The Labor Demand Implications of Brand Capital: Insights from Trademark Transactions in Italy*

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Abstract

Brand capital is an intangible asset that differentiates a firm's products from competitors and has grown in aggregate importance over recent decades. Trademarks protect property rights associated with brand capital, and are often exchanged in a firm-to-firm market. This paper studies how brand capital shapes labor demand, with a focus on heterogeneity between *production-stage* workers and *marketing-stage* workers. We assemble a new dataset linking three sources of Italian administrative records: the trademark registry, the universe of firms' financial statements, and employer-employee social security records. These data allows us to observe the firm-to-firm market for trademarks and use transactions to identify the firm-level effects of brand-capital investment. We develop a model in which firms combine three inputs: production labor, expansionary labor, and brand capital. In the model, firms can invest in brand capital by purchasing existing trademarks. This framework delivers testable predictions and informs our empirical strategy. Using a matched difference-in-differences design, we find that acquiring a trademark increases firms' intangible assets, boosts sales and value added, and expands employment. Yet, average wages are unchanged with a corresponding reduction in the labor share. Accounting for trademark sellers, we find that the trademark market improves allocative efficiency since buyers' gains exceed sellers' losses, leading to net output gains. Lastly, trademark buyers' employment growth is concentrated among *expansionary* workers—those involved with marketing and sales—rather than *production* workers, even if there is increased churn among the latter. This suggests that brand capital is not skill-neutral and leads to a reorganization within the firm.

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1 Introduction

Over the past five decades, intangible capital has grown in importance as a central input in the aggregate economy (Crouzet et al., 2022) and recent evidence suggests intangible inputs are responsible for key macroeconomic trends (De Ridder, 2024; Chiavari and Goraya, 2025). *Brand capital* is a kind of intangible asset that differentiates a firm's products, while *trademarks* grant property rights in the distinctive signs (names, logos, slogans) through which a firm creates and protects its brand capital. Recent work shows that the value of brand capital and trademarks has been rising as a share of GDP and that these assets are pervasive across a wide range of industries (Bronnenberg et al., 2022; Desai et al., 2025). Yet, despite its growing relevance, brand capital remains relatively understudied—especially with respect to its implications for labor demand. A key empirical challenge is that, despite its economic significance, brand capital is notoriously difficult to measure—even within firms' accounting records.

The lack of evidence on brand capital and labor demand stands in sharp contrast to a rich literature documenting how investments in tangible capital—e.g., machinery (Curtis et al., 2022; Aghion et al., 2024; Hirvonen et al., 2025), ICT equipment (Autor et al., 2003; Bartel et al., 2007; Akerman et al., 2015; Gaggl and Wright, 2017), and industrial robots (Acemoglu and Restrepo, 2020; Acemoglu et al., 2023)—shape employment, wages, and productivity at the *production stage* of the value chain. Brand capital, by contrast, operates at the *marketing stage*, when firms try to attract as many consumers as possible and shape preferences for their products. Because the mechanisms and skills involved in marketing differ fundamentally from those in production, the existing evidence offers little guidance on how brand-capital investment affects the composition of employment, firm productivity, the labor share, or the trajectory of firm growth. Addressing that gap is the main objective of this paper.

We propose a new way of identifying the labor demand effects of brand capital by leveraging firm-to-firm transactions in the market for trademarks. These events are uniquely suited to study the effects of hard-to-measure brand capital because they provide events where we know that brand capital is augmenting, and doing so in a sharp and discontinuous way. We implement this strategy using a newly assembled dataset that links Italian employer–employee matched records, firms' balance-sheet and income-statement data, and the national registry of trademark transfers.

Guided by a model of production, marketing, and trademark acquisitions featuring brand capital and labor, we estimate the effects of acquiring an existing trademark on firm performance and labor outcomes. Our research design is a matched difference-in-difference approach that exploits the richness of the data and its panel dimension. Motivated by our model, we highlight heterogeneous effects on two different types of labor: *production workers*, involved in producing output; and *expansionary workers*, tasked with creating new products through which to sell output (Kaplan and Zoch, 2024). Our worker-level panel data allows us to incorporate job mobility into the analysis and study brand capital effects on different types of workers, assessing whether it is skill-biased in nature. Moreover, we are able to evaluate the overall efficiency of the firm-to-firm market for trademarks by analyzing buyer and seller firms as a whole.

The paper leverages a new dataset that, through firm identifiers, merges the Italian trademark registry to the population of employer-employee Social Security records, and to firms' balance sheets and income statements. Crucially, our balance sheet data includes an "intangible capital" entry. As acquired trademarks fall under this accounting category, we can validate the records merge and our proposed method of using trademark transactions as brand capital shifters. We identify firm-to-firm transactions in the trademark registry and link the timing and identity of the firms involved (trademark buyers and sellers) to firm performance (e.g., sales and value added) and workers' outcomes (employment, compensation, job mobility). To isolate the effects of brand capital, we focus the analysis on firm-to-firm transactions that only involve the ownership change of a trademark asset, abstracting from transactions that are part of a broader merger or acquisition (a distinction that is recorded in the trademark registry).

We propose a model of firm production and trademark transactions that allows us to formalize the interaction between brands, production, and demand for different types of labor. Moreover, the model allows us to derive testable predictions and provides some guidelines on how to think about the identification of causal effects of trademark transactions.

The model has four key features. First, after generating output using production labor, a firm can sell the output as different products, each characterized by its own demand curve. Thus, creating a new product allows for an increase in sales without necessarily moving down an existing demand curve and lowering the price. Second, products differ by whether they are sold as generic (with a high demand elasticity) or as branded (with a low demand elasticity). Creating both types of products requires hiring expansionary workers (e.g., specializing in marketing). Third, brand capital allows firms to create branded products more efficiently, and thus shifts the weights between revenue shares from the generic products to the branded products. Lastly, we consider a frictional trading process where a subset of firms can decide on whether and how to trade brands by paying a fixed cost. Due to the transaction cost, the model predicts that more productive firms are more likely to become brand buyers. The model also predicts that, compared with non-buyers with similar characteristics, buyers experience an expansion in revenue and a reduction in their overall labor share after a brand transaction. Production workers' labor share falls relative to the expansionary labor share in these firms as well. We bring the model insights regarding selection and the impacts of trademark transactions to the data.

We combine our firms' accounting data and trademark registry to provide a series of descriptive facts on intangible capital and trademark ownership in Italy. The importance of intangible assets as recorded in firms' balance sheets has increased steeply since the turn of the century. The value of aggregate intangibles as a share of total assets was about 3.5% in 2000 and 8% in 2019. As a share of aggregate tangible capital, intangible capital went from 15% in 2000 to 33% in 2019. Turning to brand capital, we show that—as predicted by our model—trademark buyers are concentrated in the top deciles of the sales and value-added distributions within their sectors. Additionally, we find that trademark buyers and sellers are broadly represented across all sectors of the economy, while being overrepresented in manufacturing and wholesale and retail trade, and underrepresented in construction.

Our research design leverages the richness of the administrative data in terms of firm observables and panel dimension. In particular, we estimate the effects of acquiring a trademark using a stacked matched difference-in-differences approach. Each firm that acquires a trademark is matched to one or several other firms that (i) do not acquire trademarks and (ii) share common observable characteristics prior to the purchase including, crucially, time-varying measures of firm size and productivity. In a statistical sense, identification requires that the parallel trends assumption holds within cells of firms that, prior to acquisition, share similar levels of production, employment, sector, and year of firm birth. Economically, we argue that identification is aided by the frictional nature of the trademarks market and plausible time lags between brand-investment decisions and effective trademark transfers, minimizing concerns that the precise timing of trademark acquisitions are correlated with positive firm shocks. Parallel pre-trends broadly show that trademark-buying firms and comparison-group firms were not on distinct trajectories before the acquisition event.

Equipped with our matched difference-in-differences design, we begin by examining the impact of brand capital on firm performance. As a "first stage," we show that acquiring a trademark sharply increases the value of intangible assets in the balance sheet by approximately 19% on average. This result confirms that the timing of transactions in the trademark registry coincides with discrete changes in the intangibles assets held by firms, which diminishes concerns about our estimated effects being driven by other shocks. Trademark acquisitions increase sales by 8% and firm value-added by 6% within two years.

How do trademark-induced increases in brand capital impact firms' labor demand? Trademark acquisitions give rise to significant employment growth, with total employment increasing by 5–6% within three years. This growth primarily reflects stable, long-term job creation, as permanent and full-time employment rise substantially, in proportion to overall employment. Our worker-level panel data allows us to show that employment growth results from the combination of increases in the hiring rate and the separation rate—evidence of a workforce reorganization rather than a pure increase in scale. The wage bill grows proportionally with employment, indicating no significant change in average wage rates. The wage bill, however, grows less than proportionately relative to the buyer firm's sales, leading to a 2% reduction in the firm's labor share.

Our setup enables us to extend the analysis to the broader effects of trademark transactions, particularly their aggregate efficiency. We perform a transaction-level analysis by combining the outcomes across all buyer and seller firms involved in each transaction. We find net positive effects on several performance measures: aggregate sales and value added increase, reflecting the reallocation of brand capital toward more productive firms. Aggregate employment and the aggregate wage bill also rise. Mirroring effects for trademark buyers, the wage bill grows less than sales, leading to a reduction in the combined labor share of transacting firms.

Guided by our theoretical framework, we test for heterogeneous effects of brand capital on production and expansionary labor. We employ alternative classifications to distinguish between production and expansionary workers. First, we classify workers based on their qualification recorded in social security data. We define blue-collar labor as *production workers*, given their proximity to production activities. Instead, we define white-collar employees (including managers) as *expansionary workers*, since their tasks are more closely tied to market outreach and sales. Our findings show that brand acquisitions primarily benefit white-collar employees, with their employment and wage bill increasing by about 3–4%. In contrast, blue-collar employment and wage bill experience no significant effects. Next, leveraging occupation codes available for a large subset of workers, we single out those employed in marketing- and sales-related occupations and compare their outcomes to the remaining white-collar and blue-collar workers. We find that most of the employment and wage bill gains are concentrated within the marketing/sales workers. In contrast, the rest of white-collar labor shows no significant growth. Lastly, we carry out a simpler comparison in which we benchmark effects for marketing/sales workers vs. all other workers, finding again that the largest employment and wage bill growth occurs among the former group. These findings align with our theoretical prediction that brand acquisitions enhance consumer outreach, driving demand for expansionary labor most closely involved with the marketing stage of the value chain.

Overall, our findings suggest that trademark acquisitions enhance firm performance and that the trademark market improves allocative efficiency, as buyers' gains exceed sellers' losses. The labor demand effects of brand capital are not skill-neutral, as increases in employment are driven by roles that interact most directly with brand capital—what we define as expansionary labor—while leaving production employment largely unaffected. However, wages do not increase on average, indicating limited pass-through of the acquisition-related gains to existing employees. Consequently, the firm's labor share declines following the increase in market share of revenues driven by the trademark acquisition. We interpret the decrease in the labor share as consistent with brand capital increasing firms' product market power.

Contribution to the literature

This paper contributes to four strands of literature. First, the literature on the rise of intangible assets and their economic effects (Crouzet et al., 2022; Chiavari and Goraya, 2025). Most of this literature focuses on the technological and production side of intangibles such as software or key workers' know-how (e.g., Bartel et al., 2007; Eisfeldt and Papanikolaou, 2013; Schivardi and Schmitz, 2020; De Ridder, 2024) or its financial market implications (Crouzet and Eberly, 2023; Peters and Taylor, 2017). In contrast, there is much less work on market-expansion demand-side intangibles such as brands, in spite of their growing importance (Bronnenberg et al., 2022). In the direction of demand-side intangibles, Gourio and Rudanko (2014) shows that embedding customer capital introduces volatility in labor wedges in business cycle models, Baker et al. (2023) shows that customer churn is an important driver of firms' investment activities, while He et al. (2024) documents that the firm's expenditures in sales and general administration correlate with customer-related intangibles. Our first contribution on this front is to document, leveraging new data, some novel facts on the firm-to-firm trademarks market—including key features of buyers and sellers in this market—and to illustrate how these transactions can be exploited to understand the effects of hard-to-measure brand capital. Our second contribution is to illustrate both theoretically and empirically how the accumulation of brand capital interacts with firms' labor demand. Our third contribution is to show how the secondary market of an intangible asset such as brands can increase aggregate efficiency.

Second, this paper speaks to a rich and growing literature on the interaction between capital investments and labor demand, with some recent papers leveraging firm-level variation and data, as we do. Papers studying investments in manufacturing machinery typically find skill-neutral effects on employment, limited productivity effects, and no effects on individual earnings (Curtis et al., 2022; Aghion et al., 2024; Hirvonen et al., 2025). In contrast, papers studying ICT-related investments uncover skill-biased labor demand effects and effects on individual earnings that depend on workers' skills or tasks (Autor et al., 2003; Bartel et al., 2007; Akerman et al., 2015; Gaggl and Wright, 2017). We find that the effects of brand capital—which operates on the marketing stage rather than the production stage—are qualitatively different and do not fall under either category: brand capital has skill-biased positive employment effects (favoring labor with marketing-related experience, while leaving production employment unchanged), no effects on earnings, and improved firm sales and value added that lead to lower labor shares.

Third, we contribute to the scant literature on intangibles and labor demand. While there is evidence on the labor effects of technology-enhancing intangibles such as patents (Kline et al., 2019), we lack evidence on the labor effects of demand-side intangibles that impact the marketing stage, such as brand capital. Patents typically affect production by reducing marginal costs and preventing the reduction of competitors' costs by protecting a specific technology (Akcigit and Kerr, 2018). Instead, brands impact the marketing side, after production is complete. The different nature of these investments have different theoretical implications for labor and the groups of workers who gain are, a priori, arguably distinct. On trademarks and labor demand, Desai et al. (2025) shows that, following a trademark approval, US public firms increase aggregate employment. We are able to provide a more comprehensive overview of the skill-biased labor demand effects of brand capital leveraging both firms' financial data and a worker-level panel, among a broad cross-section of firms that goes beyond publicly traded firms. In addition, we are able to study the consequences of brand capital for the labor share. Our view is that a better understanding of the effects of demand-side intangibles is important given evidence on how product demand differences are a key component of firm dynamics (Foster et al., 2008, 2016), perhaps the main driver of heterogeneity in firms' performance (Hottman et al., 2016).

Lastly, our paper uncovers a novel channel through which firms can boost markups. While recent literature has documented a sustained rise in firm profitability (De Loecker et al., 2020), much of this trend has been attributed to rising fixed costs or firm-level innovation activity (Olmstead-Rumsey, 2019; Akcigit and Ates, 2023; De Loecker et al., 2021). Our findings point to an additional, demand-side mechanism: by acquiring trademarks—and thereby expanding market access—firms increase their revenues and improve performance. This highlights brand capital accumulation and reallocation as a distinct and complementary driver of rising profitability. Furthermore, our analysis offers micro-level evidence on how this increased profitability translates into a declining labor share, consistent with the mechanism proposed by De Loecker et al. (2020).

