The Labor Demand Implications of Brand Capital: Evidence from Trademark Transactions*

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Abstract

Brand capital—an intangible asset that differentiates a firm's products—has grown in recent decades, alongside the rise of intangible investments and the decline in the labor share. *Trademarks* are legal claims on brand capital and are actively traded across firms, providing a setting to study how reallocating brand capital reshapes firm behavior and aggregate outcomes. Leveraging a novel link of Italian administrative data on trademark ownership, firms' financial statements, and employer–employee records, we exploit firm-to-firm trademark transactions to identify the effects of brand-capital investments. Guided by a model in which firms combine production labor, expansionary labor, and brand capital, we use an event-study design to estimate firm-level effects and quantify their aggregate implications. Acquiring a trademark increases intangible assets by 19%, sales by 8%, and employment by 6%, while leaving weekly earnings unchanged and reducing the firm-level labor share. Employment gains are concentrated among marketing and sales workers, indicating that brand capital is not skill-neutral. Accounting for both buyers and sellers, trademark transactions reallocate brand capital toward larger firms, raising sales and lowering the labor share. Calibrating the model to our estimates, we find that this reallocation generates a one percentage-point decline in the aggregate labor share in the long run.

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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 rising intangible inputs are responsible for key macroeconomic trends (De Ridder, 2024; Chiavari and Goraya, 2025). *Brand capital* is an intangible asset that differentiates a firm's products. It is defined as the stock of customer goodwill, loyalty, and reputation that increases customers' willingness to pay and decreases a product's substitutability. *Trademarks* grant property rights in the distinctive signs (names, logos, slogans) through which a firm creates and protects its brand capital. 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). Importantly, existing research links product-demand forces (including "brand appeal") to the sustained decline in the labor share (Kehrig and Vincent, 2021). Yet, brand capital remains relatively understudied, in particular regarding its labor demand implications. A key empirical challenge is that 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 firm performance, the composition of employment, or labor shares. Addressing this gap is the main goal of this paper.

We propose a new way of identifying the firm-level effects of brand capital by leveraging firm-to-firm transactions in the market for existing trademarks—a market in which firms engage for a variety of strategic purposes. As we show in our data, the secondary market for existing trademarks is quantitatively important. Firm-to-firm transactions are uniquely suited to study the effects of hard-to-measure brand capital, as they provide instances where brand capital at the acquirer firm increases in a sharp and discontinuous way. We implement this strategy using a newly assembled dataset that links Italian employer–employee matched records, firms' balance-sheets and income-statements, and the national registry of trademark transfers.

Guided by a model of production, marketing, and trademark transactions featuring brand capital and two types of labor, we estimate the firm-level 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. The worker-level panel data allows us to account for job mobility and study brand capital effects on different types of workers, assessing whether it is skill-biased in nature. Motivated by our model, we highlight heterogeneous effects on *production workers*—involved in producing output; and *expansionary workers*—tasked with reaching customers and selling output (Kaplan and Zoch, 2024). We also assess how the firm-to-firm market for trademarks reallocates brand capital by jointly analyzing the outcomes of buyer and seller firms.

The dataset we assemble merges the Italian trademark registry to the population of employer-employee Social Security records, and to firms' balance sheets and income statements. Balance sheets include 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 observable shifters of brand capital. 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 and workers' outcomes. To isolate the effects of brand capital, we focus only on firm-to-firm transactions that involve the ownership change of a trademark asset, abstracting from transactions that are part of a broader merger or acquisition. This distinction is recorded in the trademark registry.

Our data allow us to provide descriptive facts on intangible capital and trademark ownership in Italy. The book value of intangible assets has increased steeply since the turn of the century. The value of aggregate intangibles as a share of total assets was about 4% in 2000, yet over 8% in 2019. As a share of aggregate tangible capital, intangible capital went from 17% in 2000 to 33% in 2019. On brand capital, we show that trademark transactions largely involve established trademarks older than ten years old (likely more valuable than newly established ones), and that trademarks tend to flow from less to more productive firms. In line with these flows, trademark buyers are concentrated in the top deciles of the within-sector sales and value-added distributions. Moreover, trademark buyers are broadly represented across all sectors of the economy, yet overrepresented in manufacturing and wholesale and retail trade, and underrepresented in construction.

We develop a model that links trademark transactions, brand capital, and labor demand by embedding brand capital in a marketing stage that follows firms' production. Firms are heterogeneous in productivity and brand capital, and employ two types of labor: production workers to generate output and expansionary workers (e.g., sales and marketing) to market products. Brand capital increases the efficiency of expansionary labor and lowers demand elasticities for branded products, raising markups and profits. Trademark transactions reallocate brand capital to firms that can deploy it most effectively, leading buyers to be positively selected on productivity. An increase in brand capital raises revenue and labor demand but reduces the firm-level labor share by shifting sales toward high-markup branded products, while tilting labor demand toward expansionary workers. The model delivers testable predictions on firm selection into trademark acquisitions, changes in revenue, labor composition, and labor shares, which guide our empirical analysis.

Our research design leverages the richness of the administrative data in terms of firm observables and panel dimension. We estimate the firm-level effects of acquiring a trademark using a stacked matched difference-in-differences approach. Each acquirer firm 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 time-varying measures of firm size. 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 trademark market and plausible time lags between brand-investment decisions and effective trademark transfers, minimizing concerns that the precise timing of trademark acquisitions is correlated with unobserved and contemporaneous positive firm shocks. Supporting identification, we find parallel pre-trends between treated and matched control firms; no evidence of regression-to-the-mean in placebo tests; and similar estimates when restricting the sample to transactions involving sellers that are in the process of shutting down, where trademark sales are unlikely to be driven by buyers' contemporaneous shocks.

We begin by examining the impact of brand capital on firm performance and, as a "first stage," show that acquiring a trademark sharply increases the book value of intangible assets by approximately 19% on average. In levels, this corresponds to about 54,000 Euro, or roughly 6% of the median firm's value added. The fact that this increase coincides tightly with the time of the trademark transaction supports the interpretation that these transfers correspond to discrete, economically relevant changes in firms' brand capital. Following these acquisitions, firms expand: sales increase by 8% within two years.

Concurrently, 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. From the worker-level panel data, we see that employment growth results from the combination of positive short- and long-term effects on hiring, negative effects on separations in the short-term, and positive effects on separations in the long-term—evidence of a workforce reorganization rather than a pure increase in scale.

The effects on the wage bill are proportional to those on employment, indicating no significant effects on average earnings per week. The worker panel allows us to rule out positive earnings effects that could have gone undetected in firm-level averages due to compositional changes. The null effects on average earnings holds for *incumbents* (employees working at the buyer firm at the time of the trademark purchase, regardless of where they work in subsequent periods), and for *stayers* (employees working at the buyer firm between -3 to +3 years around the trademark acquisition). We also find that the effects on the wage bill are smaller than those on sales, which leads to a 2% reduction in the buyer firm's labor share.

In our framework, brand capital primarily raises the efficiency of *expansionary* labor—workers involved in market expansion and consumer reach. Using occupation codes and blue-/white-collar classifications, we find clear evidence of skill bias: following a trademark acquisition, the percentage employment and wage bill increase for marketing/sales workers is about twice the corresponding increase for non-marketing/sales workers. Among firms that employ both blue- and white-collar labor, employment growth is entirely concentrated among white-collar workers and managers, with no meaningful change in blue-collar employment. Moreover, within firms that already employ marketing/sales workers, nearly all of this white-collar expansion occurs in marketing/sales. Taken together, these patterns indicate that brand capital operates primarily at the marketing stage and complements workers who are most involved in this step of the value chain.

Our model implies that trademarks should be acquired by firms with higher marginal returns to brand capital. We test this empirically, studying the transaction-level reallocation effects. 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 their performance: aggregate sales 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.

Lastly, we use our model to translate the event-study estimates into aggregate, long-run implications for the labor share. The exercise captures a reallocation mechanism: trademark transfers shift brand capital toward more productive and larger firms, so revenue expands as labor shares fall. We calibrate the model's key elasticities to match our event-study estimates. We then simulate the steady-state allocation of trademark ownership implied by the observed buyer–seller flows across firm-size groups. Finally, we recompute the aggregate labor share under this counterfactual distribution. The resulting exercise suggests that the secondary market for trademarks can generate a decline in the aggregate labor share of about 1 percentage points, or

20% of the 5 percentage-point decline in the Italian labor share since the early 1990s (Autor et al., 2020).

This paper contributes to five strands of literature.

Intangible assets and their economic effects. A large literature documents the rise and distinctive properties of intangible capital, studying its implications for production, measurement, and finance (Crouzet et al., 2022; Chiavari and Goraya, 2025; Crouzet and Eberly, 2023; Peters and Taylor, 2017; Eisfeldt and Papanikolaou, 2013; Bartel et al., 2007; Schivardi and Schmitz, 2020; De Ridder, 2024). Far fewer studies examine demand-side intangibles like brands despite their macroeconomic scale (Bronnenberg et al., 2022). Related work highlights customer capital as macro-relevant: embedding it in business-cycle models affects wedges (Gourio and Rudanko, 2014); customer churn predicts firms' intangible investment activity (Baker et al., 2023); and sales and marketing outlays are central to the accumulation of customer-related intangibles (He et al., 2024). We leverage a new, comprehensive dataset on firm-to-firm trademark transactions to document novel facts about the secondary market for trademarks and show how these transactions can be used to identify the effects of hard-to-measure brand capital. We also provide theory and evidence on how brand-capital accumulation interacts with labor demand, and we show how reallocation via the secondary market can impact the labor share and the relative demand for different types of skills.

Micro-level drivers of labor-share decline. We add micro-level evidence to a literature studying the evolution of the aggregate labor share (Elsby et al., 2013; Karabarbounis and Neiman, 2014; Rognlie, 2015; Gutiérrez and Piton, 2020; Autor et al., 2020; Karabarbounis, 2024). Labor-share decline has been linked to intangibles (Koh et al., 2020) and attributed to demand-side forces leading to firm expansion and price premia that wages do not fully track (Kehrig and Vincent, 2021). In line with the evidence in Kehrig and Vincent (2021) that low-labor-share plants spend more on advertising—and their hypothesized mechanisms related to brand appeal—we show directly that brand-capital investment and reallocation lead to individual firms' expansion and labor shares reductions, via improved sales without commensurate wage increases.

Rising markups and demand elasticities. A separate literature documents sustained increases in markups (De Loecker et al., 2020; De Loecker and Eeckhout, 2018; Döpper et al., 2025). Explanations emphasize rising fixed costs or innovation (Olmstead-Rumsey, 2019; Akcigit and Ates, 2023; De Loecker et al., 2021) and, more recently, declining consumer price sensitivity (Döpper et al., 2025). We provide clear and concrete evidence for this demand-side class of mechanisms: by investing in brand capital and expanding market access, firms raise revenues by lowering demand elasticities and, in our setting, leaving wages unchanged. This highlights brand capital accumulation and reallocation as a distinct driver of rising profitability.

Capital investment and labor demand. Using firm-level variation and matched data, we study a form of capital that operates on the *marketing/demand* side of the value chain, in contrast to the forms of capital typically studied in the literature, which act as *production* inputs. Firm-level studies of manufacturing machinery typically find skill-neutral effects on employment, often with muted wage responses (Curtis et al., 2022; Aghion et al., 2024; Hirvonen et al., 2025). In contrasts, ICT-related investments are skill-biased and affect earnings in task-specific ways (Autor et al., 2003; Bartel et al., 2007; Akerman et al., 2015; Gaggl and Wright, 2017). We show that brand capital is qualitatively distinct: it induces skill-biased hiring toward marketing-experienced workers (with production employment unchanged), has null effect on earnings, and lifts sales in ways that reduce firms' labor shares.

Intangibles and labor demand. Evidence on the labor effects of technology-enhancing intangibles such as patents (Kline et al., 2019) point to wage gains concentrated among inventors. We lack evidence, however, on the labor effects of demand-side intangibles.[1] Patents typically affect production by reducing marginal costs and by preventing competitors from lowering their costs through the protection of specific technologies (Akcigit and Kerr, 2018). Instead, brands operate on the marketing side of the firm. Because these investments differ in nature, they have different theoretical implications for labor, and the groups of workers who benefit from them are, a priori, likely to differ.[2] Evidence on brands shows that after a trademark approval, US public firms increase employment (Desai et al., 2025). This paper, instead, provides a comprehensive overview of the skill-biased labor demand effects of brand capital, including effects on the labor share, among a broad cross-section of firms.

The rest of this paper is structured as follows. Section 2 provides context on the firm-to-firm market for existing trademarks. Section 3 describes our data. Section 4 presents our model and its empirical implications. Section 5 details our research design. Section 6 presents the firm-level effects of trademark acquisitions, while Section 7 presents transaction-level effects. Section 8 describes our model-based simulation on the effects of trademark transactions on the aggregate labor share. Section 9 concludes.

[1] 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).

[2] While we find null effects of brand capital on wages, Kline et al. (2019) find that valuable patents raise wages. The concentration of such effects on inventors could in principle be driven by pay-for-performance awards, which we would not expect in the context of trademark acquisitions.

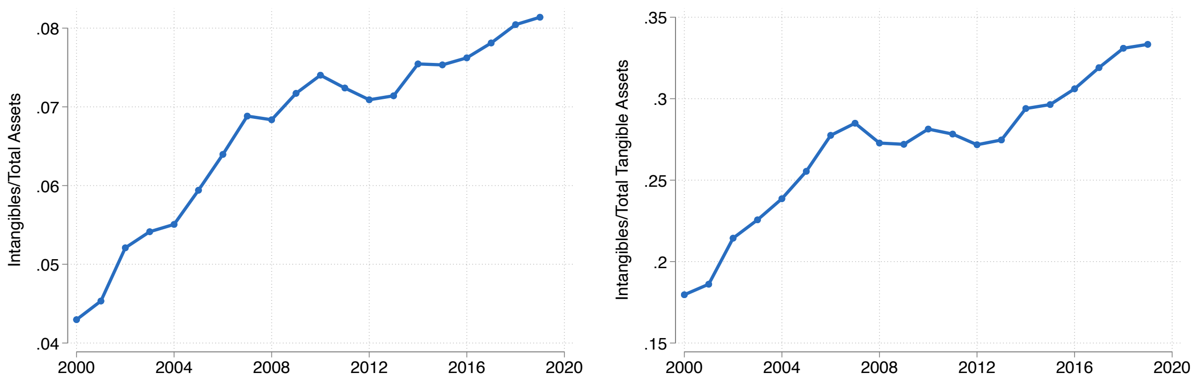
2 Intangible Capital and Trademark Transactions in Italy

2.1 The Rise of Intangible Capital

Trademarks are recorded on Italian firms' balance sheets as intangible capital ("*immobilizzazioni immateriali*"). Figure 1 highlights the growing importance of this type of capital in the Italian economy over the past two decades. Panel (a) shows that the share of total assets held as intangible capital has steadily risen, roughly doubling from about 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 17% of tangible capital in 2000, they represent 33% by 2019. The rising importance of intangible capital is also observed in the US (Crouzet et al., 2022; Corrado et al., 2022). 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 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 as a share of total assets. **(b)** Intangibles as a 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. Both series are 3-year centered moving averages.
Source: CERVED dataset (universe of non-financial Italian corporations).

2.2 The Firm-to-Firm Market for Trademarks

Trademark 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, allowing firms to acquire or monetize brand capital 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, or operational reasons. We begin by documenting the scope and economic relevance of this market, then describe the motivations of buyers and sellers, illustrate them with four case studies, and finally discuss frictions and allocative patterns

Relevance. The secondary market for trademarks is quantitatively important. Using data from the Italian trademark registry (described in Section 3), we find that transactions involving existing trademarks account for 3.1 percent of the annual flow of new trademark registrations. This figure is based on counts of trademarks, but the underlying economic magnitude is likely much larger, since many new trademarks never become marketed products. Consistent with this, Pearce and Wu (2024) document that trademark transactions are quantitatively meaningful in the US, with traded trademarks associated, on average, with products whose market shares are roughly ten times larger than those of newly created trademarks.

Why do firms buy trademarks? A product's reputation is an important determinant of its sales. Firms can invest in brand capital either by building a new trademark from scratch or by purchasing the rights to an existing one and leveraging its established reputation. Acquiring an existing and established brand allows firms to expand market access more rapidly than by developing a new one from scratch. A single trademark can be applied to multiple products, so there is not necessarily a one-to-one mapping between trademarks and products. In many cases, trademark buyers might possess stronger manufacturing, distribution, or financial capabilities, allowing them to acquire underutilized brands and scale them up beyond what the original owners could achieve. Despite owning a trademark, firms may choose to sell some of their products under an established trademark and others as "unbranded."[3] All of these aspects are incorporated into our theoretical framework.

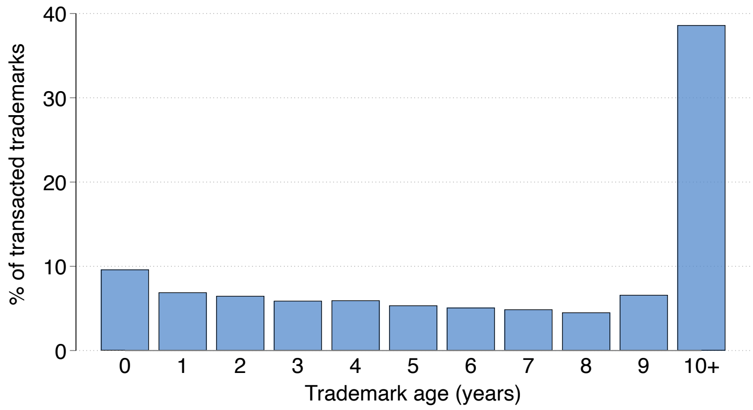
Figure 2 shows the age distribution of transacted trademarks in our data and supports the view that firms typically purchase established brands. More than 65 percent of transacted trademarks are 5 years old or more, and almost 40 percent of them are ten years old or more. Moreover, the mass at the 10+ category suggests that a meaningful share of those brands are significantly past 10 years of age.

