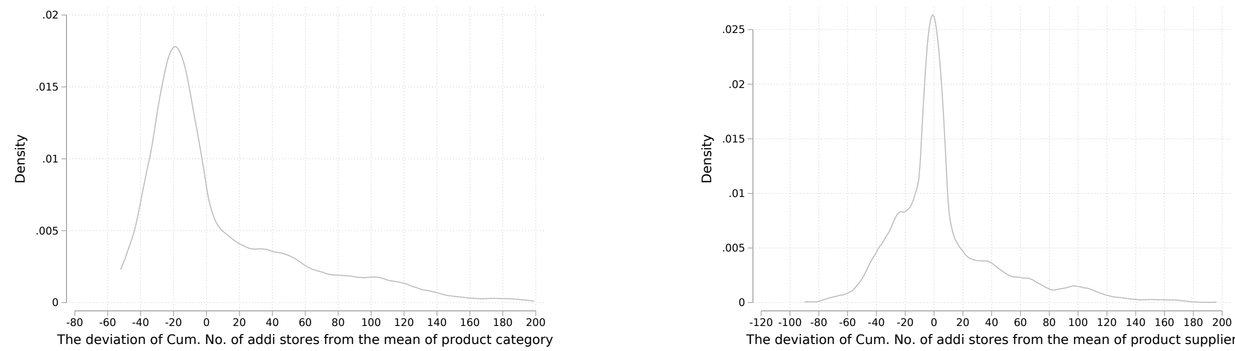
the average surviving new product reaches 39.19 additional stores after its launch, there is a large dispersion: the standard deviation of new product reach is 49.25 stores.

This large dispersion persists within supplier and product categories. Suppliers vary in their ability to distribute products to retailers, and the nature of products in different categories may dictate how likely they are to reach new stores. Figure 4 shows the distribution of the cumulative number of stores that new products enter. Conditional on the product category (i.e., absorbing category means), the standard deviation of new product reach is 47.64 stores. Conditional on the supplier, it is 39.13 stores, and conditional on the product category and supplier, it is 36.7 stores.

The heterogeneity we observe in the reach of new products does not necessarily indicate economic frictions in the rollout process, however, since the products themselves are heterogeneous. We thus analyze the trajectory of product rollouts using within-product variation. In the presence of friction, the introduction of new products shows path dependence: products are more likely to reach markets similar to those in which they have already been adopted (Alessandria et al., 2021; Morales et al., 2019). We call this path-dependence effect "gravity," which we define formally in section 5. We focus on empirically demonstrating two primary sources of frictions that contributed to this dependence: geographic frictions and demand frictions.

Geographic frictions in product rollout are caused by logistic and distribution considerations (Bronnenberg and Mela, 2004). Manufacturers and suppliers often find it more cost-effective to distribute products to stores within the same region. Corporate decisions about product rollouts may also be made at the regional level. Additionally, geographically proximate stores often share regulatory, socioeconomic, and competitive environments (Nishida, 2017). Consequently, a new product faces lower friction to enter another store in a

Figure 4: Cumulative Number of Stores a New Product Reaches After Launch



(a) Within product category (SD = 47.64)

(b) Within supplier (SD = 39.13)

Note: The figure presents the distribution of the cumulative number of stores new products enter after the first month of their launch. Panel (a) presents the distribution after demeaning by product category. Panel (b) presents the distribution after demeaning by supplier.
SD = standard deviation.

region where it is already available.

Demand frictions in product rollout arise because stores differ in the consumer segments they serve, requiring retailers and managers to tailor their approach to selling new products to the demand conditions they face. This challenge is greater for managers when a new product has not been sold in other stores with similar demand conditions to their own because there is less information on its performance. A new product faces lower friction to enter a new store if it is already available in a store that faces similar local demand conditions.

Table 5, column (1) presents the unconditional and conditional probabilities that a new product enters a store. We calculate the probability that a product enters a store by calculating the number of stores that receive a product for the first time at time t of the stores that have not yet carried the product at time $t-1$. Unconditionally, 12.96 percent of stores that do not yet carry the new product adopt it in the average quarter.

Conditional probabilities are higher: if a product has already been rolled out to a store in the same state, the probability that a store will adopt it increases to 17.70 percent; similarly, if it has been adopted in a municipality within the same quartile of GDP per capita, the probability increases to 13.41 percent.

These patterns are consistent with the presence of large geographic frictions and with differences in the nature of local demand. They would not emerge if products were introduced to stores simultaneously or rolled out solely based on their sales potential. Still, there are alternative possible explanations for these patterns. It may be that small suppliers distribute

Table 5: Probability of New Product Entering a Store

	Probability of entry in store-quarter (%)		
	(1) Overall	(2) Big suppliers	(3) Small Suppliers
Overall	12.96	19.28	9.92
Conditional on previous entry to . . .			
same state	17.70	22.76	15.25
same local GDP per capita	13.41	19.62	10.41
Push mechanism			
Product mostly managed by high-quality managers in past	24.25	29.26	20.64
Product not mostly managed by high-quality managers in past	5.28	8.89	3.99
Pull mechanism			
High-quality manager present in focal store	13.48	20.09	10.29
High-quality manager not present in focal store	12.40	18.40	9.51
N (store-product-quarter observations)	4,533,661	1,555,631	2,978,030

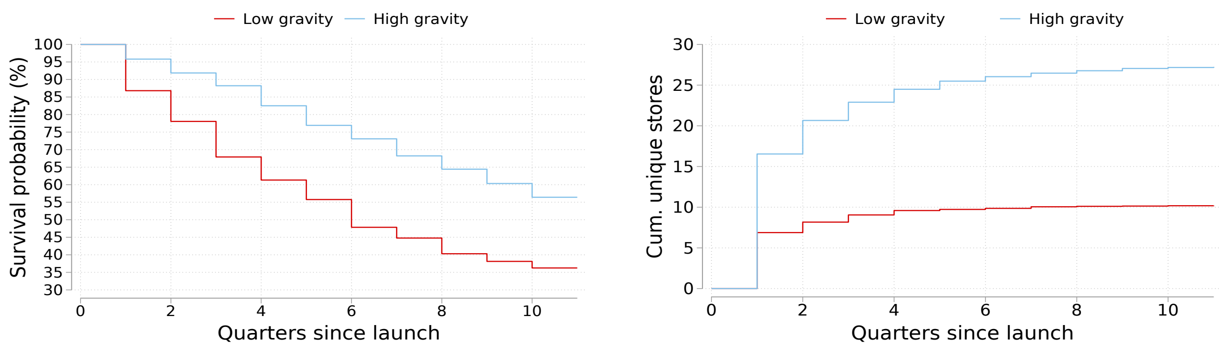
Note: This table reports the unconditional and conditional probabilities that a new product enters a store in a given quarter, among stores that did not carry the product in the previous quarter. Geographic proximity is measured by being in the same state; local GDP per capita identifies similar local demand. The *push mechanism* rows categorize products according to whether they were primarily managed by high-quality managers in the first two quarters following product launch. The *pull mechanism* rows categorize store-quarters based on whether a high-quality manager was present in the store.

locally while large suppliers distribute nationally, which could explain the aggregate patterns in Table 5, column (1). The next two columns break down the conditional entry probabilities by supplier size. The unconditional probability of entry is higher for new products from large suppliers (19.28 percent) versus small suppliers (9.92 percent). However, for both large and small suppliers, we find that a product already available in a similar market is more likely to enter another market that shares characteristics.

It is also possible that products that survive longer reach more stores, and that those stores share features with earlier adopters because the product has had more time to expand. We find that controlling for product category and the number of quarters since product launch does not alter the qualitative patterns of Table 5 (Table A.6). Qualitative results are also comparable for innovative and non-innovative products (Table A.7). These explanations do not account for the patterns we document; rather, these patterns are consistent with the presence of large rollout frictions.

These rollout frictions are likely a significant source of heterogeneity in the availability of new products among stores. In Figure 5, we visualize the cumulative impact of these effects by conducting a median split of products based on the extent to which they benefited from past-dependence (gravity) effects. By the eleventh quarter of product release, products with higher gravity levels (due to geographic proximity—i.e., being in the same state) are associated with a 20.16 percentage point higher survival rate (panel a). They also reach 17.05 more stores (panel b). Frictions cumulatively impact the overall survival of a new product as well as the extent to which it becomes widely available across the focal retailer's stores. The

Figure 5: Survival Rate and Cumulative Reach of New Products by Geographic Frictions at Time of Launch



(a) Survival rate of product

(b) Cumulative number of unique stores reached

Note: Panel (a) shows Kaplan–Meier survival estimates for new products, while panel (b) shows the cumulative number of unique stores they reached after product launch. Products are split into those that experienced low versus high levels of geographic gravity. Specifically, for each product, we identify the states in which it was launched and calculate the proportion of the retailer's 229 stores located in those states. Products with a proportion above the median in their category are classified as having high geographic gravity.

two panels of Figure 5 also jointly suggest that new products that survive longer are more likely to be widely available in more stores.

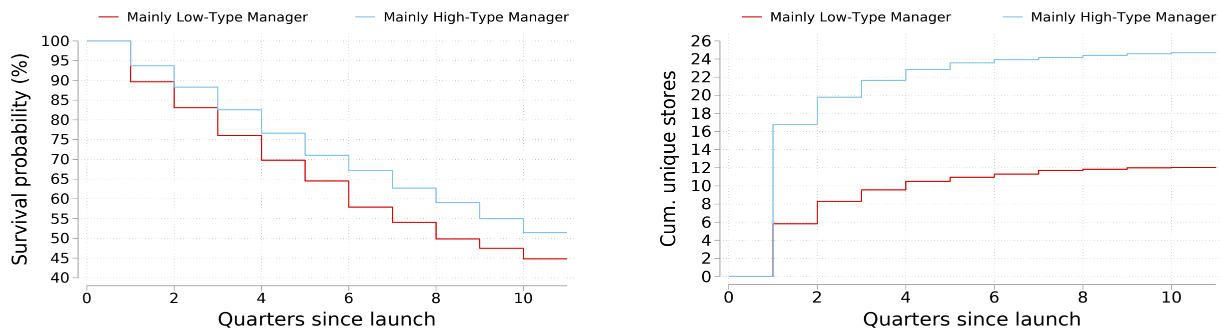
3.3 Descriptive Evidence for Push and Pull Mechanisms

Thus far, consistent with the existing literature, we have provided suggestive evidence for the presence of external frictions (among stores) in the rollout of new products. To explore whether managerial quality also impacts new product rollout by affecting internal frictions, we first present visual evidence that new products that are overseen by more high-quality managers are more successful across stores—i.e., that they become more widely available.

Figure 6 visualizes the survival rate of products based on the median split of the quality of the managers who oversaw the product at the time of its launch. Products that are met with good managers are more likely to survive and reach more stores. We find that by the eleventh quarter, a new product with better management is 6.6 percentage points more likely to survive, and it will have cumulatively reached 12.6 more stores on average. We demonstrate the robustness of this pattern, in regression form, to an intensity measure of managerial quality (Table A.9). The regressions show that higher-quality management is associated with more time on the market, higher survival rates, and a higher cumulative number of stores that a new product reaches.

These patterns demonstrate that managerial quality is associated with the reach and

Figure 6: Survival Rate and Cumulative Reach of New Products, by Managerial Quality at Time of Launch



(a) Survival rate of product

(b) Cumulative number of unique stores reached

Note: Panel (a) shows Kaplan–Meier survival estimates for new products, while panel (b) shows the cumulative number of unique stores reached after product launch. Products are split into those that experienced low versus high managerial quality. Specifically, for each product at the time of launch, we identify the proportion of stores in which it was offered that were managed by high-quality managers. Products with a proportion above the median in their category are classified as having high managerial quality.

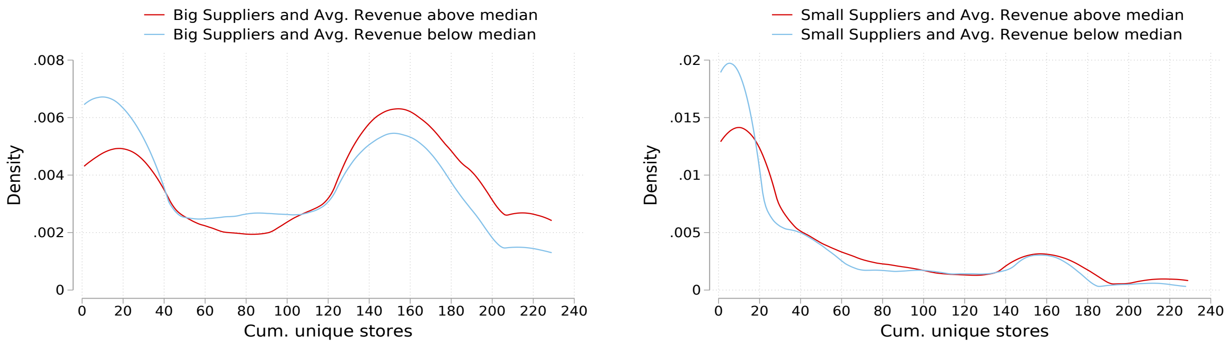
survival of new products. We now dive into descriptive evidence supporting the presence of the push and pull mechanisms.

3.3.1 Push Mechanism

Prior literature indicates that managerial quality impacts store performance (Metcalfe et al., 2023). We hypothesize that store managers, by improving the in-store performance of new products, facilitate ("push") their subsequent diffusion to other stores. This hypothesis implies that products with higher in-store revenue are more likely to be widely distributed. To test this, we calculate each product's average per-store-quarter revenue and perform a median split within its product category. We find that products with higher-than-median sales reach 44.0 percent (14.2) more stores cumulatively. Figure 7 illustrates this pattern: regardless of the size of the supplier, better-performing products reach more stores. Products from big suppliers reach 50.5 percent (23.6) more stores, and those from small suppliers reach 24.1 percent (10.3) more stores.

To further examine this relationship, we regress the number of unique stores that a new product eventually reaches on its average revenue per store-quarter during the time it is available, controlling for product category and supplier size (Table A.8). A 1 percent increase in average product revenue is associated with entry into 0.13 additional stores. Moreover, products with average revenue above the median are associated with entry into 24.5 more

Figure 7: Cumulative Number of Unique Stores a Product Enters, by Product Revenue



(a) Big suppliers

(b) Small suppliers

Note: The figure presents the distribution of the cumulative number of unique stores that a new product enters over its observed lifetime. "Big suppliers" are suppliers whose average revenue per quarter is above the 96th percentile for suppliers within the same category. Products are classified by a median split of the product's average quarterly revenue, within category and supplier size.

stores than those below the median.

Another way to quantify the impact of the push mechanism is to consider how it impacts the conditional rollout probabilities. Table 5 shows that products that have been managed by a high share of high-quality managers in the past have a 24.25 percent chance of entering a new store. In contrast, those products that have not been managed by a high share of high-quality managers only see a 5.28 percent chance of entry. This 18.97 percentage point increase in the conditional rollout probability is greater than the impact of geographic proximity, which is associated with a 10.53 percentage point increase.

These patterns are not mechanical—if store performance, or managerial quality, and product rollout were independent, such correlations would not be observed. However, these findings are only suggestive, as the allocation of high-quality managers to stores and products may not be exogenous. In the following section, we employ an event study design to first demonstrate that the arrival of a high-quality manager improves the performance of new products. We then leverage the quasi-random assignment of new products to varying levels of managerial quality at the time of product launch to demonstrate how managerial assignment affects subsequent product rollout.

3.3.2 Pull Mechanism

High-quality managers in a store that has not yet stocked a particular new product may be able to proactively seek it out ("pull") for their store. Table 5 shows that a store with a high-quality manager has a 13.48 percent probability of receiving a new product, while a store without a high-quality manager has a probability of 12.40 percent. The increase of 1.08 percent is modest compared to the magnitude of the push mechanisms described above. However, given the frequency at which managers move between stores, and at which new products are introduced, the fact that the presence of a high-quality manager impacts *where* a new product arrives is a notable pattern within the centralized rollout process.

Products vary significantly in their features, as well as in the revenue they are expected to generate for stores. These differences may generate correlations between managerial quality and product rollout. In Section 5, we estimate a stylized economic model of product entry that leverages variation similar to that of Table 5. This enables us to evaluate the magnitude of the pull mechanism compared to other sources of friction in a framework that allows for the inclusion of controls.

4 Push Mechanism

Building upon the suggestive evidence presented in section 3 that managerial quality influences the reach and survival of new products, we examine how managerial quality affects the performance of new products and their subsequent rollout. We leverage two sources of plausibly exogenous variation: the mobility of managers across stores and the quasi-random allocation of managerial quality at the time of product launch, facilitating a cohort regression analysis. These approaches jointly support our theorized push mechanism.

4.1 Managerial Quality Affects Product Performance

Managers are responsible for and thus play a critical role in their stores' management and daily operations, including decisions related to new products. We use an event study design to study whether high-quality managers (managers with an above-average level of measured productivity) positively impact the performance of new products within stores, based on previous literature that has established that management can increase the overall performance of stores or business locations (Adhvaryu et al., 2023; Bloom et al.; Metcalfe et al., 2023). Consistent with this evidence, we find that the variation in measured manager productivity is substantial, relative to the variation in store-level performance.

Using the mobility of managers across stores, we identify the causal effect of the arrival of a high-quality manager on store and new product performance. Specifically, we focus on 120 instances where a high-quality manager arrives at a store, which leads to an increase in the overall quality of management at that store (noting that stores may have multiple managers).

The event study design compares the performance of stores before and after the arrival of a high-quality manager, controlling for store fixed effects and common time trends.

4.1.1 Empirical Specification

We exploit the variation in the timing of when high-quality managers arrive in stores to isolate the effect of managerial quality on store results. Our approach takes advantage of the plausible exogeneity of manager mobility across stores with respect to the in-store performance of (new) products, as detailed in section 2.2.3. We estimate

$$y_{jt} = \sum_{\underline{C} \leq k \leq \overline{C}, k \neq -1} D^k_{jt} \beta_k + \eta_t + \phi_j + X_{jt}\zeta + \varepsilon_{jt}, \tag{4}$$

where y_{jt} is the performance measure of store j at quarter t and D^k_{st} is a relative time-to-treatment indicator for whether the store received a high-quality manager in quarter $t-k$, defined as $D^k_{jt} = 1[t = \tau_j + k]$ for $k \in (\underline{C}, \overline{C})$, $D^{\underline{C}}_{jt} = 1[t \leq \tau_j + \underline{C}]$, and $D^{\overline{C}}_{jt} = 1[t \geq \tau_j + \overline{C}]$, where $1[\cdot]$ is the indicator function, k indexes the set of time indicator variables, and τ_j is the first quarter when store j receives a high-quality manager.

The parameters of interest, β_k for $k \in [\underline{C}, \overline{C}]$, measure the impact of the high-quality manager before, during, and after the event. We normalize $\beta_{-1} = 0$ and set $\underline{C} = -6$ and $\overline{C} = 6$. We include quarter fixed effects (η_t) and store fixed effects (ϕ_j). A set of controls (X_{jt}) includes controls for other features of store management, namely the average tenure of store managers, their average age, whether the proportion of female managers is above the median across stores, the arrival of other managers (e.g., shift managers), and the total number of managers in the store. As controls for the local store environment, we include the number of suppliers that ceased operations in the store, active suppliers in the store, and the number of firms opening and closing in the city. We cluster standard errors at the store level.

4.1.2 Results

Figure 8 presents the estimated values of β_k. Panel (a) shows the impact of the arrival of a high-quality manager on the revenue of all products in the store. The arrival of a high-quality manager increases the overall performance of the store by 6.7 percent in the quarter in which he or she arrives. By the sixth quarter, the period revenue of the store increases by 15.1 percent. These patterns hold across all product categories. Panel (b) shows that, for the focal product categories, the sixth quarter revenue reaches a comparable 9.5 percent. The immediate impact of managerial quality on store outcomes are consistent with the literature showing that effective managers impact overall store performance (Metcalfe et al., 2023).

The next two panels of Figure 8 illustrate the key finding that high-quality managers enhance the in-store performance of new products. Panel (c) shows the impact of the arrival of a high-quality manager on the revenue of new products. While there is no immediate impact, the following quarters show an upward trend. The arrival of a high-quality manager increases the revenue of new products by 23.2 percent by the fifth quarter after their arrival. Panel (d) shows that the increase in revenue translates into a higher average time on market for the new product.[15] Two quarters after the arrival of a high-quality manager, the average time on market of new products on a store's shelves increases by 2.7 percent. High-quality managers contribute to the survival (longevity) of the new products made available.

How does a manager achieve this increase in revenue and performance of new products? The remaining two panels of Figure 8 show how the manager's actions cause the improvement in the performance. We find no impact of the arrival of a high-quality manager on the number of price updates, a measure of how much managers comply with pricing decisions from headquarters (panel (e)). Compared to the baseline at $t = -1$, inventory age decreases by 4.6 days two quarters after the arrival of a high-quality manager and by 8.9 days in quarter six compared with stores that did not see the arrival of a high-quality manager (panel (f)). In short, we find evidence that high-quality managers increase the performance of new products by better managing inventory levels. This is consistent with the literature suggesting that retail inventory strategy is an important metric that reflects retailer (and store) quality (Matsa, 2011).

The magnitude of the event studies is similar when using the Callaway and Sant'Anna (2021) estimator, which treats the arrival of high-quality managers in a staggered differences-in-differences framework (figure C.1). The event studies at the monthly level further demonstrate the clear shift in outcome trends after the arrival of a high-quality manager (figure C.2).

The impact of high-quality managers on new product revenue is observed across product types (Figure 9). In particular, products from big suppliers and those that require freezer space see a larger increase in in-store revenue when a high-quality manager arrives. These products may require more managerial attention because big suppliers are important for retailers and because freezer space is more limited. Similarly, innovative products experience larger increases in in-store revenue. In section 3.1, we demonstrated that innovative products are distinct from existing products in their in-store metrics. While innovative products may pose greater challenges to managers, these event studies suggest that high-quality managers may be more capable of driving their success. High-quality managers also increase the time on market of products from these groups (Figure C.3).