2 Intangible Capital and Trademarks in Italy

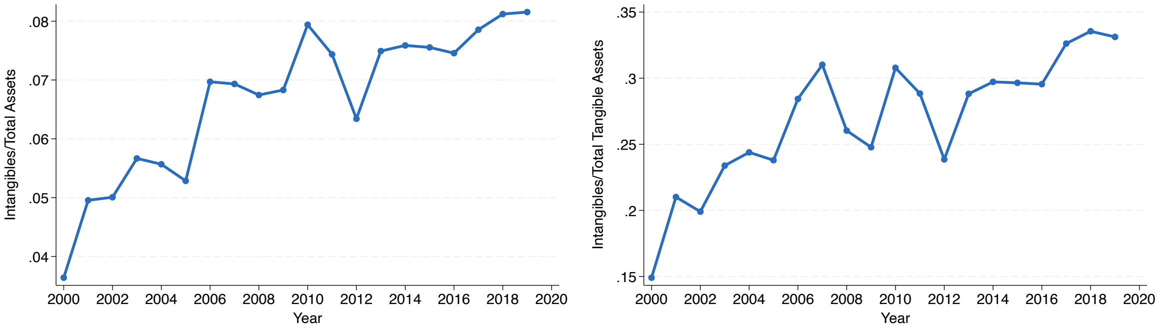
We motivate our focus on brand capital—a key component of intangible capital—documenting the rising importance of intangibles in the Italian economy. We then discuss the firm-to-firm market for existing trademarks, which forms the empirical setting of our analysis. This market not only contributes to the growing relevance of intangible assets but also facilitates the reallocation of brand capital toward acquiring firms, with potential implications for aggregate efficiency.

2.1 The Rise of Intangible Capital

Trademarks are recorded on firms' balance sheets as intangible capital. To highlight the growing importance of this type of capital, we analyze its evolution in the Italian economy over the past two decades. Panel (a) of Figure 1 shows that the share of total assets held as intangible capital has steadily risen, doubling from less than 4% in 2000 to over 8% in 2019. Similarly, Panel (b) illustrates that intangibles have become a larger component of total capital: while they amounted to 15% of tangible capital in 2000, by 2019, they represent 33%. While our balance sheet data does not allow us to separately quantify brand capital, Bronnenberg et al. (2022) shows that the value of the top 100 global brands has doubled in recent decades, contributing to the overall rise in intangible capital.

Figure 1: The rise of intangibles in the Italian economy.

(a) Intangibles share of total assets. **(b)** Intangibles share of tangible capital.



Notes: Rise in intangible capital over the period 2000-2019. Panel (a) shows the share of intangible capital over total assets in firms' balance sheets. Panel (b) shows intangible capital as a share of total tangible capital held by the firms in the sample. The sample includes all firms that are present in CERVED data (universe of non-financial Italian corporations).

2.2 The Trademark Market

The rise of brand capital as a key driver of the overall increase in intangible assets motivates the focus of our paper. To empirically examine the effects of brand capital, we leverage changes in trademark ownership resulting from trademark transactions. These transactions—the buying and selling of brand names and logos—are undertaken by firms for a variety of strategic purposes. Unlike mergers or full company acquisitions, they involve the transfer of trademark rights between independent entities, enabling firms to acquire or monetize brands without altering the broader corporate ownership. In Italy, as in other advanced economies, there exists an active secondary market for trademarks, with firms trading brand rights for strategic, financial, and operational reasons.

For trademark buyers, acquiring the rights to an existing established brand allows to expand market access faster than building a new one from scratch. In many cases, a buyer firm might have strong manufacturing, distribution, or financial capabilities, allowing it to acquire an underutilized brand and scale it up to a degree that the seller firm is not able or not willing to do.

On the other hand, a firm might decide to sell a brand following a strategic shift in their operations. Examples in Italy include fashion firms who own several brands and product lines and decide to sell one the rights to one of their brands to focus attention on the others. Additionally, selling trademark assets can be a way of raising liquidity for firms in financial trouble. Ultimately, a business that is closing down might still own valuable brands and sell them as part of their liquidation of assets.

3 Model: Production, Labor Demand, and Trademark Transactions

We present a model in which firms employ production workers to produce output, and combine expansionary workers and brand capital in the marketing stage to increase their profits. The model incorporates firms' trademark-transaction decisions, which are used to increase brand capital. The model motivates two features of our empirical design. First, it serves as a framework to think about the underlying selection into trademark purchasing. Second, the model generates predictions on the effects of brand capital for different types of workers, which our empirical findings speak to.

Model setup. Our model is static. There is a measure 1 of firms, who differ in productivity (z_j) and the amount of brand capital (b_j) they own. For simplicity of notation, we assume firms' index, j, also represents their productivity rank. Thus, firm 0 is the least productive firm, firm 1 is the most productive firm, and firm j' is more productive than firm j if $j' > j$. All firms use a linear technology to produce, so the output of firm j is $y_j = z_j l_j$, where z_j denotes the labor productivity and l_j is the number of employed *production* workers. For simplicity, we assume that total output consists of multiple product lines, each with the same marginal cost of production.[1]

We model the effect of the marketing stage and brand capital, as well as the heterogeneous effects on different types of labor, building on the model in Kaplan and Zoch (2024). In this framework, the number of products a firm can sell is endogenous.[2] Our model innovates by incorporating the role of brand capital and trademarks. Specifically, after producing total output y_j, firms can distribute the output as different products. Denoting the quantity sold through product i as q_{ij}, the firm's quantity constraint is $y_j = \sum_i q_{ij}$. Products differ in whether they are sold as generic or branded items. When sold as a generic, the product faces a demand $p_{ij} = q_{ij}^{-1/\epsilon_g}$. When sold as a branded product, the demand is instead $p_{ij} = q_{ij}^{-1/\epsilon_b}$. Our key assumption is that $\epsilon_b < \epsilon_g$. That is, a branded product faces a less elastic demand than a generic product. There are several motivations for this assumption: (i) consumers are less sensitive to price increases for a product when the brand name itself brings additional value—the goodwill theory of branding; or (ii) a branded name resolves the uncertainty regarding the quality of goods, making customers less sensitive to price changes—the information theory of branding.[3] This assumption is consistent with the empirical evidence as well. For example, Döpper et al. (2025) documents a fall in consumer demand elasticity for products in recent years, primarily due to brand preferences.

The number of products a firm operates can be chosen by hiring expansionary workers. We denote the expansionary workers for generic products as n_{jg} and for branded products as n_{jb}. The eventual number of generic products the firm operates in is n_{jg}^{γ} and that of branded products is $b_j n_{jb}^{\gamma}$, with $0 < \gamma < 1$ capturing the decreasing return in these activities. The core endogenous object in our model is brand capital, b_j. It acts as an efficiency in creating branded products. In our model, creating branded products costs less labor when the

[1] This is a simplifying assumption: product lines could instead have different marginal costs, provided that the separability across product lines in the production stage is maintained.

[2] These products can be interpreted either as explicitly demarcated products or customer segments a product has access to.

[3] Intuitively, if consumers did not know the quality of different products they would just consume the least expensive one, while if they knew that one has higher quality they might tolerate higher prices. This makes their elasticity of demand for branded good lower.

firm accumulates more brands. We interpret this as the substitution between the marketing efforts in creating a new brand in-house and using established brands acquired through transactions. Because $0 < \gamma < 1$, an increase in brand capital leads to a larger saving in marketing costs when the firm operates fewer products, capturing the imperfect substitution between creating brands and buying brands.[4] In our empirical analysis, buying an established trademark from other firms leads to an increase in brand capital b_j, allowing the firm to create branded products with less cost, equivalent to an increase in the efficiency of expansionary workers.

Firms employ both production and expansionary workers from competitive markets, taking as given wages w_l and w_n, respectively. We make the technical assumption that $\frac{w_l}{z_j}\frac{\epsilon_g}{\epsilon_g - 1} > 1$ for all j, which points to the empirically relevant case.[5]

Firms can invest in their brand capital by purchasing trademarks from other firms in a frictional market for trademarks. A pair of firms randomly meets with probability λ. They can then decide whether to engage in a transaction in which an existing trademark changes ownership. We assume the two firms need to pay a transaction cost T and split their surplus according to Nash bargaining.

Model solution. We now characterize the equilibrium choices regarding production, hiring, and trademark transactions. Because the production technology is linear in labor and the firm takes wages as given, the production decision can be analyzed product by product, independently. First, we consider the production decision within each product, which yields the profit per product for both generic and branded products. Second, we consider the optimal choice of expansionary workers, which determines the total profit of firms as a function of productivity and brand capital. Lastly, we characterize the transaction decisions. Detailed proofs and derivations are in Appendix C.

As a first step, we characterize the optimal pricing and production decision within a product i, given the demand schedule:

$$\pi_{ij} = \max_{q_{ij}} p_{ij} q_{ij} - \frac{q_{ij}}{z_j} w_l, \quad s.t.\ p_{ij} = q_{ij}^{-1/\epsilon_i},$$

which leads to the following result.

Lemma 1. *When compared to a generic product, a branded product has a higher revenue and a higher profit margin.*

Solving the firm's problem above, we find that the optimal pricing is $p_{ij} = \frac{\epsilon_i}{\epsilon_i - 1}\frac{w_l}{z_j}$, the marginal cost of the firm adjusted by the markup. As the markup decreases in demand elasticity, it follows that a branded product has a higher price under the optimal decision.

[4] For example, an established clothing brand is less valuable for each single product when the firm sells both clothes and shoes, compared to a firm that only sells clothes.

[5] Specifically, when the demand elasticity falls, two countervailing forces drive a firm's profit. The first effect is on profitability, which increases profit. The second effect is the scale effect, which increases revenue when the price exceeds 1 and decreases it when the price is less than 1. Our assumption ensures that both effects lead to a higher profit.

Correspondingly, the revenue of the firm from product i is $r_{ij} = \left(\frac{w_l}{z_j}\frac{\epsilon_i}{\epsilon_i - 1}\right)^{1-\epsilon_i}$. Given our assumptions, a fall in the demand elasticity leads to an increase in revenues. Lastly, the profit equals revenues adjusted by the profit margin $\pi_{ij} = \frac{r_{ij}}{\epsilon_i}$, where the profit margin is the inverse of the demand elasticity, the Lerner index. There are two effects of a fall in demand elasticity on the profits. First, it increases revenue by fixing the profit margin. Second, it increases profit margin when we fix revenues. Both effects lead to higher profits under branded products.

The problem of choosing expansionary labor is thus:

$$\max_{n_{jb}, n_{jg}} \quad b_j n_{jb}^{\gamma} \pi_{bj} + n_{jg}^{\gamma} \pi_{gj} - (n_{jb} + n_{jg})$$

where we normalized $w_n = 1$. Solving the optimal expansionary labor, we find the following solutions:

$$n_{jg}^* = (\gamma \pi_{gj})^{\frac{1}{1-\gamma}}, \quad n_{jb}^* = (\gamma b_j \pi_{bj})^{\frac{1}{1-\gamma}}. \tag{1}$$

The following lemma summarizes the consequences of an increase in brand capital for employment, revenue, and the labor share.

Lemma 2. *With a small increase in brand capital b: (a) revenue rises, (b) the overall labor share falls, and (c) the ratio between expansionary employment and production employment rises.*

Lemma 2 is the core theoretical result. When firms' brand capital increases (in our context, this is the result of a brand transaction), total revenue expands. Since the decisions of creating branded and generic products are independent in our setting, an increase in brand capital leads to an increase in the firm's branded products. This expansion increases the firm's total revenue. In this regard, an increase in brand capital is similar to other types of capital. What distinguishes brand capital from other types of capital or productivity shocks is that brand capital complements high markup products, leading to a reallocation of the firm's wage bill from high labor share products (the generic products) to low labor share products (the branded products). As a result, the overall labor share at the firm falls. The reallocation also shifts employment shares away from production workers toward expansionary ones.

The employment of production workers does not expand as strongly as the expansion of total revenue. To see this, we note that a 1% increase in branded product revenue only leads to a $\frac{\epsilon_b - 1}{\epsilon_b}$ percent increase in production workers' wage bill (and thus employment since wage is taken as given). As the demand for branded products is less elastic, the pass-through from branded revenues to production employment diminishes. We expect a close to zero effect on production employment when the demand elasticity approaches 1. The economics of this imperfect pass-through stems from the fact that a fraction of the expansion from brand capital increase is due to the increase in profit margins, rather than the increase in the scale of production.

From the discussion so far, we can derive the optimal profit of the firm as

$$\pi(z,b) = \phi_b z^{\frac{\epsilon_b - 1}{1-\gamma}} b^{\frac{1}{1-\gamma}} + \phi_g z^{\frac{\epsilon_g - 1}{1-\gamma}} \tag{2}$$

where $\phi_b = (1-\gamma)\gamma^{\frac{\gamma}{1-\gamma}} \left(\frac{\epsilon_b^{-\epsilon_b}}{(\epsilon_b - 1)^{\epsilon_b - 1}}\right)^{\frac{1}{1-\gamma}}$ and $\phi_g = (1-\gamma)\gamma^{\frac{\gamma}{1-\gamma}} \left(\frac{\epsilon_g^{-\epsilon_g}}{(\epsilon_g - 1)^{\epsilon_g - 1}}\right)^{\frac{1}{1-\gamma}}$. Total profits are the sum of the profits from the branded and generic products. With this definition in hand, we now move on to the characterization of transaction decisions.

Trademark transactions. Our last set of results investigates the selection into transactions. We ask which type of firms are more likely to be the buyers, compared to the firms that do not engage in transactions. Because of Nash bargaining, when a firm meets another, the decision of whether to trade solely depends on whether the joint surplus increases after the trade.[6] More precisely, the joint surplus net of transaction cost between a firm j and a firm k is

$$S_{jk} = \max_{-b_j \le \tau \le b_k} \pi(z_j, b_j + \tau) + \pi(z_k, b_k - \tau) - \pi(z_j, b_j) - \pi(z_k, b_k) - T$$

where τ is the transfer of brands k firm gives to firm j.

All transactions that materialize in the equilibrium must have positive gains from trade. This is a result of two mechanisms. First, transferring 0 units of brand capital is always feasible, which delivers gains from trade of 0; thus, if a transaction happens, the gains from trade must be weakly better than 0. Second, due to the transaction cost T, the worst transaction that we observe should have positive gains from trade.

Transaction costs imply that we do not expect selection into trademark buyers to be random. The following lemma summarizes our prediction regarding selection into being a buyer. For the empirically relevant case, we focus on an interior solution of τ, where there is a non-zero amount transacted.

Lemma 3. *Compared to firms that do not engage in transactions, buyers are more productive and have higher revenues.*

Firms differ in their productivity and brand capital. We can understand the selection results along these two dimensions. Holding brand capital constant, if a transaction between firm j and firm k happens, the surplus from trade is weakly larger than the transaction cost. Another firm j' with the same brand capital as firm j but higher productivity would gain more from the transaction, because productivity and brand capital are complements in firms' profits, as in equation (2). This implies that the more productive firm j' would also engage in a transaction with firm k if they had the chance. The converse is not necessarily true, implying that brand buyers are not necessarily positively selected in terms of their productivity. Holding productivity constant, a firm with more brand capital also has more to gain from transactions, coming from the increasing return-to-scale of brand capital in firm profit (equation (2)). Thus, brand buyers are also positively selected in terms of their brand capital. As the revenue of firms increases in both productivity and brand capital,

[6]Implicitly, the Nash bargaining also determines the price for such transactions. Because both firms have linear payoffs in the transaction price, the price does not affect the surplus from trade.

selection in both dimensions implies that brand buyers are positively selected in terms of revenue.

