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Essays on Firm Dynamics and Acquisitions

Jacob T. Hess

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Universitat Autònoma de Barcelona

Essays on Firm Dynamics and Acquisitions

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Preface

This dissertation studies the macroeconomic implications of firm mergers and acquisitions (M&A), focusing on how these deals interact with productivity dynamics and intangible investment. In doing so, it uses a combination quantitative structural modeling and empirical analysis. The first chapter studies the impact of foreign ownership on the wage skill premium. It quantifies foreign ownership's contribution to the increase in the wage skill premium by endogenizing skill-biased technological change with intangible-skill complementarity in production. Foreign-owned firms, who are more intangible-intensive and enter the economy through acquisition, amplify the mechanism. The chapter develops a quantitative general equilibrium firm dynamics model that accounts for 39% of the wage skill premium increase in Spanish manufacturing between 2002 and 2017, with about 24% of this increase attributed to foreign ownership. It concludes by emphasizing that recent Spanish policies that subsidize intangible investment by foreign multinationals are beneficial for GDP and aggregate productivity, but they also carry unintended consequences for labor income inequality and create uneven welfare outcomes across skill groups.

The second chapter studies how corporate US firms strategically choose to recognize (or not) acquired intangibles from M&A in their business accounts and its implications for the measurement of economic profits and the labor share. The analysis is informed by a business accounting change in the early 2000s that forced acquirer firms to report acquired intangibles from M&As. Before the accounting change, firms with an incentive to frontload profits used an accounting method (pooling) to omit intangibles from both the income statement and balance sheet, raising not only reported accounting profits, but potentially economic profits too. After correcting for the omitted acquired intangibles at the firm level before and after the accounting change, measures of economic profits and the labor share are found to be relatively trendless. The third chapter studies how M&As affect revenue total factor productivity (TFPR), markups, and input-output measures using a nationally representative firm level dataset for Spain. Through a difference-in-differences analysis the results show that M&A lead to gradual increases in TFPR and markups, with significant gains observable only several years after the deal. Additionally, we find declines in sales, value added, number of employees, and total assets for the combined entities, suggesting a downsizing process post-M&A.

Chapter 1

Multinationals, Intangibles and the Wage Skill Premium

Abstract

This paper studies the impact of foreign ownership on the wage skill premium by endogenizing skill biased technological change with intangible skill complementarity in production. Increased intangible investment raises the relative demand for skilled labor, which in turn raises the wage skill premium. Foreign owned firms, who are more intangible intensive, amplify this effect. I provide supporting empirical evidence from Spain, documenting aggregate increases in intangible investment and skilled labor compensation. Foreign owned firms operate at a large scale and I show that a change to foreign ownership leads to a scaling up of production, as well as, higher relative employment of skilled workers. I develop a quantitative firm dynamics model with intangible skill complementarity in production and heterogeneity in ownership. Foreign multinationals endogenously enter through acquisition and their subsidiaries receive a technology transfer prompting them to invest at higher levels. An exogenous decline in the intangible investment price triggers the mechanism and further increases foreign entry. Upon matching the decline to the data, the model accounts for nearly forty percent of the increase in the wage skill premium between 2002 and 2017 where about a quarter is attributed to foreign ownership. Through the lens of the model, intangible investment subsidies exclusively for foreign owned firms can increase aggregate output and total factor productivity, but also have welfare implications.

1.1 Introduction

Since the 1980s, countries worldwide have opened their economies to foreign ownership, leading to a rise in the presence of multinational corporations. The economic literature has emphasized the benefits of openness to foreign ownership. Macroeconomic studies have documented large gains for aggregate productivity, while the empirical literature has found that foreign-owned firms often have superior management practices, innovate more and generate positive spillover effects for domestic firms.[1] However, while the benefits of foreign ownership are well-documented, little is known about how these benefits are distributed and their implications for wage inequality. This paper addresses the gap in the literature by examining the impact of foreign ownership on the wage skill premium, or the wage differential between skilled and unskilled workers.[2] The rise in the wage skill premium is typically attributed to skill-biased technological change (SBTC), where technological progress disproportionately benefits skilled workers, resulting in an increase in demand for their labor relative to the unskilled.[3] I introduce a novel mechanism that endogenizes SBTC and accounts for recent economy-wide changes: intangible-skill complementarity. Intangible capital, which encompasses non-physical assets such as intellectual property, software and organizational capital, has been growing in prominence across economies. When these assets complement skilled labor, increased intangible investment raises the demand for skilled workers, resulting in an increase in the wage skill premium. Foreign ownership plays an important role, as foreign-owned firms tend to be more intangible-intensive and thus further drive the rise in the wage skill premium when they enter or expand within the economy.

My country of analysis is Spain and I begin by establishing three stylized facts at both the aggregate and firm levels that offer support for intangible-skill complementarity and the role of foreign ownership in amplifying it. First, since the 2000s the aggregate intangible share of investment nearly doubled and labor compensation share paid to skilled (tertiary-educated) workers surpassed that of unskilled. The second stylized fact is that foreign ownership is greater in intangible/skill-intensive sectors, where foreign ownership is defined as firms with a majority ownership by a foreign entity. These firms are few in number as they comprise less than 1% of all firms, yet have a large presence in aggregate production, accounting for more than 25% of total revenue. The number of foreign-owned firms has increased over time, coinciding with the trends in the first stylized fact. This influx primarily occurred through acquisitions of already existing Spanish firms. In Spain, as in other advanced economies, multinational entry primarily takes the form of mergers and acquisitions (M&A) (Barba-Navaretti & Venables, 2004).[4] The third stylized fact is that at the firm level a change to foreign ownership is associated with scaling up production

[1] Macro literature: Burstein and Monge-Naranjo (2009); McGrattan and Prescott (2009, 2010a); Ramondo and Rodríguez-Clare (2013). Empirical literature: Bloom, Sadun, and Van Reenen (2012); Fons-Rosen, Kalemli-Ozcan, Sørensen, Villegas-Sanchez, and Volosovych (2017); Guadalupe, Kuzmina, and Thomas (2012)

[2] Countries where foreign ownership makes up a larger share of aggregate sales revenue tend to have a higher skill premium (Figure A.5.1).

[3] See Acemoglu and Autor (2011); Violante (2008) for surveys.

[4] Multinational entry is considered to be inward foreign direct investment (FDI) which takes two primary forms: greenfield or M&A. Greenfield investment involves a multinational parent company establishing an enterprise in another country by building it from the ground up. On the other hand, M&A involves a multinational parent acquiring a controlling stake in an already existing firm in another country.

and a change in the skill composition toward more skilled labor. I use firm-level data of Spanish manufacturing firms from 1990 to 2017 and analyze the impact of foreign ownership on various outcomes following acquisitions by foreign multinationals. The results show that acquisition by a foreign multinational is positively associated with increased productivity, higher investment and a disproportionate rise in skilled labor employment. The change in the labor skill composition after foreign acquisition, marked by a significantly greater increase in demand for skilled labor compared to unskilled labor, is a novel finding.

Building on the empirical facts, I develop a framework to quantify foreign ownership's contribution to the wage skill premium and study policy implications. I formulate a variant of the firm dynamics model from Hopenhayn (1992) with endogenous entry and exit. Heterogeneous firms invest in intangible and tangible capital while hiring skilled and unskilled labor. Households differ by skill type and endogenously supply labor. I extend the standard model in two distinct dimensions. The first being that I introduce the concept of intangible-skill complementarity in production similar to that of Krusell, Ohanian, Ríos-Rull, and Violante (2000). Increased intangible investment drives up the relative demand for skilled labor and consequently, the wage skill premium. Second, I incorporate ongoing acquisition where domestic firms endogenously agree to transfer ownership rights to foreign multinational entrants. These extensions lead to two aggregate effects that influence both the firm distribution and the wage skill premium. The selection effect arises from the dynamics of entry and exit. The other is the foreign ownership effect. Prior to acquisition, this effect impacts domestic firms through anticipation as they elevate their investment levels when they expect to be acquired. As a result, this raises firm value and makes them more attractive acquisition targets. Post-acquisition, firms receive a technology transfer from their foreign parent which differentiates them from their domestic counterparts by increasing their productivity and leading to higher investment levels. Both the anticipation before the acquisition and the increased investment afterward work to amplify the impact of foreign ownership on the wage skill premium.

I analyze the model in general equilibrium and in a stationary environment without aggregate uncertainty. The model is calibrated to match sector and firm-level moments in Spanish manufacturing during the period 2002-2006, which is the first five years of the sampling period. The model's outcomes correspond with the empirical observations. Specifically, it generates positive selection in acquisitions where the largest and most productive firms are predominantly acquired. In addition, foreign-owned firms are few in number but account for a large share of output, in line with the second stylized fact. The model generates post-acquisition changes consistent with the third stylized fact, despite not being explicitly targeted. There are minor gains in TFP post-acquisition, alongside more substantial increases in investment and output.

I study how the model is affected by an intangible-investment-specific technological change. This change is modeled as an exogenous decline in the price of intangible investment relative to the final output good, which has been in decline over time across advanced economies.[5] Cheaper intangible

[5] The decline in the relative price of intangible investment can be interpreted as an improvement in the quality of intangible investment goods or a reduction in their cost. This price decline is one force (but not the only) that can lead to a change in the investment composition in equilibrium and therefore account for the rise of intangible investment. Some papers that have documented the decline are Zhang (2024) and Lashkari, Bauer, and Boussard

investment raises its share of overall investment and increases the likelihood of acquisitions. In addition, due to intangible-skill complementarity, this technological change is skill-biased. I then analyze how foreign ownership contributes to skill-biased change to account for the rise in the wage skill premium and affects other equilibrium outcomes. I evaluate the model's ability to account for empirical trends by comparing two steady states. One is the initial steady state calibrated to the start-of-sample years (2002-2006) and the other is the new steady state where the relative intangible investment price is set to that from the end-of-sample period (2013-2017), ie after the technological change has occurred. The model accounts for 39% of the observed increase in the wage skill premium and 12% of the acquisition rate.[6] Furthermore, it is also consistent with the changes in the investment and compensation shares as documented by the first stylized fact. The model explains 22% of the increase in the intangible share and predicts a change in the skill composition, accounting for a portion of the rise in the skilled labor share and a decline in the unskilled share. Along with the wage skill premium, aggregate output and TFP are higher in the new steady state. Through a decomposition, I show that approximately 24% of the increase in the wage skill premium can be attributed to foreign ownership, while it is behind about 37% of the increases in output and TFP. Despite being few in number, the substantial size of foreign-owned firms means that they have an impact in the aggregate. Aggregate consumption also increases, but is uneven as about two-thirds of the increase comes from skilled households, driven by the higher skill premium. I quantify the overall welfare impact on skilled and unskilled households in the new steady state and find that the skilled are better off while the unskilled are worse off. This outcome is primarily due to the labor hours supplied by each household, which increase for both. Although both groups experience welfare gains from increased consumption, the additional labor supplied by unskilled households offsets these gains, resulting in a net welfare loss.

Having documented the mechanism's ability to account for recent trends, as well as foreign ownership's non-trivial role shaping these trends, the paper concludes by studying policy implications. Recently, the current government in Spain has used COVID-19 recovery funds to encourage foreign multinationals to increase intangible investment. Through the lens of the model, foreign ownership, acting through an endogenous mechanism of skill-biased technological change, contributes to increases in output and TFP but also helps widen the wage gap between skilled and unskilled households. Policies that seek to either subsidize or expand this small group of firms can increase long-run output and TFP, but also carry unintended consequences for wage inequality which affects welfare. I analyze a policy that subsidizes intangible investment by foreign-owned firms. This policy not only raises intangible investment done by existing incumbents, but also increases acquisitions due to the higher expected returns. However, this policy is inherently skill-biased, disproportionately benefiting skilled workers and further widening the wage gap

(2024).

[6] Intangible-skill complementarity, coupled with the decline in the relative intangible investment price, is one mechanism among several that potentially contribute to the change in the wage skill premium over time. Furthermore, the model only accounts for how foreign ownership affects the wage skill premium through intangible-skill complementarity. The unexplained portion of the wage skill premium increase could contain other mechanisms that are strongly influenced by foreign ownership.

between skilled and unskilled households. The challenge is to find an optimal subsidy rate that balances higher output and TFP brought by foreign ownership with the costs of increasing wage inequality. The optimal subsidy rate that maximizes aggregate welfare in the model is 7.7%, leading to an increase in the wage skill premium, output and TFP. While skill groups experience uneven welfare gains, they are positive for both.

Related Literature This paper contributes to the macroeconomic literature on growth and multinational production. Papers such as Burstein and Monge-Naranjo (2009) and McGrattan and Prescott (2009, 2010a) quantify gains from openness to multinational production. These papers utilize multi-country models that abstract from firm heterogeneity and do not distinguish between entry mode, with the only friction being a barrier to foreign entry. The mechanism in these models is that a multinational's technology is non-rival and shared across borders through its subsidiaries. Such technology can be managerial knowledge (Burstein & Monge-Naranjo, 2009) or a parent's accumulated know-how from investing in intangible capital (McGrattan & Prescott, 2009, 2010a). Takayama (2023) is recent work that incorporates heterogeneity and entry mode. Their model has heterogeneous multinationals who choose between mode of entry (greenfield or M&A). My paper is also connected to the macro-trade literature that has augmented models of trade to incorporate the establishment of subsidiaries abroad by multinational corporations, in addition to being able to export (Arkolakis, Ramondo, Rodríguez-Clare, & Yeaple, 2018; Ramondo & Rodríguez-Clare, 2013; Tintelnot, 2017). These papers emphasize that analyzing exporting and FDI in isolation may generate inaccurate estimates of the gains from openness. In contrast with all of these papers, I study the benefits and drawbacks from multinational production through a dynamic quantitative model with heterogeneity that incorporates endogenous multinational entry.

The heterogeneity of local firms in my quantitative framework links to the voluminous empirical literature that studies foreign ownership's association with productivity, investment and skill composition of acquired subsidiaries. The most extensively studied outcome is the effect on productivity, being either TFP and/or labor productivity.[7] In advanced economies this literature typically finds modest increases in TFP but larger increases in production and labor productivity. Some explanations for improvements following ownership transfer are better management (Bloom et al., 2012) or an international market demand shock (Guadalupe et al., 2012). A smaller group of empirical papers study foreign ownership's association with the skill composition of employment. Using firm-level data from three advanced and two developing countries, Hijzen, Martins, Schank, and Upward (2013) find that the average wage and employment increase following acquisition. They argue that the increase in wages probably comes from the creation of new skilled jobs. Koch and Smolka (2019) argue that foreign acquisition is skill-biased and find that acquired firms hire more recent university graduates.

Finally, I contribute to research on the increase of intangible investment and its implications

[7] See Fons-Rosen, Kalemli-Ozcan, Sørensen, Villegas-Sanchez, and Volosovych (2021) for a survey concerning the effects on TFP and labor productivity. Estimates for TFP in advanced economies range from nil to 5% (much higher increases are typically found in developing countries), while increases in labor productivity tend to be between 9 % to 16%.

for the aggregate economy (Corrado & Hulten, 2010; Koh, Santaeulàlia-Llopis, & Zheng, 2020; McGrattan & Prescott, 2010b), where I emphasize complementarity of skilled labor and intangible capital. The idea of skilled labor and capital being complements reaches back to Griliches (1969). Krusell et al. (2000) embed capital-skill complementarity in a nested production function and argue that, when accompanied by falling equipment investment prices, it can account for mostly all of the wage skill premium increase in the US between 1960-1990. Some papers have recently emphasized that advances in information and communication technologies (ie, computers and software) and its complementarity relationship with skilled labor as opposed to equipment (Eckert, Ganapati, & Walsh, 2022; Lashkari et al., 2024). Other papers exclusively focus on software (Aum, 2020; Aum & Shin, 2024).

Outline The paper is organized as follows. Section 3.4 documents the empirical evidence. Section 1.3 describes the model and defines the stationary recursive competitive equilibrium. Section 1.4 covers calibration and validation. Section 1.5 presents the main results of the paper. Section 1.6 discusses policy implications. Section 3.5 concludes.