[15] For each new product in a store-period, we calculate the number of periods the new product has been on the shelves of a store. We then take the average of this metric across all new products in that store-period.

High-quality managers do not increase the revenue of new products at the cost of existing products. Figure C.4a shows that the arrival of a high-quality manager increases the in-store sales of existing products by 17.3 percent within six quarters of their arrival. A high-quality manager is able to increase the time on market of even existing products.

Overall, the event studies demonstrate that managerial quality significantly affects the performance of new products through better management of inventory. The impact of high-quality managers is particularly pronounced for products whose performance managers are more strongly incentivized or better equipped to enhance.

4.2 Managerial Quality Affects Subsequent Rollout

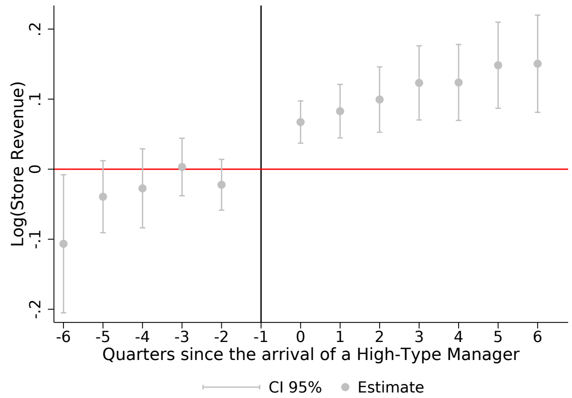
The event studies show that the arrival of a high-quality manager boosts the in-store performance of new products and offer suggestive evidence for underlying mechanisms. We now investigate whether better in-store managerial quality affects subsequent rollout of new products.

4.2.1 Empirical Specification

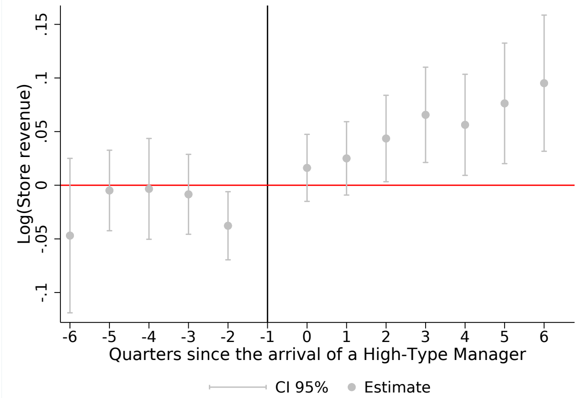
To address this question, we implement a cohort regression design inspired by Argente et al. (2024). Our empirical strategy leverages quasi-random variation in the allocation of managerial quality at the time of product launch. The initial decision about which stores will receive a new product when it first enters the retailer is based on logistic considerations, store characteristics, and supplier needs rather than on the quality of store managers. In other words, the product introduction decision is independent of individual managers due to institutional practices. The fact that managers move between stores for reasons orthogonal to product performance, as we demonstrated when estimating managerial quality (Section 2.2.3 and Appendix B), supports our assumption. Consequently, depending on the timing of a product's launch and the stores to which it is allocated, it may initially be placed in stores managed by more or fewer high-quality managers.

In the baseline specification, we use an across-cohort design, where each cohort consists of products launched in the same month. We conduct a median split of product cohorts based on the average number of high-quality managers allocated to the products in that cohort at the time of launch. The subsequent rollout of products initially allocated to more high-quality managers is then compared with those allocated to fewer high-quality managers to examine the impact of managerial quality on product diffusion. We estimate

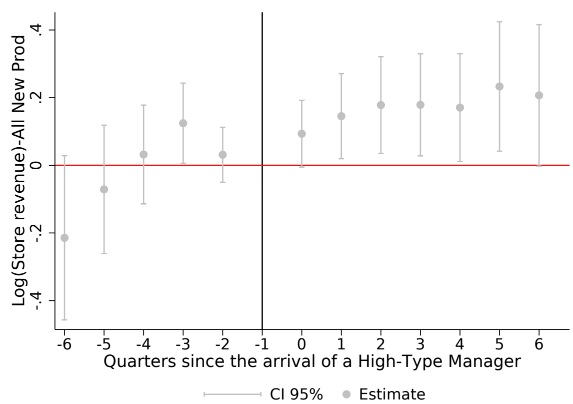
Figure 8: Event Study of the Arrival of a High-Quality Manager



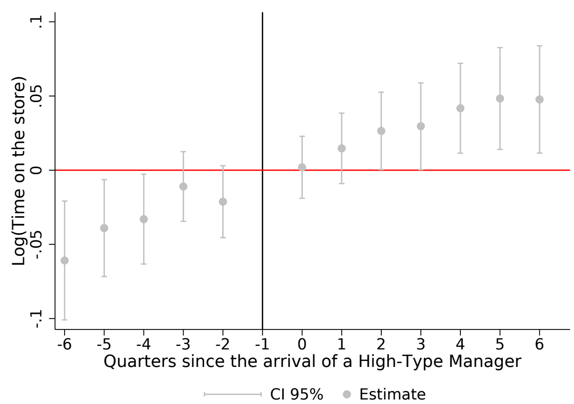
(a) Log store revenue based on all product categories



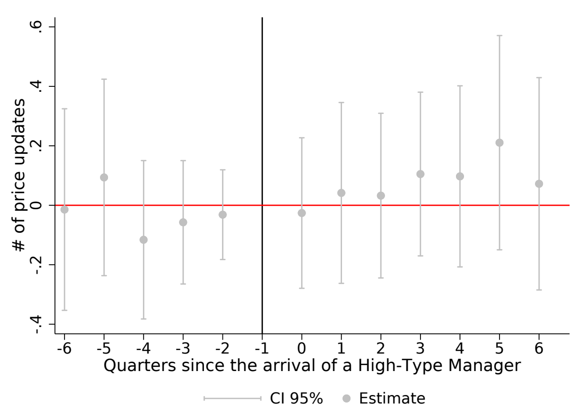
(b) Log store revenue based on focal product categories



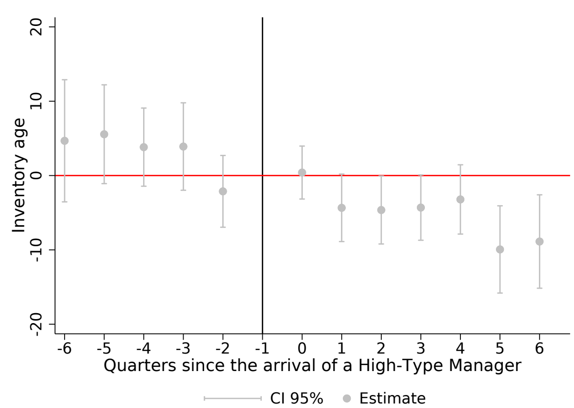
(c) Log store revenue of new products



(d) Log time on market of new products in store



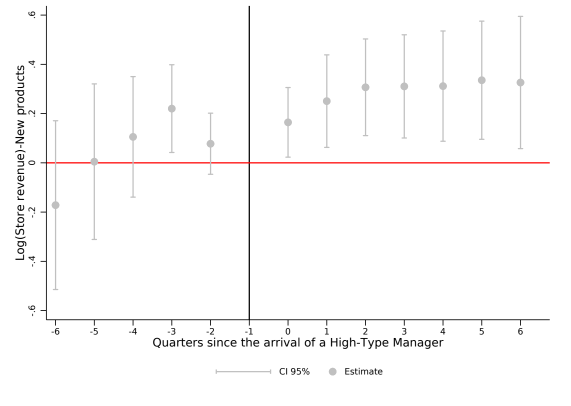
(e) Number of price updates for new products



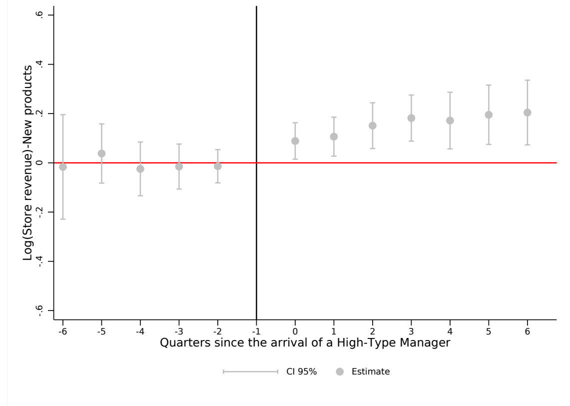
(f) Inventory age of new products in store

Note: This figure presents the estimated impact of a high-quality manager's arrival on six outcomes: (a) the overall store revenue, (b) the store revenue in focal categories, (c) the store-level revenue of new products, (d) the time new products spend on the market in a store, (e) the number of price updates for new products, and (f) the inventory age of new products. The event study is specified in equation (4), and 95 percent confidence intervals (CIs) based on standard errors clustered at the store level are presented.

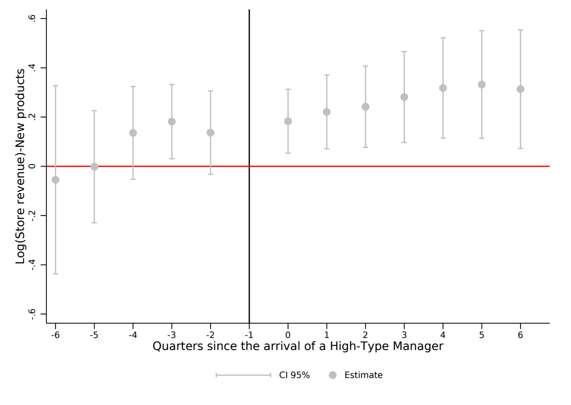
Figure 9: Event Study for Log Store Revenue of New Products, by Product Type



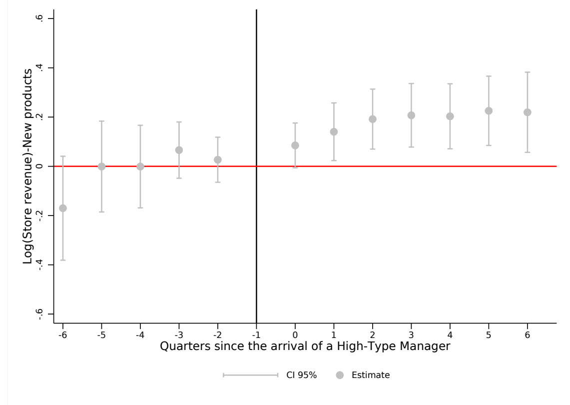
(a) Big suppliers



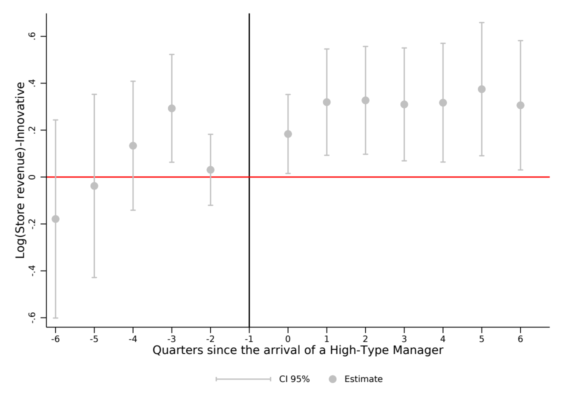
(b) Small suppliers



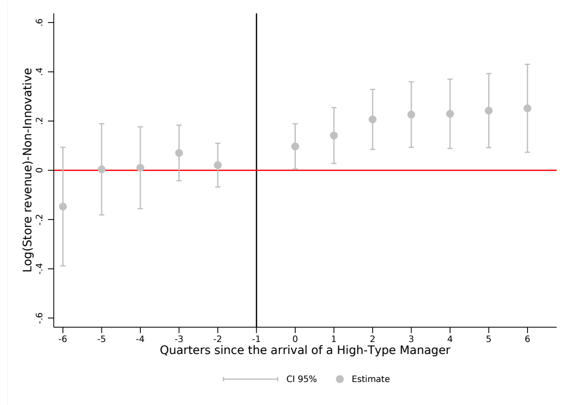
(c) Freezer space required



(d) No freezer space required



(e) Innovative products



(f) Non-innovative products

Note: This figure presents the estimated impact of a high-quality manager's arrival on log store revenue for new products in focal categories: (a) products from big suppliers, (b) products from small suppliers, (c) products requiring freezer space, (d) products not requiring freezer space, (e) innovative products, and (f) non-innovative products. The event study is specified in equation (4), and 95 percent confidence intervals (CIs) based on standard errors clustered at the store level are presented.

$$y_{it} = \underbrace{\alpha + \sum_{a=2}^{11} \beta_a D_{ia}}_{\text{baseline age effect}} + \underbrace{\alpha^+ D_i^+ + \sum_{a=2}^{11} \beta_a^+ D_{ia}^+}_{\text{high-quality manager age effect}} + \gamma_{category(i),t} + \theta_c + \varepsilon_{it}\,, \tag{5}$$

where y_{it} is the additional number of stores product i reaches since its launch in period t. D_{ia} is an indicator variable that takes a value of 1 when product i is of age a (a periods since product launch) and is defined as $D_{ia} = 1[a = t - \tau_i]$, where τ_i is the quarter that product i was launched. β_a captures the reach of a product that has been in the retailer for a quarters.

If a product is allocated to more high-quality managers at the time of product launch, an additional set of coefficients, denoted by $+$, capture the additional impact of high managerial quality on product reach. D_i^+ is an indicator that product i belongs to this group of products, and D_{ia}^+ is the interaction between D_{ia} and D_i^+ for each value of a. β_a^+ is the coefficient of interest, the additional impact of initial high managerial quality on subsequent product reach.

To address product attrition, only products observed in the data for at least 11 months—the median lifespan of new products—are analyzed. $\gamma_{category(i),t}$ and θ_c represent category-month and cohort fixed effects, respectively. Cohort fixed effects capture factors unique to the cohort that influence product diffusion. Category-month fixed effects account for unobserved heterogeneity across product categories and launch periods. Standard errors are clustered at the cohort-category level to account for potential correlations within cohorts, and additional controls are incorporated to isolate the effect of managerial quality.

4.2.2 Results

Figure 10 visualizes the results of our preferred specification (Table 6, column 2). In 11 months, a product launched with a below-median number of high-quality managers reaches 25.78 stores after its launch. A product that was allocated to stores with more high-quality managers reaches an additional 7.35 stores, or 28.5 percent more stores, in 11 months. We noted in Section 3.2 that the standard deviation of 11-month product reach, the cumulative number of stores that products enter, is 36.7. The impact of the initial allocation of managerial quality thus corresponds in magnitude to 20.0 percent of this dispersion in store reach.

Table 6 presents additional robustness checks. The magnitude of managerial impact on subsequent rollout is not impacted by the addition of supplier-specific category-time fixed effects (column 3). Heterogeneity in the rollout across suppliers does not drive our results.

Our baseline across-cohort design compares product rollout across different launch cohorts. The movement of individual store managers is unlikely to be timed with the introduction of new products. The across-cohort design fully leverages the quasi-random allocation of managerial quality across months as new products are introduced.

However, the estimator may be susceptible to confounding factors that vary between cohorts, such as seasonal demand fluctuations. An alternative within-cohort design examines whether, within the same cohort, products benefiting from a higher allocation of high-quality managers reach more stores than those exposed to fewer high-quality managers. The within-cohort design enables us to account for unobserved heterogeneity within each cohort. Although noisy, estimates using an across-cohort design show that the positive impact of initial managerial quality on subsequent rollout is robust to the use of this alternative source of variation (Table 6, column 4). Finally, our results are robust to alternative definitions of managerial quality (Table D.1).

The impact on subsequent rollout of initially allocating a new product to high-quality managers is similar in magnitude to reducing its geographic or demand rollout frictions. Table D.2 presents a cohort regression in which products are grouped based on the geographic gravity of the stores in which they were launched (i.e., the number of stores in the same state as those stores). Products launched in stores with above-median geographic gravity reach, on average, 5.7 additional stores within 11 months compared to those launched in lower-gravity areas. Reducing demand frictions produces effects of comparable size: products launched in stores with above-median demand gravity (i.e., those launched in stores with more stores that share similar local demand conditions) reach 5.3 additional stores within 11 months (see Table D.2). Since the gravity that a store exerts does not vary over time, these estimates are noisier. It is nonetheless notable that the impact of the initial allocation of managerial quality is comparable in size to the effects of store conditions and frictions.

Products vary in how much they are impacted by initial managerial quality. The impact is more pronounced for products from large suppliers, those that don't require freezer space, and those that are less perishable (Table D.3). At the category level, the impact on beer and sugars is most pronounced (Table D.4). Initial allocation to more high-quality managers also decreases a product's exit rate (Table D.5).

4.3 Discussion

We discuss two mechanisms that may influence our findings: the centralized rollout process and supplier–retailer arrangements.

4.3.1 Centralized Rollout of New Products

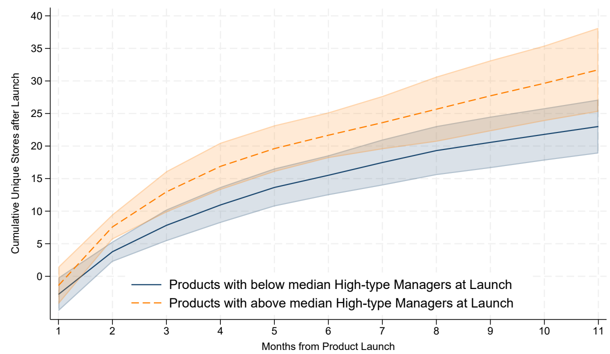
The retailer centralizes decisions about new product rollout, which may appear to conflict with how store managers influence the diffusion of new products (Gibbons and Henderson, 2012). Our conversations at the retailer's headquarters reflect this tension, as they stressed

Table 6: Cohort Regressions of Cumulative Store Reach

	Cumulative unique stores after launch			
Variables	(1)	(2) Within	(3) Within	(4) Across
$\mathbb{1}$ [Age = 2]	8.188***	6.552***	7.631***	6.291***
	(0.687)	(0.797)	(1.952)	(0.830)
$\mathbb{1}$ [Age = 3]	13.10***	10.60***	13.66***	11.07***
	(1.238)	(1.242)	(3.234)	(1.509)
$\mathbb{1}$ [Age = 4]	16.72***	13.73***	18.13***	15.07***
	(1.581)	(1.409)	(3.467)	(2.019)
$\mathbb{1}$ [Age = 5]	19.41***	16.42***	20.99***	17.89***
	(1.764)	(1.491)	(3.609)	(2.261)
$\mathbb{1}$ [Age = 6]	21.37***	18.29***	22.76***	19.89***
	(1.841)	(1.564)	(3.830)	(2.294)
$\mathbb{1}$ [Age = 7]	23.27***	20.25***	25.82***	21.90***
	(2.049)	(1.803)	(4.290)	(2.452)
$\mathbb{1}$ [Age = 8]	25.20***	22.08***	26.59***	24.27***
	(2.159)	(1.922)	(4.589)	(2.660)
$\mathbb{1}$ [Age = 9]	26.87***	23.34***	28.71***	26.08***
	(2.281)	(2.019)	(4.815)	(2.852)
$\mathbb{1}$ [Age = 10]	28.50***	24.57***	29.44***	27.78***
	(2.337)	(2.053)	(4.408)	(2.976)
$\mathbb{1}$ [Age = 11]	30.21***	25.78***	30.45***	29.76***
	(2.443)	(2.113)	(4.825)	(3.154)
Above median no. of good managers = 1		1.366	−4.958	−0.265
		(1.475)	(3.547)	(0.287)
$\mathbb{1}$ [Age = 2] × Above-median no. of good managers		2.443**	1.975	3.736**
		(0.988)	(2.088)	(1.472)
$\mathbb{1}$ [Age = 3] × Above-median no. of good managers		3.780**	2.869	3.997*
		(1.616)	(3.330)	(2.237)
$\mathbb{1}$ [Age = 4] × Above-median no. of good managers		4.563**	3.859	3.228
		(1.852)	(3.693)	(2.675)
$\mathbb{1}$ [Age = 5] × Above-median no. of good managers		4.601**	4.639	2.981
		(1.825)	(3.564)	(3.036)
$\mathbb{1}$ [Age = 6] × Above-median no. of good managers		4.784**	5.436	2.861
		(1.791)	(3.173)	(3.274)
$\mathbb{1}$ [Age = 7] × Above-median no. of good managers		4.755**	5.200	2.648
		(2.087)	(3.400)	(3.361)
$\mathbb{1}$ [Age = 8] × Above-median no. of good managers		4.994*	7.781**	1.779
		(2.552)	(3.543)	(3.653)
$\mathbb{1}$ [Age = 9] × Above-median no. of good managers		5.784*	7.928*	1.474
		(2.779)	(4.362)	(3.920)
$\mathbb{1}$ [Age = 10] × Above-median no. of good managers		6.479**	8.634**	1.325
		(2.956)	(4.010)	(3.944)
$\mathbb{1}$ [Age = 11] × Above-median no. of good managers		7.346**	10.46**	0.795
		(3.291)	(3.956)	(3.911)
Constant	−1.585	−2.776*	−3.458	−1.418
	(1.623)	(1.322)	(2.966)	(1.611)
Observations	14,619	14,619	14,619	14,619
R-squared	0.212	0.220	0.617	0.213
Cohort fixed effects	Yes	Yes	Yes	Yes
Category × time fixed effects	Yes	Yes	No	Yes
Firm × category × time fixed effects	No	No	Yes	No

Note: This table reports estimates for equation (5). The dependent variable is the cumulative number of stores reached by each product. The coefficients for age indicators and their interactions with an indicator for products with above-median managerial quality (measured by the number of high-quality managers at time of launch) are reported. Column (1) presents estimates from a model without an interaction with managerial quality. Columns (2) and (3) split product cohorts (defined by launch month) into above- or below-median managerial quality based on their average number of high-quality managers in the first three months after launch (across-cohort design). Column (4) splits products by above- and below-median good managers within each cohort-category (within-cohort design). Controls include cohort fixed effects, category-month fixed effects, and, in column (3), firm × category × month fixed effects. In all columns, the sample is restricted to new products that survived at least 11 months, the median new product lifespan. Standard errors are clustered at the cohort-category level.