To make the conceptual framework intuitive, we assumed away the lifecycle of firms. One should expect similar predictions when we introduce dynamic fluctuations of the productivity of firms into the model. In the empirics, we will exploit the longitudinal component of the data. For this reason, when linking the model to the data, we recognize that the productivity index from our model encompasses a range of factors, both static and dynamic. From the lens of the workhorse firm dynamics models (Hopenhayn, 1992), we will also include firm size growth as control.

Summary of the model predictions: Combining all results presented in this Section, we reach the following predictions regarding the causal effects of an increase in brand capital through a trademark transaction:

1. Selection into transaction: when compared to non-transacting firms, trademark buyers are more productive and larger in size.

2. Firm-level responses: revenue of the buying firm increases, its total wage bill increases while its labor share falls.

3. Transaction-pair responses: after a transaction occurs, the sum of profits of the firms involved increases.

4. Heterogeneous workforce responses: the ratio between expansionary employment and production employment rises.

Discussion. We relate our framework to existing models on capital-augmenting technologies and discuss how we link the model to the data. A central question is what distinguishes brand capital from other forms of capital, such as machinery, software, or general technological investments. A large body of work has explored how different types of capital affect labor demand (Uzawa, 1961, Arrow et al., 1961, Acemoglu, 2002, Acemoglu and Autor, 2011, Acemoglu and Restrepo, 2019). The traditional view argues that capital-augmenting technologies raise both labor demand and the labor income share, based on the consensus from the literature that capital and labor are gross complements. A more recent strand of literature, based on task-based technological change, argues that intangible capital can simultaneously raise output while reducing labor demand and labor share because it substitutes for labor in some tasks. Our framework departs from both literatures. On the one hand, brand capital does not substitute for labor in production activities but rather it enables market expansion, thereby increasing both output and labor demand. On the other hand, despite higher labor demand, the firm's labor share declines as increased brand capital allows for greater markups.

Our framework also yields distinct predictions compared to models in which market power arises from firm size (Atkeson and Burstein, 2008). In size-based models, markups rise as firms expand production and market share, since customers face greater difficulty substituting away from their products. This mechanism operates without requiring any reallocation of the wage bill across worker groups. By contrast, our framework predicts both a decline in the overall labor share and a reallocation of the wage bill from production workers to expansion-oriented workers.

An alternative interpretation of brand expansion is quality differentiation. We formalize this in Appendix C.4, following the literature in treating product quality as a shift in demand levels while holding demand elasticity constant. Under this interpretation, brand acquisitions do not generate markup changes. Consequently, one should not expect a decline in labor share after firms acquire brands—a prediction that contrasts with the core mechanism of our model and with our empirical evidence.

4 Data

We assemble a novel dataset merging several administrative sources, which provides us with panel data on trademark transactions linked to worker-level and firm-level outcomes.

4.1 Trademark deposit and transaction data

We gather information on trademark transactions from the *Italian Patent and Trademark Office* (UIBM) at the *Italian Ministry of Economic Development* (MISE).[7] The data contains the universe of trademark exchanges for the period 2007 to 2021. There are about 5,300 trademark transactions per year, which correspond to approximately 8% of the average number of deposited brands in a single calendar year. A transaction can involve multiple trademarks and multiple buyers and sellers. For each of them, we observe the Social Security Number (SSN) of the parties involved, the transaction identifier, the trademarks included, and some information on the motivation of the transaction. Due to privacy restrictions, we can match transactions to social security data only by combining the year of the transaction with the identities of the sellers and buyers involved. Accordingly, we define a transaction as a unique buyers-sellers-year combination. In the raw data, we occasionally observe multiple transaction identifiers associated with the same groups of sellers and buyers within a given year. These are instances where the same firms exchange different sets of trademarks. For our analysis, we treat these as a single transaction.

For a trademark transaction to be considered in our analysis, it must satisfy two conditions. First, the transacting parties must be Italian firms. We exclude transactions in which the seller or buyer is a physical person or a non-Italian firm. Second, we exclude trademark transactions that are part of a broader firm acquisition. That is, we exclude transactions that are part of a merger or the acquisition of a company branch. We are able to identify such cases through a dedicated variable in the trademark registry. As such, we avoid conflating the effects of brand-capital investment with the effects of a firm-acquisition operation.

Information on firms' SSN was missing for some firms in the original data. Using the information contained in the registries of the Chamber of Commerce, the corporate name

[7] The name of the Ministry has recently been changed into *Ministry of Enterprises and Made in Italy* (MIMIT).

(*ragione sociale*), and municipality, we were able to recover many of these missing records. If multiple firms with the same corporate name exist in a given municipality we leave the SSN missing and exclude the transaction from our sample. After imposing these restrictions, we are left with 15,082 trademark transactions linked to 10,567 sellers and 10,333 buyers (Table 1). Additional details on the dataset building procedure are in Appendix B.1.

Table 1: Trademark Sample Construction

Panel A - Number of Trademark Transactions:	
2007–2021	30,621
Corporate Firms Only	28,943
Italian Firms	22,934
Excluding Mergers and Acquisitions	15,420
Non-missing SSN	15,082
Panel B - Number of Firms After Restrictions:	
Buyers	10,333
Sellers	10,567

Notes: Panel A shows the number of transactions in the various steps of our sample selection procedure. Each line applies all the restrictions from previous lines. For this reason the number of observations drops consistently across lines. Panel B refers to the number of distinct buyers and sellers SSNs in the transactions left after the last restriction.

4.2 Firm-level and worker-level panel data

Firms' balance sheets and income statements: We link trademark data to firms' balance sheet and income statement outcomes coming from the *Chamber of Commerce* (Camere di Commercio) and provided by CERVED. In particular, we employ measures of sales, value added and intangible capital to study the consequences of trademark acquisitions for firm's performance. This data is available for the entire period covered by trademark data and it covers the universe of non-financial corporations.

Social security records: We build labor-related outcomes using the universe of social security data provided by the Italian Institute of Social Security (INPS). The dataset consists of matched employer-employee records for the population of private sector, nonagricultural firms. It contains worker-level information on demographic characteristics such as age and sex, and information about labor contracts. For each labor spell we observe starting and ending date that we use to build a tenure measure, the wage, and the type of contract (part-time vs full-time; permanent vs temporary). Crucially for our analysis on the complementarities between labor inputs and trademarks, we also have information on a worker's qualification that distinguishes between apprentices, blue-collars, white-collars, and managers. For a subset of workers (more than 86% of the total on average), we also observe the occupation code.[8] We employ these occupation codes to define workers employed in

[8]Occupation information is available for at least 86% of the workforce in every year from 2008 onward. The occupation code is reported in mandatory declarations that firms must file whenever a worker's contract

marketing- and sales-related tasks.[9] We create our wage outcomes using the total taxable income of each contract as a measure of total labor earnings. We winsorize this variable at the 99.9th percentile in each year. Exploiting the information described above on workers demographics and contract types, we can study labor market outcomes of different subsets of a firm's workforce. We also access firm information about the sector and location. In each year of data we restrict our attention to workers who are at least 16 years old, and who worked at least three months in the year.

4.3 Linking trademarks to firm and worker data

We can accurately link trademark transactions data to firm and worker outcomes since we observe firms' SSN unique identifiers in both data sources. When we perform this match, we are able to link firms' accounting data to a total of 7,881 trademark transactions, involving 9,309 buyers and 9,822 sellers.

4.4 The characteristics of brand buyers and sellers

We use this new dataset to present descriptive evidence on the firms involved in trademark transactions in Italy. Figure 2 Panel (a) studies the sectoral distribution of trademark buyers and sellers. While trademark transactions are widespread across all sectors, they concentrate more in some industries. Given that trademarks protect goods and services, transacting firms are disproportionately concentrated in manufacturing and wholesale and retail trade. Specifically, while 23% of all firms operate in manufacturing and 24% in wholesale and retail trade, these sectors account for 41% and 29% of trademark buyers, respectively. In contrast, buyers are underrepresented in less tradable sectors such as construction and hospitality, which account for only 1% and 3% of buyers, compared to 13% and 7% of all firms.

Our theoretical framework predicts that trademark buyers are, on average, more productive and larger than non-transacting firms. We provide descriptive evidence consistent with this prediction by examining the distribution of trademark buyers across sales and value added deciles. Figure 2 Panel (b) plots the share of buyers across within-sector-times-year sales and value added deciles, computed for the entire population of firms. If buyers were similar in size to the broader firm population, their distribution would be uniform, with each bar equal to 0.1. Instead, we observe a skewed pattern: buyers are underrepresented in the bottom seven deciles and increasingly overrepresented in the top three. Notably, nearly 37% of buyers fall within the top decile of within-sector-year sales, and 33% are in the top decile of within-sector-year value added. This highlights the disproportionate participation of larger and more productive firms in trademark transactions.

Overall, the main takeaways of Figure 2 are that (i) we observe activity in the market for trademarks across a broad cross-section of the Italian economy in terms of sectors, and (ii)

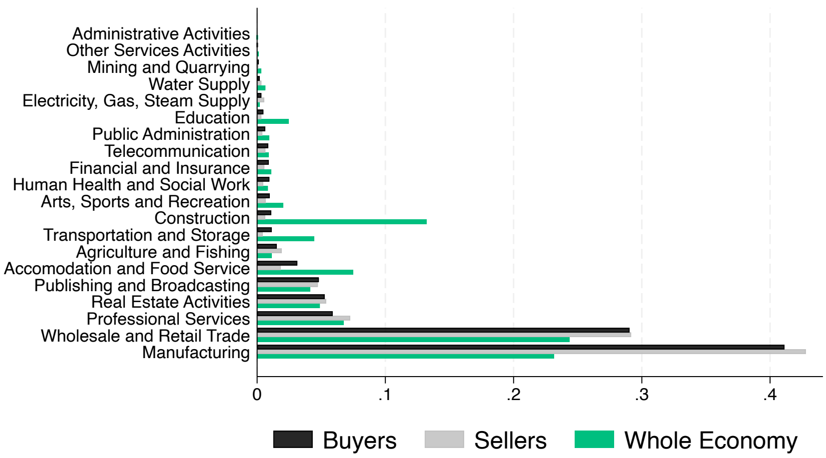
changes. Since these declarations have been collected only from 2010 onward, we observe occupation data for all workers who experienced at least one contractual change (e.g., promotion, hire, layoff, or retirement) after that year even for contracts that had been in place before 2010.

[9] Appendix B.2 reports more details on the occupation codes used to create the two occupational sub-groups.

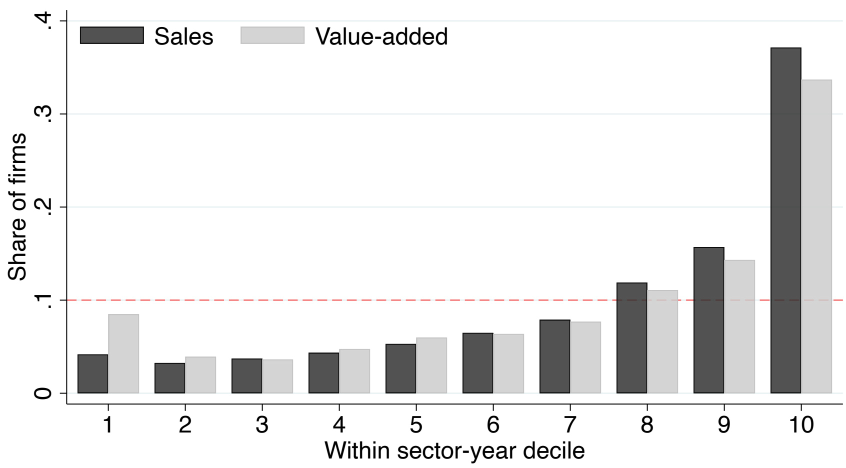
trademark transactions are concentrated among the largest set of firms within each sector. We interpret this as further evidence of the aggregate relevance of brand capital in general and trademark transactions in particular.

Figure 2: The characteristics of trademark buyers and sellers.

(a) Sectoral distribution



(b) Size and value-added distribution



Notes: Top panel: distribution of trademark buyers and sellers across sectors compared to all firms in our sample. Bottom panel: size distribution of trademark buyers compared to the entire economy. The horizontal axis is the within-sector and year sales and value-added deciles computed on all firms in the economy. The vertilcal axis shows the share of buyers whose sales or value-added fall in a given decile. If buyers were similarly sized compared to the rest of the economy, their bars should all be equal to 0.1 (dased horizontal line).

5 Empirical Approach: Event Studies Around Brand Transactions

5.1 Matching

We use a stacked matched difference-in-differences approach to study the causal effects of trademark acquisitions. Each firm that acquires a trademark is matched to one or several other firms that (i) do not acquire trademarks and (ii) share common observable characteristics prior to the purchase. The latter group of firms acts as comparison group and under a parallel trends assumption represent the counterfactual outcomes that trademark-buyer firms would have experienced in the absence of the trademark purchase (for research using matched difference-in-differences to study the effects of firm-level treatments, see Davis et al., 2014; Arnold, 2022; Colmer et al., 2025; Jäger et al., 2024; Daruich et al., 2024; Alfaro-Ureña et al., 2025). Motivated by the conceptual framework in Section 3, a key firm characteristic to account for is time-varying size.

We start by keeping trademark buyers that were involved in only one transaction event within our panel. We match each treated firm f in year t_f to the firm or set of firms that share the following characteristics: value of production at $t_f - 1$ and $t_f - 3$, employment at $t_f - 1$ and $t_f - 3$, 1-digit sector, and year of firm birth.[10] We denote the interactions between these variables as *matching cells*, where a matching cell can contain several treated and control firms. We further require firms in the matched sample to exist three years before and after the purchase year to be able to estimate our event study in a balanced panel.[11]

Our *matched sample* is composed of firms that acquire a trademark during our sample period and are matched to at least one comparison firm. We match 88% of the firms that are left after restricting to firms with only one acquisition event and to those who are active for the entire window around the acquisition event. This leaves us with a total of almost 2,000 transactions left involving 1,910 buyers.

Table 2 reports summary statistics for the matched sample of buyer firms and their matched controls. As expected, Panel A shows that the two groups are similar across the variables used in the matching procedure. Buyer firms are slightly larger in terms of employment, sales, and value added. This difference is driven by firms in the right tail of the size distribution, as medians for these variables are nearly identical across the two groups. Panel B presents the main outcome variables used in the analysis, measured on the year before the acquisition event. Buyers hold more intangible assets, both on average and at the median. Consistently with their larger employment size, they display higher average weeks worked, wage bills, and labor shares. However, even in this case the medians appear similar across groups. Finally, comparing the number of workers in the different occupations with the average and median employment, we find that buyers employ a smaller share of blue-collar workers and are more intense in marketing- and sales-related labor.

5.2 Firm-level Event Studies

We use the matched sample to estimate regression models of the following form:

$$y_{ft} = \alpha_f + \alpha_{s(f)t} + \alpha_{c(f)t} + \sum_k \theta_k D^k_{ft} + \sum_k \beta_k (D^k_{ft} \times \text{Trademark Buyer}_f) + \varepsilon_{ft}, \qquad (3)$$

[10] For value of production, employment, and year of firm birth, we match based on discrete binned categories.

[11] This restriction excludes, among others, transactions where the buyer firm is created in the year of acquisition, possibly inheriting part of its initial workforce from the seller. We interpret such cases as firm reorganizations rather than true transfers of trademark ownership.