Why do firms sell trademarks? Firms may choose to sell the rights to a brand as part of a strategic reorientation of their operations. In Italy, for instance, fashion houses that own multiple brands and product lines may divest one of their brands to concentrate resources on others. Additionally, selling trademark assets can be a way of raising

[3] A common example is private-label suppliers in the supermarket sector: these firms sell unlabeled products to retailers to be marketed under the supermarket's private label while simultaneously selling the same or similar products under their own established trademark. This is a sizable market segment, representing about 30% of sales in the Italian retail market (NielsenIQ, 2024).

liquidity for firms facing financial distress. Finally, even firms exiting the market may own valuable brand assets, which can be sold as part of the liquidation process. In our sample, for instance, 40% of trademark sellers cease operations within four years of the trademark sale.

Figure 2: Transacted trademarks' age distribution



Notes: Trademark age distribution among trademarks that are transacted between 2007–2021. We are not able to observe exact age for trademarks that are ten years old or more because their IDs change at each renewal (which occurs every ten years). Consequently, we include in the 10+ category all transacted trademarks whose IDs were created during a renewal event.
Source: Italian Patent and Trademark Office (UIBM).

Case studies. To shed further light into the firm-to-firm market for trademarks, we describe four illustrative case studies of transactions that are present in our data. These cases involve different combinations of the motivations discussed above, involve firm-to-firm transactions that were exclusively composed of trademark assets, and preview the role of market frictions and reallocation from less to more productive firms. Appendix C offers additional details for each of them.

Canned tomatoes. In 2017, the agricultural cooperative *Consorzio Casalasco del Pomodoro* acquired the *De Rica* canned-tomato brand from *Generale Conserve*—a firm producing canned food that decided to specialize in seafood products and was refocusing on that core business. The acquisition was purely for the brand name, with production moved to *Casalasco*'s facilities in Cremona. The operation aligned with *Casalasco*'s broader strategy to consolidate and expand in tomato derivatives.

Gorgonzola. In 2018, producer of Gorgonzola cheese *IGOR Srl* purchased the *Quattrorose* brand from *Santi Spa* at an auction following *Santi*'s 2014 failure. The acquisition solely covered *Santi*'s brands (*Quattrorose* and others), with production integrated into *IGOR*'s dairies. *IGOR* framed the purchase as restoring a well-known premium label under its own manufacturing footprint.

Shoes. When the historic children's footwear maker *Balducci* went out of business, *Asso Spa*—a larger shoe manufacturer from the Marche region—acquired its trademarks. The purchase fit *Asso*'s strategy of reviving recognizable "Made in Italy" brands within a modern production system, leveraging *Balducci*'s long-standing reputation for quality while scaling up output.

Resorts. After the resort chain *Valtur Spa* went bankrupt, the travel group *Nicolaus Tour* purchased the *Valtur* brand in 2018. *Nicolaus* subsequently relaunched the name to market a new network of resorts, reviving *Valtur*'s legacy as a heritage Italian leisure brand.

Frictions. Transaction frictions are pervasive in this market, contributing to illiquidity. Legacy trademarks are highly differentiated assets, as established brands are typically associated with specific products and have a distinct character. Oftentimes, a potential firm buyer might *wish* to purchase a suitable legacy trademark to strengthen their products portfolio, but such a trademark might not exist or not be for sale. Moreover, even when a match occurs, the transaction process can be complex and protracted. Firms must conduct some due diligence, negotiate over the price, and, in some cases, secure some external funding to finance the operation. As a result, the timing of the actual trademark acquisition could be disconnected from time in which the buyer firm makes the purchase decision. For instance, in the *Gorgonzola* case study, four years spanned between the failure of the seller firm and the effective purchase of the trademark by the buyer firm.

Reallocation. Trademark registry data suggest that transactions tend to move brands from smaller or less productive firms toward larger or more productive ones. Table 1 shows the transition matrix by firm size category of sellers and buyers. "Upward" transactions amount to 40.5% of all transactions, same-size transactions are 30.5%, and "downward" transactions the remaining 29%. As we show in Section 8, this reallocation can have meaningful implications for revenue shares across firm-size groups and the aggregate labor share.

3 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.

3.1 Trademark Deposit and Transaction Data

We gather information on trademark transactions from the *Italian Patent and Trademark Office* (UIBM) at the *Ministry of Enterprises and Made in Italy* (MIMIT). The data contains the universe of trademark exchanges for the period 2007 to 2021. There are

Table 1: Seller-Buyer Matrix by Firm Size: Sellers as Rows, Buyers as Columns

Seller ↓ / Buyer →	**Sole Prop**	**0–9**	**10–49**	**50–99**	**100+**	**Foreign**	**Total**
Sole Proprietor	1,039	370	231	65	146	410	2,261
0–9	426	298	186	60	79	196	1,245
10–49	112	141	108	44	94	168	667
50–99	22	31	47	12	40	67	219
100+	56	45	65	33	123	213	535
Foreign	276	149	116	39	137	200	917
Total	**1,931**	**1,034**	**753**	**253**	**619**	**1,254**	**5,844**

Notes: Number of trademark transactions by size category of the seller firm (rows) and size category of the buyer firm (columns). The sample is constructed from the original dataset keeping only trademark transactions for which we observe both buyer and seller information. 0–9, 10–49, 50–99, and 100+ refer to number of employees. Since the information on this table is not linked to the worker panel, we proxy firm size dividing firms' wage bill by average annual earnings. We interpret sole proprietorship firms and foreign firms as smallest and largest size categories, respectively.
Source: Italian Patent and Trademark Office (UIBM).

on average about 2,000 trademark transactions per year, which correspond to approximately 3.1% 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 whether the transaction is a standalone transfer or part of a broader merger/acquisition. We also observe certain trademark characteristics including age (i.e., years since it was first registered). Unfortunately, we do not observe transaction price. We can match transactions to social security data 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.

To be included in our analysis, trademark transactions must satisfy two conditions. First, the transacting parties must be Italian corporations—we exclude transactions in which the seller or buyer is a physical person or a non-Italian firm because they cannot be matched to the remaining data sources. 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.[4]

The original trademark registry data included SSNs for 45% of firms. However,

[4]In addition, we exclude transactions in which the buyer firm was created in the transaction year and shares more than 55% of its workforce with the corresponding seller. This restriction helps eliminate cases where transactions merely reflect internal restructurings that involve a change in the firm's social security number (SSN) rather than a genuine transfer of ownership.

records in the registry data with missing SSNs still featured firms' identifiable information that allowed us to link them to publicly available registries of the Italian Chamber of Commerce, which include SSN. The variables we used for this match were corporate name (*ragione sociale*) and municipality. This procedure allowed us to increase the share of firms with SSN in the trademark registry from 45% to 77%.[5] We exclude from the analysis transactions corresponding to the remaining firms with missing SSN. As it turns out, after imposing other sample restrictions, missing SSN results in a very low number of trademark transactions being excluded from our analysis sample (Table 2).

After imposing these restrictions, we are left with 15,082 trademark transactions linked to 10,567 sellers and 10,333 buyers (Table 2). Additional details on the dataset building procedure are in Appendix B.1.

Table 2: 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.

3.2 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 Chambers of Commerce (*Camere di Commercio*) and provided by CERVED. We employ measures of sales, value of production, and intangible capital to study the consequences of trademark acquisitions for firm's performance. These data are available for the entire period covered by trademark data and cover 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,

[5] If multiple firms with the same corporate name exist in a given municipality we exclude the transaction from our sample.

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, the wage, and the type of contract (part-time vs full-time; permanent vs temporary). Crucially for our skill-bias analysis, 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), we also observe occupation codes.[6] We employ these occupation codes to define workers employed in marketing- and sales-related tasks.[7] 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.

3.3 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. Starting from the trademarks sample in Table 2, we perform this match and are able to link firms' accounting data to a total of 7,881 trademark transactions, involving 9,309 buyers and 9,822 sellers.[8]

3.4 The Characteristics of Brand Buyers and Sellers

We use this new dataset to present descriptive evidence on the firms involved in trademark transactions. Figure 3(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

[6]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 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.

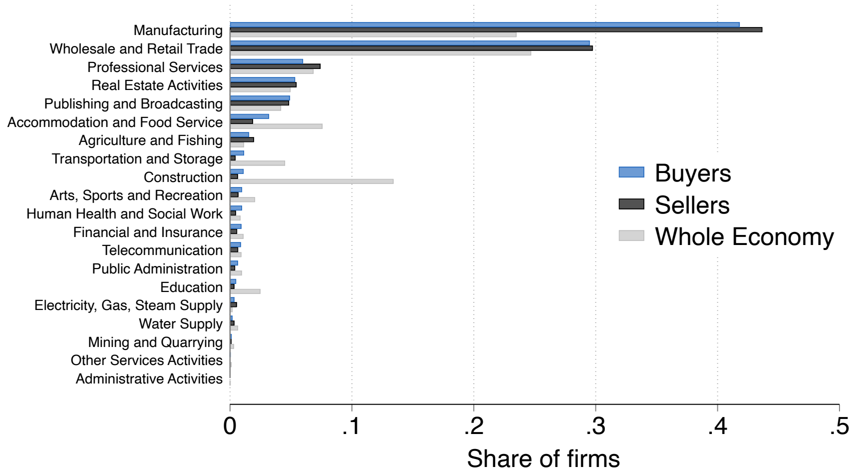
[7]To proxy for workers' *expansionary* skills, we classify them as marketing/sales or not based on whether they ever hold such an occupation within our sample period. As such, this is a time-invariant classification for any given worker. See Appendix B.2 for a detailed outline of the occupations included in the marketing/sales group.

[8]The lower number of linked firms and transactions relative to Table 2 is due to firms without registered employees and firms in the agricultural sector not covered by our social security data.

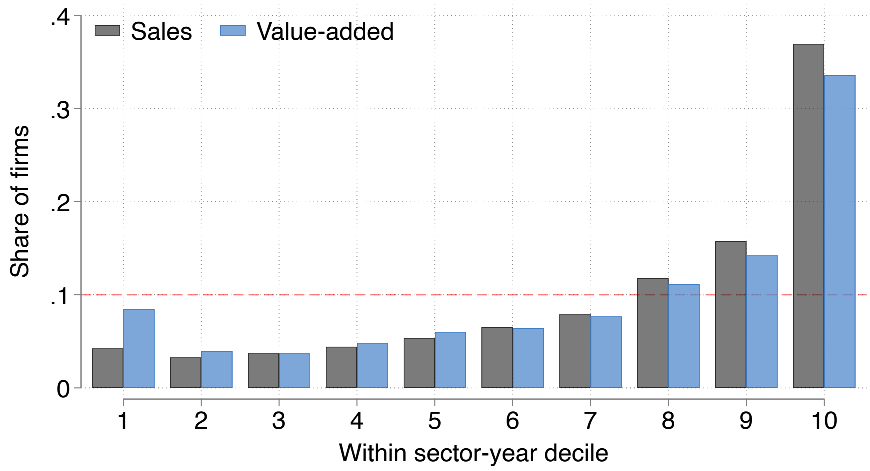
trademark buyers, respectively. In contrast, buyers are underrepresented in less tradable sectors such as construction and hospitality, which account for only 1% and 3% of buyers, compared to 13% and 7% of all firms.

Figure 3: The characteristics of trademark buyers and sellers.

(a) Sectoral distribution



(b) Size and value-added distribution



Notes: Panel (a): distribution of trademark buyers and sellers across sectors compared to all firms in our sample. Panel (b): 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).

Figure 3(b) shows that trademark buyers are larger and more productive than non-transacting firms. As discussed in Section 4, this pattern is consistent with the predictions of our conceptual framework. Figure 3(b), plots the share of buyers across deciles of sales and value added, calculated for the entire population of firms within sector-year combinations. This ensures that differences between buyers and other firms are not driven by sectoral composition or time trends. 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 3 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) 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.

4 A Model of the Link between Trademark Transactions, Brand Capital, and Labor Demand

We develop a model to link trademark transactions and brand capital to labor demand. The model captures the key features of the trademark market described above and generates testable predictions. We incorporate brand capital into a marketing stage following production—building on Kaplan and Zoch (2024)—and allow for an endogenous number of products.[9] The key innovation in our model relative to Kaplan and Zoch (2024) is to incorporate brand capital and a market for trademarks.

The model is static and features a measure 1 of multi-product firms. Firms differ in productivity z and the amount of brand capital b they own, drawn from a joint distribution $F(z, b)$. Firms choose marketing and production inputs, hiring *expansionary workers* to expand market scope and *production workers* to generate output.

Marketing. At the marketing stage, a firm hires expansionary workers (e.g., marketing and sales employees) to market products by performing tasks related to customer outreach, brand management, and reputation-building. Products can be distributed either as generic or branded goods. Hiring n_G expansionary workers allows the firm to operate $m_G = n_G^\gamma$ generic products, while hiring n_B expansionary workers allows it to operate $m_B = bn_B^\gamma$ branded products. Brand capital b is the key object in our model: it increases the efficiency of creating branded products by reducing the amount of labor required per product. Intuitively, a firm with more brand capital can operate a larger portfolio of branded products for a given level of marketing labor.

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

The parameter γ captures the scalability of expansionary labor into product scope. It governs the elasticity of the number of products a firm can operate with respect to expansionary labor (keeping brand capital fixed, in the case of branded products). We assume $0 < \gamma < 1$, reflecting diminishing returns to expansionary labor as product scope expands. $\gamma > 0$ also implies complementarity between brand capital and expansionary workers: higher brand capital raises the marginal profitability of hiring expansionary workers, while a firm that already hires more expansionary workers also gains more from further increases in brand capital.

The key distinction between generic and branded products lies in their demand elasticities. When sold as a generic good, a product faces demand $p_G = q_G^{-1/\epsilon_g}$; when sold as a branded good, the demand is instead $p_B = q_B^{-1/\epsilon_b}$, where q_G and q_B denote quantities, while p_G and p_B denote prices. We assume that $\epsilon_B < \epsilon_G$, implying that branded products face less elastic demand than generic products. There are several motivations for this assumption. First, consumers may be less sensitive to price increases when a brand name conveys additional value—the goodwill theory of branding. Second, branding may reduce the uncertainty about product attributes, making customers less price-sensitive—the information theory of branding (Bagwell, 2007). This assumption is also consistent with empirical evidence documenting a negative relationship between marketing investments and demand elasticities (Boulding et al., 1994).

Production. Given the number of generic and branded products to market, a firm hires l production labor to produce output. All products are produced using the same linear technology, so total output equals the total quantity sold across all operated products:[10]

$$zl = n_G^\gamma q_G + b n_B^\gamma q_B.$$

The firm employs both production and expansionary workers from competitive labor markets, taking wages as given. We normalize the wage of production workers to be 1 and denote by w_n the expansionary workers' relative wage.

Market for Trademarks. A firm can invest in brand capital by purchasing trademarks from other firms in a frictional market for trademarks. A pair of firms randomly meets with probability λ and decides whether to engage in a transaction that transfers ownership of τ units of brand capital. We assume that completing a transaction involves a cost T, and that the resulting surplus is split according to Nash bargaining.

[10]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.

Firms' Optimal Choice. The following equations summarize the firm's problem in a single optimization, given z and b:

$$\pi(z,b) \equiv \max_{n_B,n_G,p_B,p_G} m_B p_B q_B + m_G p_G q_G - w_n(n_B+n_G) - l \tag{1}$$

s.t.

$$\begin{aligned} m_B &= b n_B^{\gamma}, \quad m_G = n_G^{\gamma} && \text{(Marketing)} \\ zl &= m_B q_B + m_G q_G && \text{(Production)} \\ p_B &= q_B^{-1/\epsilon_B}, \quad p_G = q_G^{-1/\epsilon_G}. && \text{(Demand)} \end{aligned}$$

Because the production technology is linear in labor and the firm takes wages as given, production decisions can be analyzed independently at the product level. We proceed in three steps. First, we characterize the production decisions for each product, deriving per-product profits for generic and branded products. Second, we analyze the optimal choice of expansionary labor, which determines the firm's total profits as a function of productivity and brand capital. Lastly, we characterize the firm's trademark transaction decisions. Detailed proofs and derivations are in Appendix D.

The optimal price of products is $p_i = \frac{\epsilon_i}{\epsilon_i - 1}\frac{1}{z}$, $i \in \{G, B\}$. Because branded products face lower demand elasticity, they have a higher markup and profit margin. Given the profits associated with branded and generic products, the firm chooses the optimal allocation of expansionary workers across the two product categories. The optimal allocation of expansionary workers equalizes the marginal profit from operating an additional product in each category with the marginal labor cost, which implies the following total profit among all products, as a function of productivity and brand capital:

$$\pi(z,b) = \phi_B z^{\frac{\epsilon_B - 1}{1-\gamma}} b^{\frac{1}{1-\gamma}} + \phi_G z^{\frac{\epsilon_G - 1}{1-\gamma}}, \tag{2}$$

where $\phi_i = (1-\gamma)\,\gamma^{\frac{\gamma}{1-\gamma}} \left(\frac{\epsilon_i^{-\epsilon_i}}{(\epsilon_i - 1)^{\epsilon_i - 1}}\right)^{\frac{1}{1-\gamma}}$, $i \in \{G, B\}$.

The following lemma characterizes the comparative statics of a firm's outcomes with respect to changes in brand capital.