Figure 10: Cumulative Reach of New Products by Managerial Quality at Launch



Note: This figure visualizes the cohort regression presented in Table 6, column (2), and presents the cumulative number of stores a new product has reached since its launch. Cohorts of new products (those launched in the same month-category) are split by whether the average number of high-quality managers at launch is above or below the median. Standard errors are clustered at the cohort level. Only products observed for at least 11 months—the median lifespan of new products—are included.

that rollout decisions are made centrally—implying limited scope for store-level influence.

Our results in this section do not contradict the retailer's claim. Rather, they highlight that rollout decisions are conditional on each product's demonstrated performance, which managers can shape.[16] Interviews with individual store managers corroborate this. They shared that they are very attentive to new products. Managers track the performance of new products in their own and other stores; key metrics are shown in their dashboards. Despite uncertainties due to the lack of previous performance data, new products offer opportunities to outperform peers. The importance of performance metrics intensifies this focus.

4.3.2 Supplier–Retailer Arrangements

Suppliers may be able to direct the performance of products as well as guide new products to stores with effective managers. Managers acknowledged that representatives from suppliers may visit their stores to understand product performance. Yet store managers have the final responsibility for enforcing pricing or product placement decisions, even if directives are given from headquarters or suppliers. For example, suppliers can suggest, but not implement, planograms (shelf layouts). This institutional feature suggests that supplier intervention is unlikely to be a key driver of our results. The fact that we find an effect for smaller suppliers, who are less able to send representatives to stores, is also consistent with this narrative.

In summary, the evidence in this section establishes the push mechanism, that is, the impact of store managerial quality on a new product's subsequent rollout. First, effective

[16]This link between managerial quality and centralized rollout became evident to retailer leadership once we shared our preliminary results with them.

managers impact the performance of new products in particular within stores. Second, the performance improvements caused by managerial quality affect the rollout of new products to other stores. This is a novel source of the heterogeneity of product availability across stores.

We now turn to examine the pull mechanism.

5 Pull Mechanism

We build on the evidence presented in section 3.3, which suggests that the presence of high-quality managers in stores that do not yet carry a new product is associated with a greater likelihood that that product will be introduced. To formalize the relationship between managerial quality and product entry—the pull mechanism—we adopt a stylized gravity model of product rollout, which allows us to quantify the magnitude of the impact of managerial quality on cross-store frictions.

5.1 A Model of New Product Rollout

We describe a stylized model of new product rollout that accounts for past dependence based on gravity effects. Product i's profit at quarter t that it is present ($d_{ijt} = 1$) in store j is

$$\pi_{ijt} = \underbrace{r_{ijt}}_{\text{revenue}} - \underbrace{s_{ijt} \times (d_{ij,t-1} = 0)}_{\text{entry cost}}, \tag{6}$$

where r_{ijt} is the revenue net of costs associated with selling the product in that store-period. An entry cost, s_{ijt}, is incurred when a product is newly adopted by store j. This cost is incurred when a product was not present in the previous quarter, as indicated by $d_{ij,t-1} = 0$, but is present in the current one ($d_{ijt} = 1$).

Product i is present in store j in quarter t when its expected profit is positive, such that

$$d_{ijt} = \mathbb{1} \times \{\hat{r}_{ijt} - s_{ijt} \times (d_{ij,t-1} = 0) > 0\}, \tag{7}$$

where $\hat{r}_{ijt}$ is expected revenue. s_{ijt} is a function of the commonality between the focal market (j) and the past markets to which product i has already been rolled out. In particular, we allow geographic proximity to markets where a product has already been rolled out to affect entry costs. This builds on the effects demonstrated in section 3.2, that products are more likely to enter a store if they are already available in a geographically nearby store.

Formally, this gravity effect is captured by a dummy variable that equals 1 if the product has already been rolled out to any other store in the same state:

$$Grav.\ State_{ijt} = \mathbb{1}\left\{ \sum_{\tilde{j}\ \text{s.t.}\ St(\tilde{j})=St(j),\ \tilde{j}\neq j}\ \sum_{\tilde{t}<t} d_{i\tilde{j}\tilde{t}} > 0 \right\}, \tag{8}$$

where $St(j)$ is a function that indicates store j's state. This variable captures the presence of gravity effects due to geographic proximity, and is akin to Morales et al.'s (2019) implementation of gravity effects.[17] Gravity effects are time-variant, as a market-product pair "acquires" gravity after the product has been rolled out to a nearby store. With this formulation of gravity, the cost of entry takes the form

$$s_{ijt} = \alpha_0 + \alpha_1 \left(Grav.\ State_{ijt}\right), \tag{9}$$

where α_0 captures the baseline nature of state dependence: the extent to which, if a product was not available in the previous quarter, it is not likely to be available in the next one either. α_1 captures the effect of gravity on the likelihood of store entry.

While we primarily consider geographic gravity effects, we also explore gravity effects associated with local demand. *Grav. GDPpc* captures store-product pairs in which the product has been rolled out to other municipalities with the same quantile of local per capita GDP levels. It is defined analogously as *Grav. State*.

5.1.1 Incorporating the Role of Managers

We modify the model to let the cost of entry to a retailer be a function of the quality of the manager in store j at time t (m_{jt}), such that

$$s_{ijt} = \alpha_0 + \alpha_1 \left(Grav.\ State_{ijt}\right) + \alpha_2 \cdot m_{jt} + \alpha_3 \left(Grav.\ State_{ijt}\right) \cdot m_{jt}, \tag{10}$$

where m_{jt} equals 1 if a high-quality manager is present at the focal store and 0 otherwise. Managerial quality moderates rollout frictions, both by directly impacting entry costs (α_2) and by moderating gravity effects (α_3).

[17] Morales et al. (2019) distinguish gravity effects caused by markets in which the product was available at launch from those caused by markets that received the product after launch. For simplicity, we combine these two sources of gravity for our analysis.

5.1.2 Estimation

We identify the model parameters by comparing the incidence of product availability across stores. We estimate the linear probability model

$$
\begin{aligned}
d_{ijt} = & \beta_1 r\hat{e}v_{ijt} + \beta_2 m_{jt} + \gamma_i + \gamma_t + \gamma_{storetype(j)} \\
& + \mathbb{1}\left(d_{ij,t-1} = 0\right) \cdot \left[\alpha_0 + \alpha_1 \left(Grav.\ State_{ijt}\right) + \alpha_2 \cdot m_{jt} + \alpha_3 \left(Grav.\ State_{ijt}\right) \cdot m_{jt}\right] + \varepsilon_{ijt}.
\end{aligned}
\tag{11}
$$

The terms on the first line capture expected revenue. We require an estimate of predicted revenue ($r\hat{e}v_{ijt}$) even for store-product-quarter combinations in which we do not observe actual rollout. We use the estimated fixed effects from an auxiliary regression of realized revenue on store, product, and quarter fixed effects to estimate potential revenue.

We assume that expected revenue is known up to an error term. There may be other shocks, which we do not observe, that were anticipated in making the product rollout decisions. To account for such shocks, γ_i, γ_t, and $\gamma_{storetype(j)}$ are product fixed effects, quarter fixed effects, and type-of-store fixed effects, respectively. We probe the robustness of our findings to alternative specifications of expected revenue and the shocks we control for.

The second line represents entry costs, including the impact of gravity effects. If the impact of managerial quality on entry costs is empirically relevant, we expect the presence of high-quality managers to be associated with a higher likelihood of entry. Similar to the conditional entry probabilities shown in Table 5, the parameters inform the impact of gravity and managerial quality in a model that includes empirical controls.

5.2 Results

5.2.1 Gravity Effects

Table 7 presents our estimates in the absence of managerial characteristics. Column (1) presents the unconditional effect of past entry. *Entry* is an indicator variable that is set to 1 if the product was not present in the store in the previous quarter ($d_{ijt-1} = 0$). It represents stores that would incur an entry cost if a new product were rolled out to them. A negative coefficient on *entry* thus indicates that if a store did not have the product in the previous quarter, it is also unlikely to have it in the current quarter.

The gravity effects help us to understand the magnitude of past dependence. Columns (2) and (3) sequentially add a baseline effect for geographic gravity as well as gravity interactions with *entry*. Column (2) shows that a store in the same state as a store in which the product was launched is more likely to also carry the product. Column (3) shows that this effect can be loaded onto the interactions with *entry*. The estimates suggest that geographic gravity positively impacts new product rollout by reducing entry costs. The model provides an economic interpretation of the gravity effect: a non-carrying store that is in the same state as a store in which the product is already available is 12.6 percentage points more likely to carry the product. As discussed before, this gravity effect captures benefits associated with geographical proximity, such as reduced distributional costs and agglomeration economies. For products entering distant markets, geographic frictions are substantial.

Columns (4) and (5) report the results of a similar analysis of demand gravity. The positive impact of demand gravity is also meaningfully captured through its interaction with entry costs. The gravity effect for stores in markets with the same local income levels is 11.1 percentage points. When a product has already been rolled out to a market with similar demand conditions, the entry costs are smaller, potentially because the cost to figure out how to sell the product is reduced, given that more information is available.

Column (6) includes both sets of gravity variables in the same model. While the magnitude of the geographic gravity effects is comparable to the model in which only geographic gravity is included (11.4 percentage points versus 12.6 percentage points in column 3), the magnitude of the demand gravity effects is smaller than in the model in which only demand gravity is included (4.7 percentage points versus 11.1 percentage points in column 5). Nonetheless, both sources of gravity continue to represent significant reductions in baseline frictions.

Our estimated gravity effects may be sensitive to our proxy for expected revenue ($\hat{rev}$). They capture drivers of demand that would otherwise make the product rollout confounded with the error term. In Appendix E, we probe the robustness of our results to more flexible specifications of expected revenue. In particular, we allow predicted revenue to vary within product categories and at the same level of granularity at which gravity effects vary (i.e., across states or across stores with the same local income levels). The estimated gravity effects do not vary in economically meaningful magnitudes across these specifications, suggesting that the estimated gravity effects are reflective of frictions associated with the rollout of new products rather than of unobserved demand conditions confounded with rollout.

Overall, Table 7 demonstrates that gravity effects capture statistically and economically meaningful decreases in rollout frictions. The frictions present when products enter markets that don't benefit from gravity effects, by contrast, are substantial.

5.2.2 Managerial Impact on Gravity Effects

Table 8 shows the results of estimating the full model (11), which incorporates managerial quality. Column (1) presents a baseline interaction of managerial quality with *entry*. The presence of high-quality managers in and of itself is not associated with a change in entry

Table 7: Model of Product Rollout with Gravity Effects

VARIABLES	(1) Presence	(2) Presence	(3) Presence	(4) Presence	(5) Presence	(6) Presence
Entry	−0.556***	−0.550***	−0.659***	−0.556***	−0.662***	−0.693***
	(0.006)	(0.006)	(0.008)	(0.006)	(0.012)	(0.012)
Grav. State		0.075***	−0.038***			−0.030***
		(0.002)	(0.007)			(0.007)
Entry × Grav. State			0.126***			0.114***
			(0.008)			(0.007)
Grav. GDPpc city				0.039***	−0.067***	−0.034***
				(0.001)	(0.012)	(0.011)
Entry × Grav. GDPpc city					0.111***	0.047***
					(0.012)	(0.011)
Observations	4,533,661	4,533,661	4,533,661	4,533,661	4,533,661	4,533,661
R-squared	0.615	0.619	0.621	0.616	0.616	0.621
Avg. dep. var.	0.230	0.230	0.230	0.230	0.230	0.230
SD dep. var.	0.420	0.420	0.420	0.420	0.420	0.420
Lincom estimate Grav. State			0.088***			0.084***
Lincom SE Grav. State			0.002			0.002
Lincom estimate Grav. GDPpc city					0.044***	0.013***
Lincom SE Grav. GDPpc city					0.001	0.001

Note: The unit of observation is at the product-store-quarter level, encompassing all product-store-quarter combinations where a product was or could have been available for purchase. The dependent variable is an indicator equal to 1 when a product is present in the store. *Entry* is an indicator variable that equals 1 if the product was not present in the store in the previous quarter, representing stores where entry costs would be incurred upon rollout. *Grav. State* is an indicator variable that equals 1 if the product is already available in another store in the same state. *Grav. GDPpc city* is an indicator variable that equals 1 if the product is already available in another store within the same quartile of local per capita GDP levels. All models control for predicted revenue and include fixed effects for product, quarter, and store type. Standard errors are clustered at the product category level.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

costs. When interactions with *entry* are additively included, as in column (3), we find that the presence of a high-quality manager is associated with a 0.4 percentage point increase in the likelihood of entry. This impact is largely independent of the effect of geographic gravity, as a comparison with column (2), which reproduces a model with geographic gravity, shows.

Column (4) interacts the geographic gravity effect with managerial quality. Having a high-quality manager is associated with a 1.1 percentage point increase in the geographic gravity effect (from 12.0 to 13.1 percentage points), or more than 9 percent. The large effect of high-quality managers when interacted with gravity effects in column (4) contrasts with the comparatively smaller baseline effects in columns (2) and (3).

These results suggest that managers enhance the impact of geographic proximity on entry costs, rather than influencing entry costs directly. The effect of geographic gravity on product entry in column (4) is 12.0 percentage points, whereas that of high-quality managers is 1.1 percentage points. Since geographic gravity reflects how much more likely entry becomes when a nearby store already carries the product, it serves as a benchmark for the magnitude of geographic frictions. Relative to this benchmark, the presence of a high-quality manager increases the likelihood that a product is present in a store by 9.2 percent.

Table F.1 examines how managerial quality influences demand gravity effects. Both demand gravity and the presence of a high-quality manager reduce entry costs. However, the impact of the manager on demand gravity is limited.

5.2.3 Robustness

The significant effect of managerial quality in enhancing geographic gravity effects is robust to various alternative specifications.

If high-quality managers influence the rollout of new products through channels other than reducing entry costs, this could affect our estimate of the impact of managerial quality on product rollout. We test the robustness of this effect. First, in Table 9, columns (2) and (3), we directly control for manager characteristics—specifically, age and tenure—which are correlated with managerial quality (Table A.5). Controlling for these variables allows us to isolate the impact of managerial quality, conditional on key observables that may influence the retailer's personnel decisions.

Second, in column (4), we estimate the model using an alternative measure of predicted revenue that varies with managerial quality. This approach explicitly captures the impact of managerial quality on expected revenue by allowing predicted revenue to vary at the manager-product–category-quarter level.

We also test robustness to how we account for managerial quality and the set of products included in estimation. Column (5) uses an alternative definition of managerial quality. Column (6) evaluates the impact of product attrition by estimating the model on products that survive longer than the median lifespan of new products.

Managerial quality is consistently associated with stronger geographic gravity effects, and the magnitude of these impacts remains stable across different specifications. Table 9 replicates our preferred specification in column (1). Across all specifications, the presence of a high-quality manager in a store, through their effect on geographic gravity, is associated with a 1.0 to 1.7 percentage point increase in the likelihood of a particular new product being introduced in the focal store. The consistency of these estimates suggests that managerial quality is associated with an increase in geographic gravity, rather than that our results capture strategic co-location of product rollout and personnel allocation.

5.2.4 Heterogeneous Results

We study heterogeneity in the role managers play in influencing rollout frictions.

Supplier size. In section 3.2 we demonstrated that gravity effects vary by supplier size. Using the empirical model, we ask whether the differences across supplier size show up as

Table 8: Model of Product Rollout with Gravity Effects and Managerial Quality

VARIABLES	(1) Presence	(2) Presence	(3) Presence	(4) Presence
Entry	−0.556***	−0.659***	−0.661***	−0.658***
	(0.006)	(0.008)	(0.008)	(0.008)
Grav. State		−0.038***	−0.038***	−0.038***
		(0.007)	(0.007)	(0.007)
Entry × Grav. State		0.126***	0.126***	0.120***
		(0.008)	(0.008)	(0.008)
High-quality manager	0.004***		0.004***	0.004***
	(0.001)		(0.001)	(0.001)
Entry × high-quality manager	−0.000		0.004***	−0.002**
	(0.001)		(0.001)	(0.001)
Entry × Grav. State × high-quality manager				0.011***
				(0.001)
Observations	4,533,661	4,533,661	4,533,661	4,533,661
R-squared	0.615	0.621	0.621	0.621
Avg. dep. var.	0.230	0.230	0.230	0.230
SD dep. var.	0.420	0.420	0.420	0.420
Lincom estimate high-quality manager	0.004***		0.008***	0.013***
Lincom SE high-quality manager	0		0	0.001
Lincom estimate Grav. State		0.088***	0.088***	0.093***
Lincom SE Grav. State		0.002	0.002	0.002

Note: The unit of observation is at the product-store-quarter level, encompassing all product-store-quarter combinations where a product was or could have been available for purchase. The dependent variable is an indicator equal to 1 when a product is present in the store *Entry* is an indicator variable that equals 1 if the product was not present in the store in the previous quarter, representing stores where entry costs would be incurred upon rollout. *Grav. State* is an indicator variable that equals 1 if the product is already available in another store in the same state. *High-quality manager* is an indicator variable that equals 1 if a high-quality manager is present in the store. All models account for predicted revenue and include fixed effects for product, quarter, and store type. Standard errors are clustered at the product level.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

differences in frictions, and whether the manager's impact on the rollout frictions varies by the size of the supplier. Table F.2, column (1), shows that without an interaction with supplier size, the impact of a high-quality manager on the rollout friction remains comparable to the estimates from Table 8: a high-quality manager enhances the gravity effect by 1.1 percentage points. Column (2) introduces a further interaction between the gravity effect, supplier size, and managerial quality. Two observations stand out: the baseline impact of a high-quality manager on gravity effects is still present (0.8 percentage point boost), but the impact is greater for products from big suppliers (0.9 percentage points). The gravity effect that products from big suppliers enjoy is further enhanced by the presence of a high-quality manager. In other words, supplier size affects the availability of products within retailers, and the effect is strengthened by managerial quality.

Product categories. While perishable products generally see a smaller rate of entry (2.9 percentage points smaller), the presence of high-quality managers is associated with a 0.9 percentage point increase in the entry of perishable products (Table F.2, column 4). While products that require freezer space generally see a smaller rate of entry (4.7 percentage points smaller), the presence of high-quality managers is associated with a 1.1 percentage point

Table 9: Model of Product Rollout with Gravity Effects and Managerial Quality: Robustness

Variables	(1) Presence	(2) Presence	(3) Presence	(4) Presence	(5) Presence	(6) Presence
Entry	−0.658***	−0.658***	−0.658***	−0.658***	−0.656***	−0.673***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Grav. State	−0.038***	−0.038***	−0.038***	−0.038***	−0.038***	−0.019***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Entry × Grav. State	0.120***	0.120***	0.121***	0.120***	0.116***	0.087***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
High-quality manager	0.004***	−0.002	0.008***	0.004***	0.004***	0.005***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Entry × high-quality manager	−0.002**	−0.002**	−0.002**	−0.002**	−0.004***	−0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Entry × Grav. State × high-quality manager	0.011***	0.011***	0.010***	0.011***	0.017***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	4,533,661	4,533,661	4,533,661	4,533,661	4,533,661	3,391,168
R-squared	0.621	0.621	0.621	0.621	0.621	0.653
Avg. dep. var.	0.230	0.230	0.230	0.230	0.230	0.230
SD dep. var.	0.420	0.420	0.420	0.420	0.420	0.420
Lincom estimate high-quality manager	0.013***	0.008***	0.016***	0.013***	0.016***	0.012***
Lincom SE high-quality manager	0.001	0.001	0.001	0.001	0.001	0.001
Lincom estimate Grav. State	0.093***	0.094***	0.093***	0.093***	0.095***	0.077***
Lincom SE Grav. State	0.002	0.002	0.002	0.002	0.002	0.002

Note: Each column represents a variant of column (4) in Table 8, replicated here as column (1). See Table 8 for descriptions. Column (2) includes the average age of managers along with its interaction with the high-quality manager indicator. Column (3) includes the average tenure of managers and its interaction with the high-quality manager indicator. Column (4) uses an alternative estimate of expected revenue. For this model, predicted expected revenue includes interactions with high-quality manager and with category-quarter fixed effects, in addition to other controls. Column (5) uses an alternative definition of managerial quality, where a high-quality manager has a fixed effect surpassing the median of the connected set. Column (6) restricts the sample to products with a lifespan of over 11 months.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

increase in the entry of products that need freezer space (column 6).[18]

Important categories. Because both products from big suppliers and those that are perishable or need freezer space require particular managerial attention, that the effect of managerial quality is greater for these product categories paints a picture of an effective manager who is particularly attentive to products that are aligned with their incentives.

To further examine this idea, we leverage the cross-store variation in the relative importance of products from different categories to overall store revenue. We identify products belonging to categories that contribute relatively more to a particular store's sales than they do on average across the retail chain (Table F.3).

We find that products from these more important categories gain an additional 4.3 percentage points in the geographic gravity effect, regardless of managerial quality. Notably, simply being in an important category does not directly increase the likelihood that a product is present in the store. Instead, consistent with the narrative so far, products that are more

[18]The role that high-quality managers play in decreasing frictions is comparable in magnitude for innovative as well as non-innovative products (Table F.2, column 7). At the individual category level, we find that the presence of high-quality managers is associated with increased geographic gravity in all but three categories: canned products, cereals, and cookies (Table F.4).

important for store revenue gain a greater advantage from geographic proximity—if the product is already available in nearby stores, the gravity effects are amplified.