1.2 Empirical Evidence

This section documents stylized facts at the aggregate, sector and firm levels within Spain that offer support to intangible-skill complementarity and the role of foreign ownership in amplifying it. Section 1.2.1 examines trends related to intangible investments and the labor skill composition. Section 1.2.2 looks at foreign ownership in the aggregate and across sectors. Section 1.2.3 analyzes foreign ownership at the firm level.

1.2.1 Aggregate Trends in Spain

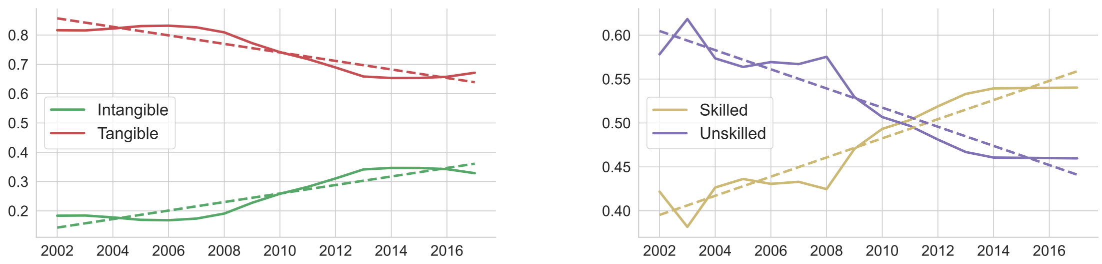
I use aggregate and sector level data from the EUKLEMS-INTANProd Database.[8] Documentation regarding data collection and construction is provided in Bontadini, Corrado, Haskel, Iommi, and Jona-Lasinio (2023). EUKLEMS-INTANProd, henceforth KLEMS, is a harmonized set of country and industry national accounts developed initially by a number of European Institutes led by GGDC and NIESR that have subsequently been extended and developed with further funding from the European Commission. The database includes measures of gross output, intermediate inputs, gross value added, employment and compensation (also by education group), as well as investment in both tangible and intangible assets for 28 European countries at the 2-digit industry level for the years 1995-2020. A novel feature of the data is that intangible expenditures such as R&D, software, artistic originals, design, brand, organizational capital and training are treated as investment.[9] In regard to the education level of labor, KLEMS provides data at the the 2-digit industry level on the share of hours worked and compensation which are broken down into three skill groups: low skill (lower secondary education or lower), medium skill (upper secondary

[8]2023 release. Further information https://euklems-intanprod-llee.luiss.it/

[9]National accounts in the US and EU typically only treat expenditures in R&D, software and artistic originals as intangible investment.

Figure 1.1: Aggregate Trends in Spain

(a) Share of Capital Investment (b) Share of Labor Compensation



Notes: The figure displays the series of aggregate investment and labor compensation shares in Spain between 2002 to 2017. Subfigure (a) shows the shows the share of aggregate investment by capital type. Intangible investment is expenditures of R&D, software, artistic originals, design, brand, organizational capital and training. Tangible investment is expenditures on traditional forms of physical capital: equipment, non-residential buildings and structures. Subfigure (b) depicts the share of labor compensation paid to skilled workers (tertiary degree or higher) and unskilled (no tertiary degree). Series for manufacturing and business services sectors can be found in Figures A.5.5-A.5.6 in Appendix A.5. Details regarding how the shares are calculated are in Appendix A.3.2.
Source: Author's calculations using EUKLEMS-INTANProd database.

education and post-secondary non-tertiary) and high skills (tertiary degree).[10] KLEMS does not provide the number of workers by skill type. I define skilled workers as those with tertiary education and combine the low and medium skill group to form unskilled workers. The sampling time period is from 2002 to 2017.[11]

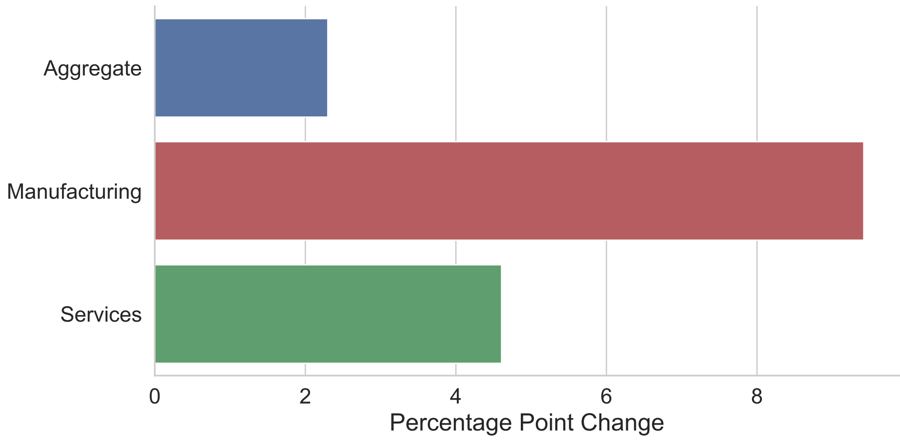
Spain is transitioning towards a more intangible intensive and skill driven economy. Figure 1.1 displays the share of aggregate investment by capital type and the share of total labor compensation by skill type. The intangible share of investment rose from 0.2 in 2002 to 0.35 in 2017, marking an 75% increase. The share of tangible investment, which includes expenditures on equipment and non-residential buildings, declined from 0.8 in 2002 to 0.65 in 2017. While intangible investment in KLEMS embodies many different expenditures, its growth over this period was driven by expenditures in R&D and software (Figure A.5.7 in Appendix A.5). Figure 1.1b shows the composition of labor compensation, which also underwent significant changes over this period. The share of compensation for unskilled labor dropped from 0.58 in 2002 to 0.46 in 2017, a 21% decline, while the share of compensation for skilled labor increased and surpassed that of unskilled labor. Similar trends in investment and compensation are observed in both manufacturing and services, but they differ in magnitude (Figures A.5.5-A.5.6 in Appendix A.5). The services sector closely resembles the overall aggregate, while the manufacturing sector is significantly more intangible-intensive and experienced much stronger shifts in skill compensation.

The increase in the share of labor compensation going to skilled workers and the coinciding decline to unskilled can partly be attributed to the growing number of workers with tertiary education. However, this shift may also be driven by a widening wage differential between skill types. Figure 1.2 shows the percentage point change in the average wage skill premium between

[10]KLEMS aggregates education levels according to the International Standard Classification of Education (IECED). Low skill: IECED 0-2. Medium Skill IECED 3-4. High Skill IECED 5-8.

[11]I focus on this particular time period as 2002 is the earliest year that data on labor by education group is available and 2017 is the final year in the firm-level dataset.

Figure 1.2: Wage Skill Premium Percentage Point Change in Spain (2002-2017)



Notes: This figure depicts the percentage point change from its beginning of sample average (2002-2006) to the end of sample average (2013-2017). Appendix A.3.1 provides the wage skill premium calculation. Aggregate covers ISIC rev. 4 sector codes $A - R$, manufacturing is ISIC rev. 4 sector code C and business services are ISIC rev. 4 sector codes $G - N$. About one-third of the aggregate consists of sectors outside of manufacturing and business services such as agriculture, construction, public administration and more. Table A.6.3 in Appendix A.6 contains the wage skill premium by sector.
Source: Author's calculations using EUKLEMS-INTANProd database.

the first five years (2002-2006) and the last five years (2013-2017) of the sample period. At the aggregate level, the wage skill premium modestly increased by 2.3%. Prior studies have documented stagnation or even periods of decline in the wage premium from the late 1990s to 2008 (Felgueroso, Hidalgo-Pérez, & Jiménez-Martín, 2016; Pijoan-Mas & Sánchez-Marcos, 2010), which partially overlaps with the sample period I use. While the aggregate wage skill premium shows little change, there are differences across sectors: the manufacturing sector experienced a significant increase of 9.1%, while business services saw a smaller rise of 4.6%. The lower increase in the aggregate is driven by sharp declines in public service sectors such as public administration and education. Tables A.6.2-A.6.3 in Appendix A.6 break down the wage skill premium by sector.

1.2.2 Foreign Ownership in the Aggregate

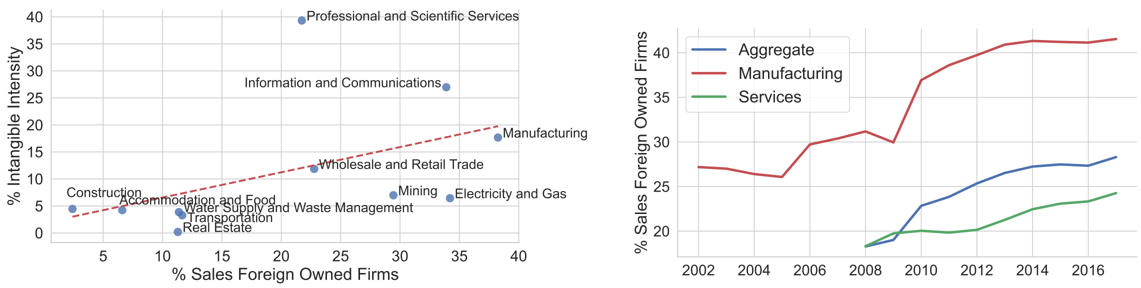
The Spanish economy is comprised of firms that are either domestically owned, headquartered within the country, or foreign owned, which are owned by multinational corporations based outside the country.[12] Foreign-owned firms can be further classified into affiliates and subsidiaries. Following the OECD's defintion, affiliates are those where less than 50% of its capital is owned by a foreign multinational, whereas subsidiaries have at least 50% ownership by the foreign parent company. For the purposes of this paper, I define foreign-owned firms specifically as subsidiaries and use the terms "foreign-owned firms" and "foreign subsidiaries" interchangeably throughout. I use aggregate and sector level data on foreign subsidiaries from the OECD's Analytical Multinational Enterprises (AMNE) and Structural and Demographic Business Statistics

[12] In 2020, the top five countries of origin for multinationals operating in Spain were France, United States, Germany, United Kingdom, and Italy. Multinationals from these countries also accounted for the majority of multinational production in Spain (INE).

Figure 1.3: Foreign Production in Spain

(a) % Foreign Sales and Intangibility

(b) % Foreign Sales Over Time



Notes: A firm is considered to be foreign owned if it is a subsidiary or at least 50% or more of its capital is owned by a foreign entity. The left subfigure has intangible intensity (intangible capital over total capital) and percentage of aggregate sales revenue done by foreign owned firms. The points are for one-digit sector averaged between the years 2008-2017. The same relationship is observed for skill-intensive sectors (see Figure A.5.3 in Appendix A.5). The right subfigure displays the percentage of aggregate sales revenue done by foreign owned firms over time. It depicts the time series at the aggregate, manufacturing (ISIC Rev. sector code C) and business services (ISIC Rev. 4 sector codes $G - N$) levels. Data collection for the aggregate and all sectors starts in 2008, except for manufacturing. Figure A.5.2 shows the percentage of foreign owned firms over time and Figure A.5.8 shows how the number of both domestic and foreign firms changed over time.
Source: Author's calculations using EUKLEMS-INTANProd and OECD AMNE and SBDS database.

(SDBS) databases which is sourced by Spain's national statistics office (INE in Spanish).[13] The databases provide information for aggregate and sector levels available from 2008, except for manufacturing, which extends further back.

Foreign ownership is greater in more intangible-intensive sectors. Figure 1.3a shows that in one-digit sectors where the percentage of sales revenue done by foreign-owned firms is higher, so is the share of intangible capital over total capital. The same relationship is observed for skill-intensive sectors (see Figure A.5.3 in Appendix A.5). Foreign-owned firms have made an increasingly significant contribution to overall production over time. Figure 1.3b shows that by 2017, these firms accounted for over 25% of aggregate sales revenue. Despite their sizable presence in aggregate production, the number of foreign-owned firms remains small. Although their numbers have grown, similar to that of trends in Figure 1.3b, they make up less than one percent of all firms in 2017 (see Figure A.5.2a in Appendix A.5). The increase in the revenue share and relative number can be attributed to the influx of new foreign firms, as opposed to the decline in the number of domestic ones. Figure A.5.8 in Appendix A.5 shows the number of firms categorized by ownership status relative to their 2008 levels. By 2017, the relative number of foreign-owned firms in Spain increased by approximately 80%. On the other hand, domestic-owned firms experienced a decline before returning to its pre-crisis level by 2016.

1.2.3 Foreign Ownership at the Firm Level

This section goes to the firm level and examines the outcomes of Spanish firms after they are acquired by a foreign multinational.

[13]AMNE: https://www.oecd.org/industry/ind/analytical-amne-database.htm
SDBS: https://www.oecd.org/sdd/business-stats/structuralanddemographicbusinessstatisticssdbsoecd.htm

1.2.3.1 Data

The firm-level data that I use is from the Survey on Business Strategies (ESEE in Spanish) which is an annual survey of the Spanish manufacturing sector carried out by the SEPI foundation and is sponsored by the Spanish Ministry of Industry.[14] The ESEE began in 1990 and covers roughly 1,900 Spanish manufacturing firms. It is a representative sample of manufacturing firms with between 10 and 200 employees and surveys the whole population of manufacturing firms with more than 200 employees.[15] The average response rate is greater than 90% and new firms are added over time to replace those that either exit or are unresponsive. Further details regarding ESEE are available in Appendix A.2.

The survey is unique in that it offers complete balance sheet and income statement information, the skill-level of its employees and whether a particular firm is foreign-owned or not. Given the panel structure this allows me to analyze the within-firm variation before and after a change in ownership. I define a firm as foreign-owned if at least 50% of its capital is owned by a foreign company. Among all firms in the data, 17.7% are foreign-owned when they first appear in the dataset and the remaining 83.3% first appear domestically owned.[16] To focus the analysis on potential acquisition targets, I narrow the sample to firms that enter the dataset as domestically owned. This leaves me with 5.9% of firms that transfer from domestic to foreign ownership at some point and the remaining 94.1% maintain domestic ownership throughout the entire sample period. I concentrate on how three outcomes are affected by foreign ownership: productivity, investment and the skill labor composition. Due to common data limitations faced in the literature, this is one of the first papers to analyze the relationship between foreign ownership and skill labor composition.

To assess the impact of foreign ownership on productivity I look at its effect on real sales and TFP where the latter is estimated using the methodology established by D. A. Ackerberg, Caves, and Frazer (2015). Additionally, I analyze the impact on investment by examining research and development (R&D) and tangible investment in property, plant and equipment (PP&E). R&D is defined as a set of expenditures that are aimed at developing new products and services or improving existing ones. The ESEE contains both intramural R&D (in-house) and extramural R&D (payments to outside R&D laboratories and research centers). For the empirical analysis I use in-house R&D to confirm that it occurs on-site after acquisition. Finally, a unique feature of the data is that it asks firms on the education level of its personnel. The ESEE classifies three education types, workers with secondary education or below, with a specialized non-tertiary

[14] https://www.fundacionsepi.es/investigacion/esee/en/spresentacion.asp

[15] The subset of firms with 200 or less but more than 10 employees are selected according to a stratified sampling scheme that guarantees that they can establish representativeness of the data for different industries and the manufacturing sector as a whole.

[16] I classify firms with minority foreign ownership, those whose percentage of capital owned by a foreign entity is greater than zero but less than 50 percent, as domestically owned. There are few firms with minority foreign ownership stake as 5.1% of all the firms first appear with it. Excluding these firms does not significantly change the empirical results. Almost all firms that report a change in ownership become subsidiaries, not affiliates. Only 35 firms (approximately 0.7% of the sample) report changes in the share of capital owned by a foreign company from zero to less than 50%. Excluding these firms does not affect the empirical results nor does including these firms in the group of foreign-acquired firms.