Lemma 1. *With a small increase in brand capital b: (a) revenue rises, (b) the overall labor share falls, and (c) the ratio between expansionary and production employment rises.*

Lemma 1 is the core theoretical result we later test. When a firm's brand capital increases (in our context, this occurs through a trademark acquisition), total revenue increases. An increase in brand capital does not change the optimal number of generic products but decreases the marginal labor cost of operating a branded product, leading to an increase in the firm's 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-profit products for which the firm enjoys greater market power, leading to a decrease in the firm-level labor share. To understand this, we start with the accounting relationship that the firm-level labor share is the revenue-weighted labor share from branded and generic products. At the product level, the labor shares are

$$\theta_i = \frac{\epsilon_i - 1}{\epsilon_i} + \frac{\gamma}{\epsilon_i},\ i \in \{G, B\}.$$

From each unit of revenue generated by a product of type i, $\frac{\epsilon_i - 1}{\epsilon_i}$ is paid to production workers as wages, while the residual share $\frac{1}{\epsilon_i}$ is split between the firm profit and the expansionary workers' wage. Due to the decreasing marginal product in expansionary work, only $\frac{\gamma}{\epsilon_i}$ is paid to the expansionary workers. Since $\gamma < 1$ and $\epsilon_B < \epsilon_G$, the labor share of branded products is lower than that of generic products. As the firm accumulates brand capital, the revenue share from branded products increases, leading to a decline in the firm-level labor share through revenue reallocation.

The shift in relative labor demand is the labor-market mirror of this revenue reallocation. Production shifts towards branded products, where expansionary workers have a greater marginal product and the revenue share of production workers $\frac{\epsilon_B - 1}{\epsilon_B}$ is lower. Production employment rises less than total revenue because branded expansion operates largely through higher markups rather than higher quantities. With less elastic demand, a given increase in branded revenue implies a smaller increase in output, so the pass-through from revenue to production labor is attenuated.

Trademark transactions. Our last set of results investigates the selection into trademark 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 increase in joint surplus after the trade exceeds the transaction cost T.[11] More precisely, we define the joint profit of the two firms as $\Pi(z, b; z', b') = \pi(z, b) + \pi(z', b')$. The surplus from trade is

$$\max\left\{\Pi(z, b+\tau; z', b'-\tau), \Pi(z, b-\tau; z', b'+\tau), \Pi(z, b; z', b')\right\} - \Pi(z, b; z', b'),$$

where τ is the transfer of brand capital. In the first case within the $\max$ operator, firm 1 is the buyer while firm 2 is the seller; in the second case, firm 1 is the seller while firm 2 is the buyer; in the last case, there is no transaction.

Lemma 2. *Compared to firms that do not engage in transactions, buyers are more productive and have higher revenues.*

[11] 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 into transactions operates along both productivity and brand capital. For a transaction to occur, the joint surplus must exceed the transaction cost. Holding brand capital fixed, a more productive firm derives a larger surplus from acquiring a trademark because productivity and brand capital are complements in profits (equation (2)). Holding productivity fixed instead, firms with greater brand capital gain more from transactions due to the increasing returns to brand capital embedded in profits. As a result, buyers are positively selected on both productivity and brand capital, and hence on revenue.

Lemma 3. *The joint labor share of buyer and seller decreases after a brand capital transfer.*

When a transaction occurs, the total number of generic products is unchanged, while revenue from branded products must increase. This follows because the buyer of the trademark must be more effective in operating the brand capital than the seller. As a result, transactions raise branded-product revenue within the buyer–seller pair. Since branded products have a lower labor share, this reallocation of revenue reduces the sales-weighted joint labor share. Trademark transactions therefore lower the labor share between the seller and buyer. We quantify the aggregate implications of this mechanism in Section 8.

Summary of model predictions. The following predictions emerge regarding the 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 and the wage bill of the buying firm increase, while its labor share falls.
3. Heterogeneous workforce responses: the ratio between expansionary and production employment rises.
4. Transaction-pair responses: total revenues of the transacting firms increase and the joint labor share decreases.

Discussion. We make several simplifying assumptions: (i) Firms take wages as given, consistent with our empirical finding that trademark transactions do not affect wages; (ii) we abstract from within-firm product interactions, such as cannibalization, as they are orthogonal to our focus on employment outcomes and do not alter the model's labor-demand predictions; (iii) we also abstract from dynamics: similar mechanisms would operate in a dynamic setting with evolving productivity (Hopenhayn, 1992), which we take into consideration controlling for firm growth in the empirical analysis; (iv) while brand capital could be interpreted as product quality, standard quality models—where quality shifts the demand intercept without affecting the elasticity (e.g. Hottman et al., 2016)—do not generate the observed changes in markups and labor shares. By contrast, interpreting quality as reduced demand elasticity aligns with our framework, in which branded products face lower elasticities than generic ones; (v) we also consider other factors of production such as materials or physical capital in Appendix D. We show that including other factors of production does not change the key model predictions.

How does brand capital differ from more heavily studied capital-augmenting technologies? Classic models emphasize capital-labor complementarity, implying that capital-augmenting technologies raise both labor demand and the labor share (Uzawa, 1961, Arrow et al., 1961, Acemoglu, 2002). Task-based models allow capital to raise output while reducing labor demand and the labor share by directly substituting for labor in specific tasks (Acemoglu and Autor, 2011, Acemoglu and Restrepo, 2019). Our framework departs from both sets of models. Brand capital does not substitute for labor in production. Instead, it expands market access, raising output and labor demand. At the same time, increases in brand capital raise markups by lowering demand elasticities, thereby reducing the firm-level labor share.[12]

5 Event Studies Around Trademark Transactions

5.1 Matching

We use a stacked matched difference-in-differences approach to study the 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.[13] Motivated by the conceptual framework in Section 4, 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 firm f that is treated in year t_f to the firm or

[12]These results arise even in a neutral Cobb–Douglas production function between brand capital and expansionary labor. Allowing for explicit gross complementarity—for example, through a CES production function with elasticity below one—would further amplify the differential labor demand effects highlighted by the model.

[13]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).

set of firms that share the following characteristics: quantiles of value of production at $t_f - 1$ and $t_f - 3$, quantiles of employment at $t_f - 1$ and $t_f - 3$, year of firm birth categories, and 1-digit sector. We denote the interactions between these variables as *matching cells*, where a matching cell can contain several treated and control firms. Our matching on pre-treatment paths follows the spirit of Arkhangelsky et al. (2021), which emphasizes aligning pre-period trends when constructing comparison units. 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.[14]

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 involving 1,910 buyers.

Table 3 reports summary statistics for the matched sample of buyer firms and their matched controls. Panel A shows that the two groups are broadly 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. These variables are not used for matching. Buyers hold more intangible assets, both on average and at the median. Consistently with their larger employment size, they display higher average weeks worked and wage bills. Moreover, average labor shares for buyers are slightly larger. However, for these variables, medians are very 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.

SUTVA violations? Only 1% of control-group firms are in the same product market as their corresponding buyer firm, where a market is defined as the interaction between province and 3-digit sector; 11% are in the same 3-digit sector; and 10% are in the same province. These relatively low shares arguably allay concerns of SUTVA violations by which a buyers' trademark purchase directly impacts the outcomes of control-group firms.

[14] 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 3: Summary statistics: Trademark buyers and matched controls, year before acquisition

	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)	11,183.96	4,856.50	11,164.48	4,864.00
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
Weeks worked	6,911.54	743.00	4,424.60	761.00
Wage bill (in thousands)	4,831.80	423.11	2,823.83	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
Wage bill blue-collar (in thousands)	1,390.83	106.87	1,150.22	155.68
Wage bill white-collar/manager (in thousands)	3,385.35	217.43	1,623.74	168.68
Wage bill marketing/sales (in thousands)	813.15	70.17	470.65	51.00
Labor share	0.23	0.11	0.17	0.11
N. firms	1,910		190,266	

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.

5.2 Firm-level Event Studies

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

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

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 capturing time-varying demand shocks, $\alpha_{c(f)t}$ are matching cell-by-year fixed effects, k indexes leads and lags with $k \in \{-3, -2, 0, 1, 2, 3\}$, $D^k_{ft} \equiv \mathbf{1}\{t = t_f + k\}$ are event-study indicators with t_f being the year that firm f acquired a trademark (for control-group firms, t_f is the acquisition year for the treated firm they are matched to), 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 that our conceptual framework pins down as a key determinant of trademark acquisitions.

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. As such, the necessary identification assumption is that the trademark transfer date is conditionally uncorrelated with the occurrence of unobserved shocks to the firm. Our matching strategy conditions on the value of production and employment at $t_f - 1$. As we argue below, the decision to invest in a new trademark is plausibly made by $t_f - 1$ and is therefore orthogonal to shocks that materialize in period t_f. This reasoning 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 institutional context and the data support the plausibility of the identification assumptions. First, the market for existing trademarks is relatively illiquid and suitable transaction opportunities might not materialize, even for firms with unmet demand. Conditional on a transaction taking place, the process of acquiring a trademark typically unfolds over an extended period, beginning with the scouting phase and culminating in the negotiation and finalization of contractual terms. In this context, conditional on information available at $t_f - 1$, it is plausible that trademark investment decisions are uncorrelated with shocks realized in period t_f. In other words, investment choices are likely to be largely locked in before the realization of within-period shocks.

Second, and also related to market illiquidity, opportunities to acquire trademarks do not arise continuously. In our empirical analysis, we conduct a robustness exercise that restricts the sample to trademark acquisitions in which the seller firm shuts down around the transaction period (Table A4). In these cases, the opportunity to acquire the trademark plausibly arises from an unanticipated contingency and the timing of the transaction is determined by the seller's closure, rather than the buyer's preferred timeline. Our results remain unchanged when focusing on this subset of events.

Third, 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.

Fourth, the divergence in outcomes occurs precisely at the time of the trademark transfer. Particularly, as we show below, balance-sheet intangibles rise sharply at the time of the acquisition. 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 Firm-Level Effects of Trademark Acquisitions

6.1 Trademark Acquisition, Intangible Assets, and Firm Performance

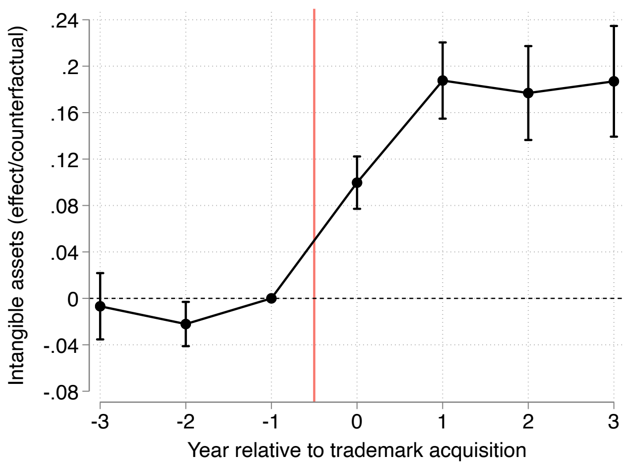
When a firm acquires a trademark, the acquisition cost should be recorded as part of its intangible assets. As a first step in our analysis, we analyze how trademark acquisitions affect the buyer firm's intangible capital. This analysis also works as validation of the accuracy of our new trademark-transactions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

Figure 4 shows estimates 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).[15] This formulation allows us to capture both intensive-

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

and extensive-margin responses.[16] While pre-acquisition trends align with control firms, trademark buyers experience a post-acquisition increase in intangibles, which stabilizes in years 1–3 at approximately 19% higher relative to the counterfactual. The pattern of coefficients—gradual increase in the transition period 0 and subsequent stabilization—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.

Figure 4: 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.

Estimating the effects of a trademarks acquisition on the *level* of intangible assets results in an average effect of around 54,000 Euro (Table A1), which corresponds to 5.8% and 2.4% of median and average value added, respectively. We interpret this as a proxy for the average trademark price for transactions within our analysis sample.

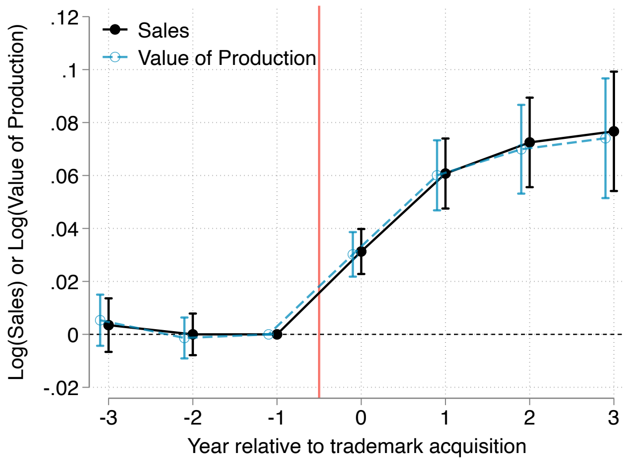
Trademark acquisitions lead to growth in firms' output. Figure 5 shows that sales and value of production gradually rise after the acquisition, stabilizing at approximately 8% above the counterfactual after two years.[17] This implies that, on average, acquiring a trademark leads to meaningful firm expansion, which could come from greater quantity, higher prices, or both. As illustrated in a model extension in Appendix D, a trademark acquisition could lead to expansion in factors of production

[16]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.

[17]Sales and value of production growing by the same amount implies that the effects on sales are not driven by existing inventory at the time of the transaction.

other than labor. We later show evidence on cost shares consistent with this channel. Under the identification assumptions, the expansion in other factors occurs as a byproduct of the scale-up induced by the brand-capital shock. The next subsection explores the role of labor inputs and wages during this period of trademark-buyers' expansion.

Figure 5: Firm Performance Effects of Trademark Acquisitions: Sales and Value of Production



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

6.2 Labor Demand Responses to a Trademark Acquisition

Figure 6(a) shows that employment headcount 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.[18] To determine whether this growth involves temporary or unstable jobs, in 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 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 transitions? The worker panel allows us to explore whether the observed increase in employment is driven by poaching workers from the trademark-selling firm. We examine log-employment excluding workers who were previously employed by the seller. Comparing the two event studies in Figure 6(a) reveals that

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

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 in Section 7 corroborates. Nevertheless, the inflow of seller-firm employees is non-trivial and reminiscent of evidence illustrating the job mobility across firms within production networks (Cardoza et al., 2025). To the extent that there exists human-capital specificity associated with brands, similar mechanisms as in Cardoza et al. (2025) could be at play in this context.[19]

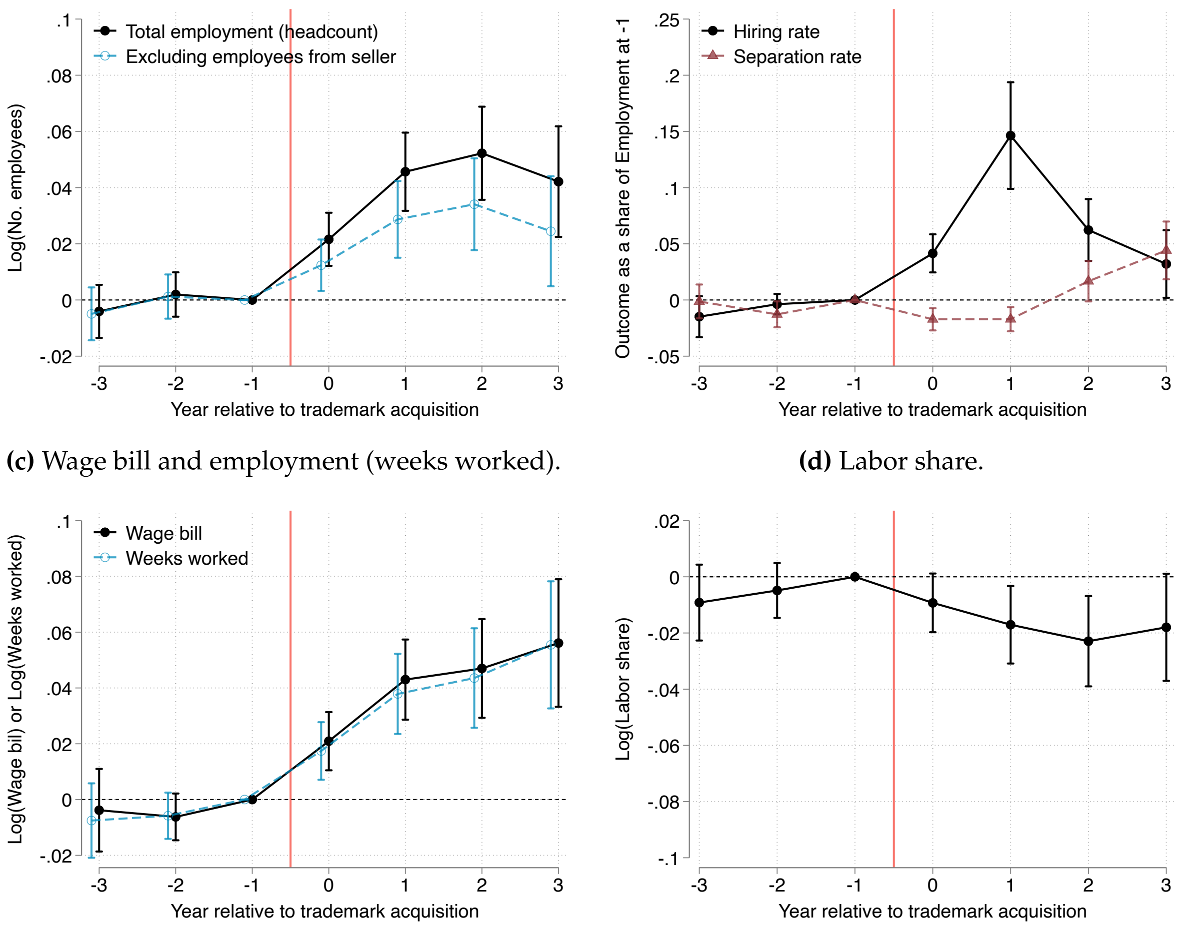
Employment churn. We examine the components driving the employment expansion by decomposing employment changes into hiring and separation margins. Specifically, we define hiring and separation rates as the number of hires and separations normalized by pre-acquisition employment. This normalization allows us to compare the magnitudes across outcomes and deal with cases of zero hires and separations. Figure 6(b) reveals that a substantial share of employment growth stems from increased hiring. In the first two years post-acquisition, the rise in new hires drives the total increase in employment. The second year after the transaction, the number of new hires is equivalent to 15% of the initial level of employment. These patterns indicate that firms increase hiring in the years immediately following a trademark acquisition to adjust to their new scale of operations. In addition, a small but statistically significant reduction in separations indicates that in the short-run the firm expands its size through an increased retention of incumbents. Over a longer horizon, cumulative hires exceed the overall employment increase. This is because the separation rate also rises to the equivalent of 5% of initial employment four years after the transaction. Hence, the firm's expansion is accompanied by substantial worker turnover 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. Figure 6(c) 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

[19]The characteristics of movers are consistent with this interpretation. 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. 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.

bill per week of work of incumbents nor of stayers. 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 event window.