For stores with a high-quality manager, more important products see a further 0.7 percentage point boost in geographic gravity. Therefore, while important products in all stores, on average, see a 4.3 percentage point increase in geographic gravity, high-quality managers are associated with a further 16 percent increase in the impact of geographic gravity.

Overall, across heterogeneous product types, we consistently find that high-quality managers enhance geographic gravity.

Limitations of gravity model. Our approach relies on a stylized model of product presence, grounded in two key simplifying assumptions. First, we characterize the economic incentives in the rollout process through entry costs, abstracting from other potential drivers, such as learning about demand or product quality. Second, we assume that any store that has not yet carried a product could have adopted it, treating all such stores as candidates for rollout.

Our primary aim is to understand the presence of high-quality managers in stores not yet carrying a new product influences rollout patterns—the pull mechanism. The robustness checks presented in this section and during the estimation of managerial quality (Section 2.2.3) suggest there is no strategic co-location of products and managers. Our findings likely do not stem from confounding factors; high-quality managers likely "pull" new products to their stores. The role of managerial quality in facilitating product adoption would likely remain a central feature in fully microfounded models.

6 Managerial Traits of High-Quality Managers

We have thus far presented evidence that high-quality managers significantly influence new product rollout through both the push and pull mechanisms. Do these managers possess specific traits that distinguish them from less-effective peers?

To investigate this question, we collected self-reported data on managerial traits using an online survey, with the support of the retailer. Descriptions of the survey metrics are available in Diaz et al. (2024). We regress each manager fixed effect on each survey variable. The estimated coefficients for select traits are presented in Figure G.1. While these relationships are correlational, two traits stand out for their significant positive correlation with managerial quality: locus of control, and positive adaptation. *Locus of control* gauges the degree to which managers believe their actions, rather than external factors, determine outcomes (e.g., "I believe my success depends on ability rather than luck"). *Positive adaptation* measures the ability to adapt and find solutions while maintaining a positive mindset (e.g., "I look for creative ways to alter difficult situations").

Table 10: Cohort Regressions, Impact of Managerial Traits

	Cumulative unique stores after launch			
	(1) Provide feedback	(2) Retaining stars	(3) Locus of control	(4) Positive adaptation
$\mathbb{1}$[Age = 2]	7.559***	7.174***	7.201***	7.459***
	(1.077)	(0.841)	(1.075)	(1.058)
$\mathbb{1}$[Age = 3]	11.83***	11.35***	11.41***	11.96***
	(1.541)	(1.224)	(1.496)	(1.546)
$\mathbb{1}$[Age = 4]	14.97***	14.55***	14.56***	15.08***
	(1.681)	(1.397)	(1.552)	(1.680)
$\mathbb{1}$[Age = 5]	17.41***	16.91***	16.83***	17.30***
	(2.021)	(1.836)	(1.786)	(1.915)
$\mathbb{1}$[Age = 6]	19.59***	19.15***	19.29***	19.40***
	(2.083)	(1.932)	(1.671)	(1.925)
$\mathbb{1}$[Age = 7]	21.52***	21.10***	21.26***	21.43***
	(2.469)	(2.297)	(2.046)	(2.285)
$\mathbb{1}$[Age = 8]	23.30***	22.69***	22.87***	22.94***
	(2.562)	(2.431)	(2.055)	(2.321)
$\mathbb{1}$[Age = 9]	24.53***	23.95***	24.20***	24.22***
	(2.735)	(2.628)	(2.247)	(2.491)
$\mathbb{1}$[Age = 10]	25.57***	25.01***	25.16***	25.22***
	(2.682)	(2.589)	(2.251)	(2.441)
$\mathbb{1}$[Age = 11]	26.05***	25.46***	25.72***	25.79***
	(2.616)	(2.529)	(2.189)	(2.384)
Above-median measure	2.527	1.973	2.232	2.321
	(1.645)	(1.417)	(1.538)	(1.548)
$\mathbb{1}$[Age = 2] × measure	1.744	2.363**	2.244*	1.864
	(1.097)	(0.922)	(1.159)	(1.100)
$\mathbb{1}$[Age = 3] × measure	3.238*	4.037***	3.789**	2.970*
	(1.547)	(1.300)	(1.604)	(1.549)
$\mathbb{1}$[Age = 4] × measure	4.329**	5.076***	4.841***	4.048**
	(1.478)	(1.209)	(1.606)	(1.556)
$\mathbb{1}$[Age = 5] × measure	5.325***	6.221***	6.016***	5.296***
	(1.258)	(1.144)	(1.400)	(1.353)
$\mathbb{1}$[Age = 6] × measure	5.361***	6.204***	5.551***	5.377***
	(1.379)	(1.415)	(1.578)	(1.515)
$\mathbb{1}$[Age = 7] × measure	5.449***	6.357***	5.535**	5.268**
	(1.770)	(1.821)	(1.929)	(1.868)
$\mathbb{1}$[Age = 8] × measure	5.671***	6.923***	5.926***	5.778***
	(1.675)	(1.795)	(1.866)	(1.789)
$\mathbb{1}$[Age = 9] × measure	6.599***	7.881***	6.638***	6.543***
	(2.042)	(2.208)	(2.090)	(2.095)
$\mathbb{1}$[Age = 10] × measure	7.682***	8.982***	7.732***	7.557***
	(2.176)	(2.313)	(2.347)	(2.205)
$\mathbb{1}$[Age = 11] × measure	9.630***	11.07***	9.523***	9.313***
	(2.772)	(2.763)	(2.932)	(2.763)
Constant	−3.857	−3.647	−3.491	−3.552
	(2.448)	(2.379)	(2.085)	(2.304)
Observations	12,001	12,001	12,001	12,001
R-squared	0.257	0.258	0.257	0.257
Cohort fixed effects	Yes	Yes	Yes	Yes
Category × time fixed effects	Yes	Yes	Yes	Yes
Firm × category × time fixed effects	No	No	No	No
Sample	Balanced	Balanced	Balanced	Balanced

Note: For each managerial trait, we show the specifications corresponding to Table 6, column (2), in which we interact the respective traits instead of an indicator for high-quality managers. Specifically, for each trait, we construct an indicator for whether the manager is above the median for that trait. See Table 6 for descriptions of each model.
** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 11: Model of Product Rollout with Gravity Effects and Managerial Quality, Impact of Managerial Traits

	Provide feedback		Retaining stars		Locus of control		Positive adaptation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Revenue	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Entry	−0.653***	−0.650***	−0.648***	−0.639***	−0.647***	−0.643***	−0.651***	−0.647***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Grav. State	−0.035***	−0.035***	−0.035***	−0.035***	−0.035***	−0.035***	−0.035***	−0.035***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Entry × Grav. State	0.136***	0.131***	0.135***	0.119***	0.135***	0.127***	0.135***	0.127***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Main effect: measure	−0.007***	−0.007***	0.003**	0.003**	0.005***	0.005***	−0.003***	−0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Entry × measure	0.010***	0.005***	0.002	−0.017***	−0.000	−0.009***	0.007***	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Entr × Grav St. × meas.	—	0.009***	—	0.033***	—	0.015***	—	0.015***
		(0.001)		(0.001)		(0.001)		(0.001)
Observations	2,366,494	2,366,494	2,366,494	2,366,494	2,366,494	2,366,494	2,366,494	2,366,494
R-squared	0.631	0.631	0.631	0.632	0.631	0.631	0.631	0.631
Avg. dep. var.	0.250	0.250	0.250	0.250	0.250	0.250	0.250	0.250
SD dep. var.	0.430	0.430	0.430	0.430	0.430	0.430	0.430	0.430
Lincom est. for measure	0.003***	0.007***	0.004***	0.019***	0.005***	0.011***	0.004***	0.010***
Lincom SE for measure	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001
Lincom est. Grav. State	0.101***	0.105***	0.100***	0.117***	0.101***	0.107***	0.101***	0.107***
Lincom SE Grav. State	0.002	0.002	0.002	0.003	0.002	0.003	0.002	0.003

Note: For each managerial trait, we show the specifications corresponding to Table 8, columns (3) and (4), in which we interact the respective traits instead of an indicator for high-quality managers. Specifically, for each trait, we construct an indicator for whether the manager is above the median for that trait. See Table 8 for descriptions of each model.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

These findings are noteworthy because, as discussed in section 2.2.3, demographic variables such as tenure or the nature of the training a manager has received do not meaningfully predict managerial quality. Even though demographics do not predict managerial quality, our survey results demonstrate that our measure of managerial quality likely captures meaningful sources of heterogeneity among managers rather than spurious correlations in the data.

The two identified traits—locus of control and positive adaptation—are consistent with managers who effectively allocate their attention. These support the patterns, shown in sections 4 and 5, that effective managers exert a particularly strong influence on the rollout of products from big suppliers, those requiring scarce shelf space (e.g., freezers), and those in revenue-critical product categories.

To illustrate how these traits relate to the push and pull mechanisms, we replicate our previous analyses using these traits in place of our baseline managerial quality measure. In support of the push mechanism, we run the cohort regression using these traits in place of our baseline managerial quality measure, presented in Table 10. The effects associated with these traits are similar in magnitude to those obtained using the high-quality manager indicator: products managed by a higher proportion of individuals with an above-median locus of control (compared to those managed by high-quality managers) are rolled out to an additional 9.5 (vs. 7.3) stores within 11 months.

Similarly, in support of the pull mechanism, table 11 shows estimates of the gravity model. Managers with an above-median locus of control (compared to high-quality managers) are associated with a 1.5 (vs. 1.1) percentage point increase in the geographic gravity effect. The impact of these traits is comparable for the pull mechanism as well.

Taken together, these results show not only that key traits, including locus of control and positive adaptation, correlate with our measure of managerial quality but also that these traits similarly predict managers' ability to drive both the push and pull mechanisms.

7 Conclusion

We examine how managerial quality influences the diffusion of new products in a retail setting. Using data from a large Colombian retailer, we document substantial heterogeneity in new product reach, show that high-quality managers boost the performance of new products, and demonstrate that this improvement facilitates the broader rollout of these products. We identify two key mechanisms through which high-quality managers impact product rollout: a "push" mechanism, by which they enhance new products' in-store performance, leading to broader adoption across the retailer, and a "pull" mechanism, by which they actively seek to introduce new products in their stores, reducing rollout frictions.

We discuss three key implications of our findings. First, managers impact the frictions that govern innovation diffusion within organizations. In particular, effective managers—those adept at raising overall store revenue—also facilitate the spread of new products. This suggests that the skills that enable managers to boost store performance are closely tied to their ability to promote new product rollout.

Second, our findings indicate that decisions about where to introduce new products and how to assign managers are interconnected. Manufacturers and retailers may find opportunities to coordinate or contract on these terms when rolling out new products.

Finally, our study suggests that even after a product is accepted by a retailer, significant heterogeneity exists in how it diffuses among consumers. We find that large suppliers face fewer rollout frictions—especially in the presence of high-quality managers—and that their products receive more managerial attention once in stores. This highlights a mechanism that contributes to the disparities in the availability of new products by supplier size *within* retailers, beyond the dynamics between suppliers and retailers often considered by policymakers.

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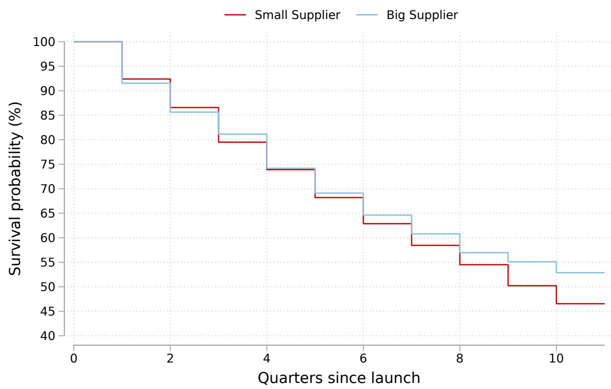
Online Appendix

A Appendix: Additional Summary Statistics

Figure A.1: Survival Analysis by Supplier Size



Note: This figure presents Kaplan–Meier survival estimates for products from big suppliers versus products from small suppliers. Big suppliers are in the top 4th percentile by average quarterly revenue from new and existing products. The y-axis shows the survival rate, defined as the probability that a product is still available on the market. The x-axis represents the number of quarters since the product's launch.

Figure A.2: Distribution of Managerial Tenure and Age

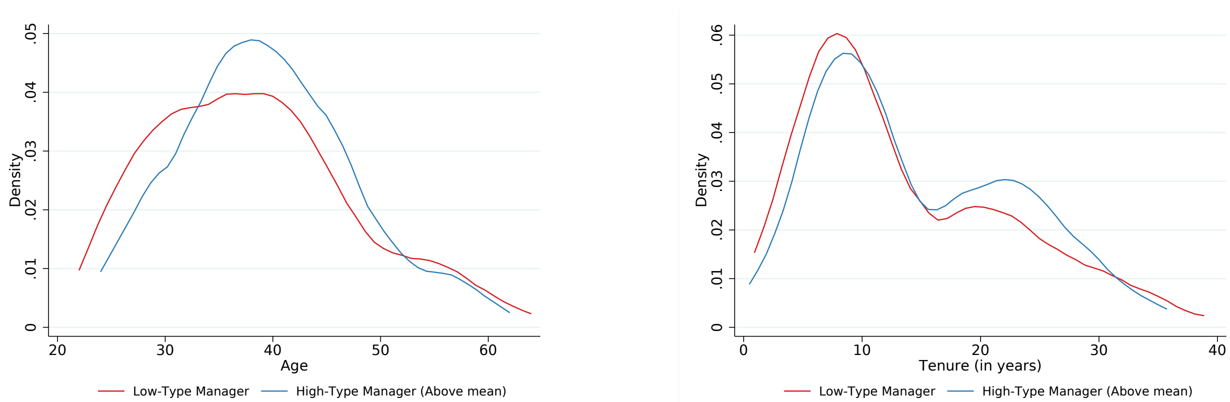


Figure A.3: Histogram of New Products Introduced by Quarter

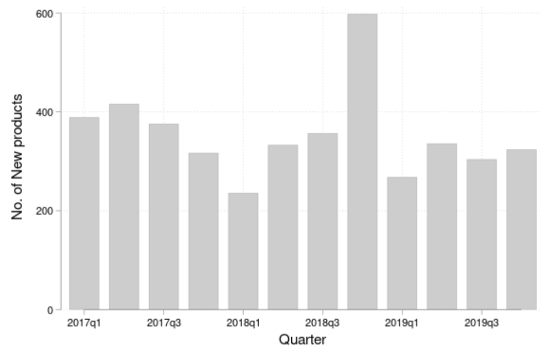
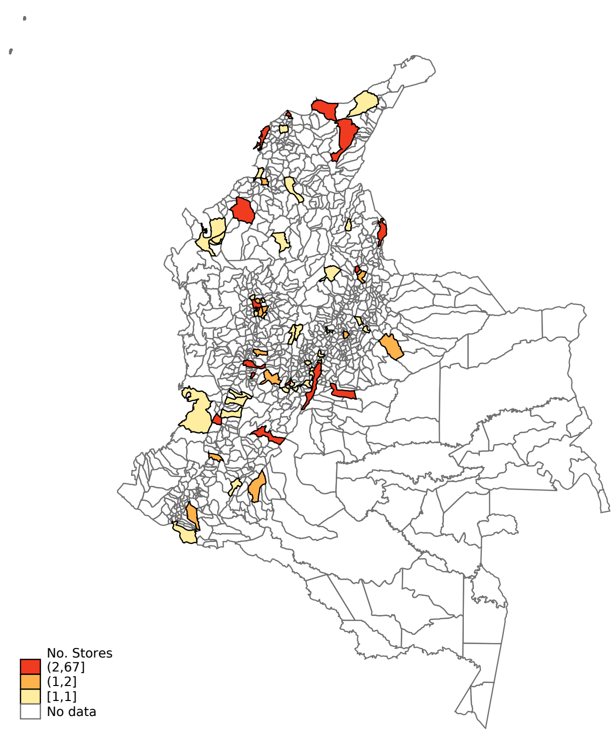


Table A.1: Number of Stores per State and City

State	Unique stores
Antioquia	47
Atlántico	10
Bolívar	11
Boyacá	5
Caldas	2
Caquetá	2
Casanare	2
Cauca	2
Cesar	3
Córdoba	3
Cundinamarca	81
Huila	6
La Guajira	1
Magdalena	5
Meta	6
Nariño	3
Norte de Santander	4
Quindío	3
Risaralda	4
Santander	9
Sucre	4
Tolima	4
Valle del Cauca	12
Total	229

This table displays the number of unique stores in each state (administrative department).



This map displays the cities where stores are located, with the unique store distribution.

Table A.2: Number of Stores by Local Per Capita GDP Quartile

Per capita GDP quartile	Unique stores
< 25th percentile	33
25th to < 50th percentile	28
50th to < 75th percentile	50
> 75th percentile	118
Total	229

Note: This table displays the number of unique stores in each of four quartiles of cities classified based on their GDP per capita: cities below the 25th percentile, cities equal to or above the 25th but below the 50th percentile, cities equal to or above the 50th but below the 75th percentile, and finally, cities equal to or above the 75th percentile.

Table A.3: Suppliers of Existing and New Products

Category	Suppliers	Existing products (avg.)	Existing products (SD)	New products (avg.)	New products (SD)
Beer	37	4.05	10.24	4.81	9.12
Breads and desserts	205	4.66	16.5	3.75	12.82
Canned products	58	2.16	4.28	2.05	4.09
Cereal	42	4.21	8.82	3.69	5.67
Cheese	102	4.2	8.32	3.01	4.93
Chips	55	3.93	7.42	3.13	7.83
Cookies	96	3.35	7.88	4.04	10.54
Energy and hydration drinks	24	1.96	2.33	1.33	2.16
Grains	147	2.63	5.69	2.17	6.55
Ice cream	39	4.21	10.23	3.64	8.87
Liquor	174	8.33	19.31	4.58	10.98
Milk	77	4.29	7.85	2.18	4.67
Cooking oils and vinegars	114	2.45	4.35	1.91	3.09
Soda	22	6.36	12.48	5.55	13.65
Sugars	80	2.26	3.11	1.24	1.81
Yogurt	40	8.45	15.6	6.75	12.94
Total	829	6.86	18.59	5.13	15.04

Note: Column (1) displays the number of unique suppliers per product category. Column (2) presents the average number of unique existing products by supplier, and column (3) presents the standard deviation across suppliers. Columns (4) and (5) present corresponding metrics for new products.

Table A.4

Variable	(1) Small supplier Mean and (SE)	(2) Big supplier Mean and (SE)	(2)−(1) Pairwise t-test Mean difference
Product launch replacing a product from the same supplier	0.133 (0.001)	0.448 (0.001)	0.314***
Number of observations	144,158	125,802	269,960

Note: This table details the instances in which a store's introduction of a new product corresponds with the discontinuation of another product by the same supplier. The analysis is conducted at the store-product level, concentrating on the initial introduction quarter of a product. The focal variable takes a value of 1 when a product launch is accompanied by the exit of a different product from the same supplier within the same category. Big suppliers are those in the top fourth percentile of average-quarter revenues by category.

Table A.5: Correlation of Managerial Quality and Observables

	(1) Low-quality manager Mean and (SE)	(2) High-quality manager Mean and (SE)	(2)−(1) Pairwise t-test Mean difference
Age	38.163	39.518	1.354*
	(0.530)	(0.479)	
Tenure (in years)	12.352	13.350	0.999
	(0.511)	(0.498)	
Female manager	0.350	0.369	0.019
	(0.027)	(0.029)	
Training (overall)	0.351	0.366	0.015
	(0.020)	(0.020)	
Training (corporate culture)	0.199	0.213	0.014
	(0.013)	(0.013)	
Training (organizational performance)	0.227	0.234	0.007
	(0.015)	(0.015)	
Number of observations	306	282	588

Note: This table compares the observables of low-quality and high-quality managers. We test differences in managers' age (in years), tenure (the number of years they have worked at the company), and gender, for those managers for whom we observe these values. We also test differences in managers' training, including the average training level for each manager across quarters in any form of training and in specific training programs: "Corporate Culture Training" and "Training in Organizational Performance."

Table A.6: Probability of New Product Entering a Store (Controlling for Category and Quarters since Launch)

	Probability of entry in store-quarter (%)
Overall	9.25
Conditional on previous entry to . . .	
same state	10.51
same local GDP per capita	9.38
Push mechanism	
Product mostly managed by high-quality managers in past	13.45
Product not mostly managed by high-quality managers in past	4.99
Pull mechanism	
High-quality manager present in focal store	9.61
High-quality manager not present in focal store	8.64
Average across 176 product category-(quarters since launch)	

Note: The table presents unconditional and conditional entry probabilities for the average across 176 product category-(quarters since launch). The entry probability of a given product is the fraction of stores that it enters in quarter t, among the stores in which it was not present in quarter $t-1$. The average value within each product category-(quarter since launch) is then calculated. The same-state conditional entry probability is calculated as the entry probability for stores in a state the product has previously entered. Other conditional probabilities are calculated similarly. To construct the push variable, we calculate the average number of high-quality managers in a store in the first two quarters after each product's launch. Then, the products were divided between the above- and below-median high-quality managers within each cohort category.

Table A.7: Probability of New Product Entering a Store (Innovative vs. Non-innovative Products)

	Probability of entry in store-quarter (%)	
	Innovative products	**Non-innovative products**
Overall	11.90	13.51
Conditional on previous entry to . . .		
same state	15.84	18.65
same local GDP per capita	12.35	13.96
Push mechanism		
Product mostly managed by high-quality managers in past	22.78	24.98
Product not mostly managed by high-quality managers in past	4.32	5.83
Pull mechanism		
High-quality manager present in focal store	12.36	14.05
High-quality manager not present in focal store	11.39	12.92
N (store-product-quarter observations)	1,492,607	3,041,054

Note: This table presents unconditional and conditional entry probabilities for innovative and non-innovative products. The entry probability of a given product is the fraction of stores that it enters in quarter t, among the stores in which it was not present in quarter $t-1$. The same-state conditional entry probability is calculated as the entry probability for stores in a state the product has previously entered. Other conditional probabilities are calculated similarly. To construct the push variable, we calculate the average number of high-quality managers in a store in the first two quarters after each product's launch. Then, the products were divided between the above- and below-median high-quality managers within each cohort category. Based on their product descriptions, products are classified into those that are likely to be extensions of existing products (e.g., a new package size or flavor variant) and products that are likely to be innovative (because of the lack of existing products with a similar product description).