Table 2: Summary statistics on trademark buyers and matched controls, measured on the year before the acquisition event

	Buyers		Matched controls	
	Mean	Median	Mean	Median
Panel A: Variables used in matching				
Employment	195.36	18.00	120.29	18.00
Emp. growth	0.09	0.00	0.09	0.00
Value production (in thousands)	11090.00	4826.00	11063.05	4835.00
Val. production growth	0.11	0.04	0.10	0.04
Firm age	15.45	11.00	15.55	11.00
Construction	0.01	.	0.01	.
Manufacturing	0.47	.	0.47	.
Services	0.51	.	0.51	.
Panel B: Main outcome variables				
Intangible capital (in thousands)	337.03	83.00	226.86	31.00
Value added (in thousands)	2261.43	928.50	2237.51	908.00
Weeks worked	6911.54	743.00	4424.60	761.00
Wage bill (in thousands)	4831.80	423.11	2823.83	417.37
Emp. blue-collar	87.77	6.00	65.99	8.00
Emp. white-collar/manager	104.57	8.00	51.35	6.00
Emp. marketing/sales	46.40	3.00	24.44	3.00
Labor share	0.23	0.11	0.17	0.11
N. firms	1910		190266	

Notes: This table presents summary statistics for buyer firms in our sample and their matched controls. Panel A reports the variables used in the matching procedure, while Panel B summarizes the main outcomes analyzed in the paper. Statistics are computed in the year before the treatment ($t_f - 1$). For comparability, control firms are weighted using the same weights applied in the difference-in-differences analysis.

where y_{ft} is the outcome of interest for firm f in year t, α_f are firm fixed effects, $\alpha_{s(f)t}$ are 3-digit sector-by-year fixed effects, $\alpha_{c(f)t}$ are matching cell-by-year fixed effects, k indexes leads and lags with $k \in \{-3, -2, 0, 1, 2, 3\}$, $D^k_{ft} \equiv \mathbf{1}\{t_f = t + k\}$ are event-study indicators with t_f being the year that firm f acquired a trademark (or so did the firm for which f serves as a matched control), Trademark Buyer$_f$ is an indicator equal to one for trademark buyer firms and zero for control firms, and ε_{ft} is an error term. The parameters of interest are β_k, which capture differential trends around the time of purchase for trademark buyers, relative to matched controls on the year before the acquisition. Since a matching cell can contain several treated and control firms, we employ weights ensuring that within each matching cell the total number of treated firms equals the total weighted number of comparison firms. We cluster standard errors at the firm level.

5.3 Identification Assumptions

The parameters $\{\beta_0, \beta_1, \beta_2, \beta_3\}$ in equation (3) capture the dynamic causal effects of the trademark purchase under a parallel trends assumption by which the outcomes of the trademark-buyer firms would have evolved in parallel to those of the matched control firms in the absence of the trademark acquisition. While this assumption is inherently untestable, pre-trend estimates of $\{\beta_{-3}, \beta_{-2}\}$ allow us to assess the plausibility of the identification assumption. Moreover, the richness of our data in terms of size and covariates allows us to match on fine-grained pre-existing characteristics, including measures of time-varying firm size and productivity that our conceptual framework pins down as a key determinant of trademark acquisition.

We argue that the plausibility of the parallel trends identification assumption rests on the timing of the brand capital investment decisions. Threats to identification would arise from unobserved shocks to firms' productivity, product demand, or labor demand that are systematically correlated, within matching cells, with the timing of trademark acquisitions. Building on the notion that trademark exchanges typically involve protracted search, valuation and legal-due-diligence phases that begin well before the transfer date, the necessary identification assumption is that the trademark transfer date is conditionally uncorrelated with the occurrence of unobserved shocks to the firm. Since our matching strategy conditions on the value of production and employment at $t_f - 1$, the decision to invest in a new trademark is plausibly made by $t_f - 1$ and thus unrelated to shocks that materialize in period t_f. This logic mirrors the timing assumption in Olley and Pakes (1996) and related literature, where capital-investment decisions are locked in before current output is realized.

Several features of the context and data support the plausibility of this assumption. The first feature is the institutional setting. As aforementioned, the process of acquiring a trademark typically requires time, beginning with the scouting phase and culminating in the negotiation and finalization of contractual terms. In such a context, conditional on $t_f - 1$ information, it is plausible that trademark investment decisions will be uncorrelated with period t_f shocks. That is, it is arguably plausible that, in most cases, investment choices are locked in prior to the realization of within-period shocks.

Second, our event studies below indicate no evidence of anticipatory effects as trademark buyers are on similar trends relative to their matched controls, with estimates of $\{\beta_{-3}, \beta_{-2}\}$ typically close to or indistinguishable from zero. Moreover, we later discuss placebo tests (Figure A7) showing that our matching strategy does not give rise to issues related to spurious regression to the mean.

Third, the divergence in outcomes occurs precisely at the time of the trademark transfer. Particularly, balance-sheet intangibles rise sharply at the time of the acquisition (Figure 3).

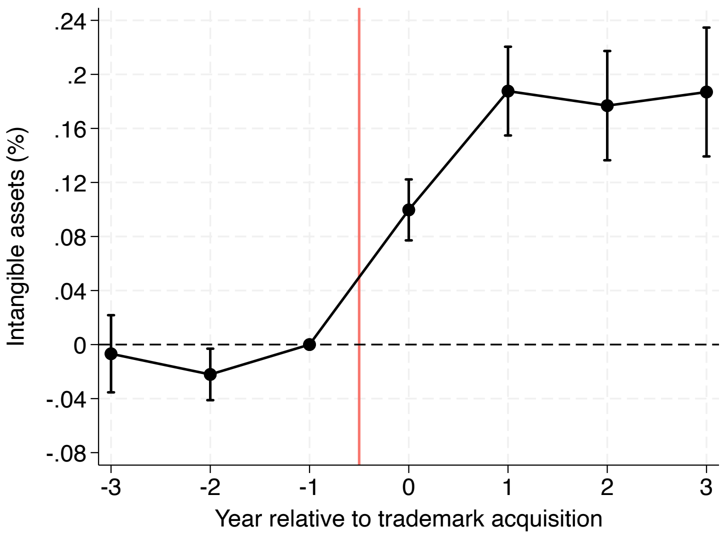
The boost in intangibles stabilizes in period 1, after the transitory period 0. This supports the idea that a sudden, discrete increase in brand capital occurs precisely at the time of the recorded trademark transaction. Additionally, the asymmetric effects we find across different labor types—especially the results on marketing workers—suggest that a brand capital shock is indeed behind the dynamic effects we document.

6 Results

6.1 Trademark acquisition and firm performance

When a firm acquires a trademark, the acquisition cost should be recorded as part of its intangible assets. As a first step in our analysis, we analyze how trademark acquisitions affect the buyer firm's intangible capital. This analysis also works as validation of the accuracy of our new brand-transactions dataset and its merge with firms' balance sheet records.[12]

Figure 3: Effect of Trademark Acquisition on Balance Sheet Intangibles.



Notes: Poisson QML estimates and 95% confidence intervals of parameters β_k in an exponential version of equation (3) when outcome variable is equal to the value of intangible assets that firm f holds on its balance sheet in year t. Standard errors clustered at the firm level.

Figure 3 shows estimates of of β_k from an exponential version of equation (3), with intangible capital as the dependent variable, estimated by Poisson quasi-maximum likelihood (Chen and Roth, 2024). This formulation allows us to capture both intensive- and extensive-margin responses.[13] While pre-acquisition trends align with control firms, trademark buyers experience a post-acquisition increase in intangibles, which stabilizes at approximately

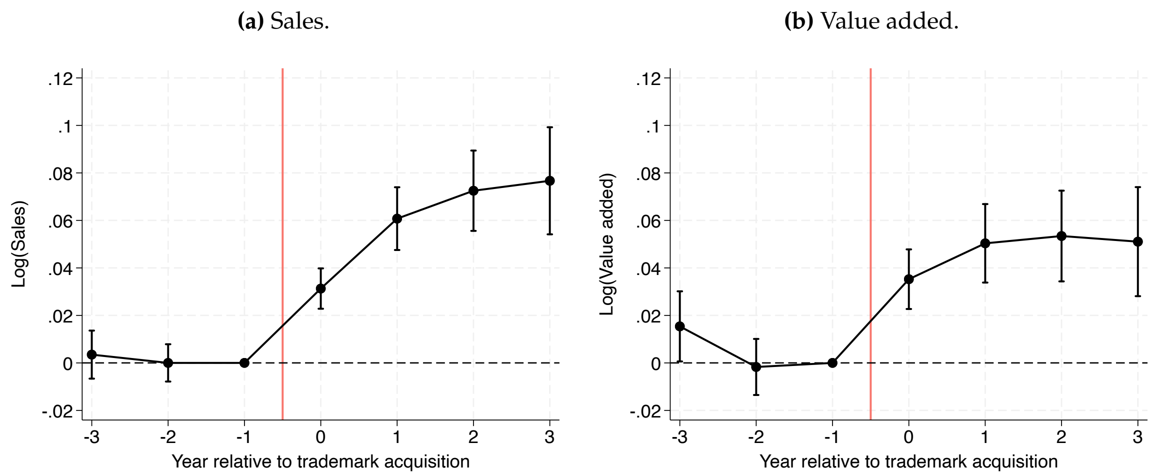
[12]Table A1 summarizes the effects of trademark acquisitions on firm's intangibles and performance.

[13]Figure A1 presents results using a binary indicator for holding strictly positive intangible assets as the dependent variable. Approximately 92% of trademark buyers report positive intangibles before the acquisition, and we estimate an 8 percentage point increase in the likelihood of holding any intangible following the event. This confirms that, after the transaction, virtually all buyers record intangible assets on their balance sheets.

19% higher relative to the counterfactual. The pattern of coefficients—gradual increase in the transition period 0 and stabilized effects in periods 1–3—are consistent with a discrete, one-off purchase of a new trademark that augments book-value intangibles by the purchase amount. This result confirms that the timing of transactions in the trademark registry coincides with discrete changes in the intangibles assets held by firms, which diminishes concerns about our estimated effects being driven by other shocks.

Trademark acquisitions grow firms' sales and value added. Panel (a) of Figure 4 shows that sales rise immediately after the acquisition, stabilizing at approximately 8% above the counterfactual after two years. This suggests that trademark acquisitions are instrumental to expand a firm's customer base. Similarly to the pattern in intangibles, sales take a couple of years to reach their new level. Panel B indicates that this sales growth translates into a medium-run increase in value-added, which rises by about 6%. The next subsection explores the role of labor inputs and wages during this period of trademark-buyers' expansion.

Figure 4: Firm Performance Effects of Trademark Acquisitions: Sales and Value Added



Notes: Estimates and 95% confidence intervals of parameters β_k in equation (3) when outcome variable are sales (left panel) and value added (right panel). Standard errors clustered at the firm level.

6.2 Labor demand responses to a trademark acquisition

Panel (a) of Figure 5 shows that employment rises following a firm's trademark acquisition, with log-employment increasing immediately after the event and peaking at approximately 5–6 log-points above the baseline after three years.[14] To determine whether this growth involves temporary or unstable jobs, in Appendix Figure A2 we analyze the employment of different contract types and find that the employment increase is primarily driven by permanent and full-time workers, whose employment increases by nearly 6% and 5% respectively, while the shares of these types of contracts out of total employment

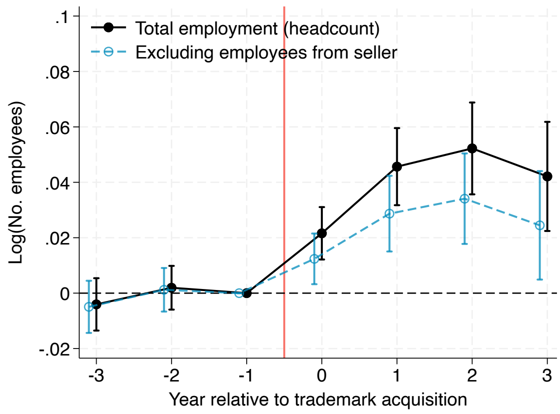
[14] Appendix Table A2 summarizes the effects acquiring a trademark on firm labor outcomes.

remain stable. This indicates that the firm's expansion generates a significant number of stable jobs and that the firm's contract mix is not affected by the employment expansion.

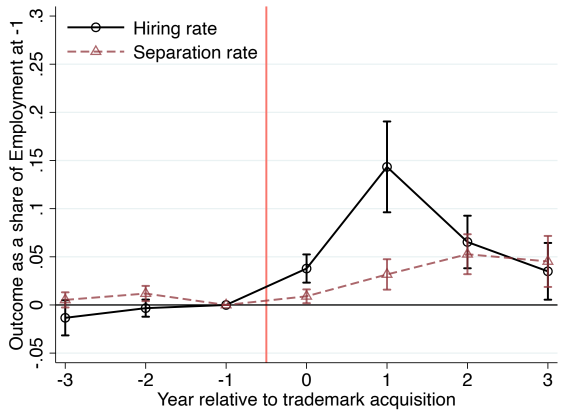
Seller-to-Buyer employee moves? The worker-level panel dataset allows us to explore whether and to what extent the observed increase in employment is driven by poaching workers from the trademark-selling firm. To this end, we examine log-employment excluding workers who were previously employed by the seller. Comparing the two event studies in Panel (a) of Figure 5 reveals that employment grows by about 4%, rather than 6%, when former seller-firm employees are excluded. This suggests that most of the employment growth is not driven by seller-firm former workers, a finding that the transaction-level analysis below corroborates. Nevertheless, the inflow of seller-firm employees is non-trivial and reminiscent of recent evidence illustrating the job mobility across firms within production networks (Cardoza et al., 2024). To the extent that there exists human-capital specificity associated with brands, similar mechanisms as in Cardoza et al. (2024) could be at play also in this context. The characteristics of movers are consistent with this interpretation. Appendix Table A3 reports summary statistics for seller-to-buyer movers after trademark acquisitions. As a comparison group, we consider employees leaving matched control seller firms over the same period, selected applying the procedure described in Section 5.1 to sellers. Relative to the employees who leave control firms, movers are older, more likely to hold permanent and full-time contracts, and more concentrated among blue-collar workers and in occupations unrelated to marketing and sales. These occupational differences cannot be attributed to the industry mix, since sellers and controls are matched on their macro-sector, which guarantees a balanced sectoral composition across the two groups. Taken together, these patterns suggest that buyer firms may be acquiring production-related know-how to support the introduction of new product lines into their portfolios.

Figure 5: Labor Demand Effects of Trademark Acquisitions

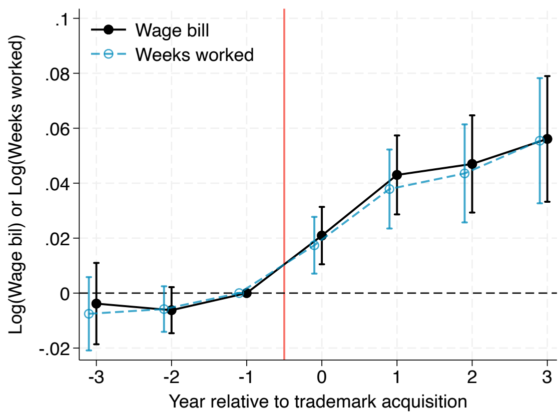
(a) Employment (headcount).