Table 1.1: ESEE Summary Statistics (1990-2017)

Avg. Variable (in logs)	Domestic Never Acquired	Foreign *Before*	Foreign *After*	Obs.
Sales	15.40	17.57	17.96	39,011 / 2,271 / 1,727
TFP	-0.051	0.027	0.039	32,791 / 1,853 / 1,640
Intangibility	-3.10	-2.64	-2.63	27,427 / 1,710 / 1,563
In-House R&D	11.99	13.02	13.15	9,241 / 1,198 / 970
Tangible Inv.	11.86	13.87	14.18	27,593 / 1,988 / 1,485
Skilled Emp.	1.44	2.54	3.00	12,580 / 681 / 504
Unskilled Emp.	3.71	5.30	5.51	12,580 / 681 / 504

Notes: Variables in constant 2015 prices. Intangibility is the share intangible fixed assets over total fixed assets (tangible and intangible). Extended Table A.6.1 in Appendix A.6 contains additional variables.
Source: Author's calculations using ESEE.

certificate and with a tertiary degree or higher. Upon collecting information on the total numbered employed the ESEE asks for the number of workers that fall into each of the three categories. The ESEE initially collected this variable every four years but it became an annually collected variable since 2015. As in the previous section, I classify skilled labor as those with a tertiary degree or higher and the rest as unskilled.

Summary Statistics Table 1.1 provides the summary statistics, pooling observations across all years and presenting the averages for domestically owned firms never acquired, domestically owned firms before acquisition, and foreign-owned firms. There are considerable differences across the three groups. On average, acquired firms operate at a much larger scale and are more intangible-intensive than their domestic peers prior to acquisition, and they tend to scale up further post-acquisition. In addition to differences in productivity, firms differ in levels of investment and skill-compositions. The number of firm-year observations are reported in the final column and differ for a number of reasons. Sales has no missing observations in the dataset. An observation for TFP is missing if any input used in the estimation procedure (capital, labor hours, intermediate expenses) is missing. Tangible investment is lumpy, resulting in fewer observations compared to sales and TFP, and even fewer for R&D, which is inherently subject to higher rates of inaction. Finally, the skilled employment levels are observed less frequently as data on the skill composition of the firm was only collected every four years starting in 1990 and began as an annual variable after 2015.

1.2.3.2 Controlling for Selection and Empirical Results

Table 1.1 shows that foreign-owned firms tend to operate at a much larger scale than their domestic peers, yet these domestic firms also did so prior to acquisition.[17] The superior performance of

[17]Foreign multinationals often target subsidiaries that resemble them closely for several strategic considerations. Firstly, such acquisitions provide an immediate presence in target markets, expediting market penetration. Secondly, this approach is cost-effective, as acquiring sizable and productive subsidiaries allows foreign multinationals

Table 1.2: P.S. Reweighted Regressions of Productivity and Investment Outcomes

	Productivity		Investment	
	(1) Sales	(2) TFP	(3) In-House R&D	(4) Tangible
Lag Foreign	0.131***	0.039***	0.283***	0.248**
	(0.043)	(0.012)	(0.106)	(0.104)
Obs.	33249	32064	8895	24059
R-squared	.96	.659	.785	.738

Notes: * p<0.10; ** p<0.05; *** p<0.01. Standard errors clustered by firm in parentheses. All regressions include firm and industry-year effects. All dependent variables are in logs. Lag foreign is a dummy variable for foreign ownership in previous period (equal to one if at least 50% the firm's capital is foreign owned by and zero otherwise). The characteristics used to obtain the propensity score are log sales, log labor productivity (value added over employment), sales growth, labor productivity growth, log average wage, log total fixed assets (tangible plus intangible), R&D status, and a year trend. All the previously mentioned variables are lagged one period relative to acquisition. I allow for this relationship to vary across industries by estimating the propensity score separately for each industry. I ensured that only observations within the region of common support are included. I performed the standard tests to check that the balancing hypothesis holds within each industry and found that all covariates are balanced between treated and control observations for all blocks in all industries.

foreign-owned firms could stem from the selection of higher-performing domestic firms (Guadalupe et al., 2012). To mitigate selection bias I follow the literature by employing a propensity score reweighting estimator to assess the impact of foreign ownership on Spanish firms, where foreign ownership is considered to be the treatment variable. The propensity scores denote the likelihood of being acquired and are calculated by categorizing firms acquired in a given year as treated observations and those never acquired as control observations. The observations in each group are then aggregated across all years and the propensity scores are estimated by running industry-specific probit regressions of foreign ownership on a set of observable variables. These variables are log sales, log labor productivity (value added over employment), sales growth, labor productivity growth, log average wage, log total fixed assets (tangible plus intangible), R&D status, and a year trend. All the previously mentioned variables are lagged one period relative to acquisition. The estimated propensity scores p are subsequently used to reweigh treated firms by $1/p$ and control firms by $1/(1-p)$. I ensure that only observations within the region of common support are included. Finally, I verify that the balancing property is satisfied across all industries.

Having developed a method to control for selection bias I turn to regressing a set of variables on a lagged dummy variable of foreign ownership. All regressions include firm and industry-year effects and standard errors are clustered at the firm-level. All dependent variables are in logs. The first two columns in Table 1.2 consider two different measures of firm productivity in sales and total factor productivity (TFP). I find that, on average, sales increase by 13.1% following an acquisition by a foreign multinational. Sales only partially measures productivity, as it does not consider the use of other inputs, such as capital and intermediate goods. In contrast, TFP is a more comprehensive measure of productivity that captures how effectively all inputs are used in

to leverage existing operational structures operating at scale. This facilitates smoother integration into the multinational's distribution network.

Table 1.3: P.S. Reweighted Regressions of Labor Skill Composition

	(1) Skill Emp. Ratio	(2) Skilled Employment	(3) Unskilled Employment
Lag Foreign	0.183***	0.247***	0.064
	(0.066)	(0.075)	(0.053)
Obs.	6473	6473	6473
R-squared	.272	.237	.151

Notes: * p<0.10; ** p<0.05; *** p<0.01. Standard errors clustered by firm in parentheses. The dependent variables are observed every 4 years between 1990-2014 and annually after. All regressions include firm and industry-year effects. All dependent variables are in logs. Lag foreign is a dummy variable for foreign ownership in previous period (equal to one if at least 50% the firm's capital is foreign owned by and zero otherwise). The characteristics used to obtain the propensity score are log sales, log labor productivity (value added over employment), sales growth, labor productivity growth, log average wage, log total fixed assets (tangible plus intangible), R&D status, and a year trend. All the previously mentioned variables are lagged one period relative to acquisition. I allow for this relationship to vary across industries by estimating the propensity score separately for each industry. I ensured that only observations within the region of common support are included. I performed the standard tests to check that the balancing hypothesis holds within each industry and found that all covariates are balanced between treated and control observations for all blocks in all industries.

generating output. Here, a change to foreign ownership modestly increases TFP by 3.9%, which is at the higher end of the 0 to 5% range commonly observed in the literature.[18] The third and fourth columns in Table 1.2 show how foreign ownership is associated with investment. Following acquisition, investment levels are higher as there is a large and significant increase of 28.3% for in-house R&D and an 24.8% increase in tangible investment.

The dependent variable in the first column of Table 1.3 is the ratio of skilled employees to unskilled within a given firm. The estimate indicates that after acquisition by a foreign multinational the ratio of skilled employment increases on average by 18.3%. This suggests that newly acquired foreign subsidiaries experience a change in the skill composition, favoring skilled workers. The second and third columns of Table 1.3 show the changes for employment level by skill. These two variables are the numerator and denominator of the skill ratio. Following an acquisition, the number of skilled employees within the firm on average undergoes a statistically significant increase of 24.7%. Conversely, there is a smaller yet statistically insignificant increase in unskilled employment. These results suggest a distinct bias toward skilled employment following a change to foreign ownership. Regressions for additional variables are in Table A.6.5 in Appendix A.6.

1.2.3.3 Concern For Lingering Endogeneity

The empirical evidence broadly aligns with a common finding in the literature that, after controlling for selection bias, being acquired by a foreign multinational is positively associated with an increase in productivity and investment. My contribution is that in addition to this, I find that the labor composition changes in response to foreign acquisition as the demand for skilled labor increases significantly more than for unskilled. The question is whether to interpret these estimates as causal. The foreign acquisition literature that uses propensity score reweighting

[18] Table A.6.6 in Appendix A.6 provides regressions for different measures of TFP. The results are very similar.

typically argues that controlling for selection gives way for causal interpretation. The argument and assumptions required are as follows. There are two effects of foreign ownership. The first is the selection in acquisition effect where foreign multinationals "cherry-pick" domestic firms who are already superior relative to their domestic competition. The second is the exogenous treatment effect. That is, changes that occur in the firm after being acquired are because of foreign ownership and would not have occurred had the firm remained domestically owned. In this sense, by controlling for selection in acquisition, one is estimating the average treatment effect of foreign acquisition. The critical assumption in the estimation is that conditional on observable characteristics that affect selection, acquisition (ie the treatment) is random. Consequently, the outcomes of acquired firms are solely attributable to acquisition by foreign multinationals. This assumption requires that the balancing property is satisfied. That is, observations with the same propensity score must have the same distribution of observable covariates independent of treatment status. Implicitly, this also assumes that this holds for the distribution of unobservable characteristics as well.

While such an assumption would alleviate any endogeneity concerns, there remains a lingering worry that endogeneity that may still yet bias the empirical results. Exogenous technological changes such as the rise of intangibles or specific policies targeting foreign multinationals, could still endogenously influence acquisitions by foreign firms. Unobservables may also still be a problem. The assumption that firms in the two groups share identical expectations regarding acquisition does not hold if they are a function of idiosyncratic unobservable characteristics. For instance, firms may differ in their preferences for being acquired. Some firms might actively seek acquisition, investing heavily to spur growth and attract potential buyers. In contrast, a manager of a similar firm might never be open to the idea of acquisition, perhaps to maintain family ownership. This emphasizes the need for a cautious interpretation of the empirical findings.

1.3 Model

I construct a model of firm dynamics along the lines of Hopenhayn (1992) with endogenous entry and exit. I augment the model in two distinct dimensions. The first is the presence of intangible-skill complementarity in production. An increase in intangible investment pushes up the relative demand for skilled labor and, in turn, the wage skill premium. The second is ongoing acquisitions where domestic firms endogenously agree to sell their ownership rights to foreign multinationals. These augmentations result in two aggregate effects that impact both the distribution of firms and the wage skill premium. The first is the selection effect, which arises through entry and exit. The second is the foreign ownership effect which stems from ownership transfer. This impacts firms before and after acquisition. Domestic firms anticipate acquisitions ex-ante and increase their investment levels when they expect to be acquired. Post-acquisition, firms receive a technology transfer from their foreign parent which differentiates them from their domestic counterparts by increasing their productivity and investment levels.

1.3.1 Environment

Time is discrete and infinite. The economy is populated by a continuum of firms that compete in a perfectly competitive final good market. The final good serves as the numeraire in the economy. Firms face persistent idiosyncratic productivity shocks which together with endogenous entry and exit, generate heterogeneity in production. They invest in intangible k_I and tangible k_T capital and own the stocks, which depreciate at rates δ_I and δ_T. They employ both skilled l_s and unskilled l_u labor types. Firms are either domestic or foreign owned $o = \{d, f\}$ where foreign-owned firms operate as subsidiaries and send dividends abroad. The final good is sold to skilled and unskilled households with masses (N_s, N_u), who supply labor hours endogenously. I consider only the equilibrium of the domestic economy (one country model). I study a stationary general equilibrium without aggregate uncertainty.

Production Firms with TFP z combine both types of capital with skilled and unskilled labor to produce the final good. Similar in nature to Krusell et al. (2000), the production function is Cobb-Douglas over tangible capital and has a nested CES structure over the remaining inputs

$$\mathcal{F} = z k_T^{\alpha} \left[(1-\varsigma)\, l_u^{\sigma} + \varsigma \, \left(\varrho l_s^{\rho} + (1-\varrho) k_I^{\rho} \right)^{\frac{\sigma}{\rho}} \right]^{\frac{(1-\alpha)\nu}{\sigma}} . \tag{1.1}$$

The parameters $(\sigma, \rho) \in (-\infty, 1) \times (-\infty, 1)$ determine the elasticities of substitution. The elasticity of substitution between skilled (or intangible capital) and unskilled labor is $\frac{1}{1-\sigma}$ and the elasticity between skilled labor and the intangible capital is $\frac{1}{1-\rho}$. If $\sigma > \rho$ then the relative demand for skilled labor increases with intangible capital and there is intangible-skill complementarity in production. The share parameters are (ς, ϱ). The parameter $\nu \in (0, 1)$ is the span-of-control and generates decreasing returns; a necessary condition that ensures a well-defined firm distribution.

Idiosyncratic TFP A firm's underlying TFP a follows a AR(1) process in logs with persistence ρ_a and normally distributed i.i.d. innovations $\varepsilon \sim N(0, \sigma_a^2)$ with variance σ_a^2. The process is normalized to have mean one. TFP used in production z depends on ownership as described in equation (1.3). If a firm is domestically owned then z takes the same value as a. A foreign-owned firm's TFP is enhanced through technology provided by the foreign parent. The scaling parameter ϑ represents the enhancement that a foreign multinational brings independent of any particular subsidiary. The elasticity parameter is θ, and when $\theta < 1$, the marginal productivity difference relative to domestic firms is small for high values of a and large for low values. The opposite is true for $\theta > 1$. A special case arises when $\theta = 1$, where the marginal TFP difference is the same across all levels of a. When $\vartheta > 1$ and $\theta > \frac{\ln(a/\vartheta)}{\ln(a)}$, this enhancement makes all subsidiaries operate at a larger average firm size compared to their domestic peers. Productivity improvements from technology transfer can arise through various mechanisms. I abstract from a specific mechanism, however, existing literature suggests several contributors, which include latent intangible variables such as better management practices (Bloom et al., 2012), superior R&D know-how (McGrattan & Prescott, 2009, 2010a), or a permanent demand shock due to expanded access to international markets (Guadalupe et al., 2012).[19] The underlying TFP process is

$$\ln(a') = \rho_a \ln(a) + \varepsilon' \tag{1.2}$$

where TFP used in production differs by ownership

$$z = \begin{cases} a & \text{if } o = d \\ \vartheta a^{\theta} & \text{if } o = f \end{cases} \tag{1.3}$$

1.3.2 Incumbent Firms

An incumbent hires labor and invests in capital each period, making production decisions after acquisitions occur. Per-period profits are given by

$$\pi = \max_{l_s,\, l_u} \mathcal{F} - w_s l_s - w_u l_u - \kappa_{op}. \tag{1.4}$$

Wages (w_s, w_u) are paid to skilled and unskilled types. The parameter κ_{op} is a fixed operational cost that the firm must incur each period. Firm value depends on current period profits and its expected future value. The incumbent with ownership o solves the following recursive dynamic problem

$$V(a, k_I, k_T, o) = \max_{k'_I, k'_T} \pi - p_I x_I - p_T x_T + \frac{1-\xi}{1+r} \max\left\{\mathbb{E}_a\left[\mathcal{V}(a', k'_I, k'_T, o')\right], 0\right\}. \tag{1.5}$$

subject to

$$x_I = k'_I - k_I(1 - \delta_I) \qquad\qquad x_T = k'_T - k_T(1 - \delta_T).$$

Investment in each capital type is subject to prices (p_I, p_T). The firm decides to exit when its continuation value is less than or equal to the value of exiting, which is normalized to zero. The exit decision is denoted by $\chi(a, k_I, k_T, o) = \{0, 1\}$. The expected continuation value $\mathcal{V}$ is conditional on the current productivity level a. Firms discount the future at $(1-\xi)/(1+r)$ where ξ is an exogenous exit shock and r is the interest rate. The continuation value of the domestic incumbent incorporates that it can either continue as domestically owned or that it is acquired and changes ownership in the next period. On the other hand, a foreign subsidiary's continuation value does not consider the prospect of acquisition nor returning to domestic ownership.[20]

1.3.3 Entry

Domestic Entrant Each period there is an endogenous mass M of potential domestic entrant firms. A potential entrant pays a fixed cost of entry κ_e and enters the economy in the next period.