Table A.8: Relationship between the Cumulative Number of Unique Stores a Product Enters and Product Performance

	(1)	(2)	(3)	(4)
VARIABLES	Cum. unique stores	Cum. unique stores	Cum. unique stores	Cum. unique stores
Actual revenue	0.000			
	(0.000)			
Actual revenue (in dollars)		0.001		
		(0.002)		
Log(actual revenue)			12.826***	
			(0.784)	
Avg. sale above median				24.527***
				(1.931)
Observations	4,254	4,254	4,254	4,254
R-squared	0.213	0.213	0.267	0.243
Avg. dep. var.	63.45	63.45	63.45	63.45
SD dep. var.	70.11	70.11	70.11	70.11

Note: The dependent variable is the number of unique stores a product enters cumulatively. The unit of observation is defined at the product level. The principal independent variable is the average revenue of the product calculated between stores and quarters. Column (1) assesses revenue in Colombian pesos (COP). Column (2) assesses revenue in USD, converting COP at an average daily rate of 3062.95 COP/USD (Jan 1, 2017–Dec 31, 2019). Column (3) analyzes the log of average revenue. Column (4) uses an indicator variable for whether the average revenue is above the category median. All models control for category dummies and whether the product is from a big supplier. Robust standard errors are given in parentheses.
** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table A.9: Survival Analysis on Managerial Quality

Variables	(1) Time on the market	(2) Product dies	(3) Non-launch cum. unique stores
Managerial quality (intensity)	0.015***	−0.003***	0.286***
	(0.002)	(0.000)	(0.019)
Observations	4,254	4,254	4,254
R-squared	0.041	0.046	0.100
Avg. dep. var.	4.840	0.370	19.37
SD dep. var.	3.150	0.480	35.32

Note: This table presents regression results to examine product longevity in quarters (time on the market), discontinuation status (product dies), and expansion beyond launch stores (non-launch cum. unique stores). The analysis is at the product level. The independent variable is intensity of managerial quality, calculated as the average proportion of stores with high-quality managers stocking the product each quarter. Robust standard errors are given in parentheses.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

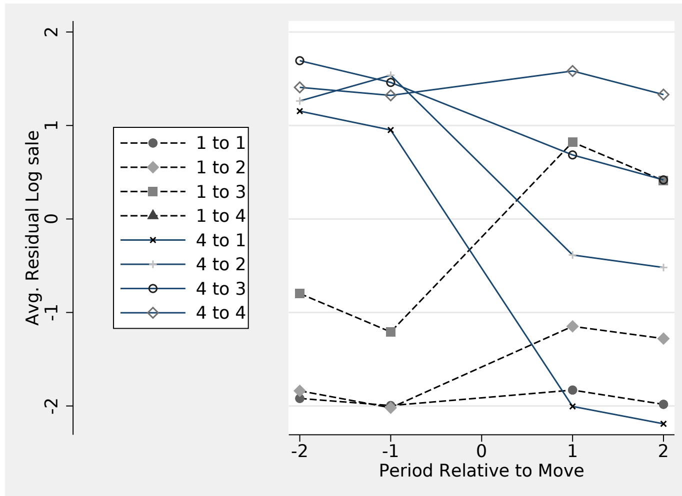
B Appendix: Estimating Managerial Quality

Identifying the manager and store fixed effects requires the assignment of managers to workers to be conditionally mean-independent of past, present, and future values of ν_{kt}. Note that these conditions permit managers to be assigned to stores on the basis of the permanent component of managerial ability (θ_k) and store productivity ($\psi_{J(k,t)}$) so that sorting on the fixed effects *is* allowed. However, this assumption excludes the possibility that managers sort into stores on the basis of their match-specific component of log sales ($\eta_{k,J(k,t)}$) or transitory shocks to store performance (ϵ_{kt}). We would get biased and inconsistent estimates of the fixed effects under these forms of endogenous mobility.

We test for endogenous mobility. We follow Card et al. (2013) and Adhvaryu et al. (2020) and compute an event study to test whether moves are systematically driven by productivity shocks or by sorting on the match-specific component of log sales. We compute the average store performance relative to months in which stores experience changes in management, classifying stores that managers move away from and that they move to by quartiles of the average sales. Figure B.1 plots the raw sales of the stores that managers move to and from on the y-axis, one and two months before the move from the origin store, and one and two months after the move to the new store. We limit the analysis to moves away from either the top quartile (quartile 4) or the bottom quartile (quartile 1) in terms of average store sales for readability.

If match-specific components ($\eta_{k,J(k,t)}$) are not important in driving moves, on average, high-quality managers should have the same effect (on log sales) regardless of the store. That is, we should expect to find that, when a manager moves to a more productive store, he

Figure B.1: Event Study around Moves

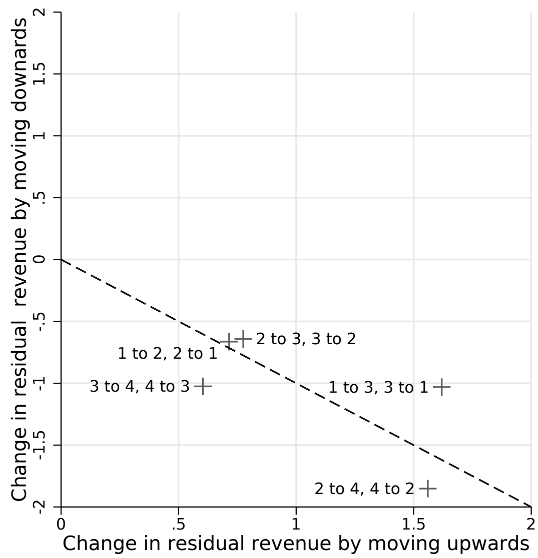


Note: We rank movers in terms of (i) quartiles of the average log revenue of the store they moved away from and (ii) quartiles of the average log revenue of the store they moved to. The average log revenue is computed over the entire sample period, and quartiles are calculated by store. We plot the average residual log revenue of the mover on the y-axis, computed five to nine quarters (Period $= -2$) and two to four quarters (Period $= -1$) before the move from the origin store, and two to four quarters (Period $= 1$) and five to nine quarters (Period $= 2$) after the move to the new store on the x-axis. The graph only considers moves away from stores in the top quartile (i.e., stores in quartile 4) or stores in the bottom quartile (i.e., stores in quartile 1). To calculate manager-level residual log revenue, we run an OLS regression of log revenue quarterly of the manager on connected set fixed effects, as well as quarter fixed effects. We use this regression to calculate the residual revenue of each manager. Standard errors are clustered at the store level in this regression.

or she becomes more productive; when a manager mores to a less productive store, he or she becomes less productive. The magnitude of these changes in productivity should be comparable. Consistent with this, Figure B.1 does not show evidence of match effects as the changes in log sales are symmetric——managers who move to less productive stores tend to lose performance and those who move to more productive stores tend to gain performance. We also perform a full symmetry test across all potential combinations of origin and destination stores, reported in Figure B.2. The figure shows that moving to a less productive store results in a loss in sales and moving to a more productive store results in a gain in sales. Moreover, the losses and gains from moves down and up, respectively, are symmetric.

To validate the absence of match-driven sorting, we estimate a more flexible saturated model with manager-by-store fixed effects and compute the adjusted R^2. If a match-specific component is present, a saturated model should increase the fit compared to the log-additive-separable model presented in equation (1). Table B.1 shows that the adjusted R^2 improves marginally from 0.988 to 0.990, suggesting that match-specific components play a relatively

Figure B.2: Symmetry Test for Endogenous Mobility



Notes: We rank movers in terms of (i) quartiles of the average log revenue of the store they moved away from and (ii) quartiles of the average log revenue of the store they moved to. We compute the average log revenue over the entire sample period, and quartiles are computed by store. This figure shows the average change in residual log revenue for movers (managers) from stores in quartile X to quartile Y, against the change in residual log revenue for movers in the opposite direction (e.g., "2 to 3, 3 to 2" indicates the average change for movers from stores in quartile 2 to quartile 3, plotted against the change for movers from stores in quartile 3 to quartile 2). The changes are calculated for average residual log revenue in the four quarters before the move and the four quarters after the move. To calculate manager-level residual log revenue, we run an OLS regression of log revenue quarterly of the manager on connected set fixed effects, as well as quarter fixed effects. Standard errors are clustered at the store level in this regression. The dashed line corresponds to the 45-degree line.

minor role in explaining variation in sales, such that sorting on such components is limited.

Finally, to test the log-additive separability assumption of our model, Figure B.3 plots the average residuals from the estimated AKM (equation 1) for each cell defined by quartiles of estimated store and manager fixed effects. The average residuals are small for all groups, suggesting that match effects are not quantitatively relevant in our context, providing support to the additive log-separability specification of equation (1).

Second, manager moves may coincide with transitory shocks (ϵ_{it}) (i.e., managers who experience a positive transitory shock move to more productive stores). Figure B.1 shows that there are no systematic trends before the move takes place and that managers do not sort into stores based on the drift component.

Taken together, the analysis presented in this subsection supports the aforementioned identification assumptions. That is, mobility does not seem to be driven by match-specific

Table B.1: Fit of Saturated Model

	(1)	(2)	(3)	(4)
Observations	6,053	6,053	6,053	6,053
R-squared	0.856	0.958	0.990	0.992
Adjusted R-squared	0.856	0.953	0.988	0.990
Time fixed effect	Yes	Yes	Yes	Yes
Manager fixed effect	No	Yes	Yes	No
Store fixed effect	No	No	Yes	No
Manager-by-store fixed effect	No	No	No	Yes

Note: This table reports the estimates of equation (1) following the two-way fixed effects estimation procedure in Abowd et al. (1999), using the natural logarithm of sales (y) as the outcome in an OLS regression. The unit of observation encompasses managers, stores, and quarterly periods.

Table B.2: Estimates of Sorting Pattern

	Baseline model	Bias correction Andrews et al. (2008)	Leave-out estimator Kline et al. (2020)
	(1)	(2)	(3)
$Var(y)$	1.7645	1.7645	2.1781
$Var(\theta)$	0.0197	0.0143	0.0544
$Var(\psi)$	2.0285	2.0236	2.0655
$Var(\psi)/Var(\psi+\theta)$	0.9532	0.9523	0.9685
'$Corr(\psi, \theta)$	0.1997	0.2560	0.0192

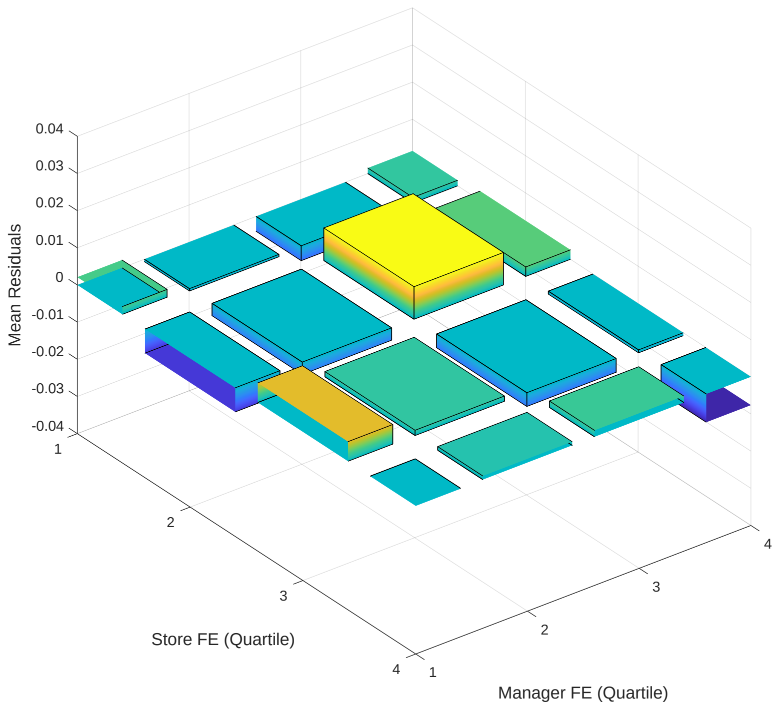
Note: Column (1) displays the OLS estimates resulting from the two-way fixed effects estimation procedure as outlined in Abowd et al. (1999). The log of sales is the outcome variable (y). The parameter θ is the manager fixed effect, while ψ is the store fixed effect. In column 2 we implement the Andrews et al. bias correction procedure to deal with limited mobility bias. In column 3, we allow for heteroskedasticity and implement the leave-out estimator proposed by Kline et al. (2020). These statistics are estimated only for the first connected set, which is the largest one (74% of the sample). In line with limited mobility bias not being substantial in our setting, we show that our key findings are robust to all these types of corrections.

components of log sales or by other unobserved time-varying worker components.

Table B.2 reports the results of a variance decomposition exercise that demonstrates how manager and store fixed effects contribute to the overall variance in log store sales.[19] We demonstrate the robustness of our estimated fixed effects by comparing the estimates to those from two other estimators. Andrews et al. (2008) take a bias-correction approach to accounting for limited mobility bias. The estimates are comparable to ours, owning to the rich movement in managers we observe in our data. Kline et al. (2020) take an approach based on a leave-out estimator that is consistent under looser restrictions on the distribution of error terms. The magnitudes are generally comparable to our preferred specification.

[19] These variances are computed across all store-quarter observations. Manager and store fixed effects are weighted by the periods observed. This contrasts with the discussion in Section 2.2.3, where we study the variance of the unweighted fixed effects.

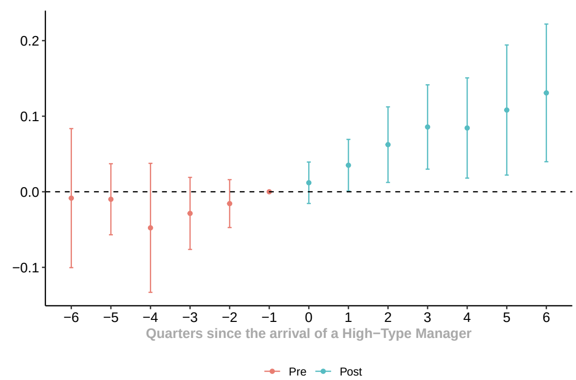
Figure B.3: Mean Residuals by Quartiles of Store and Manager Fixed Effects



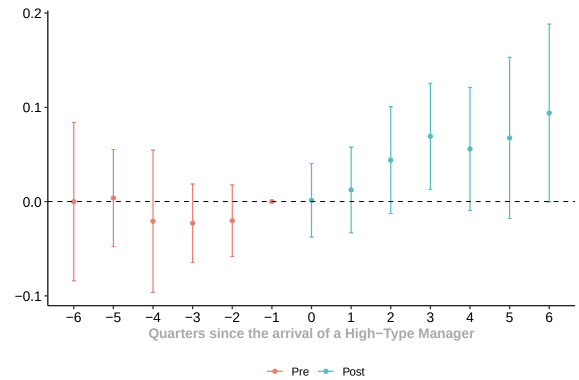
This figure reports the estimates of equation (1) following the two-way fixed effects estimation procedure in Abowd et al. (1999), using the natural logarithm of sales (y) as the outcome in an OLS regression. The figure reports mean residuals by the quartiles of the estimated manager and store fixed effects. The unit of observation encompasses managers, stores, and quarterly periods. The data span from Q1 2017 to Q2 2020. Our sample includes 616 managers and 246 stores.

C Appendix: Additional Event Study Plots

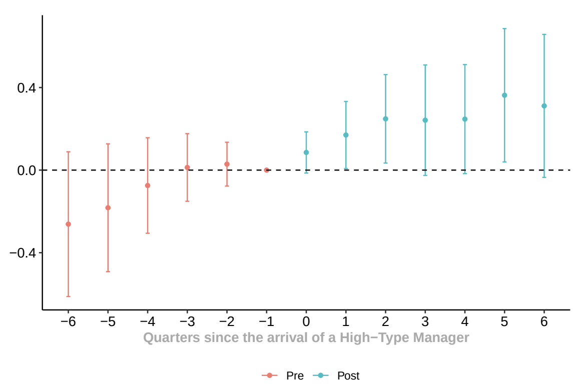
Figure C.1: Event Study of the Arrival of a High-Quality Manager (Alternative Estimator)



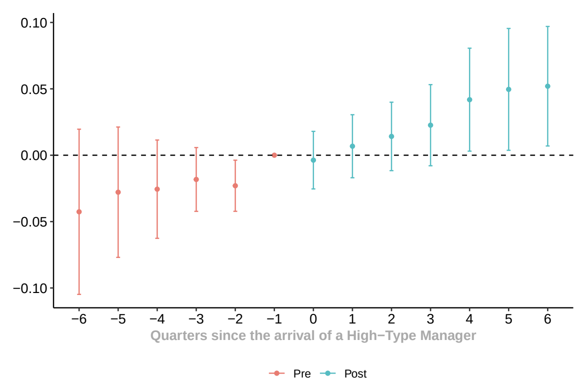
(a) Log store revenue based on all product categories



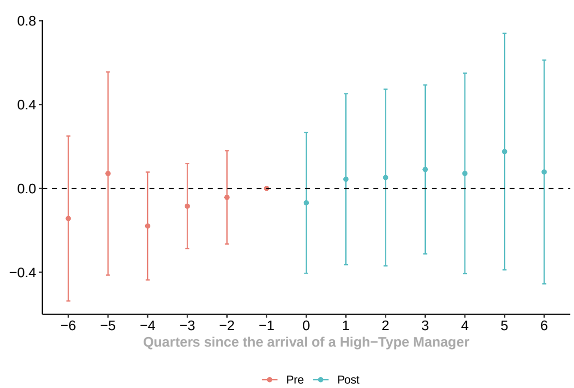
(b) Log store revenue based on focal product categories



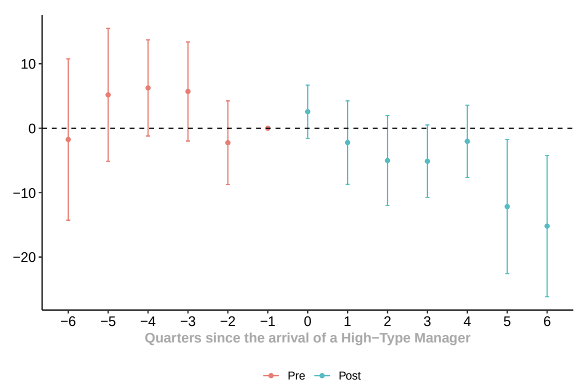
(c) Log store revenue of new products



(d) Log time on market of new products in store



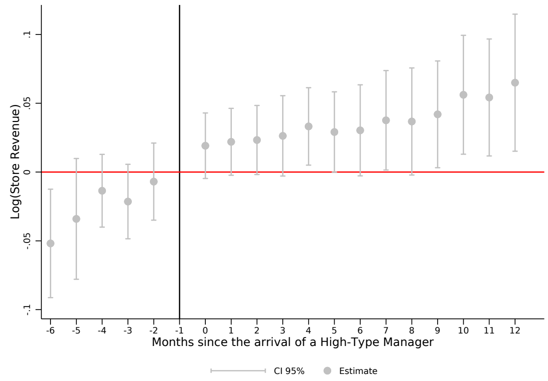
(e) Number of price updates for new products



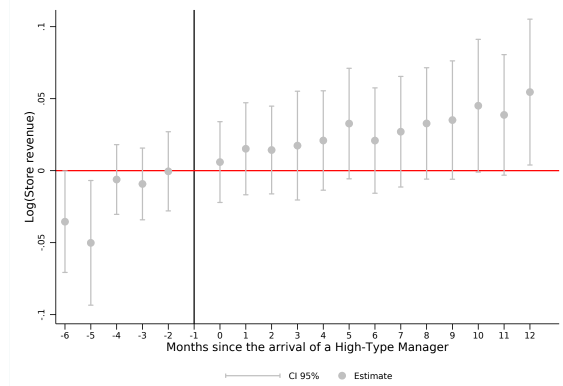
(f) Inventory age of new products in store

Note: This figure presents the estimated impact of a high-quality manager's arrival on six outcomes: (a) the overall store revenue, (b) the store revenue in focal categories, (c) the store-level revenue of new products, (d) the time new products spend on the market in a store, (e) the number of price updates for new products, and (f) the inventory age of new products. The estimating equation for the event study is presented in (4) using the Callaway–Sant'Anna estimator, and 95 percent confidence intervals based on standard errors clustered at the store level are presented.