Figure 6: 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) 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/value of production). Standard errors clustered at the firm level.

Comparing the 5–6% increase in the wage bill to the approximately 8% rise in sales (Figure 5) suggests that the buyers' labor share declines following a trademark acquisition. This finding is confirmed in Figure 6(d), where we use the buyer's log labor share as the dependent variable.[20] The labor share declines monotonically following

[20] Following De Loecker et al. (2020), we define a firm's labor share as the ration of the wage bill to the value of production, since value added can be negative for some observations, rendering the outcome undefined. Figure A4 shows results for labor share in levels rather than logs.

the trademark acquisition, with a drop of up to two percent in period 3. As reference, Autor et al. (2020) documents that Italy's labor share has declined by about five percentage points since the early 1990s, or a 7% decline. 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 shows that trademark acquisitions lead to firm expansion and accompanying employment growth. Firms that acquire trademarks hire more workers but also experience greater turnover. Importantly, employment growth does not translate into higher average earnings and the decline in labor shares 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.

Intermediate inputs provide additional evidence consistent with rising markups. 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.[21] As a result, the share of raw materials in total sales declines. Assuming firms are price-takers in input markets, this pattern is 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 how firms allocate costs between labor, capital, and materials. Cost shares of these factors remain virtually unchanged before and after a trademark acquisition (Figure A6). This stability suggests that the production technology itself is not substantially altered. The extension of the model in Appendix D.6 illustrates this interpretation explicitly.

Our findings provide direct micro-level evidence for the demand-side mechanism underlying labor share declines emphasized by Kehrig and Vincent (2021). Leveraging plant-level data on prices and quantities, they show that firm expansion is accompanied by rising prices and markups alongside weak wage responses, which they interpret as evidence of demand-side forces rather than cost reductions. We document similar within-firm dynamics following discrete increases in brand capital: by exploiting trademark transactions, we provide evidence that demand-side intangibles can generate these labor-share effects.

[21] Raw materials rise by 4.5%, while sales in the same group of firms increase by more than 5.5%.

6.3 Robustness

Restricting to events with failing sellers: We replicate the analysis on the subset of events in which the seller exits the market within the post-event period. This restriction isolates cases in which the opportunity to trade arises for reasons that are plausibly exogenous from the buyer's perspective. Table A4 reports the results for the main outcomes discussed in the previous sections. The estimates are both qualitatively and quantitatively similar to those in the baseline analysis. The main difference is a stronger decline in the labor share, driven by a smaller increase in the wage bill and a larger rise in revenues relative to the baseline.

Placebo event-studies. 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.

6.4 Skill-Biased Labor Demand Effects of Brand Capital

Our conceptual framework differentiates between production and expansionary labor. In our model, brand capital makes expansionary workers more efficient and it is thus expected to primarily boost employment engaged in tasks related to market expansion. We test this prediction by leveraging occupational codes observed for a large subset of employees, and the blue-collar versus white-collar/manager distinction available for the full sample.

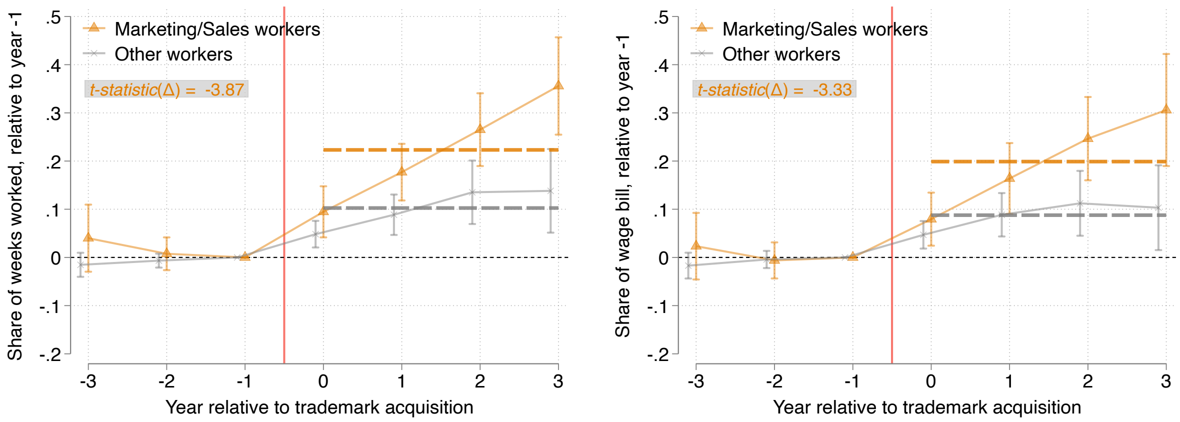
Marketing/sales workers vs. others: Extensive- and intensive-margin effects. Figure 7 shows estimates of a triple-differences extension of equation (3) that allows for heterogeneous effects across marketing/sales workers compared to other employees.[22] We use occupational codes to classify workers as belonging to the "marketing/sales" group if they are ever observed in an occupation related to these tasks. The

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

outcome variables for workers of type $l \in \{\text{marketing/sales}, \text{other}\}$ in Figure 7 are defined as the employment or wage bill of type-l employees relative to total employment or wage bill in the year prior to the acquisition. These changes are then rescaled by the average pre-acquisition share of type-l workers across buyer firms. This double normalization allows us to (i) incorporate the extensive margin by including firm-year observations with zero type-l workers, and (ii) express the estimates relative to the baseline importance of each worker group. Each coefficient can therefore be interpreted as the percentage change in the employment or wage bill of a given labor-type, which directly corresponds to the model-relevant estimand highlighted in our theoretical framework.

Figure 7: Skill-Specific Labor Demand Effects: Marketing/Sales Workers vs. Others. Extensive and intensive margins.

(a) Employment (weeks worked). **(b)** Wage bill.



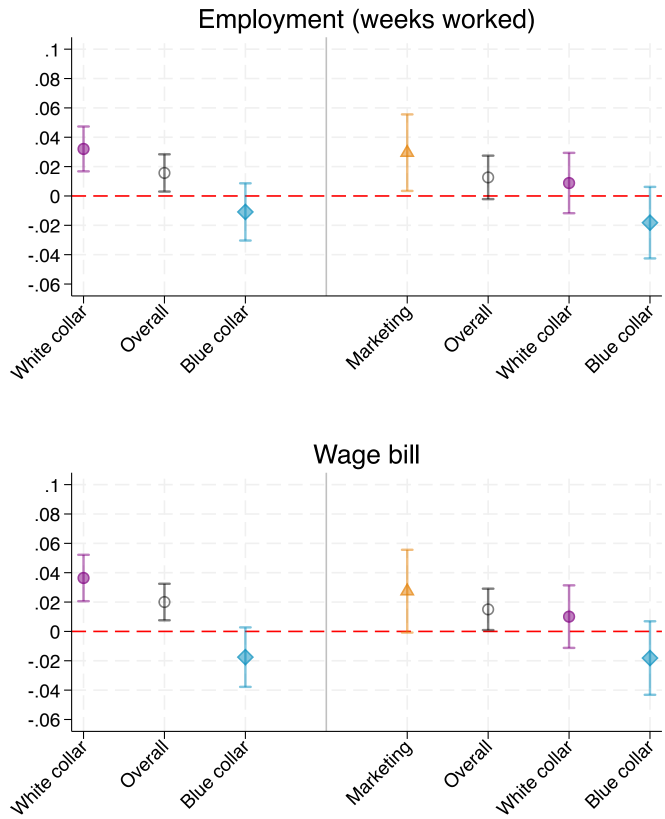
Notes: Estimates and 95% confidence intervals of parameters β_k in equation (3) for outcome variables of the form: $\frac{(y^l_{ft}/y_{f,t_f-1})}{\hat{\mathbb{E}}[(y^l_{f,t_f-1}/y_{f,t_f-1})]}$, where y_{ft} represents total weeks worked or total wage bill; y^l_{ft} represents total weeks worked or total wage bill of labor-type l, where $l \in \{\text{marketing/sales, other}\}$; $t_f - 1$ is the year prior to the trademark acquisition of firm f; and $\hat{\mathbb{E}}[\cdot]$ denotes the average across buyer firms in $t_f - 1$. Horizontal dashed lines indicate the estimate of the average of post-acquisition, period-specific effects $\hat{\bar{\beta}} \equiv \frac{1}{4}\sum_{k=0}^{3} \hat{\beta}_k$. Reported t-statistics refer to the test with null hypothesis $\bar{\beta}(\text{marketing/sales}) = \bar{\beta}(\text{other})$. Standard errors clustered at the firm level.

The effects of a trademark acquisition on non-marketing/sales workers are positive, consistent with the overall employment expansions documented in Figure 6.[23] Relative to the year before the transaction, weeks worked and wage bill for this group increase by about 11%. The key takeaway from Figure 7, however, is that the corresponding increase in marketing/sales labor is roughly twice as large, amounting to

[23]The magnitude of the employment and wage bill effects in Figure 7 are not directly comparable to those in Figure 6(c) for two reasons: first, to account for the extensive margin of marketing/sales workers, Figure 7 normalizes employment levels by the $t_f - 1$ value rather than using logs; second, Figure 7 is based on employment of the ~86% of workers for whom we observe occupations. Nonetheless, the main focus of the heterogeneity analysis is the differential response across the two groups.

22%. This finding is consistent with the predictions of our model, and we interpret it as evidence of the skill-specificity of brand capital: firms expand employment disproportionately in marketing-related occupations that interact most closely with brands.

Figure 8: Skill-Specific Labor Demand Effects: Log employment and wage bill of blue collar, white collar, and marketing/sales. Intensive margin.



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 throughout the event-study window). 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

Blue-collar, white-collar, and marketing/sales: Intensive-margin effects. Figure 8 further tests the skill-biased nature of brand capital, analyzing the blue-collar/white-collar margin among firms that employ both types of labor throughout the event-study window. Restricting our attention to firms with both groups allows us to focus on intensive-margin adjustments. Figure 8 summarizes the results showing averages of post-effects parameters $\{\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3\}$ in equation (3), estimated heterogeneously by worker type within a triple-differences specification.[24]

The left-hand segments in Figure 8 show that employment growth following a trademark acquisition is primarily driven by white-collar workers and managers, whose employment and wage bill increase 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. The difference between these two groups is statistically significant for both outcomes. Under the interpretation that white-collar workers represent *expansionary* workers and blue-collar workers represent *production workers*, this finding aligns with the evidence on skill-biased effects from Figure 7. Note that these compositional effects coexist with the null effects on firm-level weekly earnings (Figure 6(c)). The increase in white-collar employment is insufficient to materially affect average earnings through composition alone, and may be further attenuated if marginal white-collar hires are paid less than incumbents.

The right-hand segments of Figure 8 show that, within firms already employing marketing/sales workers, most of the increase in white-collar employment and wage bill comes from marketing/sales. 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 and a slightly negative effect on blue-collars. The difference between the responses of marketing and sales and the ones of blue-collar are statistically significant, while only the response on employment relative to the rest of white-collars and managers is marginally significant at 10%. This pattern provides further evidence that brand capital is complementary to *expansionary labor*, even among firms that already had marketing/sales workers in their ranks.

Discussion on skill-specific labor demand effects. The labor demand effects of brand capital 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.

There could be implications for labor market inequality following from this result. We do not observe changes in average wages across groups, so inequality is not affected through a modification of rent-sharing within the firm. Instead, asymmetric labor demand responses could lead to a widening of the economy-wide wage gap between expansionary and production workers. We discuss a plausible quantification of this channel in Section 8.

[24] Table A5 summarizes the heterogeneous effects across subgroups of the buyers' workforce. Figure A10 shows the underlying dynamic estimates.

For blue-collar workers, the net employment effect is close to zero, but the worker panel reveals that the net zero masks some underlying dynamics. After a trademark acquisition, we observe higher rates of both hiring and separations, showing that blue-collar workers also experience heightened turnover even though their overall employment level is stable (Figure A11). As discussed in Section 6.2, 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. White-collar and managers also show some increased churning in the medium-run, but experience a significant increase in hires in the short-run (Figure A11), which drives the overall firm employment expansion.

Null blue-collar effects, prices, and quantities. One might interpret the null employment effects for blue-collar workers as evidence that the revenue gains associated with trademark acquisitions operate solely through higher prices rather than higher quantities. While price effects are clearly present and consistent with the rest of our evidence, concluding that the adjustment occurs exclusively along the price margin would be too strong. The distinction between white- and blue-collar workers is necessarily coarse, and some white-collar occupations that expand following trademark acquisitions may be directly involved in the production of goods and services. For this reason, we do not take a strong stance on the relative importance of price versus quantity adjustments.

7 Transaction-Level Effects of Trademark Reallocation

Do trademark transactions allocate brand capital toward more efficient uses? Our model implies that trademarks should be acquired by firms with higher marginal returns to brand capital. We evaluate this prediction 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.[25] We restrict the sample to transactions involving buyers from the buyer-level analysis. 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.[26]

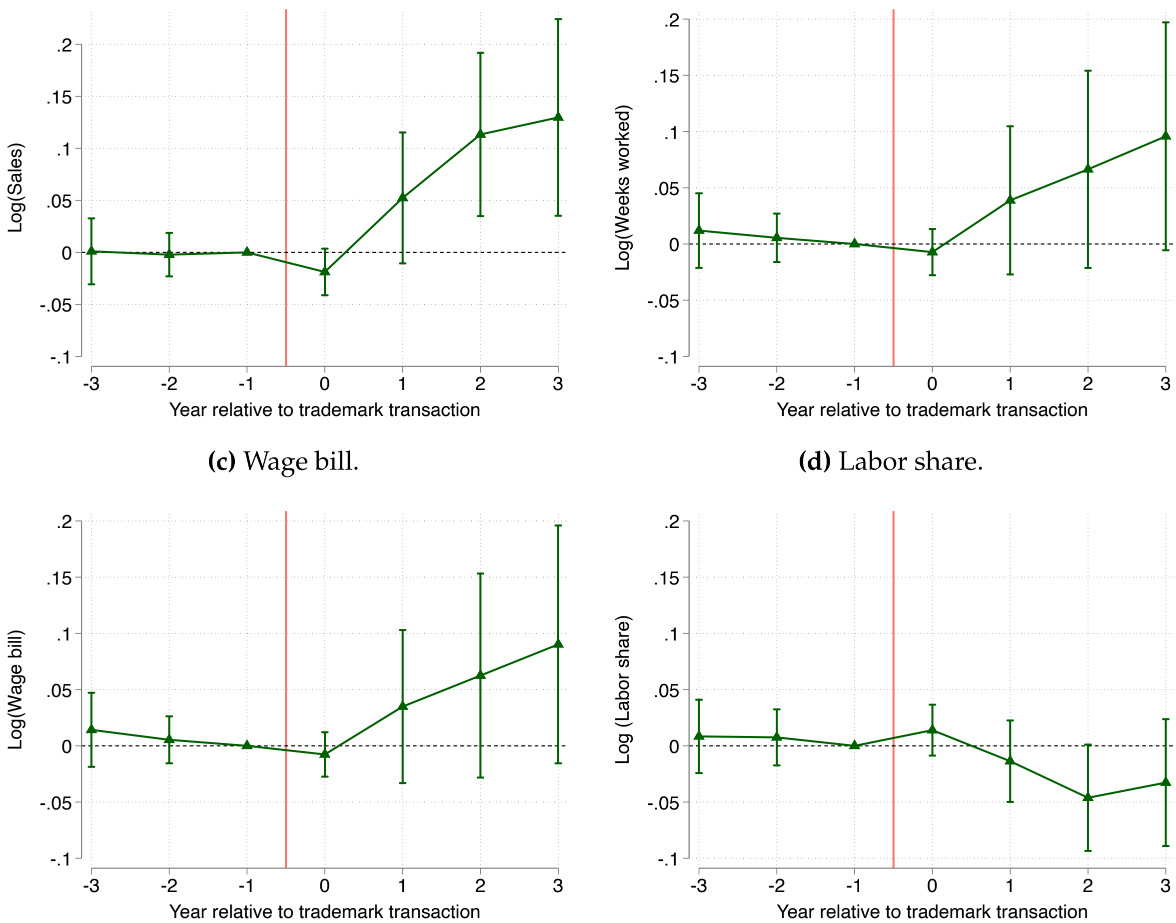
[25]Because transactions may involve multiple buyers and sellers, we cannot include matching-cell fixed effects in the transaction-level analysis.

[26]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.

Figure 9(a) shows that sales at the transaction level increase by up to 13%.[27] Complementing this, Figure A9 reports a separate analysis of trademark sellers, showing a decline in sales, with only partial recovery over the longer run. However, these losses are not large enough to offset the gains realized by buyers.

Figure 9: Trademark Transactions: Transaction-Level Effects

(a) Sales. **(b)** Employment. **(c)** 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 specification for these event studies is similar to that in equation (3) with the distinction that outcome variables are aggregated for buyers and sellers involved in a transaction and we cannot include matching-cell fixed effects (which are not feasible for the aggregated units). The comparison group results from the aggregation of matched controls for buyer and seller firms. Standard errors clustered at the transaction level.

Moving to labor outcomes, we find that total employment among the firms involved rises by 6% on average (Figure 9(b)), suggesting that trademark transactions create jobs on net by reallocating brand capital to more productive firms. The aggregate wage bill displays a similar increase.[28] The wage bill grows less than sales, leading to a decrease in the aggregate labor share of about five percent (Figure 9(d)), as

[27]Table A6 summarizes the effects of brand transactions on transaction-level outcomes.
[28]Employment and wage bill decline for sellers, but not enough to offset buyers' gains (Figure A9).

predicted by our model.[29] 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, brand-capital reallocation reduces the labor share at transacting firms, concentrating revenues and pointing to a concrete micro-level channel through which aggregate labor shares may decline.