[19]Due to data limitations, I lack firm-level information on specific characteristics of foreign acquirers. I can only observe the amount of capital owned by a foreign entity. Therefore, I do not take a specific stance on the mechanism behind TFP enhancement from foreign ownership.

[20]There a very few instances of subsidiaries that return to domestic ownership in the ESEE and I therefore abstract from this possibility.

Upon entry, firms receive their initial TFP level which is drawn from the the ergodic distribution of the log a process. If initial TFP is low enough such that the exit decision $\chi(\cdot)$ equals one then the entrant immediately exits. The present discounted value of the potential entrant is

$$V_e = \max_{k'_{I,e}, k'_{T,e}} -p_I k'_{I,e} - p_T k'_{T,e} + \frac{1-\xi}{1+r}\mathbb{E}\left[V(a', k'_{I,e}, k'_{T,e}, d)\right] - \kappa_e. \tag{1.6}$$

Firms continue to enter the economy as long as $V_e \geq 0$. In a stationary equilibrium free entry guarantees that $V_e = 0$.

Foreign Multinational There is an exogenous mass of identical foreign multinationals that have decided to enter the domestic economy. Due to data limitations I lack firm-level information on the characteristics of foreign acquirers. I therefore make as few assumptions as possible in regard to the multinational's entry decision and assume that the decision to enter is already sunk. A multinational enters the economy by acquiring an already existing domestic incumbent.[21] A foreign multinational is randomly matched with a domestic incumbent. To proceed with the acquisition, the foreign multinational must negotiate with the domestic incumbent, and both parties must agree on a sale price. If an agreement is reached then the domestic incumbent becomes a foreign subsidiary with value $V(a, k_I, k_T, f)$. In the event of no agreement, the foreign multinational does not enter the economy and the domestic incumbent continues under domestic ownership.

1.3.4 Acquisition Market

Domestic incumbents participate in a market of ownership transfer to foreign multinational entrants. In this market domestic firms face the same chance of being matched at the random rate $\mu \in [0, 1]$. Conditional on a formation of a match, the foreign multinational and domestic firm negotiate the acquisition terms following a Nash bargaining process with equal bargaining power. Only the foreign multinational can be the acquirer and I do not allow domestic incumbents to merge among themselves. The following equations are the solutions to the bargaining problem. The derivation of these results can be found in Appendix A.1.1.

The total surplus from acquisition in equation (1.7) is the value generated from a deal between a domestic firm and the foreign multinational entrant

$$S(a, k_I, k_T) = V(a, k_I, k_T, f) - V(a, k_I, k_T, d) - \kappa_{ts}. \tag{1.7}$$

Acquisitions occur if $S > 0$ for price $p_d(a, k_I, k_T)$. Agreed acquisitions are subject to a one-off integration cost κ_{ts}. This cost is incurred by the foreign multinational.[22] The acquisition price that is paid for a domestic incumbent with states (a, k_I, k_T) is the current value of the domestic

[21] Another form of entry is greenfield investment where a foreign multinational builds a subsidiary. I abstract from greenfield and restrict the only mode of entry to acquisition which is the most common form of inward FDI in Spain.

[22] Such a cost could be the search cost. It also can be the transfer cost which can include integrating IT systems, business processes, organizational structures, legal fees and external financing costs.

firm plus half of the value generated from the acquisition

$$p_d(a, k_I, k_T) = V(a, k_I, k_T, d) + \frac{S(a, k_I, k_T)}{2}. \tag{1.8}$$

If $S < 0$ then the acquisition price would be less than the value of the domestic incumbent and hence it would not transfer ownership. If $S = 0$, it would be indifferent.

Positive value generated from an acquisition comes from the value of the new foreign subsidiary. The new TFP level from equation (1.3) and its expected future values are ultimately the source behind the value of the acquired firm under the control of the foreign multinational. Outcomes of acquisitions are heterogeneous and uncertain. Being foreign-owned enhances productivity which gives the foreign subsidiary a competitive edge over its domestic rivals, but it does not insulate it as a series of negative shocks could lead to potential exit.[23]

Potential Acquisition and the Continuation Value The continuation value in equations (1.10)-(1.11) differs depending on ownership type o. Equation (1.11) is the continuation value for a firm already under foreign ownership and does not consider any potential future changes in ownership. On the other hand, the continuation value of the domestic incumbent incorporates that in the next period it either remains domestically owned or that meets a foreign multinational and is acquired. Let φ denote the product of an indicator function, which equals one when the total acquisition surplus is positive, and the probability μ of meeting a foreign multinational

$$\varphi = \mu \cdot \mathbb{1}\left\{\mathbb{E}_a\left[S(a', k_I', k_T')\right] > 0\right\}. \tag{1.9}$$

The first term in equation (1.10) is the expected firm value remaining under domestic ownership in the next period. The second term p_d is the expected acquisition price if it meets a foreign multinational and agrees to transfer ownership

$$\text{Domestic Owned:}\quad \mathbb{E}_a\left[\mathcal{V}(a', k_I', k_T', d')\right] = \mathbb{E}_a\left[(1-\varphi)V(a', k_I', k_T', d') + \varphi p_d(a', k_I', k_T')\right] \tag{1.10}$$

$$\text{Foreign Owned:}\quad \mathbb{E}_a\left[\mathcal{V}(a', k_I', k_T', f')\right] = \mathbb{E}_a\left[V(a', k_I', k_T', f')\right]. \tag{1.11}$$

The acquisition price is strictly positive under any agreement and is increasing the arguments (a', k_I', k_T'). Its inclusion increases the continuation value and incentivizes the firm to invest more in both types of capital. Anticipation is driven by the domestic firm's perception of the possibility of an acquisition. On one hand, future productivity a' is exogenous, yet if a firm expects a high TFP level in the future then it expects a higher sale price. On the other hand, the firm can endogenously affect the increase price by choosing a higher capital stocks (k_I', k_T').

[23]Allowing for idiosyncratic outcomes following acquisitions could reflect a foreign multinational that thought the acquired firm had more growth potential than it actually did or could also be poor management on the foreign multinational's part.

1.3.5 Households

There is a mass of households which differ by skill type $i \in \{s, u\}$ and are fully insured against income risk. They get utility U from consumption and disutility from work. The mass of type i workers in the labor force is N_i; the total household mass is $N = N_s + N_u$. I assume that N_i is exogenous. Thus, I abstract from the extensive margin where an unskilled household chooses to become skilled and vice versa. All individual households are endowed with one unit of time per period and endogenously supply labor $h_i \in (0,1)$ on the intensive margin. Time not spent working is leisure. Since investment decisions are made by firms, there are no dynamic linkages in the household's choices; therefore, an individual type i household maximizes the following static problem

$$U(c_i, h_i) = \max_{c_i, h_i} \ln(c_i) - \psi_i \frac{h_i^{1+\frac{1}{\chi}}}{1+\frac{1}{\chi}} \tag{1.12}$$

subject to

$$c_i = w_i h_i + \frac{\Pi_d + P_d}{N}. \tag{1.13}$$

The household gets log utility from consumption. The parameters that govern disutility of work are the frisch elasticity χ and labor disutility scalar ψ_i. The household consumes all of its labor and business income. The latter is evenly split across all households and includes dividends $\Pi_d = \Pi - \Pi_f$ paid by the domestic firms that the households own, as well as the per-period sale price P_d of domestic firms sold to foreign multinationals. The transfer of ownership impacts household consumption. The sale of domestic firms yields a one-time financial gain, yet it entails forfeiting the rights to any future dividends as they are redirected to the parent company of the foreign multinational situated outside the domestic economy. Because they are identical, all households within each type i choose the same hours to supply and have the same consumption level. However, it is important to note that consumption and hours worked differ between skilled and unskilled household types. Aggregate labor supplied by skill type i is $L_i = N_i h_i$, and total consumption is $C_i = N_i c_i$.

1.3.6 Stationary Equilibrium

The state space for an incumbent firms is $(\mathcal{A} \times \mathcal{K_I} \times \mathcal{K_T} \times \mathcal{O})$ where $(a, k_I, k_T, o) \in S$. To simplify the equilibrium exposition denote the states as $s = (a, k_I, k_T, o)$, where the state vectors for domestic and foreign ownership are $s_d = (a, k_I, k_T, d)$ and $s_f = (a, k_I, k_T, f)$. Let λ be the invariant measure of incumbent firms where P_M is the measure of domestically owned firms matched with a foreign entrant, P_U is the measure of unmatched domestically owned firms and P_F is the measure of foreign-owned firms. Denote M as the mass of potential domestic entrants who draw their initial TFP level from $G(a)$. A more formal definition is in Appendix A.1.2.

SRCE Definition A stationary recursive competitive equilibrium (SRCE) consists of prices (w_s, w_u), an invariant measure of firms λ, a constant mass of entrants M, a value function for incumbent firm $V(s)$, a value function for the entrant firm V_e, policy functions for the incumbent firm $l_s(s)$, $l_u(s)$, $k'_I(s)$, $k'_T(s)$, $\chi(s)$, and for the entrant firm $k'_{I,e}$, $k'_{T,e}$ such that

1. Given prices, the policy functions $l_s(s)$, $l_u(s)$, $k'_I(s)$, $k'_T(s)$, $\chi(s)$ solve the incumbent firm's problem in equation (1.5) with the associated value function $V(s)$. The policy functions $k'_{I,e}$ and $k'_{T,e}$ solve the entrant firm's problem with the associated function V^e in equation (1.6).

2. Given prices, households of type $i \in \{s, u\}$ with mass N_i maximize utility in equation (1.12) subject to the budget constraint in equation (1.13). Aggregate labor supplied is $L_i = N_i h_i$.

3. Matched domestic firms transfer ownership only if the total acquisition surplus in equation (1.7) is strictly positive. The aggregate sale price is $P_d = \mu \int \mathbb{1}_{\{S(s_d)>0\}} p(s_d) d\lambda(s_d)$.

4. Markets clear

   (a) Skilled labor: $L_s = \int_{\mathbf{S}} l_s(s) d\lambda(s)$

   (b) Unskilled labor: $L_u = \int_{\mathbf{S}} l_u(s) d\lambda(s)$

   (c) Goods:[24] $C + X_I + X_T + \kappa_e M = \int_{\mathbf{S}} (\mathcal{F}(z, k_I, k_T, l_s(s), l_u(s)) - \kappa_{op}) d\lambda(s) + P_d - \Pi_f$

5. The invariant measure of firms λ satisfies

$$\lambda(\mathcal{A} \times \mathcal{K_I} \times \mathcal{K_T} \times \mathcal{O}) = [P_M(s_d) + P_U(s_d) + P_F(s_f)] + M \int_{a' \in \mathcal{A}} dG(a'). \tag{1.14}$$

6. The free entry condition is satisfied: $V_e = 0$.

1.3.7 Timing

The timing of events, summarized in Figure 1.4, is as follows: incumbent firms observe the realization of their idiosyncratic TFP level a. Domestic incumbents meet a foreign multinational with probability μ and begin to bargain over an acquisition price. If an agreement is reached, the domestic incumbent transfers ownership and becomes a foreign subsidiary, otherwise it continues under domestic ownership. After the bargaining stage all incumbents choose to continue or exit the economy. Newly acquired subsidiaries never immediately exit. Finally, incumbents then hire labor and make their investment decisions. In the meantime there is a mass of domestic entrants that enter the economy having paid a fixed entry cost in the previous period. Entrant firms do not participate in the merger market prior to entering.

1.4 Calibration

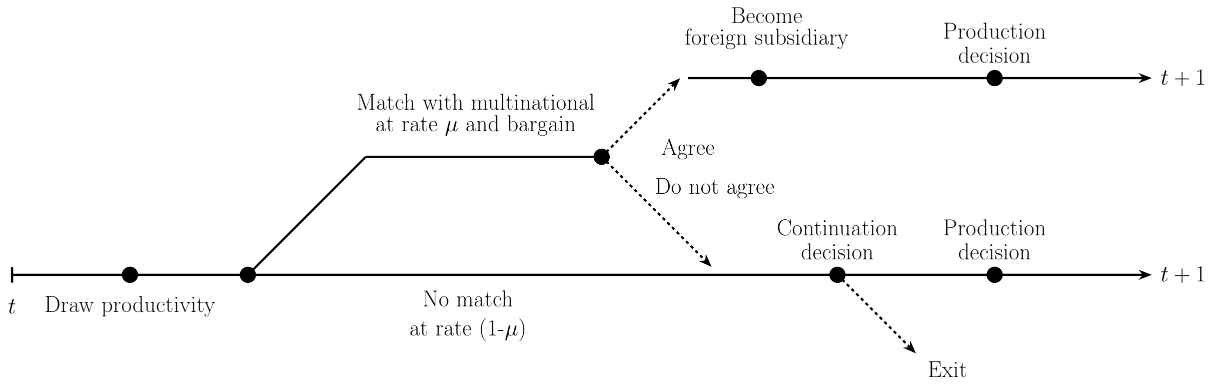
The model is calibrated to the Spanish manufacturing sector during the period 2002-2006, using several data sources. Firm-level data is taken from the ESEE, while sector-level data is obtained

[24] where

i. Aggregate profits by ownership type $o \in \{d, f\}$ are $\Pi_o = \int_{\mathbf{S}} \pi_o(s) d\lambda(s)$ and foreign dividends Π_f flow out the economy.

ii. Investment for capital type $j \in \{I, T\}$ is $X_j = p_j \int_{\mathbf{S}} (k'_j(s) - (1 - \delta_j) k_j) d\lambda(s)$.

Figure 1.4: Domestic Incumbent Timeline



from KLEMS, INE, and the OECD's AMNE and SBDS databases for foreign ownership. The skill composition of the labor force in manufacturing and hours supplied by education type is sourced from the Survey of Household Finances (EFF in Spanish), administered by the Bank of Spain.[25] The period 2002-2006 is specifically chosen because 2002 is the earliest year for which KLEMS provides labor data by skill type for Spain, and it is also the earliest available year for the EFF. Section 1.4.1 provides a detailed quantification of the model parameters. This begins with the description of externally calibrated parameters, followed by the internal calibration of remaining parameters using the Simulated Method of Moments (SMM). Section 1.4.2 discusses non-targeted moments and cross-sectional implications of the calibrated model.

1.4.1 Parameterization

Table 1.4 displays the externally and internally calibrated parameters in the model.

1.4.1.1 Externally Calibrated Parameters

I externally calibrate eleven parameters. I set the interest rate $r = 0.04$. The depreciation rates for tangible and intangible capital in the Spanish manufacturing sector are taken from KLEMS. The returns-to-scale parameter is set to $\nu = 0.85$. Two parameters govern the idiosyncratic TFP process. Estimates of the persistence parameter fall in the range 0.5 to 0.9. I opt for an intermediate value of $\rho_a = 0.7$. For the standard deviation of innovations influencing the productivity process, the literature reports a smaller range of 0.15 to 0.28. I set the standard deviation of innovations $\sigma_a = 0.2$, which is in the lower middle part of the estimated range.[26] I normalize both investment prices to one. KLEMS nor does INE publicly provide the data on the skill composition of the labor force by sector. I construct the skill composition for the manufacturing sector using the EFF. I define the manufacturing labor force as those employed and unemployed (previously employed) in the manufacturing sector. The skill ratio of the labor force is $\mathfrak{s} = \frac{N_s}{N_u} = 0.292$. In the model, I normalize the size of the unskilled labor force N_u to one, resulting in $N_s = \mathfrak{s}$. The measure of potential entrants M scales the distribution of entrants (see equation (A.1.5)) and is set such that the aggregate demand for unskilled labor

[25] https://app.bde.es/efs_www/home?lang=EN
[26] See Clementi and Palazzo (2015) for an in-depth review.