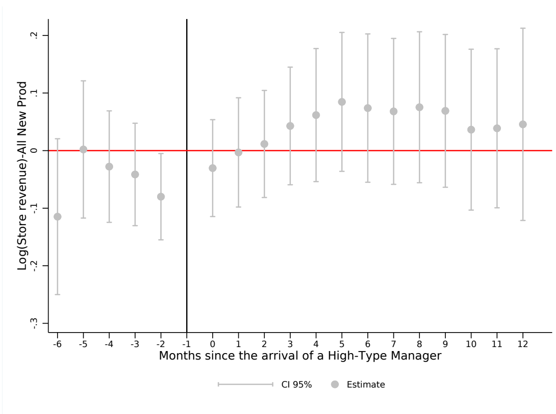
Figure C.2: Event Study of the Arrival of a High-Quality Manager (Monthly)



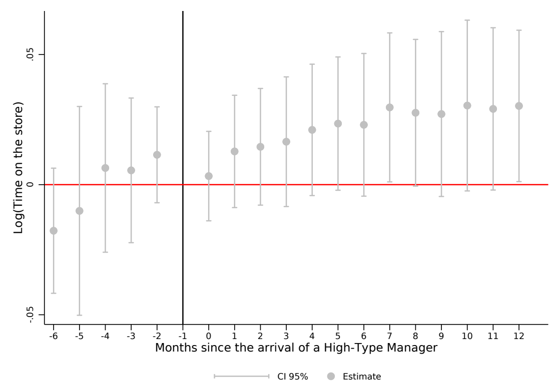
(a) Log store revenue based on all product categories



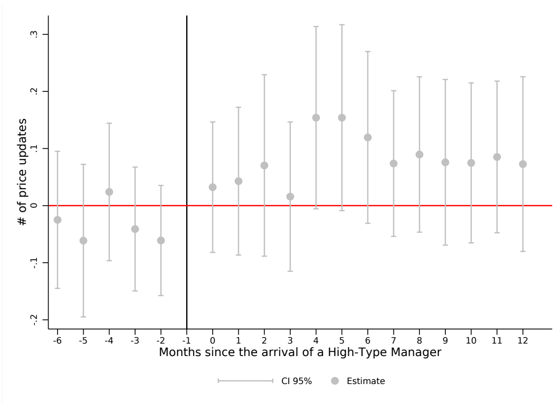
(b) Log store revenue based on focal product categories



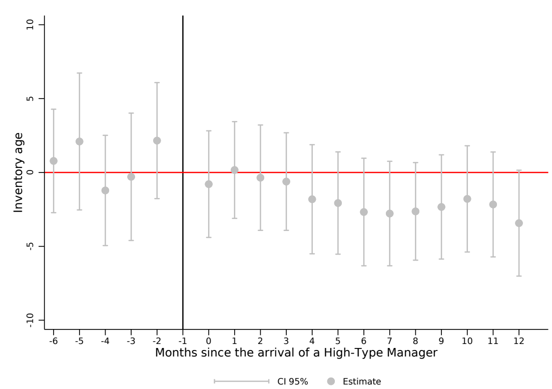
(c) Log store revenue of new products



(d) Log time on market of new products in store



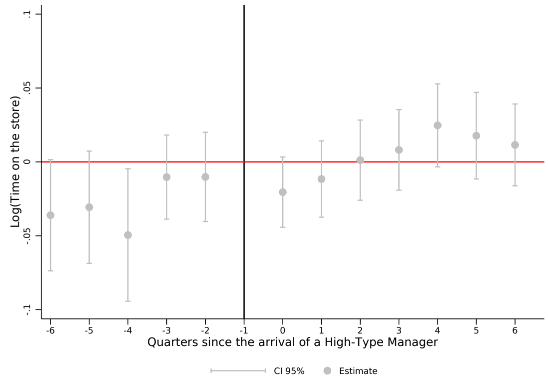
(e) Number of price updates for new products



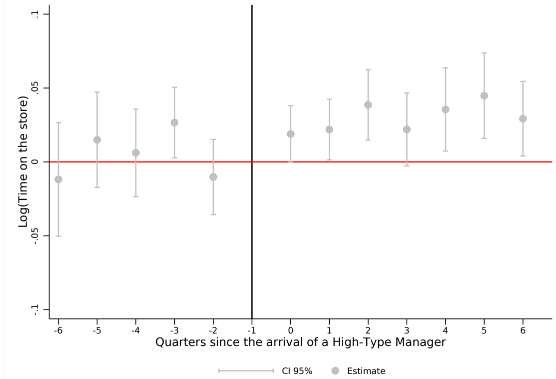
(f) Inventory age of new products in store

Note: This figure presents the estimated impact of a high-quality manager's arrival on six outcomes: (a) the overall store revenue, (b) the store revenue in focal categories, (c) the store-level revenue of new products, (d) the time new products spend on the market in a store, (e) the number of price updates for new products, and (f) the inventory age of new products. We use monthly instead of quarterly data. The estimating equation for the event study is presented in (4), and 95 percent confidence intervals based on standard errors clustered at the store level are presented.

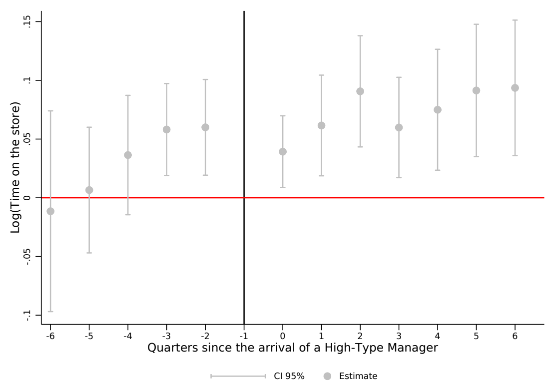
Figure C.3: Time on Market of New Products in Store, by Product Type



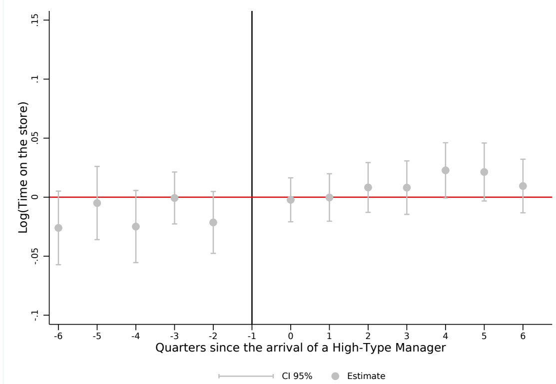
(a) Big suppliers



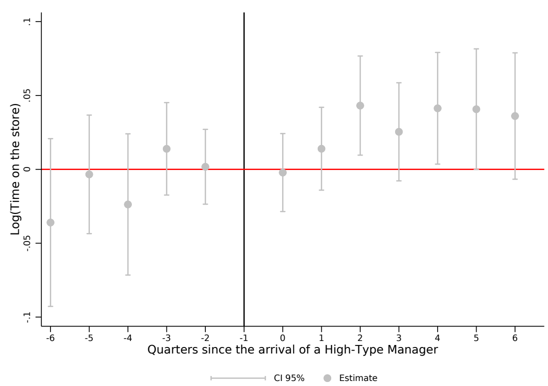
(b) Small suppliers



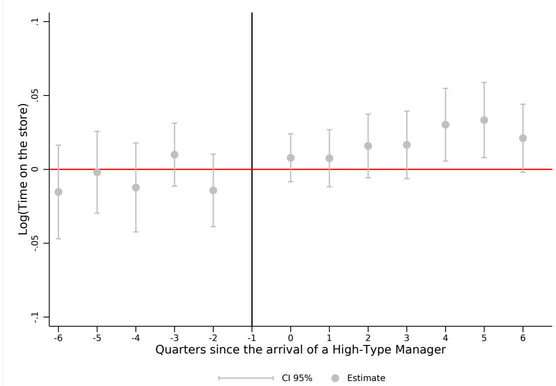
(c) Freezer space required



(d) No freezer space required



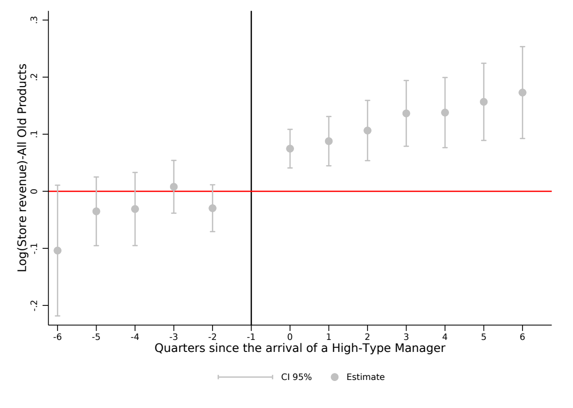
(e) Innovative products



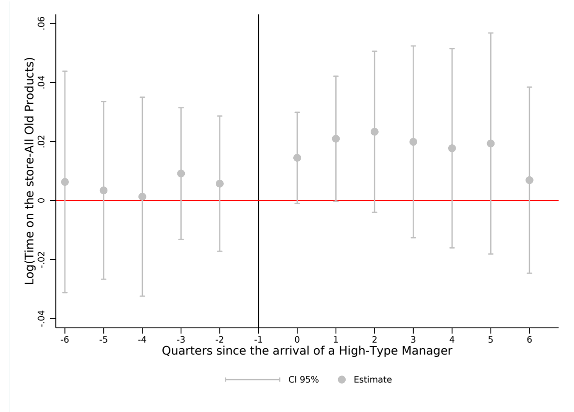
(f) Non-innovative products

Note: This figure presents the effect of a high-quality manager's arrival on the logarithm of the average time that new products are available in the store for focal categories: (a) products from big suppliers, (b) products from small suppliers, (c) products requiring freezer space, (d) products not requiring freezer space, (e) innovative products, and (f) non-innovative products. The estimating equation for the event study is presented in (4), and 95 percent confidence intervals are presented based on standard errors clustered at the store level.

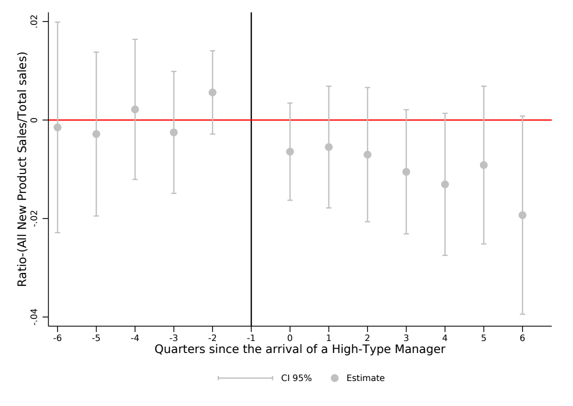
Figure C.4: Event Study of the Arrival of a High-Quality Manager (Existing Products)



(a) Log store revenue for all existing products



(b) Log time on market of all existing products in store



(c) Sales ratio of new products to total store sales

(d)

Note: This figure presents the effect of a high-quality manager's arrival on (a) log store revenues for all existing products, (b) log time on the market of all existing products in the store, and (c) the sales ratio of new products to total store sales. The estimating equation for the event study is presented in (4), and 95 percent confidence intervals based on standard errors clustered at the store level are presented.

D Appendix: Additional Cohort Regression Results

Table D.1: Cohort Regressions, Impact of Alternative Definitions of Managerial Quality

	Cumulative reach of new products					
	(1)	(2)	(3)	(4)	(5)	(6)
	Across	Across	Across	Across	Across	Across
𝟙 [Age = 2]	6.552***	7.631***	4.637***	4.409**	6.558***	6.957***
	(0.797)	(1.952)	(0.924)	(1.726)	(0.611)	(1.577)
𝟙 [Age = 3]	10.60***	13.66***	8.582***	10.47***	11.06***	12.88***
	(1.242)	(3.234)	(1.508)	(3.049)	(1.040)	(2.375)
𝟙 [Age = 4]	13.73***	18.13***	12.14***	16.68***	14.90***	18.67***
	(1.409)	(3.467)	(1.956)	(3.838)	(1.383)	(3.040)
𝟙 [Age = 5]	16.42***	20.99***	14.77***	20.37***	17.79***	22.51***
	(1.491)	(3.609)	(1.993)	(4.207)	(1.562)	(3.807)
𝟙 [Age = 6]	18.29***	22.76***	16.55***	22.17***	20.00***	25.15***
	(1.564)	(3.830)	(2.041)	(4.291)	(1.521)	(4.017)
𝟙 [Age = 7]	20.25***	25.82***	18.64***	25.59***	22.01***	27.92***
	(1.803)	(4.290)	(2.316)	(5.076)	(1.707)	(4.471)
𝟙 [Age = 8]	22.08***	26.59***	21.47***	27.08***	24.00***	29.89***
	(1.922)	(4.589)	(2.599)	(5.335)	(1.844)	(4.896)
𝟙 [Age = 9]	23.34***	28.71***	22.65***	28.63***	25.62***	31.61***
	(2.019)	(4.815)	(3.018)	(5.907)	(2.053)	(5.108)
𝟙 [Age = 10]	24.57***	29.44***	24.50***	31.37***	27.14***	33.08***
	(2.053)	(4.408)	(3.273)	(5.797)	(2.079)	(4.908)
𝟙 [Age = 11]	25.78***	30.45***	26.52***	34.22***	28.54***	34.37***
	(2.113)	(4.825)	(4.068)	(7.226)	(2.104)	(5.042)
Above managerial quality threshold	1.366	−4.958	0.152	−6.305	−0.809	−9.742
	(1.475)	(3.547)	(1.765)	(3.804)	(1.604)	(5.644)
𝟙 [Age = 2] × Above managerial quality threshold	2.443**	1.975	4.193***	5.418**	4.528***	5.419**
	(0.988)	(2.088)	(0.925)	(2.146)	(1.017)	(1.949)
𝟙 [Age = 3] × Above managerial quality threshold	3.780**	2.869	5.343***	6.019	5.722***	7.022**
	(1.616)	(3.330)	(1.549)	(4.004)	(1.297)	(2.941)
𝟙 [Age = 4] × Above managerial quality threshold	4.563**	3.859	5.417**	4.837	5.189***	5.322
	(1.852)	(3.693)	(1.902)	(4.976)	(1.615)	(4.223)
𝟙 [Age = 5] × Above managerial quality threshold	4.601**	4.639	5.512***	4.577	4.705**	4.164
	(1.825)	(3.564)	(1.846)	(5.141)	(1.931)	(4.977)
𝟙 [Age = 6] × Above managerial quality threshold	4.784**	5.436	5.729***	5.209	4.100*	3.473
	(1.791)	(3.173)	(1.842)	(5.280)	(2.167)	(5.238)
𝟙 [Age = 7] × Above managerial quality threshold	4.755**	5.200	5.504**	4.569	3.777	3.735
	(2.087)	(3.400)	(2.244)	(6.148)	(2.224)	(4.881)
𝟙 [Age = 8] × Above managerial quality threshold	4.994*	7.781**	4.469	5.843	3.737	5.128
	(2.552)	(3.543)	(2.869)	(6.164)	(2.292)	(4.214)
𝟙 [Age = 9] × Above managerial quality threshold	5.784*	7.928*	5.095	6.537	4.027	6.232
	(2.779)	(4.362)	(3.406)	(6.752)	(2.371)	(4.099)
𝟙 [Age = 10] × Above managerial quality threshold	6.479**	8.634**	4.833	4.793	4.450	5.587
	(2.956)	(4.010)	(3.701)	(5.959)	(2.578)	(3.893)
𝟙 [Age = 11] × Above managerial quality threshold	7.346**	10.46**	4.481	4.149	5.349*	7.703*
	(3.291)	(3.956)	(4.762)	(8.070)	(2.679)	(4.231)
Constant	−2.776*	−3.458	−1.800	−1.540	−1.464	−3.122
	(1.322)	(2.966)	(1.836)	(3.231)	(1.407)	(3.375)
Observations	14,619	14,619	14,619	14,619	14,619	14,619
R-squared	0.220	0.617	0.215	0.616	0.215	0.618
Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Category × time fixed effects	Yes	No	Yes	No	Yes	No
Firm × category × time fixed effects	No	Yes	No	Yes	No	Yes
Sample	Balanced	Balanced	Balanced	Balanced	Balanced	Balanced

Note: Column (1) replicates column (2) of Table 6. The remaining columns present variants of this model, altering the definition of high managerial quality. The managerial quality threshold was determined by calculating the average number of high-quality managers during the first three months post-launch for each cohort-category, then splitting cohorts based on thresholds: median for columns (1) and (2), 25th percentile for column (3) and (4), and 75th percentile for column (5) and (6). The sample includes new products that survived beyond the median (11 months). Standard errors are clustered at the product category level.

Table D.2: Cohort Regressions, Impact of Geographic/Demand Gravity

	Cumulative number of unique stores reached						
		Geographic gravity			Demand gravity		
Variables	(1)	(2) Within	(3) Within	(4) Across	(5) Within	(6) Within	(7) Across
𝟙 [Age = 2]	8.188***	7.016***	6.333***	6.966***	8.153***	7.355***	7.387***
	(0.687)	(0.628)	(1.423)	(0.881)	(0.911)	(1.796)	(0.853)
𝟙 [Age = 3]	13.10***	10.98***	10.60***	11.49***	12.84***	12.43***	11.58***
	(1.238)	(1.101)	(1.872)	(1.559)	(1.405)	(2.619)	(1.332)
𝟙 [Age = 4]	16.72***	14.81***	16.18***	15.15***	16.72***	17.59***	14.88***
	(1.581)	(1.388)	(2.427)	(2.023)	(1.896)	(3.417)	(1.641)
𝟙 [Age = 5]	19.41***	17.87***	19.91***	17.60***	19.66***	20.67***	17.43***
	(1.764)	(1.628)	(3.366)	(2.243)	(2.259)	(4.136)	(1.809)
𝟙 [Age = 6]	21.37***	20.18***	23.49***	19.27***	21.94***	22.80***	19.00***
	(1.841)	(1.603)	(3.532)	(2.308)	(2.429)	(4.343)	(1.879)
𝟙 [Age = 7]	23.27***	21.89***	26.30***	21.09***	23.90***	25.45***	20.83***
	(2.049)	(1.792)	(3.669)	(2.439)	(2.671)	(4.698)	(2.049)
𝟙 [Age = 8]	25.20***	23.98***	28.82***	23.33***	25.91***	27.77***	22.91***
	(2.159)	(2.027)	(4.063)	(2.603)	(2.856)	(5.017)	(2.214)
𝟙 [Age = 9]	26.87***	25.64***	30.94***	24.96***	27.55***	29.71***	24.47***
	(2.281)	(2.043)	(4.212)	(2.746)	(3.023)	(5.505)	(2.406)
𝟙 [Age = 10]	28.50***	27.36***	31.90***	26.59***	29.13***	30.63***	26.13***
	(2.337)	(2.101)	(3.892)	(2.940)	(3.177)	(5.357)	(2.557)
𝟙 [Age = 11]	30.21***	28.82***	33.12***	28.48***	30.66***	32.76***	28.03***
	(2.443)	(2.139)	(3.940)	(3.100)	(3.331)	(5.966)	(2.763)
Above-median number of stores with gravity = 1		0.286	−7.605	−0.103	2.755	−11.17	0.514
		(2.012)	(5.315)	(0.555)	(3.703)	(10.08)	(0.934)
𝟙 [Age = 2] × Above-median number of stores with gravity		2.475**	5.232**	2.479	0.473	3.987*	2.339
		(0.840)	(2.100)	(1.450)	(1.318)	(2.224)	(1.640)
𝟙 [Age = 3] × Above-median number of stores with gravity		4.603**	9.885**	3.273	1.599	8.110**	4.449*
		(1.625)	(3.546)	(2.342)	(1.842)	(3.410)	(2.516)
𝟙 [Age = 4] × Above-median number of stores with gravity		4.432**	9.066*	3.163	1.239	7.742	5.416*
		(2.063)	(4.437)	(2.879)	(2.377)	(4.516)	(2.920)
𝟙 [Age = 5] × Above-median number of stores with gravity		3.972	8.636	3.615	0.950	8.612	5.901
		(2.332)	(4.945)	(3.295)	(2.903)	(5.588)	(3.452)
𝟙 [Age = 6] × Above-median number of stores with gravity		3.513	6.000	4.165	0.488	9.072	6.940*
		(2.438)	(5.102)	(3.612)	(3.502)	(6.939)	(3.800)
𝟙 [Age = 7] × Above-median number of stores with gravity		4.181	5.806	4.312	0.921	9.755	7.152
		(2.699)	(5.265)	(3.815)	(3.890)	(8.257)	(4.243)
𝟙 [Age = 8] × Above-median number of stores with gravity		4.189	5.828	3.648	1.489	10.52	6.698
		(3.016)	(5.908)	(4.045)	(4.220)	(9.328)	(4.488)
𝟙 [Age = 9] × Above-median number of stores with gravity		4.626	5.949	3.689	2.519	11.32	7.039
		(2.960)	(6.124)	(4.192)	(4.637)	(10.28)	(4.677)
𝟙 [Age = 10] × Above-median number of stores with gravity		4.785	6.682	3.642	3.578	12.71	6.937
		(3.179)	(6.102)	(4.345)	(4.844)	(11.23)	(4.764)
𝟙 [Age = 11] × Above-median number of stores with gravity		5.668	8.942	3.271	5.289	13.41	6.423
		(3.420)	(6.369)	(4.322)	(5.002)	(12.09)	(4.645)
Constant	−1.585	−2.392	−2.975	−1.461	−3.378	−2.762	−1.628
	(1.623)	(1.504)	(2.272)	(1.602)	(2.616)	(5.104)	(1.618)
Observations	14,619	14,619	14,619	14,619	14,619	14,619	14,619
R-squared	0.212	0.215	0.617	0.215	0.214	0.617	0.222
Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Category × time fixed effects	Yes	Yes	No	Yes	Yes	No	Yes
Firm × category × time fixed effects	No	No	Yes	No	No	Yes	No
Sample	Balanced	Balanced	Balanced	Balanced	Balanced	Balanced	Balanced

Note: Column (1) replicates column (1) of Table 6. **Geographic gravity**: For each product, we identify the states in which the product is launched and calculate the fraction of the retailer's 229 stores located in those states. Products whose fraction exceeds the median in their category are classified as having high geographic gravity. Columns (2), (3), and (4) show the effect of high geographic gravity on product reach, corresponding to the models in columns (2), (3), and (4) in Table 6. **Demand gravity**: For each product, we identify the local GDP quartile(s) of the stores in which it is launched. We then calculate the fraction of the retailer's 229 stores that fall in the same quartile(s). Products whose fraction exceeds the median in their category are classified as having high demand gravity. Columns (5), (6), and (7) show the effect of high demand gravity on product reach. See Table 6 for detailed descriptions of each model.