8 Model Implications for the Aggregate Labor Share

We combine the theoretical framework in Section 4 with the event-study estimates to quantify the long-run effects of trademark transactions on the aggregate labor share. Our empirical findings point to a reallocation mechanism: as large firms accumulate brand capital, revenues expand while labor shares fall. The model provides a mapping from firm-level responses to aggregate outcomes, allowing us to quantify both the labor-share implications of brand reallocation across firms and the offsetting effects for brand sellers.

The exercise proceeds in three steps. First, we calibrate the core model elasticities by matching the observed responses of outcomes to trademark transactions in the data. Second, we simulate the steady-state distribution of trademark ownership across firms of different sizes as transactions unfold. Third, we recompute the aggregate labor share implied by this distribution and compare it to the observed data.

Calibration of Model Elasticities We link the estimated effects of trademark acquisitions to the core model elasticities: the cost elasticity of creating new products, γ, and the demand elasticity of generic and branded products, ϵ_G and ϵ_B, respectively. In addition, since we do not observe brand capital levels, we treat the share of revenues generated by branded products of the average firm, denoted as S_B, as an additional parameter for calibration.

From the model's perspective, a one percent increase in brand capital leads to changes in revenues and employment through the following elasticities:

$$\frac{d\log Rev}{d\log b} = \frac{S_B}{1-\gamma}, \qquad \frac{d\log Emp}{d\log b} = \frac{W_B(\gamma, \epsilon_G, \epsilon_B, S_B)}{1-\gamma}, \tag{4}$$

where W_B is the share of the wage bill that is generated by branded products as a function of the parameter of interest, with a closed-form expression provided in Appendix D.7. For the revenue-brand capital elasticity, we match the ratio of event-study estimates on the effect of a trademark acquisition on sales (Figure 5) and on intangible

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

assets (Figure 4), which is equal to 0.396.[30] For the employment-brand capital elasticity, we match the ratio of event-study estimates on the effect of a trademark acquisition on employment weeks (Figure 6) and on intangible assets (Figure 4), which is equal to 0.297.

The relative response of marketing/sales labor to other labor is given by the ratio $\frac{W_B^E}{W_B^P}$,

$$\frac{d \log Emp^E}{d \log Emp^P} = \frac{W_B^E(\gamma, \epsilon_G, \epsilon_B, S_B)}{W_B^P(\gamma, \epsilon_G, \epsilon_B, S_B)}, \tag{5}$$

where W_B^E denotes the share of the wage bill of marketing/sales (expansionary) workers generated by branded products, and W_B^P denotes the corresponding share for other (production) workers. We match the estimate on the relative employment changes of marketing/sales workers vs. other workers from Figure 7, which is equal to 2.575. Lastly, we use the labor share implied by the model to match the sales-weighted labor share:

$$\text{Agg. Labor Share} = \theta(\gamma, \epsilon_G, \epsilon_B, S_B). \tag{6}$$

In the sample, this share takes value 0.543. Although our model abstracts from physical capital for simplicity, a fraction of firms' residual income in the data indeed reflects capital income. As such, we adjust the observed labor share by the capital share used in the literature, 0.18 (Berger et al., 2022). This adjustment sets our aggregate labor share target to 0.663. Berger et al. (2022) report similar labor share values among US firms.

We identify the four parameters of interest by solving the system of four nonlinear equations (4)–(6). Appendix D.7 shows closed-form solutions for the four equations as a function of the parameters of interest.

Table 4 summarizes the calibration targets and resulting parameter values, showing that generic products face a more elastic demand, with a markup of 1.58, while branded products face a less elastic demand, with a substantially higher markup of 3.19. The generic-product markup is comparable to the estimates from the literature (e.g., 1.61 from De Loecker et al. (2020)). We calibrate $\gamma = 0.266$, implying that 26.6% of revenue net of production workers' wages accrues to expansionary workers, with the remainder retained as firm profits. The average firm in our sample has a revenue share in branded products S_B of 29%.

Stationary Distribution of Brand Capital We next compute the stationary distribution of trademark ownership across the firm size distribution, based on the observed trademark flows across firms of different sizes (Table 1). Specifically, we ask what the

[30] Throughout the calibration exercise, we target relative-year $t = 3$ estimates (i.e., $\hat{\beta}_3$, following the notation in equation (3)).

Table 4: Calibration: Empirical Targets and Parameter Values

Panel A. Empirical targets $\hat{\beta}_{Sales}/\hat{\beta}_{Intan}$	$\hat{\beta}_{Emp}/\hat{\beta}_{Intan}$	$\hat{\beta}_{MarketEmp}/\hat{\beta}_{OtherEmp}$	Agg. Labor Share
0.396	0.297	2.575	0.663
Panel B. Parameter values γ	ϵ_G	ϵ_B	S_B
0.266	2.730	1.457	0.291

Notes: Panel A reports the empirical moments used to calibrate model parameters. $\hat{\beta}_{Sales}/\hat{\beta}_{Intan}$ is the ratio of the event-study estimates of trademark acquisitions on sales and intangible assets; $\hat{\beta}_{Emp}/\hat{\beta}_{Intan}$ is the corresponding ratio for total employment; $\hat{\beta}_{MarketEmp}/\hat{\beta}_{OtherEmp}$ measures the relative employment response of marketing and sales workers to other workers. The aggregate labor share is computed as the ratio of the total wage bill to total revenue in the estimation sample adjusted by the capital share of 0.18 from Berger et al. (2022). Panel B reports the calibrated parameter values that jointly match these targets. γ denotes the elasticity of product creation with respect to expansionary labor; ϵ_G and ϵ_B are the demand elasticities for generic and branded products; S_B is the revenue share of branded products for the representative firm. For all event-study estimates, we target the relative-year $t = 3$ estimates (i.e., $\hat{\beta}_3$, following the notation in equation (3)).

counterfactual distribution of trademark ownership across firm-size bins would be if trademark transactions were to unfold infinitely according to these flows. We convert the flow matrix into transition probabilities and, assuming transaction opportunities arrive randomly, compute the eigenvector associated with the unit eigenvalue, which characterizes the long-run steady-state distribution of brand ownership.[31]

Figure 10(a) plots the resulting stationary distribution alongside the observed ("initial") distribution. Compared to the initial distribution, the top two size bins gain trademarks, while smaller bins lose them.

Labor Share: Observed vs. Steady-State Simulation Figure 10(b) illustrates the resulting between-firm reallocation of revenue shares and the within-firm effects on labor shares. The steady-state trademark reallocation leads to an expansion of revenues among larger firms.[32] When translated into revenue shares, only the largest size group experiences a net increase, amounting to 0.5 percentage points.[33] Figure 10(b) shows that the firm-level labor shares increase for the two largest bins and increase for the two smallest bins after these simulated trademark transactions. As revenue shares reallocate from the smaller bins towards the largest bin, the aggregate labor share reflects a revenue-weighted combination of these changes, amplifying the declines among large

[31] The exercise abstracts from firm entry and exit as well as the creation of new trademarks.

[32] To map trademark counts into brand capital levels, we calibrate the level of brand capital for the average firm in the model so that its revenue share from branded product matches S_B. Dividing this calibrated level by the sample average number of trademarks per firm, we obtain the brand capital per trademark. We then compute the brand capital for firm-size bins at the initial and stationary distributions using this capital-per-trademark multiplied by the number of trademarks in each bin.

[33] Although the second-largest bin gains brand capital, it loses revenue share because the largest firms expand branded output more aggressively. Due to the complementarity between brand capital and expansionary labor, larger firms hire disproportionately more expansionary workers, which raises their revenue per unit of brand capital. As a result, revenue shares shift toward the largest firms at the expense of the second-largest group.

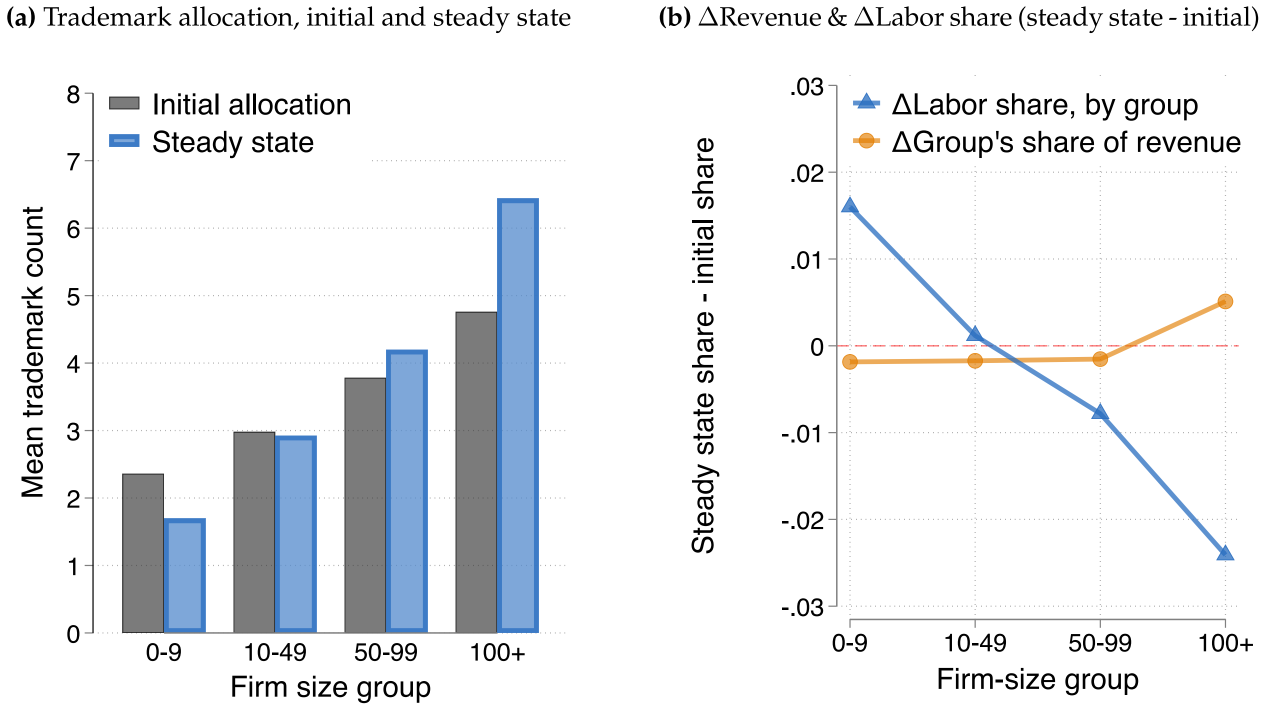
firms and attenuating the increases among smaller ones.

We compute the change in the aggregate labor share by combining the steady-state revenue reallocation across firm-size groups with within–firm-size changes in labor shares. The aggregate labor share can be defined as:

$$\text{Agg. Labor Share} = \sum_{g\in\{1,2,3,4\}} RevShare_g \times \theta_g, \tag{7}$$

where g indexes firm-size groups, $RevShare_g$ is the revenue share of group g, and θ_g is the group-specific labor share.

Figure 10: Steady-state Simulation: Trademarks, Labor Share, and Revenue Share



Notes: Panel (a) shows the initial and steady-state allocations of trademark ownership across firm size groups. The initial allocation is the one observed in our data. The steady state is simulated using observed trademark flows, as detailed in the text. Panel (b) shows the differences between steady-state and observed (i) revenue shares across firm-size groups, and (ii) within-group changes in the labor share.

Combining Figure 10(b) with equation (7), we estimate that the unfolding of the secondary market for existing trademarks reduces the aggregate labor share by 1.02 percentage points. This is a sizeable reduction when compared to the observed decline of the Italian labor share, amounting to 5 percentage points since the early 1990s (Autor et al., 2020).

Wage differentials. Holding relative wages fixed, our model predicts a relative increase in the demand for expansionary workers compared to production workers. More precisely, the ratio of total expansionary to production employment increases from 0.24 to 0.26, corresponding to a 6% increase in relative labor demand. Allowing wages to adjust in equilibrium, the implied effect on relative wages is given by $\frac{5\%}{\eta}$, where η denotes the sum of labor supply and demand elasticities. For example, combining an intensive-margin supply elasticity of 0.5 from Chetty et al. (2013) with a relative labor demand elasticity of 1.5 from Katz and Murphy (1992) implies a 3% wage increase for marketing/sales workers relative to other workers.

Robustness. Our calibration assumes that the estimated 19% increase in book intangibles following a trademark acquisition reflects the corresponding increase in brand capital (Figure 4). In practice, book intangibles may either overstate or understate the true change in brand capital, depending on the relative size of unmeasured brand versus non-brand intangible assets at baseline.[34]

To assess sensitivity, we rescale the estimated semi-elasticity between trademarks and brand capital and recompute the implied aggregate labor share. For each scaling factor, we recalibrate the model to match the same empirical targets and simulate the steady-state labor share (Figure A12). When the true semi-elasticity exceeds our baseline estimate (scaling factor > 1), the implied revenue and employment responses are attenuated, reducing the aggregate labor share effect. Even so, assuming a 50% larger semi-elasticity yields a 0.82 percentage-point decline in the labor share, compared to 1.02 at baseline. Conversely, if the baseline estimate overstates the true semi-elasticity (scaling factor < 1), the implied labor share decline is amplified.

9 Conclusion

This paper studies how brand capital shapes firms' labor demand, using firm-to-firm trademark transfers to obtain plausibly exogenous shifts in otherwise hard-to-measure brand assets. We show that trademark acquisitions lead firms to expand: revenues and employment rise, yet average earnings remain unchanged. Because revenue grows faster than the wage bill, trademark acquisitions reduce the acquiring firm's labor share. The effects are not neutral across job functions: employment and the wage bill rise primarily in market-facing, white-collar and managerial roles—especially marketing and sales—consistent with brand capital complementing these types of workers.

[34]To see this, let $I^* = I + I^u$, where I^* is true intangible capital, I is observed intangible capital (measured in the balance sheet), and I^u is unobserved intangible capital. Similarly, $I^* = B^* + O^*$, where B^* is brand capital and O^* is non-brand intangible capital. Our estimates imply $(I_1 - I_0)/I_0 \approx 0.19$. The true effect on brand capital can be defined instead as $(B_1^* - B_0^*)/B_0^*$. Our event-study identification assumptions would imply $(I_1 - I_0) = (B_1^* - B_0^*)$ (i.e., the level-shift in intangibles is all driven by brand capital), whereas we have that $I_0 = B_0 + O_0$ and $B_0^* = B_0 + B_0^u$. Hence, we overestimate the effect of a trademark acquisition on brand capital if $O_0 < B^u$, and underestimate if $O_0 > B_0^u$.

Looking beyond acquirers, trademark transactions reallocate brand capital toward more productive firms. At the transaction level (buyers and sellers combined), sales and employment increase on net, but the combined labor share declines. These patterns highlight a key distinction between demand-side and cost-side intangibles. While much of the intangible capital literature emphasizes innovations that lower production costs (e.g., patents or software), brand capital shifts firms' output towards high-markup products and leads to shifts in the composition of labor demand.

Methodologically, the paper highlights the value of using firm-to-firm transfers to identify the effects of an intangible asset that is otherwise difficult to measure. Trademark transactions allow us to observe discrete reallocations of brand capital across firms, allowing us to sidestep the difficulties of measuring its gradual, internal accumulation—a process that typically leaves little trace in accounting records. This transfer-based approach could be applied to other settings in which intangible assets change ownership across firms.

More broadly, our results point to a demand-side channel through which intangibles can contribute to the secular decline in the labor share. In a calibrated simulation, the continued reallocation of brand capital through the secondary market for trademarks lowers the aggregate labor share by roughly one percentage point and widens the labor-demand gap between expansionary and production labor. Taken together, the findings show that brand capital has first-order implications for labor demand and the labor share.

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- SUPPLEMENTARY APPENDICES -
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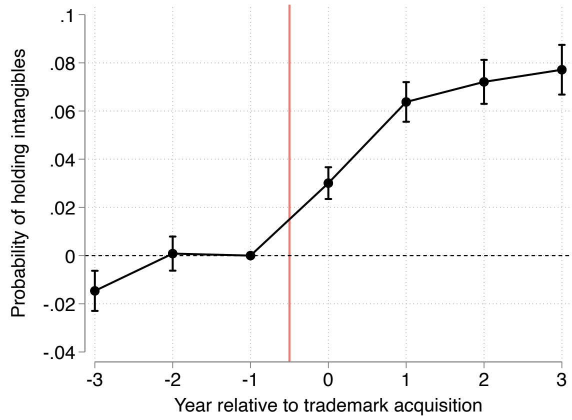
A Additional Figures and Tables

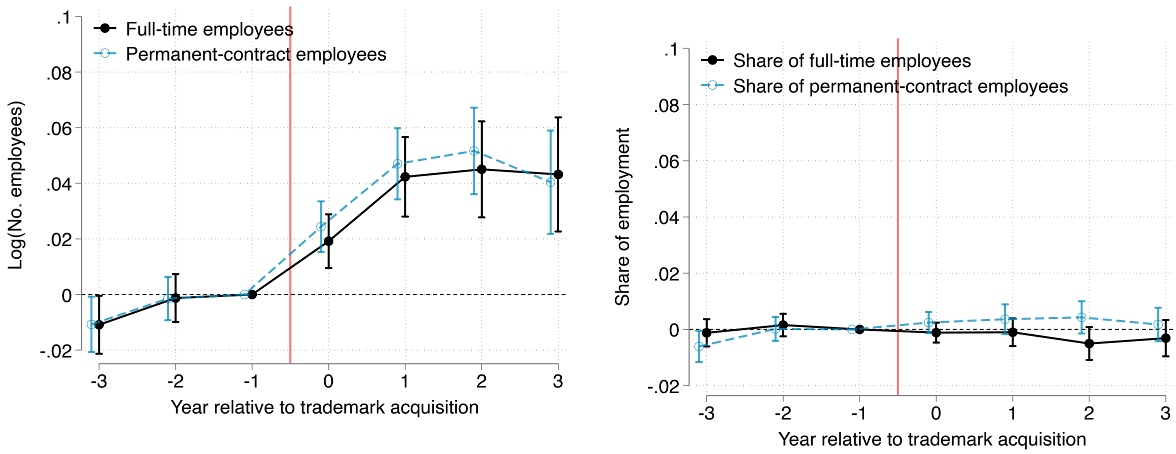
Figure A1: Effect of Trademark Acquisitions on Balance Sheet Intangibles (Extensive Margin).