Table 1.4: Parameter Values

Calibrated Parameter	Value	Description
External		
r	0.040	Annual interest rate
δ_T	0.140	Tangible depreciation rate
δ_I	0.200	Intangible depreciation rate
ν	0.850	Returns to scale
ρ_a	0.700	Persistence of AR(1) process a
σ_a	0.200	Std. dev. of AR(1) process a
$\mathfrak{s}$	0.292	Skill ratio of labor force
M	0.007	Mass of potential entrants
σ	0.579	Substitution param. skilled and unskilled labor
ρ	-0.322	Substitution param. skilled labor and intangibles
χ	0.500	Frisch elasticity
Internal		
ϑ	1.120	TFP enhancement scalar
θ	0.886	TFP enhancement elasticity
μ	0.214	Match rate
α	0.298	Tangible capital output elasticity
ς	0.634	Production function: skill and unskill share
ϱ	0.435	Production function: skilled labor and intang. share
κ_{ts}	6.234	Acquisition fixed cost
κ_{op}	0.311	Operation fixed cost
κ_e	0.796	Entry cost
ξ	0.026	Exogenous Prob. Exit
ψ_s	14.398	Skilled labor disutility
ψ_u	9.218	Unskilled labor disutility

equals $L_u = N_u h_u = 1$, which effectively clears that market. Note that h_u is a choice variable of the household.

I externally calibrate the parameters (σ, ρ) in the production function, which determine the elasticities of substitution, and internally calibrate the remaining three parameters $(\alpha, \varsigma, \varrho)$. The parameters (σ, ρ) cannot be credibly identified using firm-level data from the ESEE due to a lack of information on wages paid by skill type. The common assumption in firm dynamics models is that the parameters governing the firm-level production function are the same as those for the aggregate function. Leveraging this assumption of parameter invariance to aggregation, I estimate the substitution parameters (σ, ρ) at the sector level using the manufacturing data series from KLEMS. This approach allows for separate identification and estimation through the nested CES structure.[27] The estimate for the substitution parameter across skilled and unskilled labor hours turns out to be $\sigma = 0.579$, implying an elasticity of substitution equal to $1/(1-\sigma) = 2.375$. In the U.S., the range for this parameter varies widely, ranging from as low as 1.4 to as high as 4 (Acemoglu & Autor, 2011). Despite being an imperfect comparison, my estimate is somewhere in the middle of this range. The estimate for the substitution parameter between intangible capital

[27] Refer to the Appendix A.3.3 for more details.

Table 1.5: Moments Fit

Target Moment	Data	Model
Foreign Ownership		
Acq. rate (in pp)	0.351	0.351
Foreign output share	0.273	0.258
Acquisition distribution: Middle 30%	0.292	0.307
Acquisition distribution: Top 20%	0.591	0.631
Production		
Wage skill premium	1.426	1.426
Intangible share	0.177	0.177
Tangible share	0.271	0.271
Skilled hours supplied	0.356	0.356
Unskilled hours supplied	0.344	0.344
Selection		
Average firm size	6.374	6.369
Exit rate	0.079	0.081
Exit rate firms with emp. ≥ 20	0.026	0.026

and skilled labor is $\rho = -0.322$, implying an elasticity of substitution of $1/(1-\rho) = 0.756$.

1.4.1.2 Internally Calibrated Parameters

The remaining twelve parameters are internally calibrated using Simulated Method of Methods (SMM). The parameter vector is

$$\Theta = \{\vartheta, \theta, \mu, \alpha, \varsigma, \varrho, \kappa_{ts}, \kappa_{op}, \kappa_e, \xi, \psi_s, \psi_u\}. \tag{1.15}$$

Specifically, I search over this parameter vector to find the combination that minimizes the distance between a set of empirical moments and their equilibrium analogues. The parameter vector $\widehat{\Theta}$ minimizes the criterion function

$$L(\Theta) = \min_{\Theta} \;\; [\Psi_{\text{data}} - \Psi_{\text{model}}(\Theta)]' \;\mathbf{W}\; [\Psi_{\text{data}} - \Psi_{\text{model}}(\Theta)]\,. \tag{1.16}$$

Each moment has equal weighting and the criterion function is the sum of squared percent deviations. Here, the diagonal weighting matrix is $\mathbf{W} = \text{diag}(1/\Psi^2_{\text{data}})$ and vectors Ψ_{data} and Ψ_{model} contain the empirical and model moments. The model is just-identified.

Every targeted moment is determined simultaneously by all parameters, yet for intuitive purposes, I discuss each parameter and its relation to its moment that most directly identifies it. All empirical moments are from the ESEE, KLEMS, INE, EFF and the OECD's AMNE and SBDS databases. Table 1.5 lists the parameters, their targeted empirical moments, and the moments generated by the model. The first set of parameters $(\mu, \theta, \kappa_{ts}, \vartheta)$ concern acquisition activity and foreign production. The parameter μ is the rate at which domestic incumbents and foreign multinational entrants are matched and it is therefore important in determining the acquisition rate. I calculate the annual acquisition rate as the the percentage of firms that report being foreign owned and were domestically owned in the previous year. The average acquisition rate in the ESEE during the time period is 0.351%. The parameter θ affects the marginal productivity gain from acquisition in equation (1.3) and the parameter κ_{ts} is a fixed cost that influences the total surplus of acquisitions (equation (1.7)). I use these parameters to target the upper half of the marginal distribution of acquired domestic firms, where most acquisitions are concentrated. As θ increases, it raises the value created by high TFP domestic firms and lowers it for low TFP firms, making high TFP domestic firms more likely to be acquired in equilibrium. A high fixed acquisition cost lowers the total surplus and, as a result, acquisition of low TFP domestic firms. I construct the empirical distribution from ESEE by calculating the firm size distribution across all firms in each industry and year and counting the proportion of acquired firms that fall into each decile. I specifically target the top 20% of the marginal distribution (9th and 10 deciles) and middle 30% (6th, 7th and 8th declines). The marginal distribution below the median is untargeted. Most acquired firms are in the upper end of the firm size distribution, with 59.1% in the top 20% of firms at the time of acquisition, and 29.2% in the middle 30%.[28] The scalar parameter ϑ from equation (1.3) is an important component that the scale at which foreign subsidiaries operate. Higher values of ϑ raise the TFP level of subsidiaries relative to domestic incumbents and therefore their scale of production. I use this parameter to target the share of total output by foreign-owned firms which is calculated from the OECD's AMNE and SBDS databases.

For the production function I use the the output elasticity of tangible capital α to target the tangible capital share, defined as tangible investment over gross value added. I calibrate the share parameters of the production function (ς, ϱ) to match the wage skill premium and intangible share, defined as intangible investment over gross value added. Higher values of the parameter ς increase the skilled labor demanded by the firm. This has considerable influence on the labor compensation ratio $\frac{w_s L_s}{w_u L_u}$. As the labor demands are equated with supply in equilibrium, I target the manufacturing wage skill premium $\omega \equiv \frac{w_s}{w_u}$ which I take from KLEMS. The parameter ϱ is the share parameter for skilled labor and intangible capital and I use it to target the intangible share.

Th parameters ($\kappa_{op}, \kappa_e, \xi$) influence the entry/exit dynamics. I use the operational and entry fixed costs to target the exit rate and the average incumbent size by employment. The fixed operation cost κ_{op} has significant influence over the former, while the latter impacts the free entry condition and, consequently, the type of domestic firms entering the economy. The ESEE provides a representative sample of the Spanish manufacturing sector, although it does not aim to be representative of entry/exit flows. To calculate these moments I use data for the manufacturing sector from the Public Registry of Firms (DIRCE in Spanish), which is published by INE. The average exit rate during the time period is 0.079 and the average number of employed at a firm is 6.374. The fixed cost of operation has a strong influence over endogenous entry and exit and

[28]The empirical and model distributions appear in Figure A.5.9 in Appendix A.5

Table 1.6: Non-Targated Moments

Moment	Data	Model
Skilled Labor Share	0.181	0.166
Unskilled Labor Share	0.371	0.386
Pct. of Foreign Owned Firms	0.736%	0.787%
Average Entrant Size	2.938	3.373

primarily affects the smallest (least productive) firms. In contrast, the exogenous exit shock ξ is size-independent, allowing me to target exit events among larger firms. Using DIRCE I calculate the exit rate of firms with 20 or more employees and find it to be 0.026.[29] The final set of parameters (ψ_s, ψ_u) are the disutility of labor supplied by the household for each skill type. I target the average share of hours worked per week which is collected by EFF. I calculate them and find them to be 0.356 for skilled workers and 0.344 for unskilled. I set ψ_s and ψ_u such that the household endogenously chooses (h_s, h_u) to equal these hour shares.

The final two columns in Table 1.5 show the targeted moments from the data and the model. The fit of the model is quite accurate with respect to the majority of moments. However, it generates a lower production share by foreign firms (0.256) compared to the data (0.273). The model also slightly struggles to match the decile bins in the marginal acquisition distribution. The top 20% of the acquisition distribution consists of the largest domestic firms in terms of employment, with a share of 0.591 of acquired firms coming from this group. The model overpredicts this moment with a share of 0.631. Additionally, the model slightly overestimates the share of acquired firms from the middle 30% of the marginal acquisition distribution, where the share is 0.292 in the data and 0.307 in the model. Consequently, the marginal acquisition distribution in the model is slightly more skewed towards the largest firms than in the data.

1.4.2 Cross-Sectional Outcomes

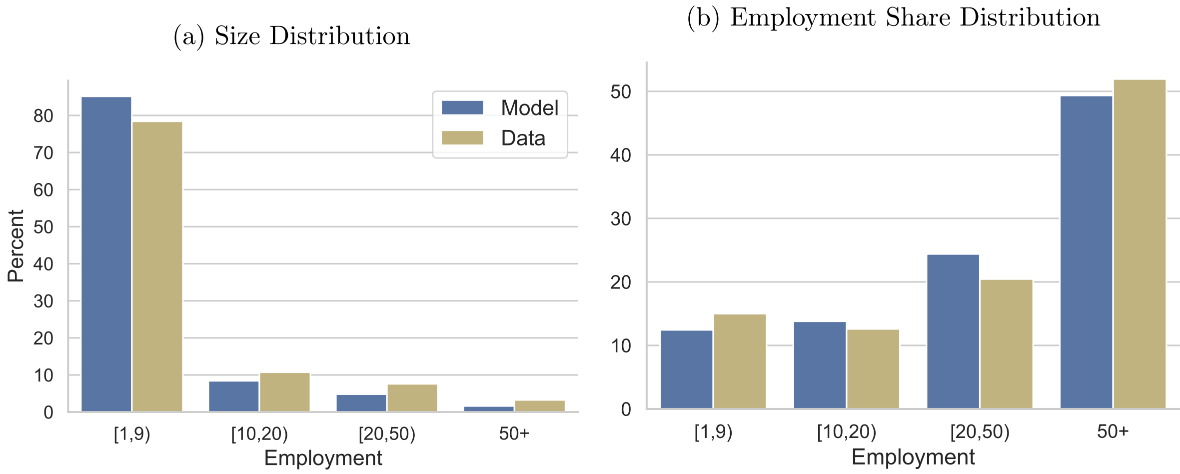
This section provides validation of the the calibrated model. Section 1.4.2.1 presents moments and distributions which are not explicitly targeted. Section 1.4.2.2 examines the cross-sectional implications of foreign acquisitions and compares it to the empirical evidence.

1.4.2.1 Non-Targeted Moments

Table 1.6 presents a comparison between the non-targeted moments predicted by the model and their empirical counterparts. The model performs well in reproducing the non-targeted moments. The first two moments are the share of labor compensation by skill type over gross value added. The skilled labor share in the model is 0.166, which is close to the empirical value of 0.181. Similarly, the unskilled labor share is slightly higher at 0.386 compared to 0.371 in the data. The

[29] 20 employees is the highest employee stratum that DIRCE publicly provides.

Figure 1.5: Firm Distributions: Model Versus Data



Notes: The figures show the firm size distributions by employment which are not targeted in the calibration. The blue bars depict the distributions from model and the yellow depict those from the data. The right figure displays the share of firms for different employment stratum. The right figure contains the employment share for different employment stratum. The empirical distributions for the Spanish manufacturing sector are from the OECD SDBS database.

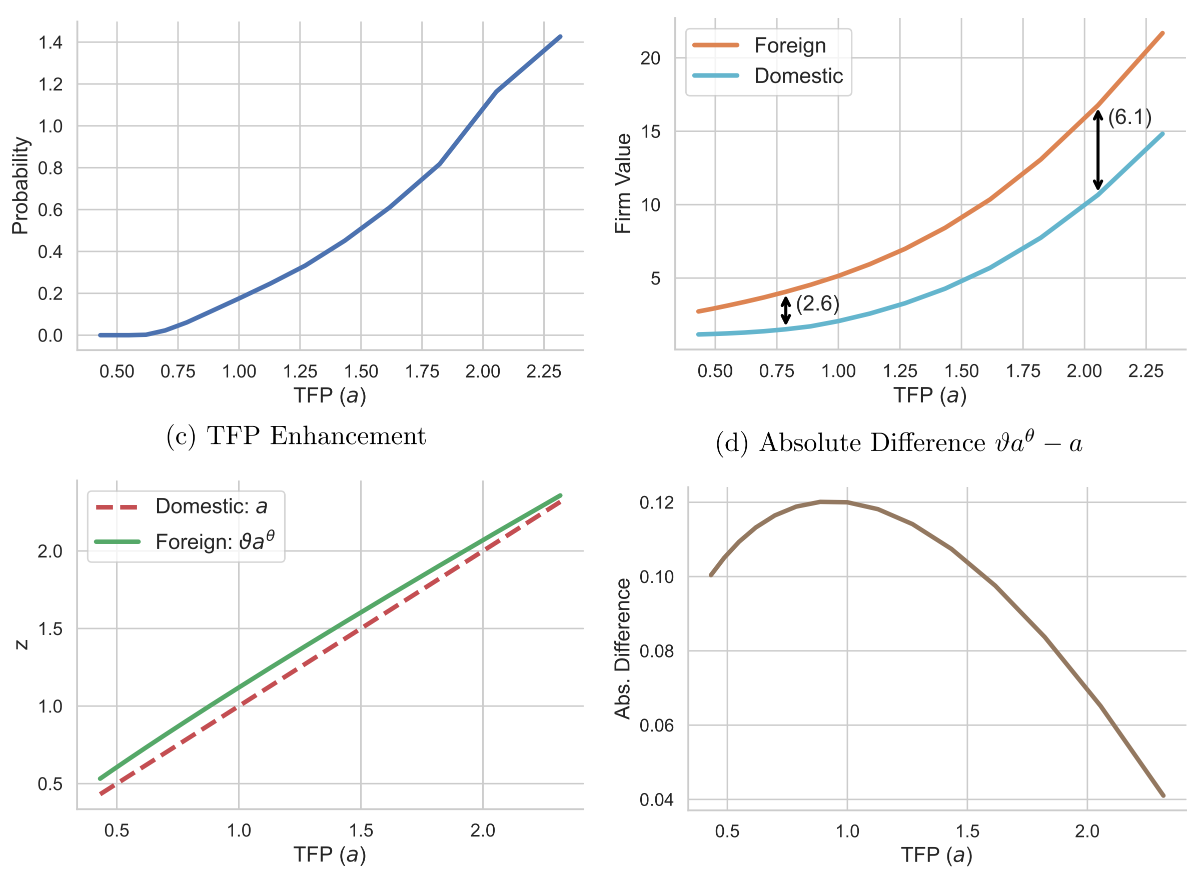
percentage of foreign-owned firms is very low in the economy, yet these firms operate on a large scale. The empirical percentage of foreign-owned firms at the beginning of the sample is 0.736%. The model predicts a similar value of 0.787%. Finally, while the average incumbent size is a targeted moment, the average entrant size is not. The model predicts a higher average entrant size, with 3.373 compared to the empirical 2.938.

Figure 1.5 compares the firm size distribution generated by the model to the empirical distribution averaged over the start-of-sample years 2002-2006. Figure 1.5a is the firm size distribution by employment stratum and Figure 1.5b is the share of employment. The model correctly predicts that the majority of the firms in the economy are small, while a small hand full of large firms account for the majority of employment. However, the model generates too few large firms. This is evident in the firm size distribution, where the tail of the size distribution is not as thick as in the data. This is also reflected in the employment share, where the proportion of employment for firms with 50 or more employees is lower than in the data.