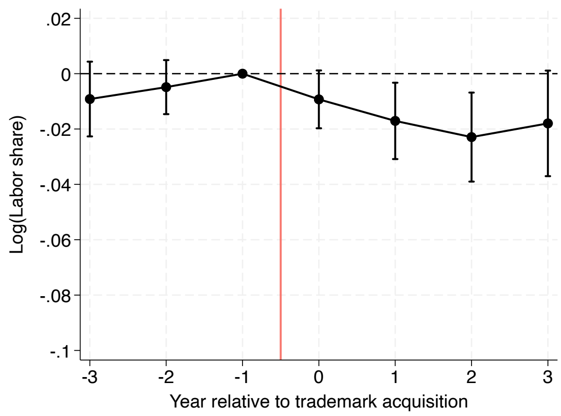
(b) Margins of employment adjustment.



(c) Wage bill and employment (weeks worked).



(d) Labor share.



Notes: Estimates and 95% confidence intervals of parameters β_k in equation (3) for the following outcome variables. Panel (a): log total number of employees and log number of employees excluding workers who were previously working at the trademark seller firm. Panel (b) Employment growth: number of employees/number of employees in year t_f-1; hiring rate: number of new hires/number of employees in year t_f-1; separation rate: number of separations/number of employees in year t_f-1. Panel (c): log wage bill and log total weeks worked at the firm. Panel (d): log labor share (wage bill/sales). Standard errors clustered at the firm level.

Employment churn. We examine the components driving the employment expansion by decomposing employment changes into hiring and separation margins. Specifically, we measure the change in employment relative to the pre-acquisition year and define hiring and separation rates as the number of hires and separations normalized by pre-acquisition employment. This normalization allows us to compare the magnitudes across outcomes and deal with cases of zero hires and separations. Panel (b) reveals that a substantial share of employment growth stems from increased hiring. In the first two years post-acquisition, cumulating the estimated coefficients we find that the rise in new hires is equivalent the total increase in employment. Over a longer horizon, hires exceed the overall employment increase. This is because the separation rate also rises so that total separations account for roughly half of the employment increase. These patterns suggest that firms increase hiring in the years immediately following a trademark acquisition to adjust to their new scale of operations. This expansion is accompanied by substantial worker turnover, which becomes more pronounced in the medium to long run, as firms stabilize at a higher level of employees' churning. This suggests that a workforce reorganization continues for several years after the acquisition.

Wage bill and labor share. Panel (c) in Figure 5 shows that the wage bill increases in line with employment, rising by approximately 5–6%. Similarly, the total number of weeks worked closely mirrors the growth in the wage bill, suggesting that average earnings per week of work remain stable and unaffected by the trademark acquisition. This is further supported by Figure A3, which shows no significant changes in the wage bill per week of work of incumbents nor stayers.[15]

Comparing the 5–6% increase in the wage bill to the approximately 8% rise in sales (Figure 4) suggests that the buyers' labor share declines following a trademark acquisition. This finding is confirmed in Figure 5, Panel (d), where we use the buyer's log labor share as the dependent variable.[16] The labor share declines monotonically following the trademark acquisition, with a drop of up to two percent in period 3. Thus, while the total wage bill rises, it does so at a slower rate than total sales, leading to a smaller share of firm revenues allocated to labor. This is consistent with the prediction of our model. We further interpret this result as micro-level evidence of the mechanism proposed by De Loecker et al. (2020), which suggests that an increase in a firm's product market share can drive a decline in its labor share of sales.

Discussion and additional evidence. Our evidence indicates that trademark acquisitions play an important role in allowing firms to expand their scale of operations. As a result, we observe a significant increase in total employment. Firms that acquire trademarks hire more workers but also experience greater turnover. Importantly, this expansion in employment does not translate into higher average earnings. At the same time, the decline in the labor share suggests that trademark acquisitions allow firms to capture additional revenues without proportionally increasing worker compensation, consistent with the view that brand capital enhances the firm's product market power.

Further evidence of rising markups comes from intermediate inputs. Among the subset of firms reporting raw material expenditures, we find a significant increase in raw materials following a trademark acquisition (Figure A5). Yet this increase is systematically smaller than the corresponding rise in sales. Raw materials rise by around 4.5%, while sales in the same group of firms increase by more than 5.5%. As a result, the share of raw materials in total sales declines. Assuming firms are price-takers in input markets, this pattern is

[15] Incumbents are defined as employees who were employed in the buyer firm in the pre-acquisition year (regardless of whether they remain in the firm or not), while stayers are those who remain at the firm throughout the analysis period.

[16] Following the literature, we define a firm's labor share as wage bill over sales, as value added can be negative for some observations, making the outcome undefined. Figure A4 shows results for labor share in levels rather than logs.

consistent with higher markups (De Loecker et al., 2020).

Despite this evidence of expansion and growing market power, we do not observe major shifts in firms' input mix. The cost shares of capital, labor, and raw materials remain virtually unchanged before and after a trademark acquisition (Figure A6). This stability suggests that the production technology itself is not substantially altered. Instead, firms operate with similar input proportions but on a larger scale and under an increased market power.

Robustness: Placebo event-studies. We asses the robustness of our empirical strategy using a placebo analysis. Following our conceptual framework, in our analysis we match firms based on covariates reflecting pre-transaction performance. A potential concern is that this approach could introduce mechanical mean reversion. To address this, we conduct placebo event studies by randomly assigning trademark transaction events across firms, matching the placebo buyer firms to a control group using the same covariates, and analyzing the performance outcomes discussed above. Repeating this process multiple times, we construct confidence intervals for the average treatment effects using the empirical distribution of the point estimates. As shown in Figure A7, all performance outcomes pass the placebo test, exhibiting zero treatment effects after the placebo transaction. These findings mitigate potential concerns about mean reversion influencing some of our results.

6.3 Effects on transacting parties as a whole

We evaluate whether trademark transactions improve efficiency by jointly analyzing outcomes for buyers and sellers. To estimate the aggregate effects, we sum outcomes across all firms involved in each transaction. The transaction-level comparison group is constructed by aggregating the matched control firms for both buyers and sellers.[17] We restrict the sample to transactions where buyers are observed throughout the pre-period. To make the transaction-level results as comparable as possible to the ones for buyers, we reweight each transaction based on the number of buyers involved.[18]

Our model predicts that trademark transactions should boost aggregate sales and value added for the firms involved. Consistent with this, Figure 6 shows that sales at the transaction level increase by up to 13% (Panel (a)).[19] Value added follows a similar trajectory, rising by 6%, although our estimates are less precise (Panel (b)). Complementing this, Figure A9 reports a separate analysis of trademark sellers, showing a decline in sales and value added, with only partial recovery over the longer run. However, these losses are not large enough to offset the gains realized by buyers.

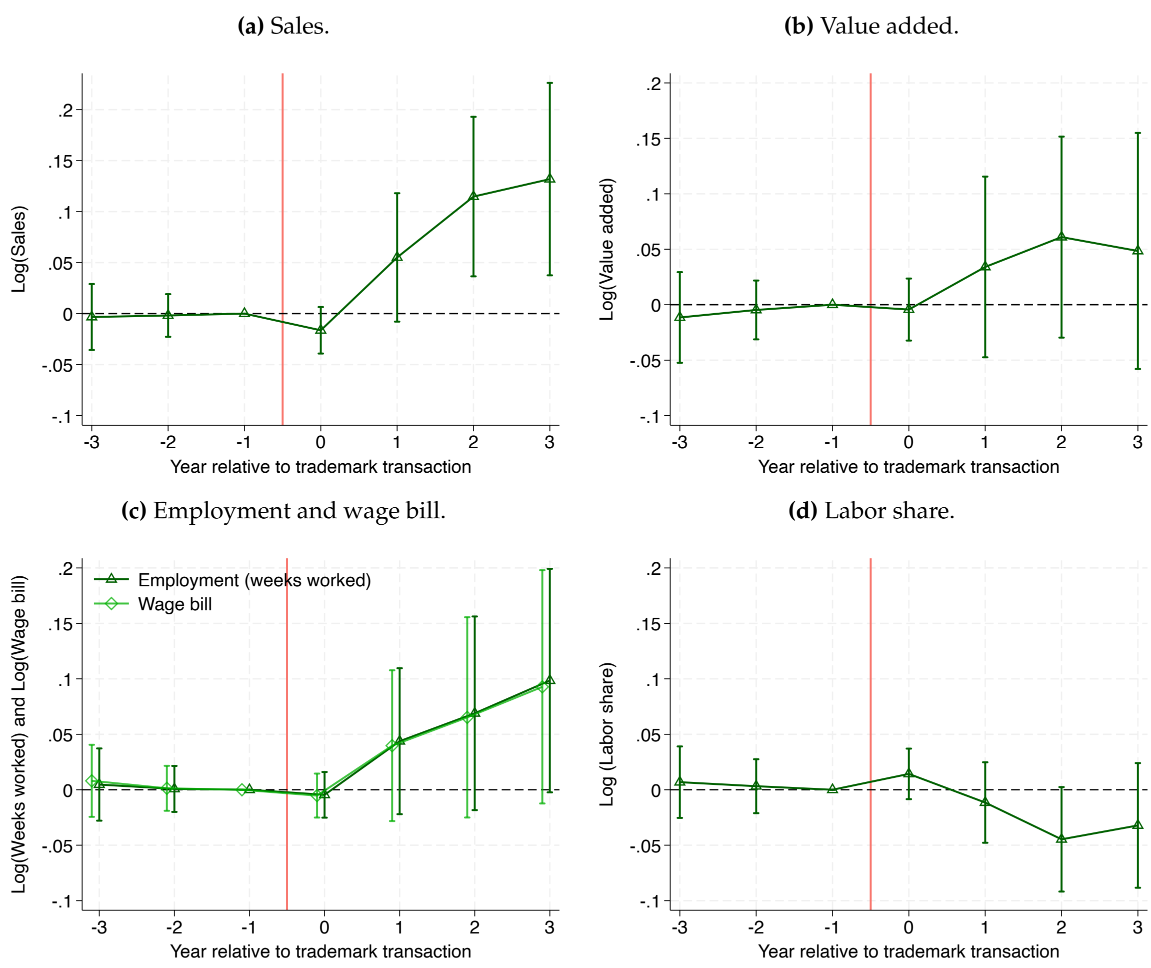
[17] Because transactions may involve multiple buyers and sellers, we cannot include matching-cell fixed effects in the transaction-level analysis. Instead, we control for non-parametric trends in the matching variables.

[18] Specifically, each buyer receives a weight of one per event year. If a buyer is involved in multiple simultaneous transactions (often times a brand acquisition involves more simultaneous transactions), we assign weight $1/NT_i$, where NT_i is the number of transactions buyer i participates in during the event year. Control transactions are weighted accordingly to ensure that the sum of control weights matches the total number of buyers in each matching cell.

[19] Table A4 summarizes the effects of brand transactions on all transaction-level outcomes.

Moving to labor outcomes, we find that total employment among the firms involved rises by 6% on average (Panel (c)), suggesting that trademark transactions create jobs on net by reallocating brand capital to more productive firms. The aggregate wage bill displays a similar increase.[20] The wage bill grows less than sales, leading to a decrease in the aggregate labor share of about five percent (Panel (d)).[21] This pattern mirrors the buyer-level results and highlights that while trademark transactions enhance firm performance, the gains are not fully passed on to labor. Instead, the reallocation of brand capital amplifies revenue concentration and might contribute to a declining labor share.

Figure 6: Trademark Transactions: Transaction-Level Effects



(a) Sales. **(b)** Value added. **(c)** Employment and wage bill. **(d)** Labor share.

Notes: Event-study estimates and 95% confidence intervals of the transaction-level effect of a trademark transaction, aggregating the outcomes of seller and buyer firms. The comparison group results from the aggregation of matched controls for buyer and seller firms. Standard errors clustered at the transaction level.

[20] Employment and the wage bill decline for sellers, but not enough to offset buyers' gains (Figure A9).

[21] Figure A8 shows results using labor share in levels rather than logs.

6.4 Skilled-biased brand capital? Heterogeneity in labor demand effects

Our conceptual framework differentiates between production and expansionary labor. Brand capital is expected to primarily boost employment engaged in tasks related to market expansion, such as reaching new consumers and brand management, while production employment is less likely to be affected. We test this prediction by employing alternative definitions of production and expansionary labor. First, we exploit the universal coverage of our data on worker's qualifications to identify blue-collar employees as *production labor*, given their proximity to production facilities. Conversely, we classify white-collar employees and managers—whose tasks are more closely tied to marketing and sales—as *expansionary labor*.

We then leverage information on workers' occupations, which offers more detailed classifications but covers only a subset of the workforce, albeit a large one. Using this information, we isolate the subset of the workforce of a firm employed in sales- and marketing-related tasks.[22] We first compare this group to the rest of white collar workers and to blue collar workers. We then simply compare marketing-sales workers to all other workers. To explore the heterogeneity between the various groups of labor, we employ a triple-differences extension of equation (3) on the subsample of firms with at least one employee in each worker group in the pre-acquisition year.[23]

Figure 7 summarizes the heterogeneity in labor demand effects by showing averages of post-effects parameters $\{\beta_0, \beta_1, \beta_2, \beta_3\}$ in equation (3), estimated heterogeneously by worker type.[24]

White-collar and managers vs Blue-collar: The left segments in each of the two panels of Figure 7 show that the employment growth following a trademark acquisition is primarily driven by white-collar workers and managers, whose employment and wage bill increases by approximately 3–3.5%. In contrast, there is no effect on the employment of blue-collar workers as the estimates for this group are close to zero and non-significant. This pattern aligns with the idea that trademark acquisitions facilitate reaching new consumers, prompting firms to expand their ranks of workers engaged in such expansionary tasks.

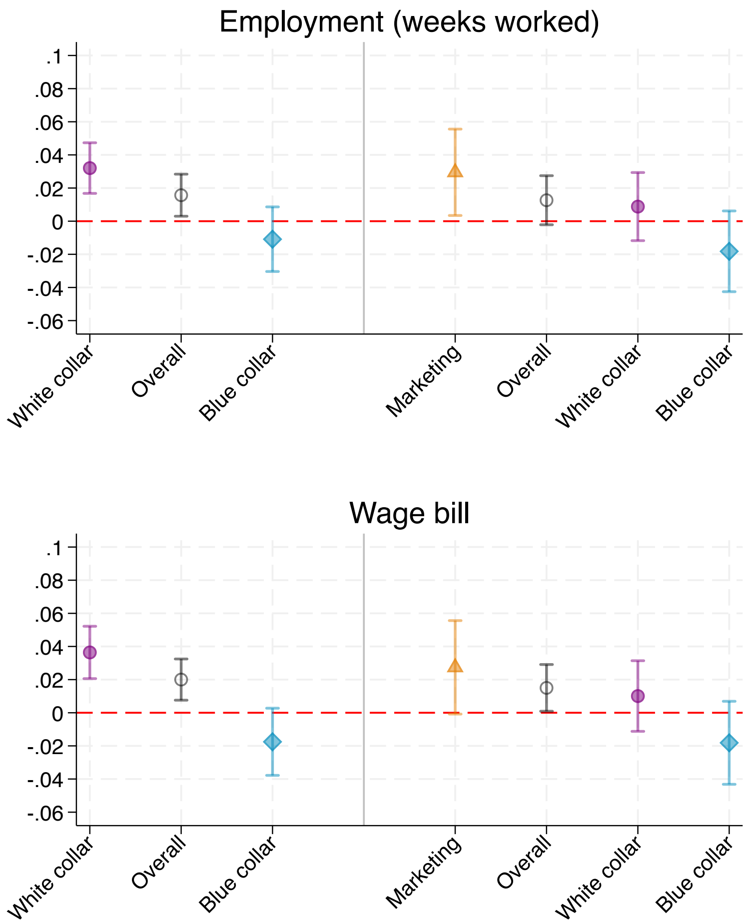
Marketing and sales employees: We next focus on the subset of white-collar workers and managers employed in marketing and sales occupations. The right segments in each of the two panels of Figure 7 show that the increases in white-collar employment and wage bill are concentrated among this group, whose tasks are most directly tied to reaching new consumers. Employment and wage bill in marketing and sales rise by about 3%. In contrast, we observe only a small and non-significant increase for other white-collar employees. This pattern provides further evidence that brand capital is complementary to *expansionary labor*.