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.

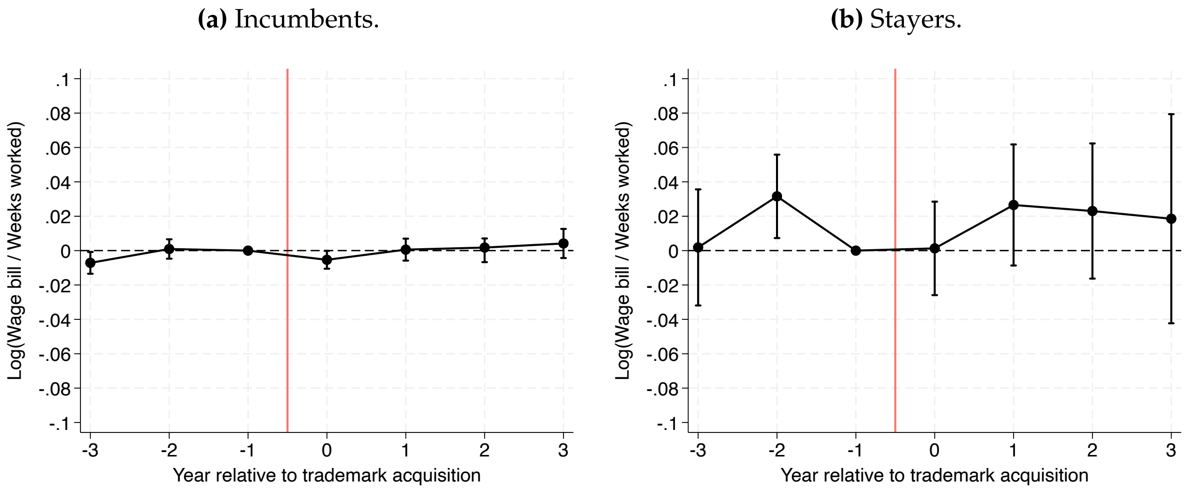
Figure A2: Effect of Trademark Acquisitions on the Firm's Contract Mix

(a) Full-time and permanent-contract employees **(b)** Empl. shares of full-time and permanent contracts



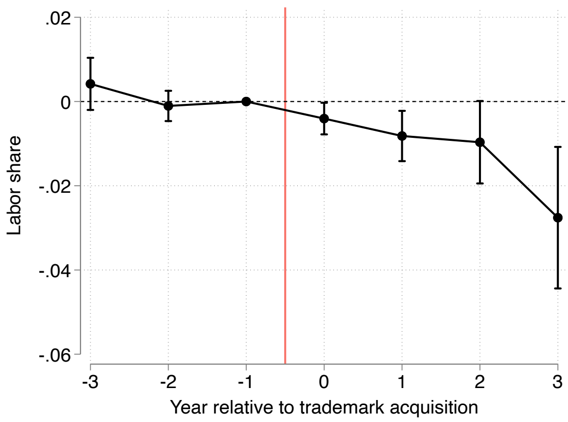
Notes: Estimates and 95% confidence intervals of parameters β_k in equation (3) for the following outcome variables. Panel (a): Full-time employees and permanent-contract employees. These two outcome variables are expressed in logs. Panel (b): Share of total employment with permanent or full-time contracts. 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.



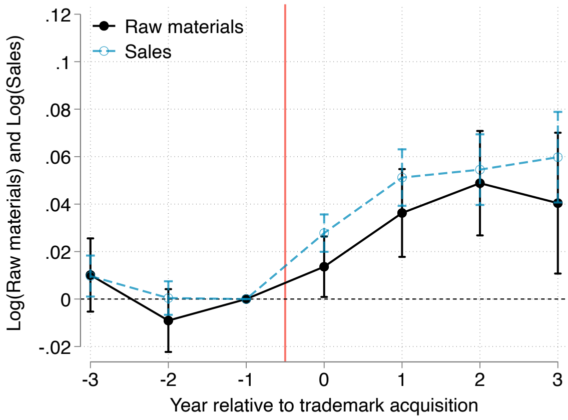
Notes: Estimates and 95% confidence intervals of parameters β_k in equation (3) when outcome variable is the log of wage bill over weeks worked. Panel (a): the outcome is defined for incumbent workers, i.e. permanent and full-time employees at the buyer firm at the time of the trademark acquisition. The outcome is measured across all firms where the incumbents work, buyer firm or elsewhere. Panel (b): 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).



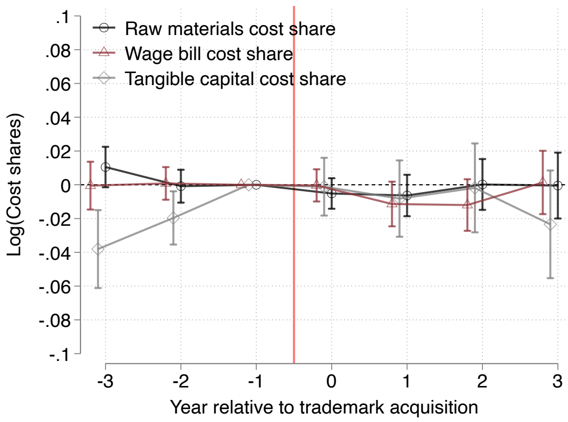
Notes: Estimates and 95% confidence intervals of parameters β_k in equation (3) when outcome variable is the labor share (wage bill/value of production) of firm f in year t. Standard errors clustered at the firm level.

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.

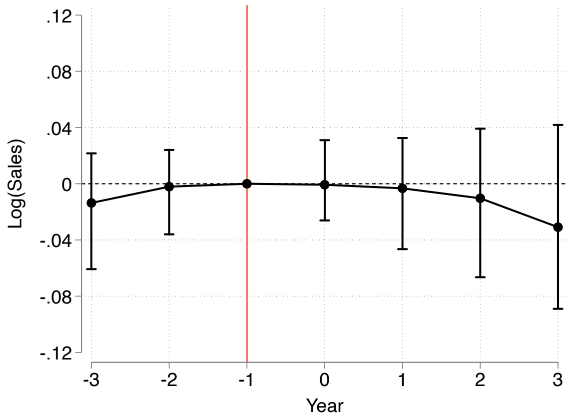
Figure A6: Effect of a Trademark Acquisition on Cost Shares.



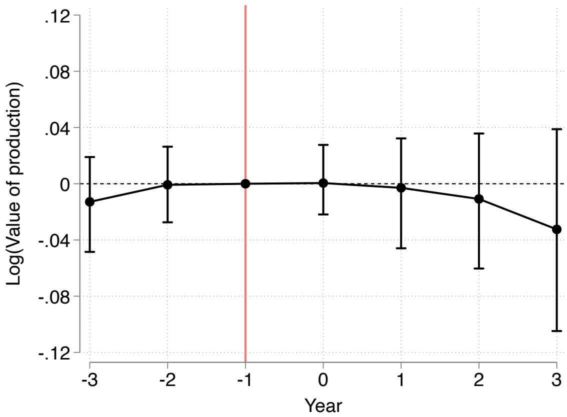
Notes: Estimates and 95% confidence intervals of parameters β_k in equation (3) when outcome variables are the log cost shares of firm f in year t. Outcomes are defined as log(cost of input k/total costs), where k is raw materials, wage bill, or tangible capital. Standard errors clustered at the firm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

Figure A7: Placebo Trademark Transactions

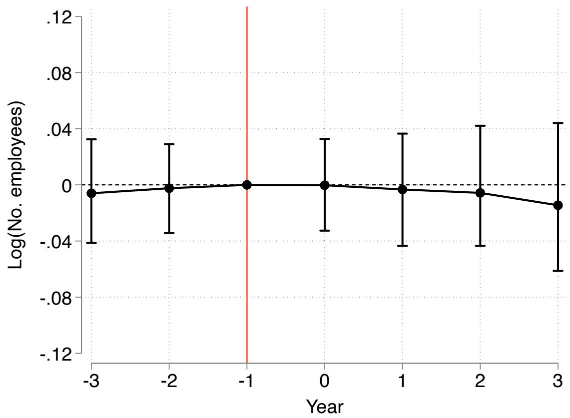
(a) Sales.



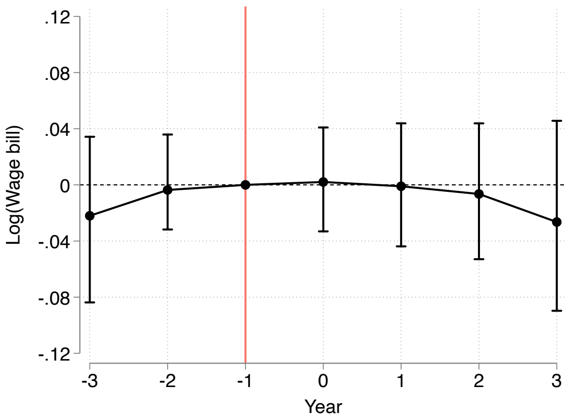
(b) Value of production.



(c) Employment.

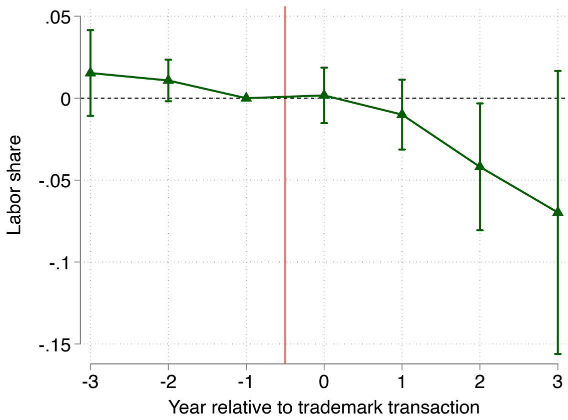


(d) Wage bill.



Notes: 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.

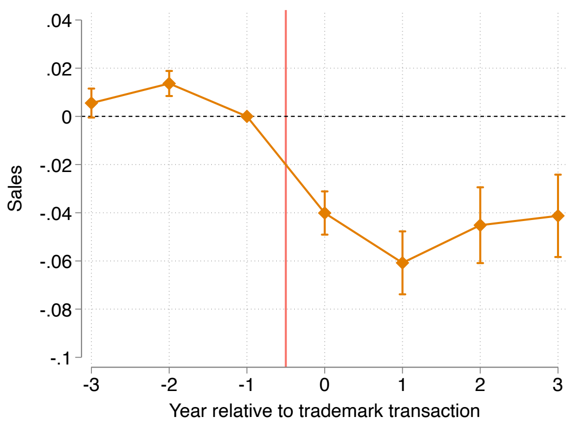
Figure A8: Transcation-Level Effects: Labor Share (Levels).



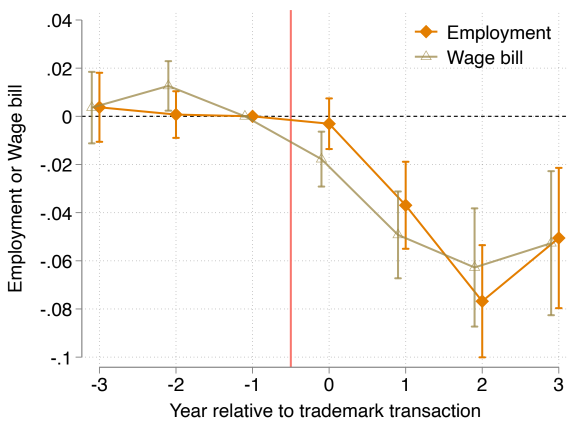
Notes: Event-study estimates and 95% confidence intervals of the transaction-level effect of a trademark transaction, aggregating the outcomes of seller and buyer firms. The specification for these event studies is similar to that in equation (3) with the distinction that outcome variables are aggregated for buyers and sellers involved in a transaction and we cannot include matching-cell fixed effects (which are not feasible for the aggregated units). The comparison group results from the aggregation of matched controls for buyer and seller firms. Standard errors clustered at the transaction level.

Figure A9: Trademark Transaction: Seller Effects

(a) Sales.



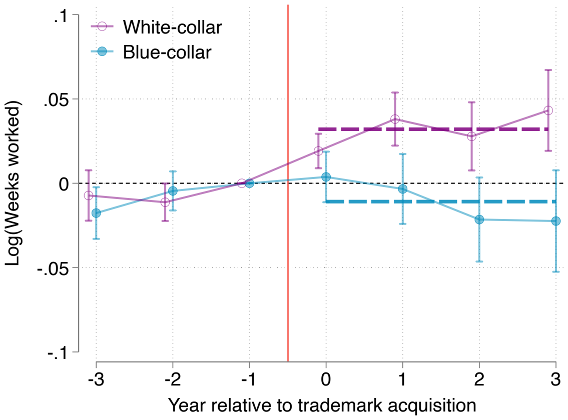
(b) Employment and wage bill.



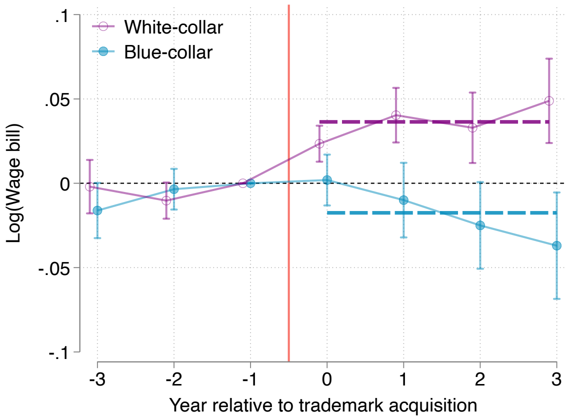
Notes: Event-study estimates and 95% confidence intervals of the effect of selling a trademark for seller firms. Poisson QML estimates of parameters β_k in an exponential version of equation (3) where treatment is defined as selling a brand. Standard errors clustered at the firm level.

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

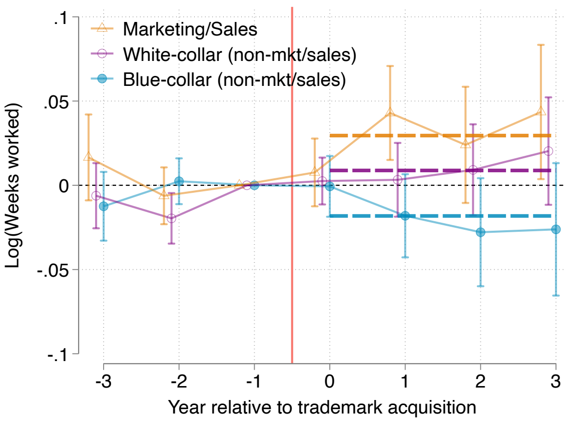
(a) Employment: Blue-collar vs. white-collar.



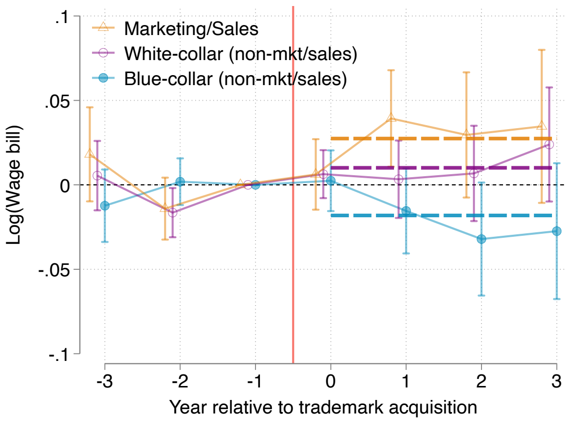
(b) Wage bill: Blue-collar vs. white-collar.



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

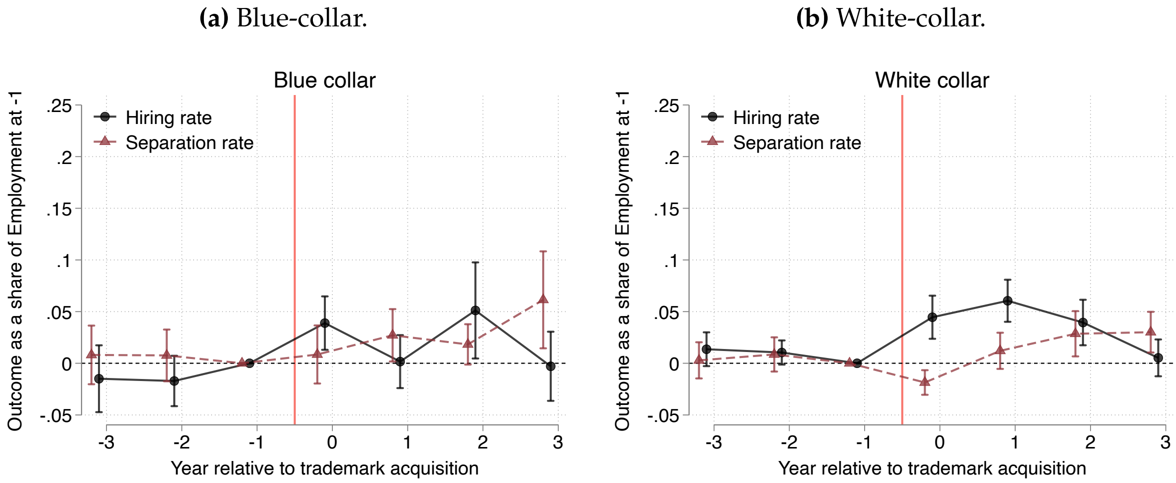


(d) Wage bill: Marketing/sales workers vs. others.