1.4.2.2 Acquisitions

There is positive selection in acquisition and most firms that are acquired are in the upper tail of the firm distribution (Figure A.5.9). The most productive (largest) firms in the economy create the most value from being acquired. Figure 1.6a displays the probability that a firm is acquired as a function of TFP. The total acquisition surplus, or the value created from acquisitions, is highest for domestic firms with an initially high level of TFP. As a result, the acquisition probability increases with TFP. This occurs because firm value is convex in TFP, a common characteristic in firm dynamics models. Consequently, even a slight increase in TFP for domestically owned firms with initially high TFP results in more value created through acquisition compared to domestic firms with initially low TFP. This is illustrated in Figure 1.6b, where the absolute difference in

Figure 1.6: Acquisition in Equilibrium and Foreign Technology Transfer



(a) Probability of Acquisition

(b) Firm Value

(c) TFP Enhancement

(d) Absolute Difference $\vartheta a^{\theta} - a$

Notes: Subfigure (a) displays a domestic incumbent's probability of being acquired as a function of TFP. Subfigure (b) shows firm value as a function of TFP, with both intangible and tangible capital at their marginal distributional median values: $V(a, med(k_I), med(k_T), o)$. Domestic firms are represented by the teal line, foreign firms by the orange, with the black arrows indicating the value difference. Figure A.5.10 in Appendix A.5 shows a the same pattern at different capital distributional percentiles. Subfigure (c) is the TFP enhancement (green line) from equation (1.3) with the calibrated parameters $\vartheta = 1.120$ and $\theta = 0.887$. The dashed red line is domestic TFP. Subfigure (d) is the absolute difference between foreign and domestic TFP.

value (indicated by the black arrows) widens.

Figure 1.6c displays the TFP enhancement function from equation (1.3) under the calibrated parameters and Figure 1.6d plots the absolute difference. The technology of the foreign multinational raises the TFP of its acquired subsidiary but is diminishing in TFP as the curvature parameter $\theta = 0.887$. Table 1.7 compares the simulated performance of firms before and after foreign acquisition. It shows the (untargeted) percentage increases under foreign ownership relative to their average levels as domestic firms. The results align with the empirical evidence. There is a modest gain in TFP and a larger increase in output. Investment patterns are similar, with intangible investment increasing more than tangible investment, though both exceed the increases observed in the data. Additionally, while the skill composition shifts toward more skilled labor, the change is slightly smaller than the observed increase. As a final exercise, I examine the role of anticipation in increasing investment by domestic incumbents. Figure A.5.11 in Appendix A.5 shows the intangible and tangible investment policy functions. The gray line represents the

Table 1.7: Model Simulation – Avg. Increase After Acquisition (in pp.)

Output	TFP	Intangible Inv.	Tangible Inv.	Skill Comp.
25.7	4.6	43.6	38.9	13.7

intangible investment level for domestic firms in the model without acquisitions, and thus, without foreign ownership. Investment is slightly lower in this case due to the absence of a potential sale price in the continuation value from equation (1.10), which reduces the expected marginal benefit of investment. While anticipation plays a role in the model, it has modest effects and only slightly increases investment primarily because the probability of acquisition is small.

1.5 Quantitative Analysis

This section provides the main results of the paper. Section 1.5.1 conducts a steady state comparison through a (skill-biased) intangible-investment-specific technological change. It first quantifies the model's ability to account for observed changes in the data and then decomposes aggregate variables to assess how much of the changes can be attributed to foreign ownership. Section 1.5.2 examines the welfare impact on household types.

1.5.1 Steady State Comparison

The previous section demonstrated that the calibrated model is consistent with the observed cross-sectional empirical patterns. This section examines how the model is affected by an intangible-investment-specific technological change and quantifies its ability to account for the observed empirical trends by comparing two steady states. This technological change is modeled as an exogenous decline in the relative intangible investment price.[30] The cheapening of investment results in greater usage of intangibles in production and increases the likelihood of acquisitions. Furthermore, due to intangible-skill complementarity, this technological change is skill-biased.

The initial steady state is the benchmark model, calibrated to the start-of-sample years (2002-2006). The new steady state is calibrated to the end-of-sample period (2013-2017) after the technological change has occurred. There are two exogenous changes in the new steady state. The first is an 8.5% decline in the relative price of intangible investment. Due to intangible-skill complementarity, this applies upward pressure on the wage skill premium, ceteris paribus. The second exogenous change is the skill composition within the manufacturing labor force. During this period the number of skilled workers grew, leading to a 7.9% increase in the skilled-to-unskilled worker ratio. Such a change exerts downward pressure on the wage skill premium, ceteris paribus. The new steady state is after the changes in both the investment price p_I and the skill ratio of the labor force $\mathfrak{s}$ have occurred, with their values set to the average levels observed during the end-of-sample

[30]The decline is prevalent across many advanced economies. Recent papers document the decline in the U.S. (Zhang, 2024) and France (Lashkari et al., 2024). The decline in the relative price of intangible investment can be interpreted as an improvement in the quality of intangible investment goods or a reduction in their cost. The cheapening of investment is one force (but not the only) that can lead to an increase in intangible investment.

Table 1.8: Steady State Comparison – Data versus Model

	Initial S.S.		New S.S.		**Change (in pp.)**	
	Data	Model	Data	Model	**Data**	**Model**
Targeted Moments						
Wage Skill Premium	1.426	1.426	1.560	1.479	**+9.4**	**+3.7**
Acquisition Rate (in pp.)	0.351	0.351	0.589	0.378	**+67.8**	**+7.8**
Foreign Output Share	0.273	0.252	0.412	0.277	**+50.9**	**+10.0**
Intangible Share	0.177	0.177	0.242	0.191	**+36.7**	**+8.2**
Tangible Share	0.271	0.271	0.265	0.266	**-2.2**	**-2.0**
Non-Targeted Moments						
Pct. of Foreign Owned Firms	0.736	0.787	1.166	1.072	**+58.4**	**+36.2**
Skilled Labor Share	0.181	0.166	0.232	0.170	**+28.2**	**+2.1**
Unskilled Labor Share	0.371	0.386	0.262	0.373	**-29.4**	**-3.3**

Notes: Initial steady state: 2002-2006 average. New steady state: 2013-2017 average.

period (2013-2017). Aside from these two changes, all other parameters in the new steady state are the same as in the initial.[31]

Table 1.8 presents the steady state comparison of the wage skill premium, foreign ownership and the income shares. The second and third columns display the data values and their corresponding model analogues for the initial steady state, representing averages from the beginning of the sample period, 2002-2006. The fourth and fifth columns show the values for the new steady state. The wage skill premium in manufacturing increased from 1.426 at the start of the sample to 1.560 by the end. Taking into account the increased skill ratio of the labor force, the model accounts for 39% of the rise in the wage skill premium. Additionally, increased investment raises the firm value of domestic incumbents and the total acquisition surplus (see equation (1.7)) leading to a higher number of acquisition deals. The acquisition rate saw an increase of 67.8% over the sample period and the model accounts for approximately 12% of its rise. The share of production by foreign-owned firms increases as well.

The next four moments in Table 1.8 present changes in the income shares of investment by capital type and the labor compensation by skill. The intangible share, defined as intangible investment over gross value added in manufacturing, increased by 36.7% by the end of the sample period. The model aligns with the observed trend of intangible deepening, accounting for approximately 22% of the increase. The model also captures the decline in the tangible share. The model predicts a change in the composition of labor compensation, defined as labor compensation over gross value added in manufacturing. These shares are not targeted in the initial steady state. By the end of the sample period, the composition of labor compensation changes in favor of skilled labor, reducing the share for unskilled labor. This change can be attributed to both the increased

[31] Appendix Section A.4 provides the steady state comparison for the changes one at a time as well as additional counterfactuals.

Table 1.9: Steady State Comparison – Changes in Aggregate Variables (in pp.)

	Aggregate		Domestic		Foreign
Wage Skill Premium $\frac{w_s}{w_u}$	+3.7		+2.8		+0.9
Output Y	+3.3		+2.1		+1.2
TFP Z	+0.8		+0.5		+0.3
	Aggregate		**Labor Income**		**Business Income**
Consumption C	+2.3		+2.8		-0.5
		Skilled HH	+2.0	Domestic Dividends	-3.3
		Unskilled HH	+0.8	Acquisition Sale Price	+2.8
	Aggregate		**Skilled HH**		**Unskilled HH**
Labor Supply Nh	+4.1		+1.8		+2.3
Avg. Hours h	–		+0.3		+2.9

Notes: Details regarding how aggregate variables are decomposed by ownership are in Appendix A.1.3. Labor income is defined as the product of the wage and hours worked $w_i h_i$ where business income is the sum of dividends paid by domestic-owned firms and the total sale price of all firms sold in a given period: $\Pi_d + P_d$. Aggregate labor supply takes into account not only hours worked, but also the number of workers in the labor force which is higher in the steady state. Average hours worked is hours supplied by skill type i and all households of each type supply the same amount.

relative demand for skilled labor and the growth in its relative supply within the labor force. The model accounts for 7% of the increase in the skilled labor share and 11% of the decline in the unskilled labor share. The final untargeted moment in the table is the percentage of foreign owned firms and the model accounts for more than half of the increase observed in the data.

The model is able to quantitatively account for a portion of the observed increases in the wage skill premium, foreign owernship and changes in investment and labor shares. In the new steady state, aggregate variables such as output, TFP and consumption are also higher. However, it raises the question of how much of the increase in the wage skill premium and other aggregate variables is attributable to foreign ownership, especially given the relatively small number of foreign-owned firms. Does their presence have a significant impact on these changes? Table 1.9 summarizes the aggregate changes along with a decomposition by ownership. The second row shows the wage skill premium where foreign ownership accounts for approximately 24% (0.9/3.7) of its increase.[32] Domestic ownership contributes more to the change in the wage skill premium because its overall distributional mass is larger relative to foreign ownership. However, foreign ownership's impact on wages is particularly remarkable, despite the small number of foreign-owned firms. This is due to their significant scale, which magnifies their influence in the aggregate.

The third and forth rows display the changes in steady state output and TFP, which experience increases by 3.3 and 0.8 percentage points. The aggregate increases stem from a combination of the selection and foreign ownership effects within the model. Holding equilibrium prices fixed, the decline of the relative investment price makes intangible investment less costly, leading to an increase in the present discounted value of entry ($V_e > 0$). In equilibrium, wages endogenously adjust upward until the free entry condition is satisfied ($V_e = 0$), which raises the entry/exit

[32] It is important to note that this is how foreign ownership affects the wage skill premium through intangible-skill complementarity. The unexplained portion of the wage skill premium increase could contain other mechanisms through which foreign ownership might have an important influence.

threshold for both domestic entrants and operating incumbents.[33] The increased presence of foreign owned firms plays an important role. These firms operate at a larger scale and have higher TFP levels on average compared to their domestic counterparts. Their larger operational scale requires more resources, which puts additional upward pressure on equilibrium prices and the entry/exit threshold. The decomposition shows that foreign-owned firms contribute to approximately 38% of the increases in both output and TFP.

In addition to increases in the wage skill premium, output, and TFP, aggregate consumption rises by 2.3%. This change can be attributed to two main components: total business income and total labor income. Total business income, which includes domestic dividends and the proceeds from selling firms to foreign multinationals, is distributed uniformly across all households since each household owns one share. The increase in foreign-owned firms leads to a 3.3% decrease in domestic dividends. The increased frequency of acquisitions raises the revenue from ownership transfers by 2.8%, however it does not fully offset the decline in dividends, resulting in an overall decrease in business income. The other component, total labor income, increases by 2.8%. This increase in labor income outweighs the decline in business income, making it the primary driver of the rise in aggregate consumption. Total labor income's increase is mainly attributed to skilled households, whose income rises by 2.0%, compared to a 0.8% increase for unskilled households. This disparity is driven by the increased wage skill premium. Finally, aggregate labor supplied increases by 4.1% where unskilled contributed more. At the individual household level, skilled hours supplied increases by 0.3% while unskilled increases by 2.9%.[34] While aggregate consumption is higher, the disparity in labor income growth and hours worked suggests that skilled and unskilled households may experience different levels of welfare gains due to different hours worked.

1.5.2 Welfare

This section determines whether the disparities in consumption and labor supplied between household types result in unequal welfare outcomes. To evaluate whether different household types are better off in the new steady state, I quantify the overall welfare impact using consumption equivalent variation. Given the form of the utility function, the welfare consequences for type i household of moving from the initial steady state with consumption-labor allocation $(c_{i,\text{initial}}, h_{i,\text{initial}})$ to $(c_{i,\text{new}}, h_{i,\text{new}})$ is

$$CEV_i = \frac{c_{i,\text{new}}}{c_{i,\text{initial}}} \exp\left(\frac{\psi_i \left(h_{i,\text{initial}}^{1+\frac{1}{\chi}} - h_{i,\text{new}}^{1+\frac{1}{\chi}} \right)}{1+\frac{1}{\chi}} \right) - 1. \tag{1.17}$$

[33] Consequently, the number of domestic incumbents and entrants decreases. The domestic entry/exit rate decreases by 24.6% and the mass of domestic entrants attempting to enter the economy shrinks by 13.6%.

[34] It is important to note that aggregate labor supplied by skilled households reflects additional hours supplied on the margin and the increase in the number of skilled workers. Almost all of the 1.9% increase in the aggregate supply of skilled labor is due to the increase in the number of skilled workers.

Table 1.10: Welfare Change Between Steady States (in pp.)

	Aggregate	Skilled	Unskilled
Total Welfare Change CEV	+1.6	+7.0	-0.5
Welfare Change from Consumption CEV_c	+2.8	+7.2	+0.6
Welfare Change from Hours Supplied CEV_h	-1.2	-0.2	-1.1

Notes: Aggregate welfare is $N_{s,\text{new}}CEV_s + N_{u,\text{new}}CEV_u$.

This measures the percentage change in consumption required to maintain the same utility level between the initial and new steady states for each household type. I further decompose CEV_i into components that stem from changes in consumption $CEV_{i,c}$ and labor hours supplied $CEV_{i,h}$.[35]

Table 1.10 presents the welfare results. The aggregate welfare change (CEV) shows an increase of 1.6%, indicating an overall positive welfare gain in the new steady state. However, this aggregate improvement masks the welfare differences across skill types. Skilled households see a welfare increase of 7.0%, where welfare from increased consumption is 7.2% and an increase in labor hours results in a welfare loss of -0.2%. This indicates that skilled households are better off in the new steady state as higher consumption levels more than offset the additional work hours. In contrast, unskilled households experience a welfare decline of 0.5%. While there is a positive increase in consumption (0.5%), it is overshadowed by the negative impact of longer working hours (-1.1%). The increased labor supplied by unskilled households offsets the gains from higher consumption, resulting in a net welfare loss. Despite an overall increase in welfare, the results show that there is an asymmetric impact on different skill types. Skilled households are better off in the new steady state, however, unskilled households are not as their limited welfare gains in consumption are offset by having to work more.