[22] See Appendix B.2 for a detailed outline of the occupations included in this group.

[23] Table A5 summarizes the heterogeneous effects of acquiring a trademark across subgroups of the buyers' workforce.

[24] Figure A10 shows the underlying dynamic estimates.

Figure 7: Labor Demand Effects of Trademark Acquisition: Heterogeneity by Worker Type.



Notes: Estimates and 95% confidence intervals of the average of post-effects parameters $\{\beta_0, \beta_1, \beta_2, \beta_3\}$ in equation (3), estimated heterogeneously by worker type. Outcome variables are log total employment (weeks worked) and log wage bill, in the top and bottom panels, respectively. Each panel shows separate estimates from two different dimensions of heterogeneity. First, white-collar vs. blue-collar workers. Second, workers who are ever employed in a marketing/sales occupations, white-collar workers excluding marketing/sales, and blue-collar workers excluding marketing/sales. Each panel also shows the overall average post-effect estimated among the subset of firms that enter each of the two different heterogeneity analyses (e.g., in the left panels, firms that employ both white- and blue-collar workers). Standard errors clustered at the firm level.

Hypothesis testing—Employment
1. t-stat(white collar = blue collar) = 4.08
2. t-stat(marketing = blue collar) = 3.45 ; t-stat(marketing = white collar) = 1.41 ; t-stat(blue collar = white collar) = 2.04

Hypothesis testing—Wage bill
1. t-stat(white collar = blue collar) = 4.97
2. t-stat(marketing = blue collar) = 2.99 ; t-stat(marketing = white collar) = 1.13 ; t-stat(blue collar = white collar) = 2.05

Discussion on labor demand heterogeneity. The heterogeneity analysis shows that the labor demand effects of trademark acquisitions are not skill-neutral. The strongest expansions occur among white-collar workers, particularly in marketing and sales occupations. This pattern indicates that trademarks and brand capital mainly affect the product marketing stage rather than the production one. In other words, acquiring a trademark expands the firm's ability to reach and attract consumers, rather than significantly changing how goods are produced.

There are implications for labor market inequality following from this result. We do not observe large changes in wages across groups, so inequality is not affected through a modification of rent sharing within the firm. Instead, inequality might increase through changes in the employment composition. The expansion of jobs after trademark acquisitions disproportionately benefits white-collar employees in marketing and sales, creating more stable positions for these groups who are paid on average more than the rest of the workforce. However, this expansion is the outcome of increased churn: hiring rises, but so do separations, meaning that the firm growth that follows brand-capital investment is accompanied by the separation of some incumbent workers.

For blue-collar workers, the net employment effect is close to zero, but the matched employer–employee data reveal that the net zero masks some important dynamics. We see higher rates of both hiring and separations, showing that blue-collar workers also experience heightened turnover even though their overall employment level is stable. In addition, some of the new hires are drawn from the trademark seller firm, suggesting that part of the adjustment takes place through poaching of experienced blue-collar workers rather than through new labor market entrants or employees from other firms.

7 Conclusion

This paper documents the effects of brand capital on labor demand. Our approach consists of leveraging shifts to hard-to-measure brand capital induced by firm-to-firm trademark transactions. We find that acquiring a trademark significantly increases a firm's intangible assets, boosts revenues and value added, and raises employment and the wage bill. However, despite the growth in sales and value added, wages remain largely unaffected at the individual level. The total wage bill grows less than proportionately relative to sales, leading to a decline in the firm's labor share. Overall, trademark transactions facilitate a reallocation of brand capital that enhances the aggregate performance of all parties involved. Additionally, trademark acquisitions are not skill-neutral and primarily benefit the types of labor they complement, which are those closely tied to market expansion. Employment and wage bills rise for white-collar employees and managers, particularly those in marketing and sales roles. As a result, within-firm inequality increases.

While most research on the economic consequences of intangible capital has centered on cost-side innovations such as patents or software, our analysis suggests that demand-side intangibles such as brand capital can operate through distinct channels. In particular, brand capital primarily affects the composition of the workforce by boosting expansionary labor, rather than increasing wages. This contrast underscores the importance of distinguishing between cost-side and demand-side sources of firm value and their effects on labor. As intangible assets continue to grow in relevance, it becomes important to develop a fine-tuned understanding of how different types of such inputs lead to differing labor demand mechanisms, effects on different types of workers, and their ultimate impact on the level of inequality and efficiency in the labor and product markets as a whole.

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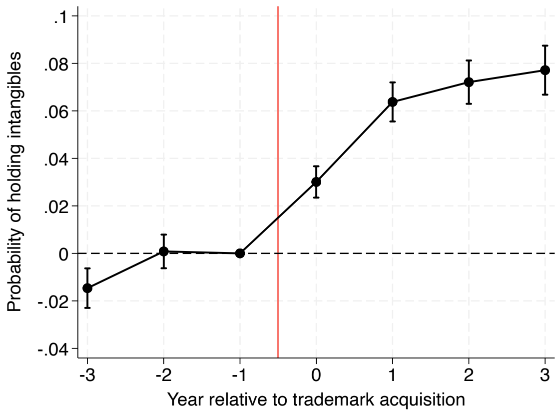
- SUPPLEMENTARY APPENDICES -
For Online Publication Only

A Additional Figures and Tables

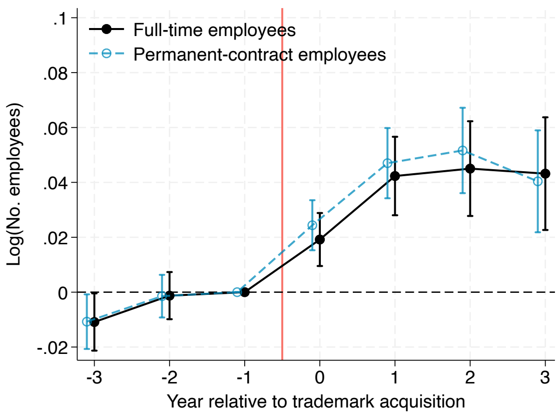
Figure A1: Effect of Trademark Acquisitions on Balance Sheet Intangibles (Extensive Margin).



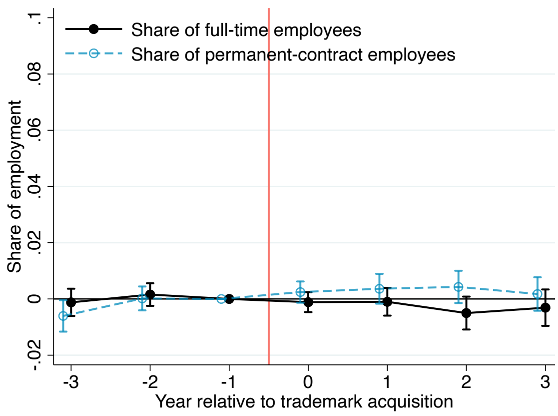
Notes: Estimates and 95% confidence intervals of parameters β_k in equation (3) when outcome variable is a dummy variable equal to one if firm f in year t held strictly positive intangible assets on its balance sheet. Standard errors clustered at the firm level.

Figure A2: Effect of Trademark Acquisitions on the Firm's Contract Mix

(a) Full-time and permanent-contract employees



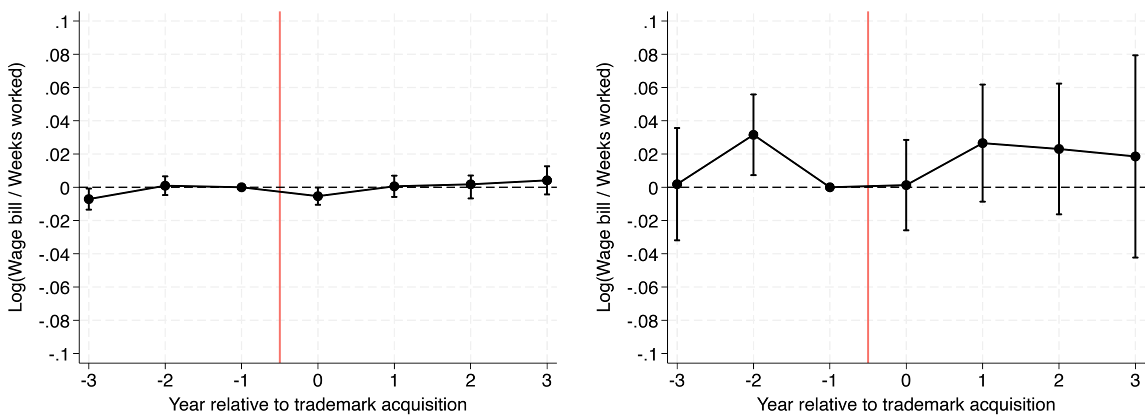
(b) Empl. shares of full-time and permanent contracts



Notes: Estimates and 95% confidence intervals of parameters β_k in equation (3) for the following outcome variables. Panel (a): Full-time employees and permanent-contract employees. These two outcome variables are expressed in logs. Panel (b): Share of total employment with permanent or full-time contracts. We define these shares using headcounts of employees present in the firm. Standard errors clustered at the firm level.

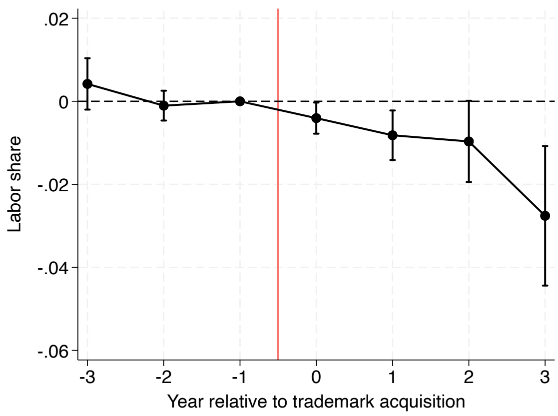
Figure A3: Effect of Trademark Acquisitions on Incumbents and Stayers: Wage Bill Over Weeks Worked.

(a) Incumbents. **(b)** Stayers.



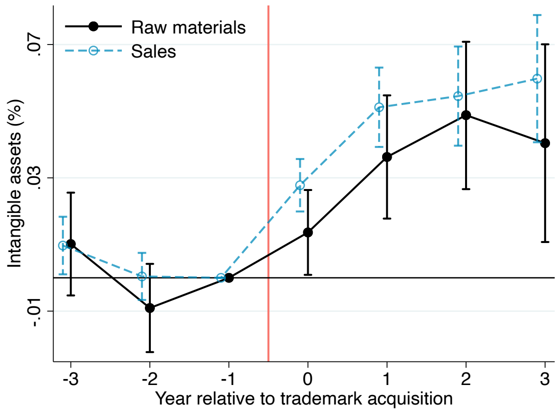
Notes: Estimates and 95% confidence intervals of parameters β_k in equation (3) when outcome variable is the log of wage bill over weeks worked. Left panel: the outcome is defined for incumbent workers, i.e. permanent and full-time employees at the buyer firm at the time of the trademark acquisition. The outcome is measured across all firms where the incumbents work, buyer firm or elsewhere. Right panel: the outcome is defined for the employees who remain at the buyer firm throughout the event window. Hence, it only considers earnings and weeks worked at the buyer firm for workers who were already employed there before the trademark acquisition. Standard errors clustered at the firm level.

Figure A4: Effect of Trademark Acquisitions on Labor Share (Levels).



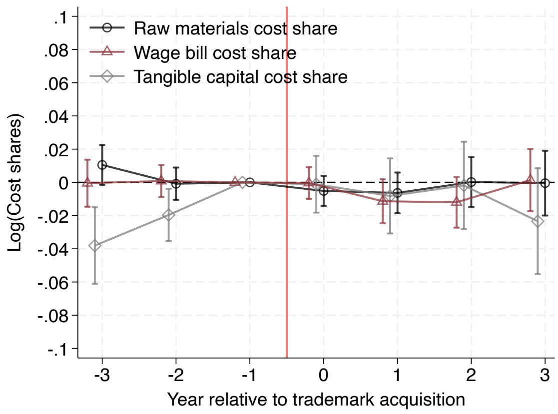
Notes: Estimates and 95% confidence intervals of parameters β_k in equation (3) when outcome variable is the labor share (wage bill/sales) of firm f in year t. Standard errors clustered at the firm level.

Figure A5: Effect of Trademark Acquisition on Raw Materials.



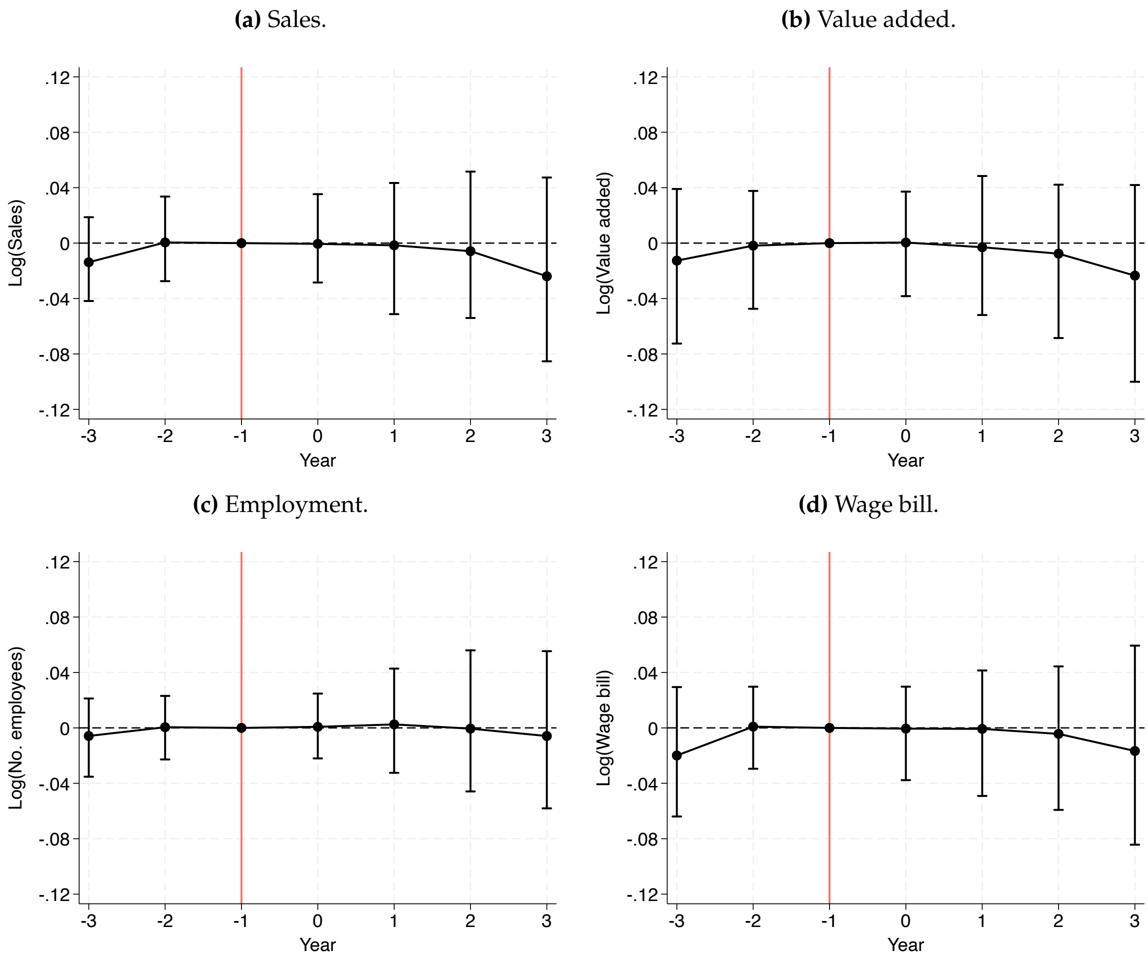
Notes: Estimates and 95% confidence intervals of parameters β_k in equation (3) when outcome variable is the log of raw materials of firm f in year t. We restrict the sample to the firms that report positive raw materials. To study the consequences of trademark transactions on the raw material share of revenues, we also report the results of the same specification using log-sales as an outcome on the same sub-sample of firms. Standard errors clustered at the firm level.