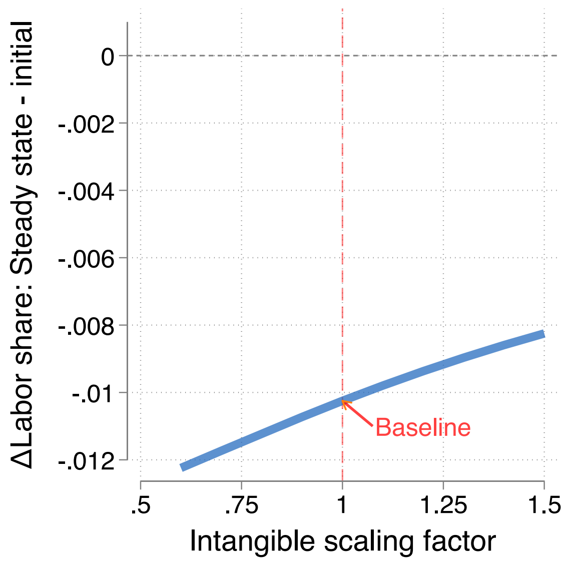
Notes: Estimates and 95% confidence intervals of parameters β_k in equation (3), estimated heterogeneously by worker type. Top panels separate between white-collar and blue-collar workers. Bottom panels separate between workers who are ever employed in a marketing/sales occupations (Marketing/Sales), 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 dashed lines indicate the average of post-acquisition, period-specific effects $\bar{\hat{\beta}} \equiv \frac{1}{4}\sum_{k=0}^{3}\hat{\beta}_k$. Standard errors clustered at the firm level.

Figure A11: Heterogeneous effects of trademark acquisitions: Hirings and separations by worker occupation



Notes: Estimates and 95% confidence intervals of parameters β_k in equation (3), estimated heterogeneously by worker type. Panels separate between blue-collar workers (Panel (a)) and white-collar (Panel (b)). The outcomes are: i) hiring rate: number of new hires/number of employees in a given occupation in year t_f-1; ii) separation rate: number of separations/number of employees in a given occupation in year t_f-1. Standard errors clustered at the firm level.

Figure A12: Robustness of the simulated change in aggregate labor share to a re-scaling of the trademark-intangible capital semi-elasticity.



Notes: Intangible scaling factor is defined as the ratio between (i) the true elasticity of brand capital with respect to a trademark acquisition and (ii) our estimate of the elasticity of intangible assets to a trademark acquisition from Figure 4. The vertical axis shows how the change in the aggregate labor share implied by the calibration in Section 8 changes as a function of the intangible scaling factor.

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

Panel A: Firm Performance			
	Intangibles (Poisson) (1)	Intangibles (Level) (2)	Sales (3)
$\bar{\beta}_k$	0.150***	53,770.391***	0.060***
	(0.014)	(4,057.197)	(0.007)
Obs.	2,922,422	3,149,664	3,149,664
N. buyer firms	1,891	1,910	1,910
N. firms	173,185	192,171	192,171

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. Sales are expressed in logs. The regression on Intangibles has fewer observations since the Poisson estimator drops some singletons. Each matched control cell is weighted by the number of buyer firms in the same cell. "N. buyer firms" reports the number of distinct buyer firms in the estimation sample. "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)	Hiring Rate (3)	Separation Rate (4)	Tot. Weeks (5)	Wage Bill (6)	Labor Share (7)
$\bar{\beta}_k$	0.040***	0.025***	0.071***	0.007	0.039***	0.042***	-0.017***
	(0.007)	(0.006)	(0.012)	(0.007)	(0.007)	(0.007)	(0.006)
Obs.	3,149,664	3,149,664	3,149,664	3,149,664	3,149,186	3,149,664	3,149,664
N. buyer firms	1,910	1,910	1,910	1,910	1,910	1,910	1,910
N. firms	192,171	192,171	192,171	192,171	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 except hiring and separation rates, which are measured as shares. The outcome "Emp. (excl. seller)" (Column 2) subtracts from total employment the employees that were employed by the selling firm before the transaction occurred. Each matched control cell is weighted by the number of buyer firms in the same cell. "N. buyer firms" reports the number of distinct buyer firms in the estimation sample. "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	10,666	803,930

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 Effects of Acquiring a Trademark: Subsample of Failing Sellers

	Sales (1)	Employment (2)	Hiring Rate (3)	Separation Rate (4)	Tot. Weeks (5)	Wage Bill (6)	Labor Share (7)
$\bar{\beta_k}$	0.076***	0.069***	0.110**	0.005	0.043**	0.034	-0.037**
	(0.018)	(0.021)	(0.051)	(0.012)	(0.022)	(0.021)	(0.017)
Obs.	745,879	745,879	745,879	745,879	745,737	745,879	745,879
N. buyer firms	237	237	237	237	237	237	237
N. firms	76,665	76,665	76,665	76,665	76,665	76,665	76,665

Notes: This table summarizes the effects of acquiring a trademark on firm outcomes for the sample of buyer firms for whom at least one seller shuts down in the years following the acquisition event. 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 except hiring and separation rates, which are measured as shares. Each matched control cell is weighted by the number of buyer firms in the same cell. "N. buyer firms" reports the number of distinct buyer firms in the estimation sample. "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 A5: The Effects of Acquiring a Trademark on Firm Labor Demand: Heterogeneous Effects

Panel A: Marketing/Sales VS Others (Intensive+Extensive Margin)		
	Tot. Weeks (1)	Wage Bill (2)
$\bar{\beta_k}^{\text{MKTSL}}$	0.234***	0.218***
	(0.036)	(0.041)
$\bar{\beta_k}^{\text{No MKTSL}}$	0.118***	0.110***
	(0.030)	(0.031)
T-stat $\bar{\beta_k}^{\text{No MKTSL}} - \bar{\beta_k}^{\text{MKTSL}}$	-3.404	-2.956
Obs.	6,298,846	6,299,328
N. buyer firms	1,910	1,910
N. firms	192,168	192,171

Panel B: Blue-collar VS White-collar/Managers		
	Tot. Weeks (1)	Wage Bill (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. buyer firms	1,157	1,157
N. firms	26,809	26,809

Panel C: Blue-collar VS White-collar/Managers VS Marketing/Sales		
	Tot. Weeks (1)	Wage Bill (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. buyer firms	802	802
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 of employment and wage bill across marketing and sales employees and all other employees. Outcome variables have the form: $\frac{(y^l_{ft}/y_{f,t_f-1})}{\hat{\mathbb{E}}[(y^l_{f,t_f-1}/y_{f,t_f-1})]}$, where y_{ft} represents total weeks worked or total wage bill; y^l_{ft} represents total weeks worked or total wage bill of labor-type l, where $l \in \{\text{marketing/sales, other}\}$; $t_f - 1$ is the year prior to the trademark acquisition of firm f; and $\hat{\mathbb{E}}[\cdot]$ denotes the average across buyer firms in $t_f - 1$. Since firms can employ zero employees of a given labor type, we allow for both intensive and extensive margin responses. Panel B 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 C, we exclude from blue-collars and from white-collar/managers the employees in marketing or sales occupations, and we restrict the sample to firms that employed at least one worker in each of the three subgroups. All outcomes in Panel B and C are expressed in logs. We report the t-statistics of the test with null hypothesis $\bar{\beta_b}^{\text{WCMNG}} = \bar{\beta_b}^{\text{No WCMNG}}$ in Panel A, $\bar{\beta_b}^{\text{BC}} = \bar{\beta_b}^{\text{WCMNG}}$ in Panel B, 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 C. Each matched control cell is weighted by the number of buyer firms in the same cell. "N. buyer firms" reports the number of distinct buyer firms in the estimation sample. "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 A6: The Transaction-Level Effects of a Trademark Transaction

	Sales (1)	Tot. Weeks (2)	Wage Bill (3)	Labor share (4)
$\bar{\beta_k}$	0.069**	0.048	0.045	-0.020
	(0.030)	(0.032)	(0.033)	(0.017)
Obs.	5,556	5,556	5,556	5,556
N. buyer firms	429	429	429	429
N. of transactions	858	858	858	858

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 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. "N. firms" reports the number of distinct buyer firms in the estimation sample. "N. of transactions" reports the number of distinct transactions (treated and control ones) in the estimation sample. Standard errors clustered at the transaction level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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 MIMIT 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 subgroup if they have ever been employed in one of the occupations included in this subgroup. Specifcally, we label as marketing- or sales-related employees those employed in one of the occupation codes of Table A7.

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

Table A7: 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 marketing- and sales-related subgroup of workers.

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 also rely on weeks of work to compute our full-time-equivalent version of employment.

We clean wage data with the following routine. First, we keep workers who are at least 16 years old 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 Trademark Transactions: Case Studies

We illustrate the four case studies discussed in Section 2.2, providing more details about the parties involved and their motivations.

C.1 Canned Tomatoes: De Rica

Buyer: *Consorzio Casalasco del Pomodoro (CCdP)* is an Italian agricultural cooperative founded in 1977 in Rivarolo del Re (Cremona) that brings together hundreds of tomato-growing farms across the Po Valley. It specialises in the cultivation, processing and marketing of industrial tomatoes and tomato-derived products, supplying brands under its own portfolio and in private label formulations. Over the years it has expanded significantly through strategic investments and acquisitions (such as its purchase of agricultural and processing firms) and has developed a robust export, with products sold in many countries. The consortium is recognised for building a vertically integrated "field-to-table" supply chain in the Italian tomato sector and for promoting sustainability in agriculture and food processing.

Seller: *Generale Conserve S.p.A.* is an Italian canned-food company founded in 1989 in Genoa, initially trading canned tuna under the trademark *ASdoMar*. Over time it expanded into canned meat and tomato-based products, acquiring—among others—the tomato brand *De Rica* from *Conserve Italia Soc. Coop.* in 2013. Following a change in top management in 2017, the company re-focused solely on canned seafood, selling off tomato and canned meat trademarks.

Trademark: *De Rica* is an Italian brand founded in 1963 in Piacenza by *Industria Conserve Alimentari De Rica S.p.A.*. It became one of Italy's best-known names in the field of preserved foods, specializing in tomato-based products such as peeled tomatoes, tomato purée, diced tomatoes, and ready-made sauces. The brand gained strong recognition thanks to its distinctive advertising, especially a 1967 TV spot on the popular show Carosello, which helped make *De Rica* a household name across Italy. It has remained associated with traditional Italian tomato products and everyday household use.

Figure A13: Canned Tomatoes: De Rica

(a) Brand Logo **(b)** Product 1 **(c)** Product 2

Notes: De Rica brand logo and two example tomato products.

Motivation: The *Consorzio Casalasco del Pomodoro* acquired the *De Rica* trademark in 2017 as part of a strategic move to strengthen its position in the Italian and international tomato products market. By taking over a brand with a long-standing reputation for quality and familiarity among Italian consumers, the consortium aimed to combine *De Rica*'s strong heritage and consumer recognition with its own vertically integrated "from field to table" production model. The acquisition also reflected the desire to bring *De Rica* back to its birthplace, restoring its historical link to the Po Valley where it was originally founded in 1963. The acquisition allowed *Consorzio Casalasco del Pomodoro* to expand its portfolio beyond industrial and private-label production, increasing its presence in the branded consumer segment. It also aligned with the consortium's goal of enhancing the value of Italian-grown tomatoes through direct control over both agricultural production and retail branding.

C.2 Gorgonzola Cheese: Quattrorose

Buyer: *IGOR S.r.l.* is one of Italy's largest and most prominent producer of Gorgonzola cheese. Founded in the Novara area, at the heart of the Gorgonzola production region, the company combines industrial-scale efficiency with adherence to the production standards of Gorgonzola DOP cheese. Over the years, *IGOR* has grown from a regional business into one of the main national producers, exporting to several markets abroad.

Seller: *Santi S.p.A.* was one of IGOR's competitors in the Gorgonzola sector, known for producing high-quality cheese under several trademarks, including *Quattrorose*. The company faced severe financial difficulties in the early 2010s and entered bankruptcy and liquidation proceedings in 2014. Its assets, including production facilities and trademarks, were subsequently auctioned.

Trademark: The *Quattrorose* brand had long been recognized as a premium label for Gorgonzola cheese, associated with artisanal production and quality. Its strong reputation among consumers and distributors made it one of the most valuable assets in *Santi*'s portfolio. Following the liquidation, the brand's future remained uncertain until it was acquired by *IGOR* in 2018, ensuring its continuity within the Italian cheese landscape.

Figure A14: Gorgonzola cheese: Quattrorose

(a) Brand Logo **(b)** Product 1 **(c)** Product 2

Notes: Quattrorose logo and two example Gorgonzola cheese products.

Motivation: *IGOR* acquired Quattrorose in 2018 during the liquidation of *Santi S.p.A.*, primarily to consolidate its position in the Gorgonzola sector and prevent the brand from being used by potential competitors. The company indicated both commercial and personal reasons for the purchase: its CEO described the brand as "strongly desired by [him] and [his] family." In the acquisition announcement, he also emphasized the company's intent to preserve *Santi*'s legacy and quality, stating that the "new" *Santi* products would continue to be made with the same type of milk, recipe, and artisanal processes that had characterized the original producer. The acquisition covered only the trademark, as the production assets had been sold off separately in earlier years.

C.3 Shoes: Balducci

Buyer: *Asso* is a leading Italian producer of children's shoes, active since 1987. Based in Fermo, in the Marche region—one of Italy's main footwear districts—it manufactures and distributes children's footwear in Italy and abroad. It combines industrial-scale production with attention to design and maintains strong ties to Italy's shoemaking tradition.

Seller: *Balducci* was a historic Italian manufacturer of children's shoes, founded in 1934. The company was known for quality craftsmanship and ergonomic design. The brand became a household name in Italy for premium children's footwear. Despite its reputation, it experienced financial difficulties during the 2010s and ceased operations, ending a long period of family-run production.

Trademark: The *Balducci* name is well recognized in Italy and has been associated with reliable, high-quality footwear for children. Its emphasis on comfort and orthopaedic design made it a respected brand in the domestic market.

Figure A15: Shoes: Balducci

(a) Brand Logo **(b)** Product 1 **(c)** Product 2

Notes: Balducci logo and two example children's shoes products.

Motivation: *Asso*'s acquisition of the *Balducci* trademark was a strategic step to expand its portfolio of recognizable "Made in Italy" brands and strengthen its position in the premium children's footwear market. The company sought to preserve *Balducci*'s high-quality image while revitalizing the brand through modern production and digital channels, notably its e-commerce platform. The deal involved only the purchase of the trademark—not *Balducci*'s production facilities or workforce—a decision that drew some criticism but aligned with *Asso*'s broader strategy of combining heritage brands with efficient, contemporary manufacturing and global distribution.

C.4 Resorts: Valtur

Buyer: *Nicolaus Tour S.p.A.* is an Italian tourism and hospitality company founded in the 2000s and based in Bari (Apulia). *Nicolaus* has become one of Italy's most prominent operators in the leisure travel sector. The company manages resorts, hotels, and holiday villages across Italy and abroad, with a focus on combining Italian-style hospitality, digital marketing, and flexible packages tailored to contemporary travelers.

Seller: *Valtur* was one of Italy's earliest resort and hospitality brands, established in the 1960s. For decades, it was known for its network of all-inclusive vacation villages. The company became a symbol of Italian mass tourism, but later faced periods of financial instability and restructuring. It subsequently entered bankruptcy proceedings, leading to the dissolution of its franchise network. The resorts were largely returned to their owners, and the brand's remaining assets were liquidated.

Trademark: The *Valtur* name has a long association with Italian seaside resorts, postwar leisure culture, and the Italian "villaggio vacanze." Despite the company's financial collapse, the brand retained significant marketing value due to its wide recognition and association with quality and tradition in Italian tourism. This made it an attractive acquisition target for any firm looking to blend modern hospitality management with heritage appeal.

Figure A16: Resorts: Valtur

(a) Brand Logo **(b)** Resort 1 **(c)** Resort 2

Notes: Valtur logo and two resorts in Calabria and in Valle d'Aosta.

Motivation: *Nicolaus* aimed to revive *Valtur*'s symbolic power, integrating its name and imagery into a more modern marketing strategy. The company relaunched the *Valtur* website and began reopening selected resorts—initially seven across five destinations—under a new, more efficient business model. The firm later obtained recognition from the Italian Ministry of Business for *Valtur* as a "Historical Brand of National Interest." While the acquisition involved only the trademark, it successfully transformed a defunct legacy into a valuable asset within *Nicolaus*'s growing hospitality network.

D Derivation of Theoretical Results

This appendix provides full derivations for the theoretical results in Section 4 and Section 8. Throughout, we maintain the baseline environment: a firm with productivity z produces using production labor with marginal cost w_l/z and chooses product-level quantities under isoelastic demand. Expansionary labor (marketing/sales) has wage w_n and maps into product scope via $m_G = n_G^{\gamma}$ (generic) and $m_B = b\, n_B^{\gamma}$ (branded), with $0 < \gamma < 1$.