Table D.3: Cohort Regressions, Impact of Managerial Quality

	Cumulative number of unique stores reached								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Across	Across	Across	Across	Across	Across	Across	Across	Across
$\mathbb{1}$ [Age = 2]	6.552***	8.113***	5.639***	5.688***	6.560***	6.647***	6.188***	5.629***	6.892***
	(0.797)	(2.136)	(0.929)	(0.645)	(0.965)	(0.508)	(1.180)	(1.310)	(0.980)
$\mathbb{1}$ [Age = 3]	10.60***	13.41***	9.226***	8.435***	10.85***	10.21***	10.49***	9.610***	11.12***
	(1.242)	(3.418)	(1.473)	(1.298)	(1.415)	(0.948)	(1.779)	(2.140)	(1.585)
$\mathbb{1}$ [Age = 4]	13.73***	19.35***	10.89***	9.593***	14.24***	12.55***	13.73***	13.50***	14.24***
	(1.409)	(3.939)	(1.770)	(1.594)	(1.547)	(1.869)	(1.937)	(2.483)	(1.920)
$\mathbb{1}$ [Age = 5]	16.42***	22.11***	13.07***	11.65**	16.99***	15.21**	16.29***	15.93***	17.15***
	(1.491)	(4.240)	(1.982)	(3.522)	(1.494)	(2.751)	(1.895)	(2.917)	(1.944)
$\mathbb{1}$ [Age = 6]	18.29***	24.88***	14.57***	13.89**	18.81***	16.87***	18.34***	18.07***	19.04***
	(1.564)	(4.472)	(2.119)	(3.513)	(1.568)	(2.713)	(2.026)	(2.827)	(2.151)
$\mathbb{1}$ [Age = 7]	20.25***	27.74***	16.47***	15.97*	20.63***	19.33**	19.93***	20.39***	20.83***
	(1.803)	(4.624)	(2.544)	(5.376)	(1.717)	(3.512)	(2.235)	(3.059)	(2.340)
$\mathbb{1}$ [Age = 8]	22.08***	29.44***	18.44***	16.92*	22.74***	21.44**	21.60***	22.44***	22.25***
	(1.922)	(4.600)	(2.978)	(5.885)	(1.803)	(4.281)	(2.342)	(3.539)	(2.315)
$\mathbb{1}$ [Age = 9]	23.34***	31.13***	19.57***	18.61*	23.91***	23.14**	22.50***	23.72***	23.43***
	(2.019)	(4.371)	(3.170)	(6.843)	(1.893)	(4.717)	(2.314)	(3.813)	(2.310)
$\mathbb{1}$ [Age = 10]	24.57***	31.23***	20.85***	19.59*	25.23***	24.55**	23.45***	25.93***	24.17***
	(2.053)	(4.181)	(3.210)	(7.090)	(1.918)	(4.886)	(2.328)	(4.014)	(2.154)
$\mathbb{1}$ [Age = 11]	25.78***	32.07***	22.50***	20.57*	26.39***	26.27**	24.58***	28.10***	25.07***
	(2.113)	(4.251)	(3.418)	(6.768)	(2.057)	(5.197)	(2.420)	(4.315)	(2.225)
Above-median number of high-quality managers	1.366	−4.770	1.507	0.967	−0.493	5.672	−1.237	2.810	0.0893
	(1.475)	(3.324)	(2.052)	(1.942)	(1.674)	(3.471)	(1.595)	(2.064)	(1.865)
$\mathbb{1}$ [Age = 2] × Above-median	2.443**	2.841	1.957*	1.317	2.964**	0.936	3.210*	0.657	3.187**
	(0.988)	(2.102)	(0.957)	(1.198)	(1.217)	(0.539)	(1.500)	(1.558)	(1.315)
$\mathbb{1}$ [Age = 3] × Above-median	3.780**	4.590	2.294	1.750	4.670**	0.327	5.175**	−0.0133	5.197**
	(1.616)	(2.831)	(1.596)	(1.990)	(1.992)	(0.493)	(2.339)	(2.400)	(2.043)
$\mathbb{1}$ [Age = 4] × Above-median	4.563**	3.841	3.659*	4.093**	5.332*	1.323	6.046**	−0.779	6.278**
	(1.852)	(3.173)	(2.035)	(1.103)	(2.440)	(1.458)	(2.695)	(2.607)	(2.144)
$\mathbb{1}$ [Age = 5] × Above-median	4.601**	4.742	3.755	4.767	5.276**	1.474	6.280**	−0.725	6.179***
	(1.825)	(3.016)	(2.296)	(2.722)	(2.359)	(2.496)	(2.527)	(3.082)	(1.765)
$\mathbb{1}$ [Age = 6] × Above-median	4.784**	5.352	3.745	3.229	5.909**	1.375	6.377**	−0.809	6.292***
	(1.791)	(3.278)	(2.295)	(2.193)	(2.363)	(1.658)	(2.665)	(2.799)	(2.014)
$\mathbb{1}$ [Age = 7] × Above-median	4.755**	5.707*	3.531	2.301	6.222**	0.150	6.931**	−1.130	6.441**
	(2.087)	(3.065)	(2.840)	(4.050)	(2.595)	(2.523)	(2.971)	(2.912)	(2.278)
$\mathbb{1}$ [Age = 8] × Above-median	4.994*	6.344*	3.326	2.643	6.214*	−0.523	7.517*	−1.051	7.346**
	(2.552)	(3.175)	(3.213)	(3.635)	(3.340)	(2.459)	(3.706)	(3.599)	(2.755)
$\mathbb{1}$ [Age = 9] × Above-median	5.784*	7.650**	3.971	2.527	7.275*	−0.855	8.960**	0.323	8.036**
	(2.779)	(2.857)	(3.523)	(4.012)	(3.617)	(2.435)	(3.776)	(4.034)	(2.895)
$\mathbb{1}$ [Age = 10] × Above-median	6.479**	9.360***	4.414	3.166	7.774*	−0.401	9.963**	0.246	9.267***
	(2.956)	(2.862)	(3.600)	(3.877)	(3.815)	(2.388)	(4.022)	(4.447)	(2.700)
$\mathbb{1}$ [Age = 11] × Above-median	7.346**	10.41***	4.827	3.041	9.009*	−0.869	11.02**	0.0535	10.40***
	(3.291)	(3.486)	(3.747)	(3.212)	(4.109)	(2.332)	(4.317)	(4.664)	(3.154)
Constant	−2.776*	1.274	−2.379	−1.625	−1.484	−4.882	−0.811	−4.767**	−1.343
	(1.322)	(2.446)	(1.980)	(4.013)	(1.277)	(4.287)	(1.817)	(2.013)	(1.422)
Observations	14,619	4,873	9,746	3,212	11,407	4,774	9,845	4,741	9,878
R-squared	0.220	0.333	0.195	0.303	0.224	0.235	0.233	0.288	0.245
Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Category × time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm × category × time fixed effects	No	No	No	No	No	No	No	No	No
Sample	Balanced	Balanced	Balanced	Balanced	Balanced	Balanced	Balanced	Balanced	Balanced

Note: Column (1) replicates column (2) of Table 6. The remaining columns present variants of this model. Column (2) restricts this sample to products from large suppliers, while column (3) focuses on products from small suppliers. Column (4) includes only products needing freezer space, whereas column (5) restricts the sample to products without freezer space requirements. Column (6) includes only perishable products, while Column (7) focuses on non-perishable products. Columns (8) and (9) analyze innovative and non-innovative products, respectively. Standard errors are clustered at the product category level.

Table D.4: Cohort Regressions, Impact of Managerial Quality by Category

	Cumulative number of stores reached after launch																
	(1) Across	(2) Across	(3) Across	(4) Across	(5) Across	(6) Across	(7) Across	(8) Across	(9) Across	(10) Across	(11) Across	(12) Across	(13) Across	(14) Across	(15) Across	(16) Across	(17) Across
𝟙 [Age = 2]	6.552***	11.33**	7.450***	9.951***	20.28***	−10.27**	16.31*	4.470	7.143	3.511	3.787	9.835***	−2.139	4.735*	14.41*	−6.844***	5.979
	(0.797)	(5.183)	(2.013)	(3.354)	(4.272)	(4.904)	(9.630)	(3.107)	(6.202)	(6.672)	(2.913)	(3.323)	(7.158)	(2.532)	(7.350)	(2.570)	(6.502)
𝟙 [Age = 3]	10.60***	22.21**	11.39***	15.69***	36.26***	−24.81***	30.86***	8.138**	11.61	8.681	4.698*	15.43***	−6.989	8.217***	27.83***	−11.82***	9.172
	(1.242)	(9.025)	(2.156)	(5.073)	(5.013)	(7.486)	(9.206)	(3.244)	(7.494)	(6.189)	(2.677)	(4.227)	(7.145)	(3.063)	(8.428)	(3.854)	(6.014)
𝟙 [Age = 4]	13.73***	36.83***	14.95***	20.33***	48.67***	−40.68***	27.47***	13.61***	14.54*	11.91*	5.077*	19.37***	−11.05	10.83***	39.52***	−19.41***	8.581
	(1.409)	(12.48)	(2.273)	(6.900)	(6.663)	(10.70)	(9.668)	(3.220)	(7.541)	(6.894)	(2.862)	(4.758)	(8.536)	(4.005)	(11.05)	(5.663)	(6.005)
𝟙 [Age = 5]	16.42***	50.82***	17.62***	24.94***	59.83***	−57.89***	25.60**	17.27***	14.77	10.24	4.693	21.28***	−7.737	13.96***	49.71***	−24.21***	8.773
	(1.491)	(16.39)	(2.332)	(8.702)	(7.932)	(13.74)	(10.53)	(3.809)	(10.39)	(7.945)	(3.206)	(4.940)	(10.59)	(4.824)	(11.37)	(7.314)	(6.230)
𝟙 [Age = 6]	18.29***	60.15***	19.28***	29.76***	71.95***	−72.03***	29.45**	20.52***	17.67*	8.172	5.857*	22.42***	−13.82	16.04***	60.65***	−29.27***	7.469
	(1.564)	(20.10)	(2.350)	(10.43)	(9.331)	(17.17)	(12.37)	(4.217)	(9.891)	(8.796)	(3.395)	(5.273)	(12.60)	(5.872)	(12.60)	(8.878)	(6.472)
𝟙 [Age = 7]	20.25***	70.36***	21.18***	33.41***	81.50***	−87.53***	33.86**	22.31***	19.89*	8.126	4.597	23.25***	−11.90	18.02***	70.46***	−33.65***	5.391
	(1.803)	(23.73)	(2.524)	(12.22)	(10.77)	(20.45)	(14.36)	(4.415)	(10.74)	(9.770)	(3.934)	(5.444)	(13.12)	(6.873)	(14.08)	(10.63)	(6.796)
𝟙 [Age = 8]	22.08***	81.98***	24.99***	37.94***	91.00***	−103.3***	34.28**	27.17***	27.51**	7.115	3.812	23.62***	−16.61	20.07**	78.95***	−38.63***	4.810
	(1.922)	(27.47)	(2.900)	(14.12)	(12.06)	(23.81)	(15.87)	(5.269)	(10.52)	(10.86)	(4.118)	(5.718)	(13.77)	(7.928)	(16.58)	(12.38)	(7.505)
𝟙 [Age = 9]	23.34***	91.41***	26.85***	43.19***	101.2***	−119.9***	36.89**	28.39***	38.87**	6.663	3.779	23.39***	−21.10	21.88**	91.53***	−45.67***	8.956
	(2.019)	(31.21)	(3.243)	(16.27)	(13.71)	(27.09)	(17.35)	(6.103)	(15.13)	(12.01)	(4.351)	(5.839)	(15.32)	(8.971)	(17.52)	(14.28)	(8.403)
𝟙 [Age = 10]	24.57***	101.7***	28.51***	47.45***	109.8***	−135.7***	42.59**	30.87***	44.74**	4.706	2.416	23.32***	−27.01*	23.53**	101.3***	−51.30***	10.63
	(2.053)	(34.93)	(3.398)	(18.09)	(15.18)	(30.34)	(18.78)	(6.366)	(21.40)	(13.11)	(4.731)	(6.039)	(15.76)	(10.10)	(21.42)	(16.18)	(9.283)
𝟙 [Age = 11]	25.78***	113.1***	31.16***	51.46**	120.1***	−151.2***	43.27**	34.19***	52.31***	1.231	3.929	25.08***	−34.76**	26.33**	114.1***	−58.53***	8.792
	(2.113)	(38.39)	(3.729)	(19.94)	(17.17)	(33.69)	(20.37)	(7.512)	(16.89)	(14.32)	(4.824)	(6.369)	(16.31)	(11.04)	(23.44)	(18.10)	(7.918)
Above-median number of high-quality managers = 1	1.366	−9.563	14.60***	9.389	−11.64**	−74.60***	15.66	14.36***	27.34	−104.2***	−5.040*	−39.53***	1.404	4.931**	−27.40***	−1.772	−3.342
	(1.475)	(8.593)	(3.497)	(6.956)	(4.779)	(9.714)	(14.47)	(4.159)	(29.50)	(22.32)	(3.056)	(8.233)	(7.042)	(2.334)	(8.156)	(2.558)	(5.804)
𝟙 [Age = 2] × Above-median number of high-quality managers	2.443**	15.76**	1.142	0.507	−0.647	−0.746	−10.68	0.118	11.27	5.804	4.500	−1.380	1.227	2.924	5.351	7.950**	0.604
	(0.988)	(7.343)	(3.090)	(4.539)	(5.882)	(4.204)	(11.53)	(3.627)	(12.22)	(7.114)	(3.674)	(3.949)	(8.428)	(3.695)	(10.06)	(3.445)	(7.896)
𝟙 [Age = 3] × Above-median number of high-quality managers	3.780**	34.20***	0.971	1.497	−1.935	1.449	−11.49	−2.104	12.42	4.205	7.325*	−1.179	2.210	3.218	6.541	11.94***	−2.546
	(1.616)	(9.835)	(3.164)	(4.668)	(5.691)	(3.849)	(10.50)	(3.745)	(12.39)	(6.506)	(3.764)	(5.258)	(9.103)	(3.196)	(9.312)	(3.080)	(7.091)
𝟙 [Age = 4] × Above-median number of high-quality managers	4.563**	38.98***	0.0223	3.342	−1.090	1.908	3.531	−5.611	11.15	2.873	8.170**	−1.675	1.255	4.898	5.481	17.32***	5.079
	(1.852)	(11.84)	(3.275)	(4.849)	(6.354)	(4.221)	(10.85)	(3.711)	(14.98)	(6.887)	(3.695)	(5.911)	(8.781)	(3.988)	(11.26)	(3.621)	(6.989)
𝟙 [Age = 5] × Above-median number of high-quality managers	4.601**	36.40***	0.0372	4.027	0.0985	4.290	11.37	−6.511	15.27	6.156	8.961**	0.100	−4.792	4.562	4.727	17.93***	6.992
	(1.825)	(12.52)	(3.321)	(4.693)	(6.830)	(3.678)	(10.47)	(4.327)	(16.22)	(7.316)	(3.862)	(5.948)	(10.42)	(3.686)	(11.02)	(3.350)	(7.343)
𝟙 [Age = 6] × Above-median number of high-quality managers	4.784**	38.64***	1.224	4.136	−1.347	3.342	16.45	−6.886	14.15	8.146	7.714*	1.760	−1.777	4.842	3.653	17.89***	6.890
	(1.791)	(12.62)	(3.346)	(5.305)	(6.566)	(4.390)	(11.24)	(4.712)	(17.53)	(7.081)	(3.956)	(6.304)	(12.20)	(4.137)	(9.786)	(3.360)	(7.354)
𝟙 [Age = 7] × Above-median number of high-quality managers	4.755**	40.06***	1.400	6.108	0.638	3.281	20.44*	−6.514	16.76	7.592	9.696**	3.850	−8.474	4.777	1.569	17.81***	8.808
	(2.087)	(13.47)	(3.672)	(5.433)	(7.094)	(4.477)	(12.05)	(4.987)	(19.63)	(7.162)	(3.937)	(6.426)	(11.33)	(3.806)	(9.522)	(3.929)	(7.250)
𝟙 [Age = 8] × Above-median number of high-quality managers	4.994*	39.14***	−1.077	4.491	3.282	3.849	23.37**	−10.93*	8.206	8.197	11.14***	5.131	−6.294	3.846	12.16	17.74***	7.226
	(2.552)	(14.05)	(3.829)	(5.410)	(6.574)	(4.767)	(11.56)	(5.733)	(20.70)	(7.200)	(4.130)	(6.758)	(11.13)	(3.939)	(9.118)	(3.922)	(7.432)
𝟙 [Age = 9] × Above-median number of high-quality managers	5.784*	41.34***	−1.446	2.543	3.423	4.646	26.01**	−10.15	−1.747	7.544	11.39**	7.281	−7.548	4.746	9.004	19.63***	4.821
	(2.779)	(13.85)	(4.154)	(6.099)	(7.246)	(4.569)	(12.02)	(6.752)	(23.74)	(7.441)	(4.432)	(7.037)	(12.77)	(3.918)	(10.45)	(4.576)	(8.455)
𝟙 [Age = 10] × Above-median number of high-quality managers	6.479**	42.02***	−1.103	2.799	5.040	5.067	24.78**	−10.97	−6.027	9.261	13.10***	8.575	−6.816	5.177	9.585	20.01***	4.126
	(2.956)	(13.14)	(4.421)	(5.805)	(6.828)	(4.599)	(12.11)	(6.742)	(28.83)	(7.485)	(4.585)	(7.601)	(12.93)	(4.499)	(11.54)	(4.404)	(9.445)
𝟙 [Age = 11] × Above-median number of high-quality managers	7.346**	41.37***	−1.500	3.868	7.139	4.714	28.28**	−12.09	−11.55	12.81*	11.21***	7.327	−4.342	2.979	7.249	20.56***	6.663
	(3.291)	(13.05)	(4.645)	(5.776)	(7.549)	(4.860)	(12.57)	(8.049)	(32.65)	(7.619)	(4.203)	(8.038)	(11.65)	(4.697)	(13.72)	(5.896)	(10.46)
Constant	−2.776*	34.24**	−9.026***	5.560	25.87***	−14.05	−29.17***	−10.92***	−1.352	74.48***	−7.132**	26.67***	−26.17***	−4.409	81.18***	−18.22***	−14.24**
	(1.322)	(13.91)	(1.776)	(4.367)	(5.438)	(11.70)	(10.46)	(2.607)	(12.79)	(16.53)	(2.859)	(6.447)	(6.284)	(2.883)	(20.53)	(5.263)	(6.671)
Observations	14,619	638	2,178	484	759	1,122	473	1,441	143	1,254	616	1,958	528	1,089	429	561	946
R-squared	0.220	0.339	0.315	0.384	0.451	0.338	0.694	0.358	0.884	0.383	0.501	0.246	0.394	0.301	0.328	0.372	0.537
Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Category × time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm × category × time fixed effects	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Sample	Balanced	Balanced	Balanced	Balanced	Balanced	Balanced	Balanced	Balanced	Balanced	Balanced	Balanced	Balanced	Balanced	Balanced	Balanced	Balanced	Balanced
Category	All categories	Beer	Breads & desserts	Canned products	Cereal	Cheese	Chips	Cookies	Energiz-ers	Grains	Ice cream	Liquor	Milk	Oils & vinegars	Soda	Sugars	Yogurt

Note: Column (1) replicates column (2) of Table 6. The remaining columns present variants of this model, restricting the sample to specific product categories. Standard errors for column (1) are clustered at the product category level, while robust standard errors are used in the other columns.

Table D.5: Cohort Regressions, Product Exit

	Cumulative product exit			
	(1)	(2) Within	(3) Within	(4) Across
𝟙 [Age = 2]	0.0306***	0.0259***	0.0204*	0.0343***
	(0.00495)	(0.00561)	(0.0107)	(0.00415)
𝟙 [Age = 3]	0.0548***	0.0487***	0.0372**	0.0600***
	(0.00490)	(0.00814)	(0.0147)	(0.00492)
𝟙 [Age = 4]	0.0731***	0.0677***	0.0556***	0.0810***
	(0.00573)	(0.00882)	(0.0156)	(0.00700)
𝟙 [Age = 5]	0.0928***	0.0792***	0.0555***	0.0983***
	(0.00743)	(0.00994)	(0.0163)	(0.00808)
𝟙 [Age = 6]	0.111***	0.0971***	0.0718***	0.116***
	(0.00838)	(0.0117)	(0.0173)	(0.00896)
𝟙 [Age = 7]	0.133***	0.121***	0.0876***	0.136***
	(0.00958)	(0.0136)	(0.0193)	(0.0102)
𝟙 [Age = 8]	0.154***	0.137***	0.102***	0.158***
	(0.0113)	(0.0161)	(0.0262)	(0.0123)
𝟙 [Age = 9]	0.173***	0.158***	0.116***	0.177***
	(0.0129)	(0.0169)	(0.0233)	(0.0136)
𝟙 [Age = 10]	0.197***	0.181***	0.128***	0.202***
	(0.0150)	(0.0191)	(0.0240)	(0.0159)
𝟙 [Age = 11]	0.220***	0.203***	0.131***	0.223***
	(0.0158)	(0.0214)	(0.0219)	(0.0177)
Above-median number of high-quality managers = 1		−0.0616***	−0.0690***	−0.147***
		(0.00829)	(0.0190)	(0.0166)
𝟙 [Age = 2] × Above-median number of high-quality managers		0.00689	0.0176	−0.00900
		(0.00839)	(0.0102)	(0.00686)
𝟙 [Age = 3] × Above-median number of high-quality managers		0.00836	0.0190	−0.0129
		(0.0110)	(0.0130)	(0.00835)
𝟙 [Age = 4] × Above-median number of high-quality managers		0.00677	0.0190	−0.0198*
		(0.0132)	(0.0168)	(0.00958)
𝟙 [Age = 5] × Above-median number of high-quality managers		0.0194	0.0420**	−0.0146
		(0.0147)	(0.0186)	(0.0105)
𝟙 [Age = 6] × Above-median number of high-quality managers		0.0198	0.0399*	−0.0134
		(0.0140)	(0.0191)	(0.0120)
𝟙 [Age = 7] × Above-median number of high-quality managers		0.0162	0.0323	−0.0108
		(0.0144)	(0.0226)	(0.0117)
𝟙 [Age = 8] × Above-median number of high-quality managers		0.0220	0.0377	−0.0143
		(0.0155)	(0.0289)	(0.0133)
𝟙 [Age = 9] × Above-median number of high-quality managers		0.0187	0.0360	−0.0168
		(0.0140)	(0.0236)	(0.0136)
𝟙 [Age = 10] × Above-median number of high-quality managers		0.0206	0.0426	−0.0182
		(0.0152)	(0.0284)	(0.0105)
𝟙 [Age = 11] × Above-median number of high-quality managers		0.0209	0.0574	−0.0154
		(0.0198)	(0.0342)	(0.0107)
Constant	0.0985***	0.139***	0.160***	0.163***
	(0.00838)	(0.00851)	(0.0123)	(0.0143)
Observations	45,837	45,837	45,837	45,837
R-squared	0.083	0.086	0.499	0.120
Cohort fixed effects	Yes	Yes	Yes	Yes
Category × time fixed effects	Yes	Yes	No	Yes
Firm × category × time fixed effects	No	No	Yes	No
Sample	Balanced	Balanced	Balanced	Balanced

Note: This table presents coefficients for age fixed effects and their interactions with an indicator for above-median managerial quality (number of high-quality managers). The dependent variable is cumulative product exit. "Age" refers to the number of months since the product's first observed sales, with $\mathbb{1}[\text{Age} = i]$ denoting an indicator variable set to 1 if the product is i months old. Following the method described for Table 6, products are split into those that benefitted from an above-/below-median number of high-quality managers at the time of launch. Controls include cohort variables (Deaton's normalization), category-month fixed effects, and, in column (3), firm × category × month fixed effects. The sample includes all new products except for the last cohort (those launched in December 2019). Standard errors are clustered at the product category level. The linear combination of coefficients for products with high-quality managers at the time of launch are statistically significant across product age.