Figure A6: Effect of Trademark Acquisitions on Cost Shares.



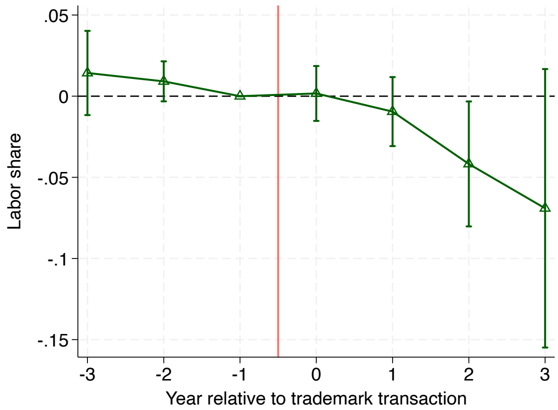
Notes: Estimates and 95% confidence intervals of parameters β_k in equation (3) when outcome variables are the log cost shares of firm f in year t. Outcomes are defined as log(cost of input k/total costs), where k is raw materials, wage bill, or tangible capital. Standard errors clustered at the firm level.

Figure A7: Placebo Trademark Transactions



Notes: This Figure shows the placebo regressions where we randomly assign trademark transaction events across firms, matching the placebo buyer firms to a control group using the same covariates discussed in Section 5 and estimating equation (3) with the newly assigned treatment. Repeating this process multiple times, we construct confidence intervals for the average treatment effects using the 2.5th and the 97.5th percentiles of empirical distribution of the point estimates. The various panels show the main outcomes discussed in Section 6.1.

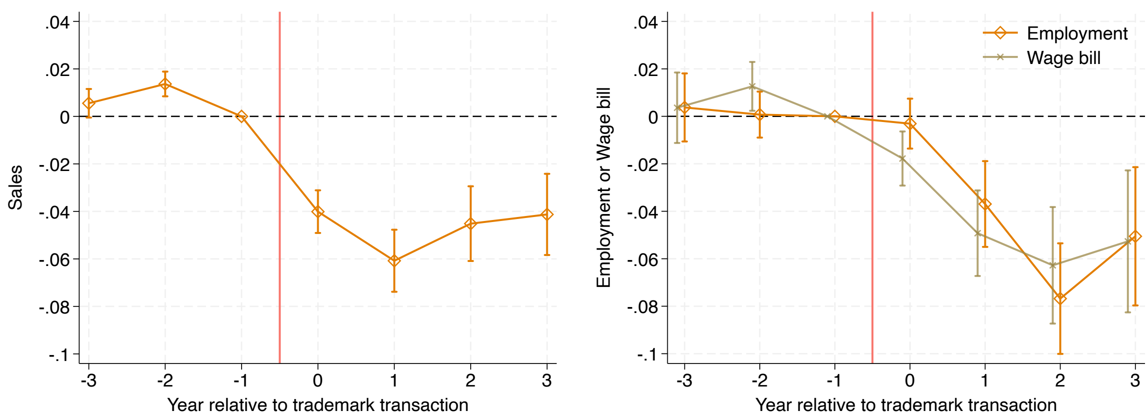
Figure A8: Transaction-Level Effects: Labor Share (Levels).



*Notes:*Event-study estimates and 95% confidence intervals of the transaction-level effect of a trademark transaction, aggregating the outcomes of seller and buyer firms. The comparison group results from the aggregation of matched controls for buyer and seller firms.

Figure A9: Trademark Transaction: Seller Effects

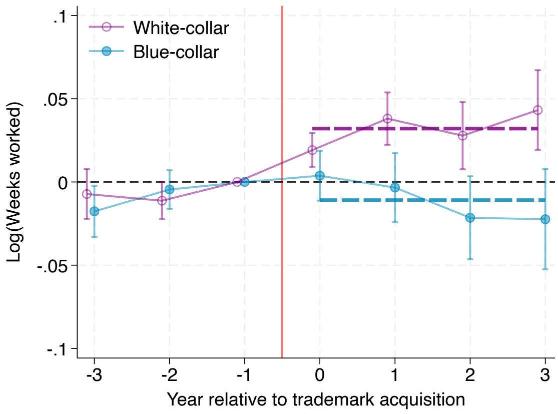
(a) Sales. **(b)** Employment and wage bill.



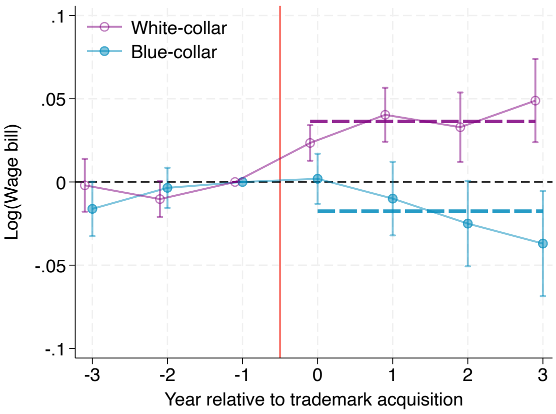
Notes: Event-study estimates and 95% confidence intervals of the effect of selling a trademark for seller firms. Poisson QML estimates of parameters β_k in an exponential version of equation (3) where treatment is defined as selling a brand. Standard errors clustered at the firm level.

Figure A10: Labor Demand Effects of Trademark Acquisitions, Heterogeneity by Worker Type: Employment and Wage Bill

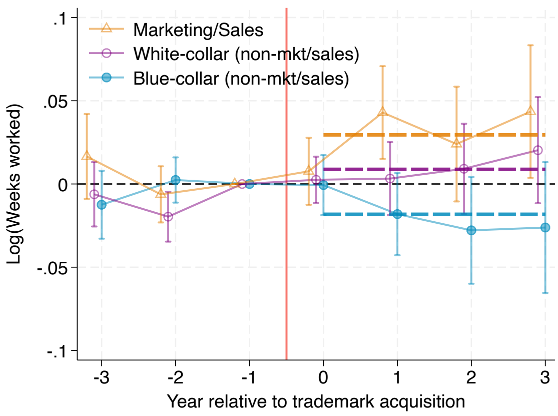
(a) Employment: Blue-collar vs. white-collar.



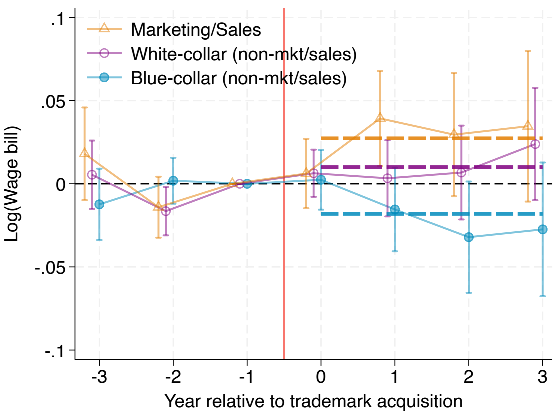
(b) Wage bill: Blue-collar vs. white-collar.



(c) Employment: Marketing and sales workers vs. others.



(d) Wage bill: Marketing and sales workers vs. others.



Notes: Estimates and 95% confidence intervals of parameters β_k in equation (3), estimated heterogeneously by worker type. Top panels separate between white-collar and blue-collar workers. Bottom panels separate between workers who are ever employed in a marketing/sales occupations (Marketing/Sales), white-collar workers excluding marketing/sales, and blue-collar workers excluding marketing/sales. Outcome variables are log total employment (weeks worked) and log wage bill. Horizontal lines indicate the average of post-acquisition, period-specific effects. Standard errors clustered at the firm level.

Table A1: The Effects of Acquiring a Trademark on Firm Performance

Panel A: Firm Performance			
	Intangibles (1)	Sales (2)	Value-added (3)
$\bar{\beta}_k$	0.150***	0.060***	0.048***
	(0.014)	(0.007)	(0.007)
Obs.	2,922,422	3,149,664	2,557,860
N. firms	173,185	192,171	162,714

Notes: This Table summarizes the effects of acquiring a trademark on firm performance. The reported coefficient $\bar{\beta}_k$ is an average among the post-transaction coefficients (*i.e.*, β_k for $k \in (0,3)$) in equation (3). We estimated the regression in column (1) through a Poisson regression to account for firms that do not hold any intangibles. All other outcomes are expressed in logs. The regression on Intangibles has fewer observations since the Poisson estimator drops some singletons. The regression on Value-Added (column 3) has fewer firms since we exclude those that have negative value-added in at least one period. Each matched control cell is weighted by the number of buyer firms in the same cell. We report the mean of the dependent variable (in levels) among controls in the year before the transaction occurred (Mean dep. var.). "N. firms" reports the number of distinct firms (treated and control ones) in the estimation sample. Standard errors clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A2: The Effects of Acquiring a Trademark on Firm Labor Demand

	Employment (1)	Emp. (excl. seller) (2)	Emp. Full-time (3)	Emp. Permanent (4)	Tot. Weeks (5)	Wage Bill (6)	Labor Share (7)
$\bar{\beta}_k$	0.040***	0.025***	0.037***	0.041***	0.039***	0.042***	-0.017***
	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)
Obs.	3,149,664	3,149,664	1,963,341	2,738,273	3,149,186	3,149,664	3,149,664
N. firms	192,171	192,171	138,350	178,125	192,171	192,171	192,171

Notes: This Table summarizes the effects of acquiring a trademark on firm labor outcomes. The reported coefficient $\bar{\beta}_k$ is an average among the post-transaction coefficients (*i.e.*, β_k for $k \in (0,3)$) in equation (3). All outcomes are expressed in logs. The outcome "Emp. (excl. seller)" (Column 2) subtracts from total employment the employees that appeared in the selling firm before the transaction occurred. Each matched control cell is weighted by the number of buyer firms in the same cell. We report the mean of the dependent variable (in levels) among controls in the year before the transaction occurred (Mean dep. var.). "N. firms" reports the number of distinct firms (treated and control ones) in the estimation sample. Standard errors clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A3: The Characteristics of Seller-to-Buyer Movers

Variable	Movers (1)	Control Movers (2)
Age	40.10	38.85
Full Time	0.89	0.76
Permanent	0.87	0.75
Tenure	0.64	0.64
Blue-collar	0.54	0.47
White-collar/Manager	0.46	0.53
Marketing/Sales	0.23	0.43
No Marketing/Sales	0.77	0.57
N	10666	803930

Notes: This table reports the characteristics of the average employee who moves from a seller to a buyer firm following a trademark acquisition (column (1)). For comparison, column (2) presents the characteristics of employees leaving matched control firms over the same period. Control firms are selected by applying the procedure described in Section 5.1 to seller firms.

Table A4: The Aggregate Effects of a Trademark Transaction

	Sales (1)	Value-Added (2)	Tot. Weeks (3)	Wage Bill (4)	Labor share (5)
$\bar{\beta_k}$	0.071**	0.035	0.052	0.048	-0.017
	(0.030)	(0.033)	(0.032)	(0.033)	(0.017)
Obs.	5,574	3,796	5574	5,574	5,574
N. of transactions	860	592	860	860	860

Notes: This Table summarizes the aggregate effects of a trademark transaction on firm performance and labor outcomes. The unit of analysis is the single transaction and outcomes are aggregated among all the buyers and sellers involved. Control transactions are built by aggregating outcomes across all matched controls in the same matching cells of the buyers and sellers involved. The regression in column (2) has fewer transactions sine we exlude those that report a negative value-added in at least one year. The reported coefficient $\bar{\beta_k}$ is an average among the post-transaction coefficients (*i.e.*, β_k for $k \in (0, 3)$) in equation (3). All outcomes are expressed in logs. We report the mean of the dependent variable (in levels) among control transactions in the year before the transaction occurred (Mean dep. var.). "N. of transactions" reports the number of distinct transactions (treated and control ones) in the estimation sample. Standard errors clustered at the transaction level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A5: The Effects of Acquiring a Trademark on Firm Labor Demand: Heterogeneous Effects

Panel A: Blue-collar VS White-collar/Managers		
	Tot. Weeks	Wage Bill
	(1)	(2)
$\bar{\beta_k}^{\text{BC}}$	-0.011	-0.018*
	(0.010)	(0.010)
$\bar{\beta_k}^{\text{WCMNG}}$	0.032	0.036***
	(0.008)	(0.008)
T-stat $\bar{\beta_k}^{\text{BC}} - \bar{\beta_k}^{\text{WCMNG}}$	-4.079	-4.967
Obs.	538,367	538,454
N. firms	26,809	26,809

Panel B: Blue-collar VS White-collar/Managers VS Marketing/Sales		
	Tot. Weeks	Wage Bill
	(1)	(2)
$\bar{\beta_k}^{\text{BC}}$	-0.018	-0.018
	(0.012)	(0.013)
$\bar{\beta_k}^{\text{WCMNG}}$	0.009	0.010
	(0.010)	(0.011)
$\bar{\beta_k}^{\text{MKTSL}}$	0.030**	0.027*
	(0.010)	(0.011)
T-stat $\bar{\beta_k}^{\text{MKTSL}} - \bar{\beta_k}^{\text{WCMNG}}$	1.409	1.131
T-stat $\bar{\beta_k}^{\text{MKTSL}} - \bar{\beta_k}^{\text{BC}}$	3.452	2.991
Obs.	538,367	538,454
N. firms	10,488	10,488

Notes: This Table summarizes the effects of acquiring a trademark on firm labor outcomes investigating the heterogeneous effects across subgroups of the firm workforce. The reported coefficients $\bar{\beta_k}$s are an average among the post-transaction coefficients (*i.e.*, β_k for $k \in (0,3)$) in an augmented version of equation (3) that allows for heterogeneous effects for subgroups of employees. We use the following definitions: BC is blue-collar, WCMNG is white-collar/managers, MKTSL is marketing/sales. Panel A studies the heterogeneous response across blue-collars and white-collar/managers on the sample of firms with at least one employee in both groups before the transaction event. In Panel B, we exclude from blue-collars and from white-collar/managers the employees in marketing or sales occupation, and we restrict the sample to firms that employed at least one worker in each of the three subgroups. All outcomes are expressed in logs. We report the t-statistics of the test with null hypothesis $\bar{\beta_b}^{\text{BC}} = \bar{\beta_b}^{\text{WCMNG}}$ in Panel A, and the two tests with null hypotheses $\bar{\beta_b}^{\text{MKTSL}} = \bar{\beta_b}^{\text{WCMNG}}$ and $\bar{\beta_b}^{\text{MKTSL}} = \bar{\beta_b}^{\text{BC}}$ in Panel B. Each matched control cell is weighted by the number of buyer firms in the same cell. We report the mean of the dependent variable (in levels) among controls for each subgroup of employees in the year before the transaction occurred (Mean dep. var.). "N. firms" reports the number of distinct firms (treated and control ones) in the estimation sample. Standard errors clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

B Data Appendix

B.1 Trademark data cleaning procedure

We clean information on trademark transactions as follows. We start keeping only transactions that are related to exchanges of trademarks that are unrelated to changes in a firm's ownership, and those that occur at the time of mergers and acquisitions. We exclude residual categories of transactions such as those related to liens, donations, and usufruct. We also drop refused and withdrawn transactions that eventually did not lead to changes in the ownership of a trademark.