D.1 Product-level pricing, revenue, and profits

Fix a firm with productivity z and brand capital b and consider one product of type $i \in \{G, B\}$ facing inverse demand

$$p(q) = q^{-1/\epsilon_i}, \qquad \epsilon_i > 1.$$

Producing quantity q requires (q/z) units of production labor at wage w_l, so the variable cost is $(w_l/z)q$. The firm chooses q to solve

$$\max_{q \geq 0}\ p(q)q - \frac{w_l}{z}q \ = \ \max_{q \geq 0}\ q^{1-1/\epsilon_i} - \frac{w_l}{z}q. \tag{A1}$$

The first-order condition is

$$\left(1 - \frac{1}{\epsilon_i}\right) q^{-1/\epsilon_i} = \frac{w_l}{z},$$

which implies the standard constant-markup solution

$$p_i^*(z) = \frac{\epsilon_i}{\epsilon_i - 1}\frac{w_l}{z}, \qquad q_i^*(z) = \left(\frac{\epsilon_i - 1}{\epsilon_i}\frac{z}{w_l}\right)^{\epsilon_i}. \tag{A2}$$

Revenues and profits of product i are

$$r_i^*(z) = p_i^* q_i^* = \left(\frac{\epsilon_i - 1}{\epsilon_i}\frac{z}{w_l}\right)^{\epsilon_i - 1}, \qquad \pi_i^*(z) = r_i^* - \frac{w_l}{z}q_i^* = \frac{1}{\epsilon_i} r_i^*(z). \tag{A3}$$

D.2 Expansionary labor, revenue shares, and labor shares (Lemma 1)

Given the product-level optimal choices characterized in Appendix D.1, the firm chooses expansionary labor to operate generic and branded products. Conditional on per-product profits $(\pi_B^*(z), \pi_G^*(z))$, the firm's problem of choosing expansionary labor is

$$\max_{n_B, n_G \geq 0}\ b n_B^{\gamma} \pi_B^*(z) + n_G^{\gamma} \pi_G^*(z) - w_n(n_B + n_G). \tag{A4}$$

The first-order conditions are

$$\gamma b n_B^{\gamma - 1} \pi_B^*(z) = w_n, \qquad \gamma n_G^{\gamma - 1} \pi_G^*(z) = w_n,$$

so the optimal expansionary labor choices are

$$n_B^*(z, b) = \left(\frac{\gamma b \pi_B^*(z)}{w_n}\right)^{\frac{1}{1-\gamma}}, \qquad n_G^*(z) = \left(\frac{\gamma \pi_G^*(z)}{w_n}\right)^{\frac{1}{1-\gamma}}. \tag{A5}$$

Thus, generic expansionary labor is independent of b, while the optimal branded expansionary labor increases strictly in b. Product scope is $m_B = b(n_B^*)^{\gamma}$ and $m_G = (n_G^*)^{\gamma}$.

Firm revenue. Per-product revenues depend only on (z, ϵ_i, w_l) (Appendix D.1). Therefore total firm revenue is

$$R(z,b) = m_B(z,b)\, r_B^*(z) + m_G(z)\, r_G^*(z), \qquad m_B(z,b) = b(n_B^*(z,b))^\gamma,\ m_G(z) = (n_G^*(z))^\gamma. \tag{A6}$$

Labor shares. Let production labor be l, pinned down by the firm's production constraint:

$$zl = m_B q_B^*(z) + m_G q_G^*(z).$$

For a given product type i, the production-labor share of revenue equals $(\epsilon_i - 1)/\epsilon_i$ under isoelastic monopoly pricing. The expansionary-labor component is obtained from the expansionary labor FOC. Multiply the FOC $\gamma b n_B^{\gamma-1} \pi_B^*(z) = w_n$ by n_B to obtain

$$w_n n_B^*(z,b) = \gamma\, b(n_B^*(z,b))^\gamma\, \pi_B^*(z) = \gamma\, m_B(z,b)\, \pi_B^*(z). \tag{A7}$$

Since $\pi_i^*(z) = r_i^*(z)/\epsilon_i$ (Appendix D.1), (A7) implies the expansionary labor wage-bill share of revenues associated with type-i products is γ/ϵ_i. Hence, the product-type labor shares are

$$\theta_i = \underbrace{\frac{\epsilon_i - 1}{\epsilon_i}}_{\text{production labor share}} + \underbrace{\frac{\gamma}{\epsilon_i}}_{\text{expansionary labor share}}, \qquad i \in \{G, B\}. \tag{A8}$$

Because $\epsilon_B < \epsilon_G$ and $\gamma < 1$, we have $\theta_B < \theta_G$.

Proof of Lemma 1. (a) *Revenue rises.* From (A5), $n_G^*(z)$ is independent of b while $n_B^*(z,b)$ increases strictly in b. Hence $m_G(z)$ is constant in b while $m_B(z,b)$ increases strictly in b. Since $r_B^*(z)$ and $r_G^*(z)$ do not depend on b, total revenue (A6) strictly increases in b.

(b) *Firm-level labor share falls.* Firm labor share is the revenue-weighted average of type-specific labor shares:

$$LS(z,b) = s_B(z,b)\theta_B + (1 - s_B(z,b))\theta_G, \qquad s_B(z,b) = \frac{m_B(z,b) r_B^*(z)}{R(z,b)}.$$

Because $m_B(z,b)$ strictly increases in b while $m_G(z)$ is constant, $s_B(z,b)$ strictly increases in b. Since $\theta_B < \theta_G$, $LS(z,b)$ strictly decreases in b.

(c) *Expansionary-to-production employment rises.* As b rises, branded scope m_B expands, which raises the expansionary wage-bill share (the γ/ϵ_i term in (A8) is larger for $i = B$ since $\epsilon_B < \epsilon_G$). Meanwhile the production-labor share shifts toward $(\epsilon_B - 1)/\epsilon_B$, which is smaller than the generic counterpart. Therefore the expansionary share rises while the production share falls, implying the ratio of expansionary to production employment rises. □

D.3 Closed-form firm profit (Equation (2))

This subsection derives the closed-form profit expression used in the transaction analysis. Total firm profit equals the sum of profits from all operated products:

$$\pi(z,b) = m_B(z,b)\, \pi_B^*(z) + m_G(z)\, \pi_G^*(z) - (n_B + n_G) w_n.$$

Using (A5) and $m_B = b(n_B^*)^\gamma$, we obtain

$$m_B(z,b) = b\left(\frac{\gamma b \pi_B^*(z)}{w_n}\right)^{\frac{\gamma}{1-\gamma}} = \left(\frac{\gamma}{w_n}\right)^{\frac{\gamma}{1-\gamma}} b^{\frac{1}{1-\gamma}} (\pi_B^*(z))^{\frac{\gamma}{1-\gamma}}.$$

Similarly,

$$m_G(z) = \left(\frac{\gamma}{w_n}\right)^{\frac{\gamma}{1-\gamma}} (\pi_G^*(z))^{\frac{\gamma}{1-\gamma}}.$$

Therefore,

$$\pi(z, b) = \left(\frac{\gamma}{w_n}\right)^{\frac{\gamma}{1-\gamma}} \left[b^{\frac{1}{1-\gamma}} (\pi_B^*(z))^{\frac{1}{1-\gamma}} + (\pi_G^*(z))^{\frac{1}{1-\gamma}}\right]. \tag{A9}$$

Finally, substituting $\pi_i^*(z)$ from (A3) yields the form stated in the main text:

$$\pi(z, b) = \phi_B z^{\frac{\epsilon_B - 1}{1-\gamma}} b^{\frac{1}{1-\gamma}} + \phi_G z^{\frac{\epsilon_G - 1}{1-\gamma}},$$

with

$$\phi_i = (1-\gamma)\gamma^{\frac{\gamma}{1-\gamma}} \left(\frac{\epsilon_i^{-\epsilon_i}}{(\epsilon_i - 1)^{\epsilon_i - 1}}\right)^{\frac{1}{1-\gamma}} \cdot w_n^{-\frac{\gamma}{1-\gamma}} w_l^{-\frac{\epsilon_i - 1}{1-\gamma}}, \qquad i \in \{G, B\},$$

and in the main text we normalize $w_l = 1$.

D.4 Transaction selection (Lemma 2)

Consider two firms (z, b) and (z', b') that meet. A trade transfers τ units of brand capital from the seller to the buyer and incurs transaction cost $T > 0$. For a candidate transfer, the joint surplus from the buyer receiving τ is

$$\Delta(z, b; z', b'; \tau) \equiv \pi(z, b + \tau) + \pi(z', b' - \tau) - \pi(z, b) - \pi(z', b'). \tag{A10}$$

Due to Nash bargaining, it is always optimal for the two parties of the transaction to choose the action that maximizes the joint surplus. A transaction occurs if $\max_\tau \Delta(\cdot) \geq T$.

Proof of Lemma 2. From Appendix D.3, $\pi(z, b) = \phi_B z^a b^c + \phi_G z^{a_G}$ where

$$a = \frac{\epsilon_B - 1}{1-\gamma} > 0, \qquad c = \frac{1}{1-\gamma} > 1, \qquad a_G = \frac{\epsilon_G - 1}{1-\gamma} > 0.$$

Hence

$$\frac{\partial^2 \pi(z, b)}{\partial z \, \partial b} = \phi_B \, ac \, z^{a-1} b^{c-1} > 0,$$

so π has increasing differences in (z, b): the marginal value of brand capital is strictly increasing in productivity. Fix a seller (z', b') and a transfer size $\tau > 0$. Define the buyer-side gain

$$G(z, b; \tau) \equiv \pi(z, b + \tau) - \pi(z, b).$$

By increasing differences, $G(z, b; \tau)$ is strictly increasing in z. Because $\gamma < 1$, G is also increasing in b. The seller-side loss

$$L(z', b'; \tau) \equiv \pi(z', b') - \pi(z', b' - \tau)$$

does not depend on the buyer's (z, b). Therefore the joint surplus

$$\Delta(z, b; z', b'; \tau) = G(z, b; \tau) - L(z', b'; \tau)$$

is increasing in the buyer's productivity z (and increasing in the buyer's brand capital b). It follows that if a firm with (z, b) finds it profitable to buy from a given seller, then any firm with weakly higher (z, b) also finds it profitable. Hence buyers are positively selected on productivity and brand capital. Since revenue is increasing in both (z, b) (Appendix D.2), buyers are also positively selected on revenue. $\square$

D.5 Joint labor share within buyer–seller pairs (Lemma 3)

Setup. Let $\theta_B < \theta_G$ denote the type-specific labor shares in (A8). For any firm, total labor share is the revenue-weighted average of type-specific labor shares. For a buyer–seller pair, define the sales-weighted joint labor share as

$$LS^{\text{pair}} = \frac{R_a LS_a + R_s LS_s}{R_a + R_s},$$

where R_a and R_s are the firm-level revenues of the buyer (acquirer) and the seller, respectively.

Proof of Lemma 3. A transaction transfers brand capital τ from the seller to the buyer. Holding product-level primitives fixed, an increase in a firm's brand capital affects only its branded scope m_B and thus only the branded revenue component. In particular, by Appendix D.2, the buyer's branded revenue share $S_B(z, b)$ strictly increases in b, while the seller's branded revenue share strictly decreases when b' falls to $b' - \tau$.

Let S_B^{pair} denote the pair's branded revenue share:

$$S_B^{\text{pair}} = \frac{R_a S_{B,a} + R_s S_{B,s}}{R_a + R_s}.$$

Because the buyer gains branded revenue share while the seller loses it, a surplus-improving trade must shift revenue weight toward the high-surplus side. Under $T > 0$, a transaction is implemented only if the maximized joint surplus is strictly positive, which (given $\pi_B^*(z) > 0$ and $c > 1$) requires that the reallocation of brand capital raises the pair's joint profit through a net increase in the value generated by branded scope. This is feasible only if the pair's revenue weight tilts toward the branded component overall, i.e. S_B^{pair} rises.[3]

Finally, the pair labor share satisfies

$$LS^{\text{pair}} = S_B^{\text{pair}} \theta_B + (1 - S_B^{\text{pair}})\theta_G.$$

Since $\theta_B < \theta_G$, an increase in S_B^{pair} implies a decrease in LS^{pair}. $\square$

D.6 Extensions to the theoretical model

We consider two extensions. The first incorporates non-labor inputs into production, providing a mapping for the empirical responses of materials. The second considers an alternative interpretation of branding as a demand shifter (quality/taste) rather than a change in demand elasticity.

Other production factors (materials or capital). Suppose a firm produces with Cobb–Douglas technology

$$y = z\, l^{\alpha}\, m^{1-\alpha},$$

[3] Intuitively: the only channel through which τ affects joint payoffs is the term associated with brand capital, so a profitable reallocation must increase the effective branded component in the pair's joint outcome.

where l is production labor, m is non-labor inputs (such as materials or capital), $0 < \alpha < 1$, and non-labor inputs have price w_m (and production still has wage w_l). The unit cost function is

$$c(w_l, w_m; z) = \frac{1}{z} \cdot \frac{w_l^{\alpha} w_m^{1-\alpha}}{\alpha^{\alpha}(1-\alpha)^{1-\alpha}},$$

so the marginal cost is $MC = c(w_l, w_m; z)$. By Shephard's lemma, conditional factor demands satisfy

$$l = \alpha \frac{MC}{w_l} y, \qquad m = (1-\alpha) \frac{MC}{w_m} y.$$

Holding prices and z fixed, MC is constant, so non-labor inputs move proportionally with output:

$$d \log m = d \log y.$$

Since in the baseline model production labor is also proportional to output, the predictions regarding production employment generalize directly: brand-capital shocks that raise revenue and shift sales toward branded products can raise output (and hence m) but raise revenue by more due to higher markups on branded products. Consistent with the empirical finding, the cost share of labor input relative to other inputs remains constant.

If, alternatively, the trademark transactions increase only the non-labor factor, m, without moving markups, we should expect an increase in l, the production labor, in proportion to the expansion of revenue. Our empirical analysis finds that production labor does not scale in the same proportion as revenue, and that expansionary labor expands more than production labor, which is inconsistent with an interpretation of trademark transactions changing only m.

Brand as quality/taste (same elasticity). An alternative modeling choice is that branded products face a higher willingness-to-pay (a demand shifter) but share the same elasticity as generic products. Let both types have elasticity $\epsilon > 1$ but branded inverse demand is scaled by $\phi_B > 1$:

$$p_i(q) = \phi_i \, q^{-1/\epsilon}, \qquad \phi_G = 1, \ \phi_B > 1.$$

With isoelastic demand, the markup remains $\epsilon/(\epsilon - 1)$ for both types, so the *revenue-to-variable-cost ratio* is identical across branded and generic products even though levels differ. In this extension, increasing brand capital still raises branded scope and shifts revenue shares toward branded products, but because markups do not differ across types, this reallocation does not mechanically lower the labor share through the "low-labor-share product" channel. Thus, the sharp prediction of a declining labor share with rising branded revenue share is a distinctive feature of the baseline model in which $\epsilon_B < \epsilon_G$.

Under the baseline model (lower elasticity for branded products), a positive shock to brand capital through a trademark transaction predicts: (i) firm revenue rises; (ii) the firm's labor share falls via reallocation toward branded products; (iii) expansionary employment rises relative to production employment. Under the quality/taste extension with identical elasticities, revenue rises and branded scope expands, but the labor share need not fall through the reallocation channel.

D.7 Exact Mapping from Event Study to Model Elasticities

This subsection derives the exact mapping between the structural parameters $\{\gamma, \epsilon_G, \epsilon_B, S_B\}$ and the empirical elasticities targeted in the calibration.

Revenue elasticity. Let total revenue be $R = R_B + R_G$, with branded revenue share

$$S_B \equiv \frac{R_B}{R}.$$

From Appendix D.2, only branded scope depends on brand capital and $R_B \propto b^{1/(1-\gamma)}$. Hence,

$$\frac{d\log R}{d\log b} = \frac{1}{1-\gamma}\frac{R_B}{R} = \frac{S_B}{1-\gamma}.$$

This moment is matched to the empirical ratio $\hat{\beta}_{Sales}/\hat{\beta}_{Intan}$.

Employment elasticity. Let the total wage bill be

$$W = W_B + W_G,$$

where the wage bill by product type satisfies $W_i = \theta_i R_i$ with

$$\theta_i = \frac{\epsilon_i - 1}{\epsilon_i} + \frac{\gamma}{\epsilon_i}, \qquad i \in \{B, G\}.$$

The branded share of total wage bill is therefore

$$wb \equiv \frac{W_B}{W} = \frac{\theta_B R_B}{\theta_B R_B + \theta_G R_G} = \frac{\theta_B S_B}{\theta_B S_B + \theta_G(1 - S_B)}.$$

Since only R_B responds to b,

$$\frac{d\log W}{d\log b} = \frac{1}{1-\gamma}\frac{W_B}{W} = \frac{1}{1-\gamma}\frac{\theta_B S_B}{\theta_B S_B + \theta_G(1 - S_B)}.$$

Since the wage is taken as given, the wage bill changes correspond to the employment changes in the data. Thus, this expression is matched to $\hat{\beta}_{Emp}/\hat{\beta}_{Intan}$.

Relative response of expansionary vs. production wage bills. Expansionary and production wage bills by type satisfy

$$W_i^E = \frac{\gamma}{\epsilon_i} R_i, \qquad W_i^P = \frac{\epsilon_i - 1}{\epsilon_i} R_i.$$

Total expansionary and production wage bills are

$$W^E = \frac{\gamma}{\epsilon_B} R_B + \frac{\gamma}{\epsilon_G} R_G, \qquad W^P = \frac{\epsilon_B - 1}{\epsilon_B} R_B + \frac{\epsilon_G - 1}{\epsilon_G} R_G.$$

Because only R_B varies with b,

$$\frac{d\log W^E}{d\log b} = \frac{1}{1-\gamma}\frac{W_B^E}{W^E}, \qquad \frac{d\log W^P}{d\log b} = \frac{1}{1-\gamma}\frac{W_B^P}{W^P}.$$

Hence, the relative response targeted in the calibration is

$$\frac{d\log W^E}{d\log W^P} = \frac{\dfrac{S_B/\epsilon_B}{S_B/\epsilon_B + (1 - S_B)/\epsilon_G}}{\dfrac{S_B(\epsilon_B - 1)/\epsilon_B}{S_B(\epsilon_B - 1)/\epsilon_B + (1 - S_B)(\epsilon_G - 1)/\epsilon_G}}.$$

This moment is matched to $\hat{\beta}_{MarketEmp}/\hat{\beta}_{OtherEmp}$.

Aggregate labor share. The model-implied labor share for the representative firm is defined as

$$\overline{LabShare} \equiv \frac{W}{R} = \frac{W_B + W_G}{R_B + R_G} = \frac{\theta_B R_B + \theta_G R_G}{R_B + R_G} = S_B\,\theta_B + (1 - S_B)\,\theta_G,$$

where $\theta_i = (\epsilon_i - 1)/\epsilon_i + \gamma/\epsilon_i$ for $i \in \{B, G\}$. This moment is matched to the empirical sales-weighted labor share in the sample.

Together, these four equations identify $\{\gamma, \epsilon_G, \epsilon_B, S_B\}$.