E Appendix: Robustness Checks of Gravity Model

Table E.1: Model of Product Rollout with Gravity Effects and Different Specifications Predicting Expected Revenue

Variables	(1) Presence	(2) Presence	(3) Presence	(4) Presence	(5) Presence	(6) Presence	(7) Presence	(8) Presence
Entry	−0.659***	−0.693***	−0.656***	−0.689***	−0.657***	−0.692***	−0.659***	−0.694***
	(0.008)	(0.012)	(0.008)	(0.013)	(0.008)	(0.012)	(0.008)	(0.012)
Grav. State	−0.038***	−0.030***	−0.037***	−0.029***	−0.039***	−0.031***	−0.038***	−0.030***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Entry × Grav. State	0.126***	0.114***	0.124***	0.113***	0.125***	0.113***	0.126***	0.114***
	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)
Grav. GDPpc city		−0.034***		−0.033***		−0.034***		−0.035***
		(0.011)		(0.011)		(0.011)		(0.011)
Entry × Grav. GDPpc city		0.047***		0.045***		0.047***		0.047***
		(0.011)		(0.011)		(0.011)		(0.011)
Observations	4,533,661	4,533,661	4,533,661	4,533,661	4,533,661	4,533,661	4,533,661	4,533,661
R-squared	0.621	0.621	0.621	0.621	0.621	0.621	0.621	0.621
Avg. dep. var.	0.230	0.230	0.230	0.230	0.230	0.230	0.230	0.230
SD dep. var.	0.420	0.420	0.420	0.420	0.420	0.420	0.420	0.420
Lincom estimate Grav. State	0.088***	0.084***	0.087***	0.083***	0.086***	0.082***	0.088***	0.084***
Lincom SE Grav. State	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
Lincom estimate Grav. GDPpc city		0.013***		0.012***		0.013***		0.013***
Lincom SE Grav. GDPpc city		0.001		0.001		0.001		0.001

Note: See Table 8 for a description of the model. Columns (1) and (2) replicate the preferred specification of columns (3) and (6) in Table 8. Specifically, columns (1) and (2) estimate baseline predicted revenues using product, quarter, and store fixed effects. Columns (3) and (4) expand this by including store and product-quarter interaction fixed effects when predicting revenues, allowing for the potential revenue from a product to vary by quarter. Columns (5) and (6) add product-state interaction fixed effects to the baseline specification, allowing for the potential revenue from a product to vary by region. Predicted revenue can vary in the same granularity as geographical gravity effects. Columns (7) and (8) incorporate interactions of product-local GDP fixed effects in addition to the baseline specification. Predicted revenue can thus vary in the same granularity as demand.[a] Across models, the economic effect and magnitude of rollout frictions stay consistent: new products enjoy a 11.3 to 12.6 percentage point increase in the likelihood of being present in a store when they are already available in the same state. In the models that include demand-side frictions, the role magnitude of this friction is comparable across models at a 4.5 to 4.7 percentage point increase in the likelihood of the new product being present. The consistency of our findings suggest that the gravity effects reflect rollout frictions rather than proxies for unobserved demand conditions that are being loaded onto the gravity effects.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

[a]For product-quarter combinations missing fixed-effect observations in our data, we assign the minimum value observed across all quarters for each product. This approach was applied to the other interactions. For missing product-state interactions, the minimum state value is used. Likewise, for missing product-local GDP fixed-effect interactions, the minimum value across local GDP fixed effects is assigned. This method ensures a realistic approximation by providing a potential value (the minimum), which acts as a lower bound, recognizing that while the truthful value is unknown, a plausible estimate is presented for analytical purposes.

F Appendix: Additional Specifications of Gravity Model

Table F.1: Model of Product Rollout with Gravity Effects of Local Demand Conditions and Managerial Quality

VARIABLES	(1) Presence	(2) Presence	(3) Presence	(4) Presence
Revenue	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Entry	−0.556***	−0.662***	−0.663***	−0.662***
	(0.006)	(0.012)	(0.012)	(0.012)
Grav. GDPpc city		−0.067***	−0.066***	−0.066***
		(0.012)	(0.012)	(0.012)
Entry × Grav. GDPpc city		0.111***	0.111***	0.110***
		(0.012)	(0.012)	(0.012)
High-quality manager	0.004***		0.004***	0.004***
	(0.001)		(0.001)	(0.001)
Entry × high-quality manager	−0.000		0.003***	0.001
	(0.001)		(0.001)	(0.001)
Entry × Grav. GDPpc city × high-quality manager				0.002***
				(0.001)
Observations	4,533,661	4,533,661	4,533,661	4,533,661
R-squared	0.615	0.616	0.616	0.616
Avg. dep. var.	0.230	0.230	0.230	0.230
SD dep. var.	0.420	0.420	0.420	0.420
Lincom estimate high-quality manager	0.004***		0.006***	0.007***
Lincom SE high-quality manager	0		0	0
Lincom estimate Grav. GDPpc city		0.044***	0.045***	0.046***
Lincom SE Grav. GDPpc city		0.001	0.001	0.001

Note: The unit of observation is at the product-store-quarter level, encompassing all product-store-quarter combinations where a product was or could have been available for purchase. The dependent variable is an indicator equal to 1 when a product is present in the store. *Entry* is an indicator variable that equals 1 if the product was not present in the store in the previous quarter, representing stores where entry costs would be incurred upon rollout. *Grav. GDPpc city* is an indicator variable that equals ‘ if the product is already available in another store in the same quartile of local per capita GDP levels. *High-quality manager* is an indicator variable that equals 1 if a high-quality manager is present in the store. All models account for predicted revenue and include fixed effects for product, quarter, and store type. Standard errors are clustered at the product level.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table F.2: Model of Product Rollout with Gravity Effects and Managerial Quality, Heterogeneous Results

	Big vs. Small supplier		Perishable vs. Non-perishable		Freezer vs. Non-freezer		Innovative vs. Non-innovative	
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Entry	−0.682***	−0.682***	−0.649***	−0.649***	−0.667***	−0.667***	−0.664***	−0.664***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Grav. State	−0.037***	−0.037***	−0.039***	−0.039***	−0.044***	−0.044***	−0.037***	−0.037***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Entry × Grav. State	0.111***	0.113***	0.118***	0.120***	0.102***	0.103***	0.125***	0.124***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
High-quality manager	0.004***	0.004***	0.004***	0.004***	0.004***	0.003***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Entry × high-quality manager	−0.002**	−0.002**	−0.002**	−0.001	−0.004***	−0.003***	−0.002**	−0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Entry × Grav. State × high-quality manager	0.011***	0.008***	0.011***	0.008***	0.016***	0.014***	0.011***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Entry × big supplier	0.048***	0.047***						
	(0.011)	(0.012)						
Entry × Grav. State × big supplier	0.025***	0.020***						
	(0.005)	(0.005)						
Big supplier × high-quality manager		−0.001						
		(0.002)						
Entry × high-quality manager × big supplier		0.002						
		(0.002)						
Entry × Grav. State × big supplier × high-quality manager		0.009***						
		(0.001)						
Entry × perishables			−0.029**	−0.029**				
			(0.011)	(0.011)				
Entry × Grav. State × perishables			0.007**	0.003				
			(0.004)	(0.003)				
Perishables × high-quality manager				−0.001				
				(0.002)				
Entry × high-quality manager × perishables				−0.001				
				(0.002)				
Entry × Grav. State × perishables × high-quality manager				0.009***				
				(0.001)				
Entry × freezer space					−0.047***	−0.047***		
					(0.013)	(0.013)		
Entry × Grav. State × freezer space					0.001	−0.005		
					(0.004)	(0.004)		
Freezer space × high-quality manager						0.001		
						(0.002)		
Entry × high-quality manager × freezer space						−0.002		
						(0.002)		
Entry × Grav. State × freezer space × high-quality manager						0.011***		
						(0.002)		
Entry × innovative							0.020	0.019
							(0.012)	(0.012)
Entry × Grav. State × innovative							−0.015***	−0.014***
							(0.003)	(0.003)
Innovative × high-quality manager								0.000
								(0.002)
Entry × high-quality manager × innovative								0.001
								(0.002)
Entry × Grav. State × innovative × high-quality manager								−0.003**
								(0.001)
Observations	4,533,661		4,533,661		4,533,661		4,533,661	
R-squared	0.621		0.621		0.609		0.621	
Avg. dep. var.	0.230		0.230		0.230		0.230	
SD dep. var.	0.420		0.420		0.420		0.420	

Note: The unit of observation is at the product-store-quarter level, encompassing all product-store-quarter combinations where a product was or could have been available for purchase. The dependent variable is an indicator equal to 1 when a product is present in the store. *Entry* is an indicator variable that equals 1 if the product was not present in the store in the previous quarter, representing stores where entry costs would be incurred upon rollout. *Grav. State* is an indicator variable that equals 1 if the product is already available in another store in the same state. *High-quality manager* is an indicator variable that equals 1 if a high-quality manager is present in the store. "Big suppliers" are suppliers whose average revenue per quarter is above the 96th percentile for suppliers within the same category. Perishables are products in the bread, milk, yogurt, and cheese categories. Products requiring freezer space are those in the milk, yogurt, cheese, and ice cream categories. A product is considered innovative if its name includes a noun or adjective not present in the existing product's initial list of nouns and adjectives. All models account for predicted revenue and include fixed effects for product, quarter, and store type. Standard errors are clustered at the product level.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table F.3: Model of Product Rollout with Gravity Effects and Managerial Quality, Revenue-Contributing Categories

VARIABLES	(1) Presence	(2) Presence	(3) Presence	(4) Presence
Revenue	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Entry	−0.670***	−0.656***	−0.656***	−0.657***
	(0.008)	(0.008)	(0.008)	(0.008)
Grav. State	−0.038***	−0.038***	−0.038***	−0.039***
	(0.007)	(0.007)	(0.007)	(0.007)
Entry × Grav. State	0.124***	0.102***	0.096***	0.099***
	(0.008)	(0.008)	(0.008)	(0.008)
Entry × important category	0.025***	−0.001	−0.001	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Entry × Grav. State × important category		0.047***	0.047***	0.043***
		(0.002)	(0.002)	(0.002)
High-quality manager			0.004***	−0.007***
			(0.001)	(0.002)
Entry × high-quality manager			−0.002**	0.012***
			(0.001)	(0.002)
Entry × Grav. State × high-quality manager			0.011***	0.007***
			(0.001)	(0.001)
Important category × high-quality manager				0.019***
				(0.003)
Entry × high-quality manager × important category				−0.025***
				(0.003)
Entry × Grav. State × important category × high-quality manager				0.007***
				(0.001)
Observations	4,533,661	4,533,661	4,533,661	4,533,661
R-squared	0.621	0.622	0.622	0.622
Product fixed effects	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes
Type-of-store fixed effects	Yes	Yes	Yes	Yes
Lincom estimate Grav. State	0.086***	0.111***	0.116***	0.117***
Lincom SE Grav. State	0.002	0.003	0.003	0.003
Avg. dep. var.	0.230	0.230	0.230	0.230
SD dep. var.	0.420	0.420	0.420	0.420
Dataset		All categories	All categories	All categories
Lincom estimate important category		0.046***	0.046***	0.046***
Lincom SE important category		0.002	0.002	0.002
Lincom estimate high-quality manager			0.013***	0.013***
Lincom SE high-quality manager			0.001	0.001

Note: The unit of observation is at the product-store-quarter level, encompassing all product-store-quarter combinations where a product was or could have been available for purchase. The dependent variable is an indicator equal to 1 when a product is present in the store. *Entry* is an indicator variable that equals 1 if the product was not present in the store in the previous quarter, representing stores where entry costs would be incurred upon rollout. *Grav. State* is an indicator variable that equals 1 if the product is already available in another store in the same state. *High-quality manager* is an indicator variable that equals 1 if a high-quality manager is present in the store. Products are defined as *important* for a store if they belong to a product category whose average share of the store's total revenue exceeds the median sales share of that category across all stores. This variable identifies categories that contribute relatively more to a store's sales than they do to other stores across the retail chain. All models account for predicted revenue and include fixed effects for product, quarter, and store type. Standard errors are clustered at the product level.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table F.4: Model of Product Rollout with Gravity Effects and Managerial Quality for Each Category

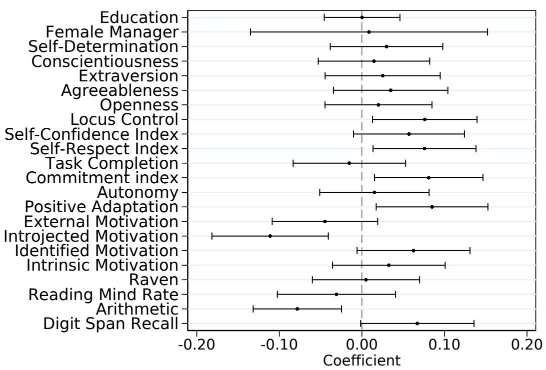
VARIABLES	(1) Presence	(2) Presence	(3) Presence	(4) Presence	(5) Presence	(6) Presence	(7) Presence	(8) Presence	(9) Presence	(10) Presence	(11) Presence	(12) Presence	(13) Presence	(14) Presence	(15) Presence	(16) Presence
Entry	−0.633***	−0.610***	−0.658***	−0.762***	−0.672***	−0.563***	−0.662***	−0.717***	−0.715***	−0.707***	−0.595***	−0.617***	−0.711***	−0.720***	−0.806***	−0.701***
	(0.035)	(0.020)	(0.031)	(0.020)	(0.020)	(0.057)	(0.021)	(0.071)	(0.018)	(0.033)	(0.017)	(0.059)	(0.041)	(0.042)	(0.031)	(0.019)
Grav. State	−0.034	0.014	−0.100***	−0.115***	0.018	−0.001	−0.141***	−0.110**	−0.017	−0.071**	0.021	−0.063	−0.084**	−0.081**	−0.033	−0.073***
	(0.028)	(0.019)	(0.036)	(0.021)	(0.020)	(0.050)	(0.020)	(0.051)	(0.014)	(0.031)	(0.016)	(0.051)	(0.040)	(0.035)	(0.028)	(0.016)
Entry × Grav. State	0.125***	0.064***	0.204***	0.211***	0.030	0.109**	0.243***	0.234***	0.074***	0.149***	0.026	0.228***	0.141***	0.265***	0.169***	0.185***
	(0.030)	(0.020)	(0.036)	(0.025)	(0.022)	(0.054)	(0.023)	(0.071)	(0.016)	(0.032)	(0.016)	(0.057)	(0.041)	(0.046)	(0.033)	(0.021)
High-quality manager	0.003	0.000	−0.008**	0.003	0.008**	0.001	−0.001	−0.002	−0.001	0.001	0.012***	−0.001	0.009***	0.005	0.005	0.001
	(0.005)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Entry × high-quality manager	−0.001	−0.000	0.009**	0.006*	−0.010***	−0.003	0.006**	0.010	−0.001	0.003	−0.014***	0.002	−0.003	−0.002	−0.004	−0.004
	(0.005)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.007)	(0.002)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.003)
Entry × Grav. State × high-quality manager	0.007**	0.013***	0.007**	0.004	0.012***	0.019***	−0.001	−0.003	0.014***	0.021***	0.005***	0.014***	0.001	0.031***	0.012***	0.020***
	(0.003)	(0.001)	(0.004)	(0.004)	(0.002)	(0.004)	(0.002)	(0.006)	(0.002)	(0.006)	(0.001)	(0.004)	(0.002)	(0.005)	(0.004)	(0.003)
Observations	202,254	765,585	131,939	157,299	347,986	167,268	398,273	35,940	346,972	147,514	918,867	156,436	229,178	137,101	119,096	271,953
R-squared	0.667	0.582	0.635	0.639	0.653	0.527	0.525	0.634	0.719	0.596	0.553	0.568	0.671	0.572	0.726	0.665
Avg. dep. var.	0.230	0.170	0.330	0.370	0.170	0.370	0.270	0.450	0.270	0.330	0.0800	0.340	0.210	0.470	0.290	0.340
SD dep. var.	0.420	0.380	0.470	0.480	0.380	0.480	0.440	0.500	0.450	0.470	0.270	0.470	0.400	0.500	0.460	0.480
Lincom estimate high-quality manager	0.01***	0.013***	0.008***	0.012***	0.01***	0.017***	0.004***	0.005	0.012***	0.025***	0.003***	0.016***	0.007***	0.034***	0.012***	0.017***
Lincom SE high-quality manager	0.003	0.001	0.002	0.002	0.002	0.003	0.001	0.005	0.002	0.004	0.001	0.003	0.002	0.004	0.003	0.002
Lincom estimate Grav. State	0.098***	0.091***	0.111***	0.099***	0.06***	0.127***	0.101***	0.121***	0.071***	0.1***	0.051***	0.18***	0.058***	0.216***	0.147***	0.132***
Lincom SE Grav. State	0.01	0.005	0.014	0.01	0.006	0.018	0.007	0.031	0.006	0.01	0.003	0.02	0.006	0.019	0.017	0.011
Category	Beer	Breads & desserts	Canned products	Cereal	Cheese	Chips	Cookies	Energiz-ers	Grains	Ice cream	Liquor	Milk	Oils & vinegars	Soda	Sugars	Yogurt

Note: The unit of observation is the product-store-quarter level, encompassing all product-store-quarter combinations where a product was or could have been available for purchase. The dependent variable is an indicator equal to 1 when a product is present in the store. *Entry* is an indicator variable that equals 1 if the product was not present in the store in the previous quarter, representing stores where entry costs would be incurred upon rollout. *Grav. State* is an indicator variable that equals 1 if the product is already available in another store in the same state. *High-quality manager* is an indicator variable that equals 1 if a high-quality manager is present in the store. All models account for predicted revenue and include fixed effects for product, quarter, and store type. Standard errors are clustered at the product level.

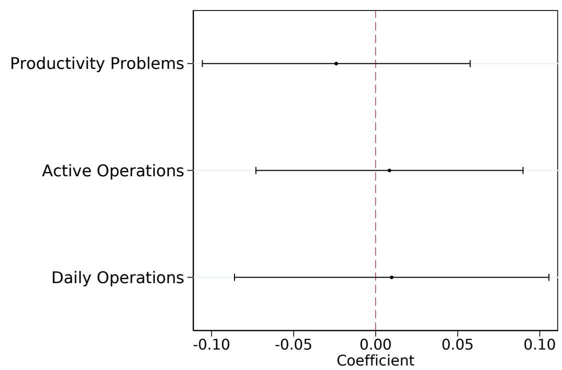
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

G Appendix: Correlation between Managerial Quality and Managerial Traits

Figure G.1: Estimated Relationship for Grouping of Managerial Traits

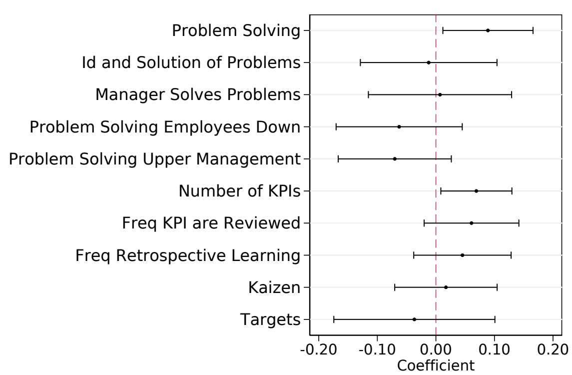


(a) Individual traits



(b) Daily activities

(c) Employee management



(d) Operations

Note: We regress manager fixed effects on the normalized measures of the traits surveyed, one at a time, controlling for the manager's age, tenure, and gender. The estimated coefficients are presented along with 90 percent confidence intervals. The managerial traits are grouped by broad categories.