Since firm SSNs are essential to merge the information on trademark transactions to social security data, we make sure that they are not missing in our data. Specifically, we fill the missing SSNs drawing from the registries of the Chamber of Commerce.[1] In particular, we use the corporation name (*ragione sociale*) that was provided by MISE to search for each business with a missing SSN. We start requiring a perfect match. In case multiple businesses share the same corporation name, we use the municipality reported in trademark data. When multiple businesses share the same name and municipality we leave the SSN missing. We then repeat the same routine allowing for a 95% match in the corporate name.

B.2 Social Security data

Data on labor market outcomes comes from the Italian Social Security Institute (INPS) and is a matched employer-employee dataset collected for social security purposes on all employee in nonagricultural firms. We focus on the years 2007-2021 to match the coverage in trademark data, although the raw data goes back until 1974. The data provides worker-level information on demographic characteristics such as age and sex, and information about labor contracts. The latter includes: i) starting and ending date of the contract; ii) type of contract (part-time vs fulltime; temporary vs permanent); iii) qualification/job title (apprentice, blue-collar, white-collar, manager); iv) wage; v) occupation code.

We use standard occupation codes provided by INPS to classify some subgroups of a firm's workforce. We observe these occupation codes since 2010 for every job flow. Importantly, the occupation code is observed also for terminations of contracts that were in place before 2010. We classify a worker in one of the subgroups if they have ever been employed in one of the occupations included in a given subgroup. Specifcally, we label as marketing- or sales-related employees those employed in one of the occupation codes of Table A6.

[1] The registry can be found here: https://www.ufficiocamerale.it/.

Table A6: Classification of Occupations

Occupation	**Occupation code**	**Description**
Marketing and Sales		
Sales and Distribution	2.5.1.5.2	Specialists in the marketing of goods and services (excluding ICT)
	2.5.1.5.3	Specialists in marketing in the ICT sector
	3.3.3.4	Sales and distribution technicians
	3.3.4.1	Freight forwarders and distribution technicians
	3.3.4.2	Sales agents
	3.3.4.3	Concessionary agents
	3.3.4.6	Commercial representatives
	5.1.1	Sales operators
	5.1.2	Sales assistants
Marketing	2.5.1.5.4	Market analysts
	2.5.1.6.0	Public relations, image specialists, and related professions
	3.3.3.5	Marketing technicians
	3.3.3.6	Advertising and public relations technicians
	3.3.4.4	Advertising agents

Notes: This Table provides the list and description of all the occupations included in our occupational subgroups of workers: marketing- and sales-related and executives.

The data contains worker and firm identifiers so that we can exploit the longitudinal dimension and be able to follow workers careers and outcomes over time. This allows us, among other things, to restrict our attention to the subgroup of incumbent workers who continuously work in a firm in the time window around a trademark transaction event.

We focus on two measures of wages: total labor earnings defined as taxable labor income on which social security contributions are computed, and a wage rate variable defined as a worker's weekly wage. Because social security contributions are measured in weeks, we rely on weeks as the most reliable information about the intensive margin of labor supply and we compute our wage rate based on it. We clean wage data with the following routine. First, we keep workers who are at least 16 years old and worked at least three months in the year and we drop anomalous observations that feature negative or missing wage variables. Then we express all wage outcomes in real terms, converting wage variables into 2015 euros using OECD conversion tables.[2]. Finally, we winsorize all wage outcomes at the 99.9th percentile in the year to avoid extreme values.

[2]Tables can be found at: https://web.archive.org/web/20201109004157/https://data.oecd.org/price/inflation-cpi.htm.

C Derivation of Theoretical Results

C.1 Proof of Lemma 1

Proof. Plugging in the demand curve, we convert the problem into an unconstrained problem in terms of q

$$\max q^{1-1/\epsilon_i} - \frac{q}{z_j} w_l,$$

The optimal choice of quantity is $q_i^* = \left(\frac{z_j}{w_l}\frac{\epsilon-1}{\epsilon}\right)^{\epsilon}$. Using the demand curve we have $p_i^* = \frac{\epsilon_i}{\epsilon_i-1}\frac{w_l}{z_j}$. By definition, the revenue of the product is $r_i^* = p_i^* q_i^* = \left(\frac{z_j}{w_l}\frac{\epsilon_i-1}{\epsilon_i}\right)^{\epsilon_i-1}$ and profit is $\pi_i^* = \frac{1}{\epsilon_i}\left(\frac{w_l}{z_j}\frac{\epsilon_i}{\epsilon_i-1}\right)^{1-\epsilon_i}$. The results in the lemma involve the comparative statics regarding ϵ_j:

(Quantity)

$$\frac{d\log q_i^*}{d\epsilon_i} = -\log p_i^* - \frac{1}{\epsilon_i - 1}$$

(Price)

$$\frac{d\log p_i^*}{d\epsilon_i} = \frac{1}{\epsilon_i(\epsilon_i - 1)}$$

(Revenue)

$$\frac{d\log r_i^*}{d\epsilon_i} = \frac{d\log p_i^*}{d\epsilon_i} + \frac{d\log q_i^*}{d\epsilon_i} = \frac{1}{\epsilon_i} - \log p_i^*$$

(Profit)

$$\frac{d\log \pi_i^*}{d\epsilon_i} = \log p_i^*$$

Given the assumption that $\frac{w_l}{z_j} < \frac{\epsilon_g}{\epsilon_g-1}$, $p_i^* < 1$. It follows the profit is higher under the branded product, the revenue is higher and □

C.2 Proof of Lemma 2

We start with the result for employment. Directly from the equation (1), an increase in b keeps n_g unchanged while strictly increasing n_b. This means the total number of branded products must increase. Because the revenue from each product stays unchanged, the total revenue must increase. To calculate the effect on labor share, we note the firm-level labor share can be written as

$$LS_j = rs_{bj} ls_{bj} + (1 - rs_{bj}) ls_{gj}$$

where $rs_{bj} = \frac{bn_{bj}^{\gamma} r_{bj}}{bn_{bj}^{\gamma} r_{bj} + n_{gj}^{\gamma} r_{gj}}$ is the revenue share of the firm from branded products, while ls_{bj} is the labor share from branded products, and ls_{gj} is the one from the generic products. In its definition

$$ls_{bj} = \frac{w_l l_{bj} + w_n n_{bj}}{bn_b^{\gamma} r_{bj}} = \frac{\epsilon_b - 1}{\epsilon_b} + \frac{\gamma}{\epsilon_b},$$

In the second equality, we plug in the optimal solution from pricing and expansionary activity. Thus, the product-level labor share is the weighted average between the cost-elasticity of production labor (1) and the cost-elasticity of expansionary labor γ, where the weight is the production-labor share $\frac{\epsilon_b-1}{\epsilon_b}$. Similarly, we have

$$ls_{gj} = \frac{\epsilon_g - 1}{\epsilon_g} + \frac{\gamma}{\epsilon_g}.$$

Because $\epsilon_g > \epsilon_b$ and $\gamma < 1$ we have $ls_{gj} > ls_{bj}$. Since the product-level labor shares are not dependent on b itself, to prove the firm-level labor share falls, it suffices to find the condition under which an increase in b leads to an increase in the branded revenue share rs_{bj}. Using the optimal solutions so far, we can write the revenue share as

$$rs_{bj} = \frac{b^{\frac{1}{1-\gamma}}\epsilon_b \pi_{bj}^{\frac{1}{1-\gamma}}}{b^{\frac{1}{1-\gamma}}\epsilon_b \pi_{bj}^{\frac{1}{1-\gamma}} + \epsilon_g \pi_{gj}^{\frac{1}{1-\gamma}}} = \frac{b^{\frac{1}{1-\gamma}}\zeta}{b^{\frac{1}{1-\gamma}}\zeta + 1}$$

where

$$\zeta = \frac{\epsilon_b}{\epsilon_g}\left(\frac{\pi_{bj}}{\pi_{gj}}\right)^{\frac{1}{1-\gamma}} = \left(\frac{\epsilon_b}{\epsilon_g}\right)^{\frac{\gamma}{1-\gamma}}\left(\frac{\frac{\epsilon_b}{\epsilon_b-1}}{\frac{\epsilon_g}{\epsilon_g-1}}\right)^{\frac{1}{1-\gamma}}$$

We can show that:

$$\frac{d\zeta}{d\epsilon_b} < 0$$

and

$$\zeta|_{\epsilon_b=\epsilon_g} = 1,$$

which implies $\zeta > 1$. This means rs_{bj} is increasing in b. This means the overall labor share must decrease in b.

Focusing on the two types of labors, for the expansionary labor, the overall share is

$$LS_j^n = rs_{bj}\frac{\gamma}{\epsilon_b} + (1 - rs_{bj})\frac{\gamma}{\epsilon_g}.$$

Since $\epsilon_b < \epsilon_g$, an increase in b increases rs_{bj} and increases the labor share for expansionary labor. Similar argument implies that the the labor share of production workers must fall.

By construction of the labor shares,

$$\frac{LS_j^n}{LS_j^l} = \frac{n}{l}.$$

As expansionary labor share rises and production labor share falls, the input ratio must rises for the expansionary-production ratio.

C.3 Proof of Lemma 3

We want to show the following statements hold:

1. if $S_{j,k} = T$ for some $0 < j < J$, then all firms that are more productive than j and more brand capital buy from k, and less productive firms or those with less brand capital do not buy from firm k
2. if $S_{0,k} > T$, then all firms buy from firm k
3. if $S_{J,k} < T$, then firms buy from firm k

We start by showing that if firm z_j buys from firm k, then firm j' buys from k if $j' > j$. Suppose in the transaction from firm k to firm j, the amount transacted is τ. This τ is also feasible in the potential transaction between j' and k. Calculating the gains from trade using τ

$$\begin{aligned}
&\pi(z_{j'}, b+\tau) + \pi(z_k, b_k - \tau) - \pi(z_{j'}, b) - \pi(z_k, b_k) \\
=&\phi_b z_{j'}^{\frac{\epsilon_b - 1}{1-\gamma}}\left((b+\tau)^{\frac{1}{1-\gamma}} - b^{\frac{1}{1-\gamma}}\right) + \pi(z_k, b_k - \tau) - \pi(z_k, b_k) \\
>&\phi_b z_j^{\frac{\epsilon_b - 1}{1-\gamma}}\left((b+\tau)^{\frac{1}{1-\gamma}} - b^{\frac{1}{1-\gamma}}\right) + \pi(z_k, b_k - \tau) - \pi(z_k, b_k) \\
=&S_{j,k} = T,
\end{aligned}$$

where the first equality uses the profit function we derived in earlier steps; the first inequality uses the fact $z_{j'} > z_j$, $\frac{\epsilon_b - 1}{1-\gamma} > 1$, and $b + \tau > b$; the second equality uses the definition of gains from trade between j and k; the last inequality uses the fact the definition of $\bar{z}_k$.

Now we want to show that any firm with $z_{j'} < z_j$ will not buy from firm k. Suppose, to the contrary, $z_{j'}$ does buy from firm k and the amount transacted is τ', this τ' is feasible also for the transaction between j and k. Repeating the earlier step, we find that the firms can strictly increase their gains from trade by transacting an amount τ', which contradicts the definition of the j-k pair.

Joining these three items, we find that, compared to firms that fail to materialize a match into a transaction, buyers are above the transaction threshold and are thus positively selected on productivity. The same logic shows that if firm j buys from firm k, then any firm with brand capital larger than b_j will buy from firm k as well.

C.4 Extensions to the Theoretical Model

We consider two extensions to the theoretical model in this section. The first extension incorporates other production factors into firms' production technology, thereby interpreting the empirical results on materials. The second extension considers an alternative model of branded products, where branded products differ from generic products in terms of demand but share the same demand elasticity as generic products. Interpreting our empirical evidence through this lens, we find support for the interpretation that branded products have lower demand elasticity, rather than merely a higher level of demand.

Other Production Factors. We assume that the production of firm j takes both labor and material as inputs:

$$y_j = z_j l_j^{\alpha} m_j^{1-\alpha},$$

where l_j is the number of production workers, m_j is the material inputs, and α is the labor input share in the production function. Firms take as given the material price w_m. The cost minimization problem of the firm yields a standard Cobb-Douglas cost function:

$$TC_j = (\alpha + (1-\alpha)w_m)\,\frac{y_j}{z_j}$$

and the marginal cost $MC_j = (\alpha + (1-\alpha)w_m)\,\frac{1}{z_j}$. The material input of the firm is proportional to its output:

$$m_j = (1-\alpha)\frac{y_j}{z_j}$$

We ask: What is the impact on materials when the firm buys a brand? Differentiating the demand for materials, we find that the percentage increase in materials should exactly match the percentage increase in output:

$$d\log m_j = d\log y_j$$

And since the brand transaction also increases the price the buying firm charges, the total percentage increase in revenue is larger than the percentage increase in materials. Since labor demand for production workers remains proportional to output, the predictions regarding employment in the baseline model hold when other inputs are also incorporated.

Brand as Quality/Taste. An alternative way to theorize the difference in branded products and generic products is that the quality/taste for branded products is higher, as models widely used in the literature (e.g. Hottman et al., 2016). More specifically, we assume that the demand curves for the branded and generic products have the same elasticity ϵ, but the willingness to pay for the same quantity is higher for branded products:

$$p_{ij} = \phi_b q_{ij}^{-1/\epsilon_g}, \quad \phi_b > 1.$$

Other elements of the model stay the same as in the baseline model. Since branded and generic products have the same demand elasticity, the optimal price charged for different products by the same firm stays the same $p_{ij} = \frac{\epsilon_g}{\epsilon_g - 1}\frac{1}{z_j}$. As in the baseline model, as the brand capital increases at the firm, the expansionary workforce indeed increases at the buying firm, and there is a reallocation of revenue shares from generic to branded products. However, since branded products and the generic products have the same markup, the revenue and the total wage bill expand by the same percentage, and the labor share of the firm stays constant.

Combining all results presented in this Section, we reach the following predictions regarding the causal effects of an increase in brand capital through a trademark transaction:

1. Firm-level responses: revenue of the buying firm increases, its total wage bill increases while its labor share stays the same.

From the empirical results from the event study, we find the data is more in support of the baseline model where branded products have lower elasticity (and higher markup) than a mere shift in demand curve with identical elasticities.