1.6 Policy Implications

Foreign ownership has a significant impact on the aggregate and policies that incentivize foreign-owned firms to either expand or enter the market have non-trivial consequences for both the overall economy and welfare. This section examines the consequences of investment subsidies. In the context of Spain, policymakers from both major political parties have long prioritized attracting investment from foreign multinationals. Following the COVID-19 pandemic, Spanish policymakers are seeking to encourage foreign multinationals to invest more in intangibles

[35]The consumption equivalent variation is formally is defined as

$$U((1 + CEV_i)c_{i,\text{initial}}, h_{i,\text{initial}}) = U(c_{i,\text{new}}, h_{i,\text{new}})$$

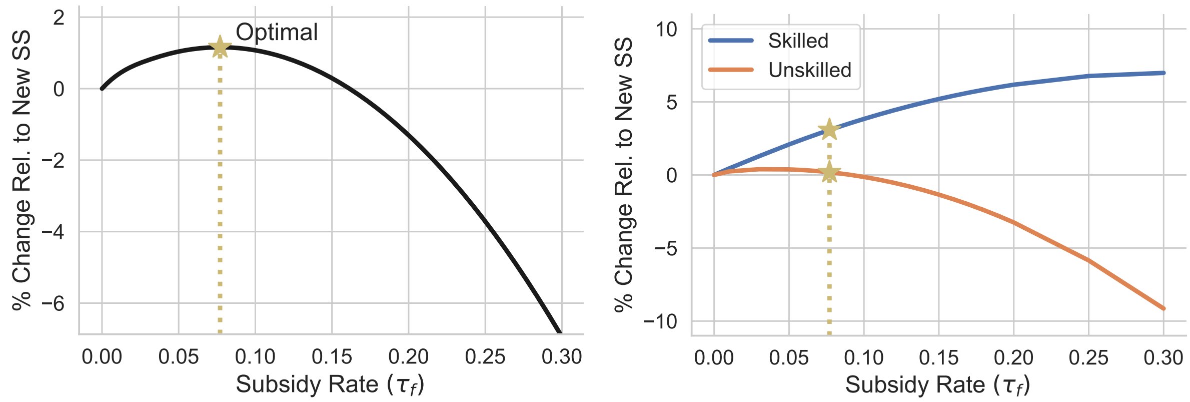
Welfare can be decomposed by changes from consumption and hours supplied (Conesa, Kitao, & Krueger, 2009). The components $CEV_{i,c}$ and $CEV_{i,h}$ are defined as

$$U((1 + CEV_{i,c})c_{i,initial}, h_{i,\text{initial}}) = U(c_{i,new}, h_{i,\text{initial}})$$
$$U((1 + CEV_{i,h})c_{i,new}, h_{i,\text{initial}}) = U(c_{i,new}, h_{i,\text{new}}).$$

It follows that $1 + CEV_i = (1 + CEV_{i,c})(1 + CEV_{i,h})$, or approximately $CEV_i \approx CEV_{i,c} + CEV_{i,h}$.

Figure 1.7: Welfare and Foreign Intangible Investment Subsidy

(a) Aggregate CEV (b) CEV_s and CEV_u



Notes: The figure displays welfare, measured in consumption equivalent variation, as a function of the foreign intangible investment subsidy τ_f. Percentage changes are relative to the new steady state. Subfigure (a) is aggregate welfare $CEV = N_s CEV_s + N_u CEV_u$. Subfigure (b) shows welfare by skill type. Additional figures shows the changes in the wage skill premium, output, TFP and the acquisition rate are in Figure A.5.12 in Appendix A.5. The gold stars are the values at the optimal policy rate.

such as R&D and software.[36] The rationale is that such investments can improve competition and potentially create positive spillovers. An additional benefit is the creation of employment and is a key aspect that policymakers emphasize when promoting such policies to Spanish voters. Indeed, these policies are not misguided, as foreign ownership is beneficial for output and TFP, as both this paper and the literature argue. However, they carry unintended consequences by amplifying skill-biased technological change.

I consider a policy that subsidizes intangible investments exclusively by foreign-owned firms and find the optimal rate that a Ramsey planner would choose. This policy not only encourages increased investment by existing foreign incumbents but also indirectly stimulates market entry through acquisitions. Due to intangible-skill complementarity, such a policy is inherently skill-biased, as it widens the wage skill premium and creates uneven welfare outcomes for households. The challenge for the Ramsey planner is to find a subsidy that balances the benefits of higher output and TFP with the cost of growing inequality. In the model, the addition of the subsidy τ_f modifies two equations and introduces an additional policy constraint.

Firm Maximization Problem with τ_f

$$V(a, k_I, k_T, o) = \max_{x_I', x_T'} \pi - p_I x_I (1 - \tau_f \cdot \mathbb{1}_{o=f}) - p_T x_T + \frac{1-\xi}{1+r} \max \left\{ \mathbb{E}_a \left[\mathcal{V}(a', k_I', k_T', o') \right], 0 \right\} \tag{1.18}$$

[36]The Coinvestment Fund (FOCO in Spanish) was established using relief from the NextGen Recovery Fund. This fund provides investment subsidies exclusively to foreign investors for intangible and green investments in Spain. Additionally, private agreements have been directly made with major multinationals, such as Volkswagen to expand R&D production and Cisco to establish a major subsidiary.

Table 1.11: Changes (in pp.) Under Optimal Intangible Investment Policy $\tau_f^\star$

Wage Skill Premium	Acquisition Rate	Output	TFP
+3.04	+15.31	+2.79	+0.69

	Aggregate	Skilled HH	Unskilled HH
Total Welfare CEV	+1.16	+3.08	+0.19
Consumption CEV_c	+1.35	+3.11	+0.37
Hours CEV_h	-0.19	-0.03	-0.18

Notes: All values are percentage changes under the optimal foreign intangible investment subsidy $\tau_f^\star$ relative to the new steady state from the previous section. The second row are percentage changes in aggregate variables and rates. The final three rows display welfare measured in consumption equivalent variation, where the final two decompose the welfare change resulting from changes in consumption and hours supplied. Aggregate welfare is $CEV = N_s CEV_s + N_u CEV_u$.

Household Budget Constraint of Skill Type i

$$c_i = w_i h_i + \frac{\Pi_d + P_d - T}{N} \tag{1.19}$$

Policy Budget Balance

$$\tau_f p_I \int x_I(a, k_I, k_T, f) d\lambda(a, k_I, k_T, f) + NT = 0. \tag{1.20}$$

Equation (1.18) modifies the incumbent firm's Bellman equation from equation (1.5) by including the foreign-specific subsidy for intangible investment. Since the investment is subsidized, this increases the expected value of foreign-owned firms, leading to more acquisitions. Households finance the subsidy through an equally distributed lump-sum tax T as shown in equation (1.19). Equation (1.20) imposes that the subsidy for foreign intangible investment and the lump-sum tax are budget-neutral, meaning that all subsidized investment is fully paid for by households.

I examine the effects of the policy in the new steady state, where the relative price of intangible investment and labor force skill ratio are set to their average values during 2013-2017. The optimal subsidy rate is the one that maximizes aggregate welfare, which, as shown in Figure 1.7, displays an inverted U-shape in its relationship with τ_f. As the subsidy rate τ_f increases, skilled workers experience a rise in welfare. In contrast, the welfare of unskilled workers initially shows a slight increase before eventually declining. This decline becomes large enough to offset the welfare gains made by the skilled, thus reducing aggregate welfare at higher subsidy levels. I find that aggregate welfare peaks at an optimal subsidy rate $\tau_f^\star = 0.077$.

Table 1.11 shows the percentage changes relative to the new steady state under the optimal subsidy rate. The wage skill premium and aggregate output both increase by approximately 3%, while TFP is 0.69% higher. The subsidy also increases the acquisition rate, which rises from 0.378% in the new steady state to 0.436% (an increase of 15.31%). Aggregate welfare improves by 1.16%, indicating that households are overall better off under the optimal subsidy. Similar to the previous section, breaking down welfare by skill type shows that skilled households benefit more, with an increase of 3.08%. However, unlike the previous section, unskilled households also experience a positive welfare gain. Although both skilled and unskilled households work more hours, the resulting increase in consumption for both groups is sufficient to generate a net positive welfare outcome.

1.7 Conclusion

This paper has studied how foreign ownership affects the wage skill premium through intangible-skill complementarity in production. The results show that foreign ownership contributes to a portion of the increase in the wage skill premium. While foreign ownership contributes to increased aggregate output and TFP as well, it also has implications for labor inequality and welfare. A possible extension of the model could incorporate investment or hiring frictions, which would further enrich the quantitative results. Another avenue is to explore mechanisms that prompt acquired firms to scale up. In the current quantitative model, a multinational enhances its subsidiary's TFP, leading to a higher average optimal firm size for foreign-owned firms, which implies higher investment and employment levels. The model could be extended such that the multinational parent instead enhances its subsidiary's productivity in the production of intangibles. Finally, incorporating a dataset that contains characteristics of foreign acquirers would further strengthen the empirical analysis and enhance the bargaining process in the model. All of the mentioned extensions and additions are currently being pursued.

Chapter 2

Profits, Labor Share and the Rise of Acquired Intangibles

with Luis Rojas[1], Raül Santaeulàlia-Llopis[2] and Carolina Villegas-Sánchez[3]

Abstract

We study how incorporated firms strategically choose to recognize (or not) acquired intangibles from mergers and acquisitions (M&As) in their business accounts and its implications for the measurement of economic profits and labor share. Our analysis is informed by a business accounting change in the early 2000s that forced the acquirer firms to report the acquired intangibles from M&As. Before the accounting change, acquirer firms that had the incentive to frontload accounting profits preferred to record the M&A with an accounting method (*pooling*) that did not recognize the acquired intangibles. This left acquired intangibles out of both the income statement and the balance sheet, which raises not only accounting profits (as the acquired intangibles are not amortized in the income statement) but also potentially economic profits that use, at face value, only assets recognized in the balance sheet. Further, by implementing accounting obstacles to *pooling*, target firms leveraged the acquiror's incentive to frontload profits in order to raise the price of the acquisition, extracting a larger share of the total surplus and, hence, reflecting more accurately the marginal benefit of the acquisition. However, after the accounting change, this leverage ceases to exist, increasing the proportion of the surplus captured by the acquirers as the price paid for the acquisition lowers relative to marginal benefit of the acquisition. Correcting for the omitted acquired intangibles at the firm level before and after the accounting change, we find measures of economic profits and labor share that are relatively trendless.

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2.1 Introduction

The recent debate over whether aggregate economic profits are rising has attracted significant attention across numerous fields of economics. The common measure of economic profits is straightforward: it is calculated as a firm's revenues minus expenses such as wages and R&D, as well as the user cost of tangible capital. The existing literature, however, has largely excluded intangible capital that is acquired through mergers and acquisitions (M&A). We document the growing importance of acquired intangible assets in firm production and show how their omission biases common measures of economic profits upward. Measuring acquired intangibles using financial statements is difficult, particularly because prior to 2001 firms could (strategically) choose to recognize them or not. When acquired intangibles are unrecognized, their absence from financial statements leads to an upward bias not only in accounting profits but also in economic profits. Even when acquired intangibles are reported, their recorded value may not accurately reflect the economic one. In particular, recognized acquired intangibles may fail to capture the full marginal benefit of acquisitions, especially in cases of noncompetitive M&A activity.

In this context, we explore the role of a change in the standards of financial accounting regarding M&As from the "*pooling-of-interest method*" (PoIM) to "*purchase acquisition methods*" (PAM) in the year 2001. In PoIM, financial statements were merged across firms by asset category (at book value) and intangible assets (e.g. goodwill) were not included in the calculation. Under PAM, assets are merged at market price and intangibles are part of the calculation. Importantly, under PAM, intangibles are subject to amortization rates (and annual impairment after 2001) which are subtracted from earnings. In contrast, unrecognized intangibles under PoIM had no impact on earnings, effectively providing a vehicle for firms to report higher profits.

In 2001 the Financial Accounting Standards Board (FASB) banned the usage of PoIM and required that PAM be the only accounting method. As as result, firms have to report all acquired intangibles in their financial statements. Even after this change, however, measuring acquired intangibles remains an unresolved. Before 2001, target firms leveraged the PoIM accounting treatment to drive up acquisition deal prices. Aware of the accounting benefits associated with PoIM, they could create accounting obstacles to prevent acquirers from using this method.[4] This bargaining power allowed target firms to capture a larger share of the surplus generated from the transaction. However, the 2001 accounting change removed this advantage and enabled acquirers to capture a greater portion of the deal's surplus. We document this shift in bargaining power in different two ways. First, using a difference-in-differences analysis, we find that cumulative abnormal returns (CAR) to the market valuation of acquiring firms are significantly higher following M&A deal announcements after 2001. A CAR is the percentage deviation of the actual return from its expected. Larger variation in CARs indicates that acquirers experience a greater increase in firm value, and hence capture a greater share of the surplus when PoIM is no longer an option. Second, we show that the relative size of acquirers has increased over time, indicating that acquiring firms have gained a stronger negotiating position. The shift in bargaining power

[4]The pooling-of-interests method had strict eligibility criteria. For instance, target firms were prohibited from repurchasing shares or issuing special dividends in the year leading up to a deal.

pushes acquisition prices further away from the marginal benefit of acquisitions (i.e., the price in a competitive market). Consequently, the acquisition price, largely composed of acquired intangibles, fails to fully reflect the true economic value of acquired intangible capital and even less so after the accounting change.

To compute economic profits, it is necessary to assign a user cost (or rate of return) to acquired intangibles. In principle, this object could help correct for mismeasurement. However, determining the appropriate rate is nontrivial. We develop a dynamic model with strategic business accounting that aims to provide an accurate estimate of the user cost of acquired intangible capital. The model features two firms, an acquirer and a target. Each firm is managed by a CEO who makes production decisions by balancing market value and accounting profits, as higher reported accounting profits lead to higher executive compensation. Firms actively search for acquired intangibles and strategically choose their accounting methods. When two firms are randomly matched, they must mutually agree on the accounting approach through a strategic game. The acquiring firm may propose the use of PoIM, but the target firm has the potential to block it. Using our model, we show that omitting acquired intangibles introduces a theoretical upward bias in the marginal products of capital and labor. As a result, this leads to an upward bias in economic profits and markups.

We demonstrate that as target firms invest more heavily in intangible capital, the volume of acquired intangibles through M&A increases accordingly. When these acquired intangibles are omitted from measurement, the resulting distortion inflates economic profits and markups. This bias grows with the scale of acquired intangibles, creating the illusion of rising economic profits and markups. Although these distortions occur in latent variables, they have observable consequences. In particular, we show that the bias is closely linked to CARs. An increasing level of acquired intangible capital raises CARs as it reflects the unrecognized intangible value.

To address this measurement distortion directly, we use the model to impute the user cost of acquired intangible capital. This user cost reflects the opportunity cost of capital based on the marginal product of capital and the acquirer's share of the surplus, both of which vary with bargaining power. In the model, when acquirers have greater bargaining power, they acquire capital at a price below its marginal product, resulting in a higher user cost. We exploit the model's mapping between the user cost and CAR, both of which depend on the underlying bargaining power of the acquirer. Applying this model-based user cost allows us to systematically correct for the downward bias in measured acquired intangibles and recover a more accurate estimate of economic profits. Once the user cost correction is applied, the apparent upward trend in profits disappears.

Related Literature Our paper offers a potential reconciliation between national accounts and firm level data and the long-run trends of economic profits and the labor share. The growing industrial concentration in the US has sparked a debate over whether the underlying driver is rising market power (De Loecker, Eeckhout, & Unger, 2020) or a distributional shift toward more productive "superstar" firms (Autor, Dorn, Katz, Patterson, & Van Reenen, 2020). The literature typically uses firm level data taken from financial statements. In doing so, it follows standard business accounting assumptions where internally produced intangibles (e.g., R&D and software) are treated as expenses. However, in national accounts intangibles are capitalized. Depending on whether intangibles are capitalized or expensed result in different implications in the measurement of economic profits and the labor share (Karabarbounis & Neiman, 2014; Koh et al., 2020). We show that when accounting for acquired intangibles using firm-level data economic profits are relatively trendless.

We contribute to the literature on intangibles by showing how accounting choices in M&As create significant discrepancies between the reported and economic value of acquired intangible assets. Through a model we estimate the user cost of acquired intangibles, similar in approach to models that infer latent intangibles (Bhandari & McGrattan, 2021; McGrattan & Prescott, 2005, 2010b). We also contribute to the literature that uses firm level data to study the relationship between intangibles and market power. Much of the existing literature focuses on internally produced intangible assets (R&D and software). The implications for economic rents vary depending on whether intangible expenditures are expensed as in business accounting (De Ridder, 2024) or capitalized (Crouzet & Eberly, 2023). We emphasize that the current literature generally overlooks acquired intangibles and their omission leads to an upward bias in economic profits.

Outline Section 2.2 explains the business accounting behind intangibles and different accounting treatments for acquired intangibles before and after 2001. Section 2.3 recovers acquired intangibles from business accounts and documents the shift of bargaining power in favor of acquirers after the accounting changes. Section 2.4 develops a dynamic model with strategic accounting with which we show that the omission of acquired intangibles upward biases economic profits. Section 2.5 concludes and discusses the next steps.

2.2 Business Accounting Rules for Intangibles

Expensing vs. capitalizing intangibles matters not only for accounting profits but also for economic profits and the labor share. The dilemma is whether to expense or to capitalize the flow of intangibles x_t. The accounting treatment of intangibles in national accounts differs from business accounts. In national accounts R&D, software and artistic orginals are considered to be intangibles and are capitalized. Other forms of intangibles like marketing or training are considerd to be intermediates. In business accounting all intangibles produced in house are expensed whereas intangibles that are acquired from other firms are capitalized.

For example, suppose that firm i produces with only intangible capital k_I and hires labor n for wage w. The firm makes an intangible expenditure $x_I = k_I$. Table 2.1 shows how the expenditure is treated across the three financial statements of the firm. If it is expensed then it appears in the income statement and reduces earnings. On the other hand, if it is capitalized then it appears on the balance sheet and only a portion of the expensed is amortized at rate δ. Taking the balance sheet at face value, economic profits would be

Table 2.1: Accounting Profits

	Income Statement	Balance Sheet	Cash Flow
Expensed	$\pi^{acc} = \underbrace{f(k_I, n)}_{\text{Sales}} - \underbrace{wn}_{\text{Wage Bill}} - \underbrace{x_I}_{\text{Expense}}$	$k_I = 0$	-
Capitalized	$\pi^{acc} = \underbrace{f(k_I, n)}_{\text{Sales}} - \underbrace{wn}_{\text{Wage Bill}} - \underbrace{\delta k_I}_{\text{Amortization}}$	k_I	$\underbrace{x_I}_{\substack{\text{Expense} \\ \text{(if acquired)}}}$

$$\pi = \underbrace{f(k_I, n)}_{\text{Sales}} - \underbrace{wn}_{\text{Wage Bill}} - \underbrace{rk_I}_{\text{User Cost of Capital}} \qquad \text{with} \qquad rk = \begin{cases} 0 & \text{if expensed} \\ rk_I & \text{if capitalized} \end{cases}$$

where r is the user cost of using intangible capital. For economic profits, if intangible capital is expensed then it does not affect economic profits as the existing stock will always equal zero, $k_I = 0$. In other words, expensing intangible capital increases economic profits relative to capitalizing it. It also has potential implications for the labor share measurement of the firm if part of rk_I is labor.

2.2.1 In-House Intangibles

Intangibles in business accounting differ significantly depending on whether they are produced in-house or acquired. As mandated by the US GAAP accounting standards, these types are subject to different treatments and are reported across three financial statements: the income statement, balance sheet, and cash flow statement. Intangibles produced in-house, such as R&D, design, software, marketing, and training, appear only in the income statement and are fully expensed in the fiscal year they are incurred (FASB 2, 1974).[5] These expenses directly impact reported earnings.

For example, suppose that firm i invests in R&D x_{iot} in-house denoted by o and hires labor n_{it} for the wage rate w_t. Table 2.2 shows the three financial statements of the firm. In business accounting both the R&D and wage bill are considered to be expenses in the income statement which reduces earnings. Because R&D is not capitalized, it is not recorded in the balance sheet nor does it appear in the cash flow statement. This is in contrast with the national accounts administered by the BEA who recently focused on capitalizing R&D expenditures starting in 2013 (and retrospectively). The same can be done in business accounts where an R&D stock is accumulated at the firm level (Crouzet & Eberly, 2023).

[5]Some R&D costs may be capitalization under certain circumstances (ASC 730). Expenditures on materials, equipment, and facilities that are purchased or constructed for R&D activities and that have an alternative future use are permitted to be capitalized. There are also some exceptions for software development (ASC 985). Software development costs must be expensed until the product achieves technological feasibility, after which subsequent costs may be capitalized and amortized. Capitalization ends when the product is ready for general release.

Table 2.2: Accounting Rules for In-House Intangibles

Income Statement	Balance Sheet	Cash-Flow Statment
$\pi_{it}^{acc} = \underbrace{f(k_{iot}, n_{it})}_{\text{Sales}} - \underbrace{x_{iot}}_{\text{R\&D Expense}} - \underbrace{w_t n_{it}}_{\text{Wage Bill}}$	$k_{iot}^{acc} = 0$	—

2.2.2 Acquired Intangibles

Most externally acquired intangible capital occur from acquisitions of entire firms. Under the current US GAAP standards, such assets are capitalized and amortized on the balance sheet while acquisition-related expenses paid in cash (e.g., deal prices or legal fees) appear in the cash flow statement. Amortization impacts reported earnings, whereas expenses recorded in the cash flow statement do not. The accounting treatment for acquired intangibles is more complex, as they are categorized into identifiable intangible assets and goodwill:

$$k_{a,t}^{acc} = k_{ID,t}^{acc} + k_{g,t}^{acc} \tag{2.1}$$

An intangible asset is considered identifiable if it satisfies either (i) the separability criterion, meaning it can be sold independently of the entity, or (ii) the contractual-legal criterion, meaning control of its future economic benefits is established through contractual or legal rights. Examples include client lists, patents, copyrights, internet domains, and brand names. Post-acquisition, these assets are capitalized on the firm's balance sheet at their fair value. Other intangibles that do not need the criterion are classified as goodwill which is the residual value of the acquisition price less identified intangible assets and less already existing net tangible/intangible assets on the target's balance sheet. In other words, goodwill is the premium that the acquiring firm pays and embodies unidentifiable intangibles such as corporate culture and management quality. Like identifiable assets, goodwill is also capitalized and amortized at fair value on the balance sheet.

The accounting treatment of acquired intangibles has varied over time, particularly in the case of goodwill. Before 2001, there were two distinct accounting methods: the Purchase Accounting Method (PAM) and the Pooling of Interest Method (PoIM). PAM, which forms the basis of current accounting standards, required both identifiable intangible assets and goodwill acquired in an acquisition to be capitalized and amortized at fair value on the balance sheet. Additionally, cash expenses related to the acquisition, such as deal prices and legal fees, were recorded in the cash flow statement. In contrast, PoIM involved transferring identifiable intangible assets at book value, provided they were already recorded on the target firm's balance sheet. Goodwill, under PoIM, was neither capitalized nor amortized, nor did it appear in the income statement, effectively excluding it from reported earnings. The rationale for these two methods was that PAM was intended for acquisitions, while PoIM applied to mergers. However, the distinction between mergers and acquisitions from an accounting perspective was often ambiguous. For instance, a firm undertaking an acquisition could meet the financial criteria to apply PoIM even if it should have used PAM. The preference for PoIM was clear: it avoided any impact on reported earnings, whereas PAM reduced earnings through the fixed amortization of goodwill.

In June 2001 the FASB issued Statement 141 which eliminated the PoIM method and required that all businesses were to use the purchase accounting method effective immediately. The statement cited the reason for the change was that the two accounting methods produced "dramatically different financial statements" for similar business combinations. The FASB stated that PoIM allowed businesses to inflate reported earnings because the method did not recognize goodwill and expressed concern that the two accounting methods "affected competition in markets for mergers and acquisitions". In addition, the statement adopted the the contractual-legal criterion to identify acquired intangible assets, inline with IFRS standards (IAS Statement 38). Such guidelines were much more explicit in determining whether an intangible asset should be recognized separately from goodwill. For instance, client lists, copyrights, licensing, trademarks and more were to be considered identifiable acquired intangible assets whereas before it was ambiguous. The changes brought from Statement 141 were unpopular, especially given that the purchase accounting method required that amortization of both identifiable intangibles and goodwill be set fixed at the time of acquisition.

Six months later in December 2001, the FASB issued Statement 142 which offered a compromise by introducing significant changes to the amortization of acquired intangible assets. Under Statement 142 goodwill and most identifiable intangible assets were no longer considered to have finite useful lives. Consequently, these assets were exempted from fixed amortization over a predetermined period as before.[6] However, there had to be a way to get acquired intangibles off the balance sheet; they could not be there forever. For that reason Statement 142 mandated that businesses conduct annual assessments to determine if the balance sheet value of acquired intangibles exceeded their fair market value (something which businesses determined themselves). If such an excess was identified, the business was required to make an *impairment*, adjusting the intangible asset balance sheet value downward to its fair value. This impairment loss would then be deducted the business's earnings, similar to the effect of amortization.

Table 2.3 illustrates an example involving two firms, i and j, that produce using intangible capital (both in-house k_{iot} and acquired k_{iat}) and labor n_{it} as factors of production. Both firms intially do not posses acquired intangible capital. For simplicity assume that there are no identifiable intangibles in the deal ($k_{ID}^{acc} = 0$), hence by equation (2.1) all acquired intangibles are goodwill ($k_a^{acc} = k_g^{acc}$). The table demonstrates the impact on firm i's financial statements when it acquires firm j. Alongside the M&A, firm i invests in R&D in-house (x_{iot}), which is expensed in the income statement and excluded from the balance sheet. Its treatment remains unaffected by the acquisition.

[6]Some identifiable intangible assets were still considered to have finite useful lives and would continue to be amoritzed over their estimated useful lives. Examples include patents and copyrights, whose useful lives are limited by legal or contractual terms. In contrast, other identifiable intangible assets, such as certain trademarks and brand names, may be classified as having indefinite useful lives if no legal, regulatory, contractual, competitive, economic, or other factors limit their expected contribution to the company's cash flows. It's important to note that while the term "indefinite" is used, it doesn't mean infinite; rather, it indicates that the asset's useful life isn't currently determinable. This classification affects their accounting treatment: finite-lived intangibles are amortized over their estimated useful lives, whereas indefinite-lived intangibles are not amortized but are tested annually for impairment.

Table 2.3: Accounting Rules for Acquired Intangibles

Method	Income Statement	Balance Sheet	Cash-Flow Statement
PAM (Pre-2001)	$\pi_{it}^{acc} = \underbrace{f(k_{iot}, k_{iat}, n_{it})}_{\text{Sales}} - \underbrace{x_{iot}}_{\text{R\&D Expense}} - \underbrace{w_t n_{it}}_{\text{Wage Bill}} - \underbrace{\delta_a^{acc} k_{iat}^{acc}}_{\text{Amortization}}$	$k_{iot}^{acc} = 0$ $k_{iat}^{acc} = \underbrace{p_{a(ij)t} - 0}_{\text{Goodwill}}$	$p_{a(ij)t}$
PoIM (Pre-2001)	$\pi_{it}^{acc} = \underbrace{f(k_{iot}, k_{iat}, n_{it})}_{\text{Sales}} - \underbrace{x_{iot}}_{\text{R\&D Expense}} - \underbrace{w_t n_{it}}_{\text{Wage Bill}}$	$k_{iot}^{acc} = 0, \quad k_{iat}^{acc} = 0$	$p_{a(ij)t}$
PAM (Post-2001)	$\pi_{it}^{acc} = \underbrace{f(k_{iot}, k_{iat}, n_{it})}_{\text{Sales}} - \underbrace{x_{iot}}_{\text{R\&D Expense}} - \underbrace{w_t n_{it}}_{\text{Wage Bill}} - \underbrace{\delta_{at}^{acc} k_{iat}^{acc}}_{\text{Amortization}}$	$k_{iot}^{acc} = 0$ $k_{iat}^{acc} = \underbrace{p_{a(ij)t} - 0}_{\text{Goodwill}}$	$p_{a(ij)t}$

Table 2.3 compares three accounting approaches and their influence on firm i's financial statements. Acquired intangibles k_{iat}^{acc} are goodwill which are calculated as the acquisition price $p_{a(ij)t}$ minus existing net intangible assets on the target's balance sheet (assumed to equal 0). Were firm i to use PAM (Pre-2001) then goodwill is recorded on the balance sheet and amortized at a fixed rate ($\overline{\delta_a^{acc} k_{iat}^{acc}}$) in the income statement. In contrast, if firm i were to use PoIM (Pre-2001) then goodwill is omitted from the balance sheet and consequently not amortized in the income statement. This omission results in a higher accounting profit (π_{it}^{acc}) compared to PAM. The acquisition price appears in the cash flow statement regardless of the chosen accounting method. Finally, for acquisitions after 2001, firm i must adopt PAM as the accounting method. The key distinction is that the amortization rate (δ_{at}^{acc}) can now be updated annually.

2.2.3 Target's Leverage: Accounting Obstacles to *Pooling*

Companies often structured acquisitions and invested substantial resources to qualify for the pooling-of-interests accounting treatment. Research by Ayers, Lefanowicz, and Robinson (2002) in the Journal of Accountancy shows that firms pursuing mergers and acquisitions were willing to pay higher acquisition premiums to utilize the pooling-of-interests method instead of the purchase method. Similarly, Moehrle, Reynolds-Moehrle, and Wallace (2000) found comparable results. To apply the pooling-of-interests method, a merger had to meet twelve specific criteria (see Appendix B.1). For example, targets were prohibited from issuing special dividends or repurchasing significant quantities of their own stock in the fiscal year preceding a deal. Targets resisting a takeover could intentionally violate such criteria to prevent the acquirer from using pooling, thereby gaining leverage in negotiations.

This strategy is exemplified in the 1991 AT&T-NCR acquisition case. AT&T prioritized ensuring the acquisition qualified for pooling-of-interests accounting. However, NCR resisted by employing various defensive tactics, including stock repurchases, adopting a qualified employee stock ownership program to consolidate voting power within the company, and issuing a special $1.00 dividend. These actions suggest that NCR leveraged AT&T's desire to utilize the pooling method to negotiate a higher acquisition premium. Eventually, in May 1991, NCR agreed to the deal and reversed its defensive measures by withholding dividends and reissuing stock prior to the merger.

The AT&T-NCR case illustrates how the preference for pooling accounting can significantly influence acquisitions. AT&T's strong inclination for pooling stemmed from its intent to avoid the substantial write-offs associated with the purchase method. NCR astutely capitalized on this preference, using it as leverage to secure a higher price. The prolonged negotiation process, marked by a series of escalating bids from AT&T, underscores the extent to which NCR exploited AT&T's accounting objectives. Ultimately, the removal of the accounting obstacles that prevented the use of pooling appears to have been a critical factor in enabling the deal to proceed, further underscoring the influence of accounting considerations on the outcome of this high-profile acquisition.

2.3 Data and Stylized Facts

2.3.1 Data

2.3.1.1 Annual Financial Statements from Compustat

We use data from Compustat which provides comprehensive financial information on publicly traded companies in the US extending back to the 1950. Compustat offers detailed financial statement items such as sales, research and development expenses (R&D), cost of goods sold (COGS), selling, general and administrative expenses (SG&A), as well as tangible and acquired intangible assets. This information is sourced from the financial statements that publicly listed companies are legally required to file with the Securities and Exchange Commission. We restrict our focus to the years 1980 to 2023 and our sample contains 324,266 firm-year observations and 29,102 unique firms.[7]

2.3.1.2 Daily Securities from CRSP

We use daily security information from 1925-2023 provided by the Center for Research in Security Prices (CRSP). It provides comprepensive data on securities, including pricing, returns and volume for US companies listed on the NYSE, AMEX and NASDAQ markets. We follow the literature and keep common shares and share classes A,B or that are missing. We merge CRSP with the Fama-French three-factor dataset which provides daily market factors like the risk free rate of return for given day. The merged dataset serves as our sample of securities runs from 1968 to 2023 with about 68 million observations and 31,995 unique CUSIP securities.

2.3.1.3 Merging with Thomson SDC Platinum

For M&A deals we use the Thomson SDC Platinum (henceforth SDC) database which contains 274,550 transactions between 1965-2023 where both the acquirer and target are based in the US. SDC covers all corporate transactions whose value is at least $1 million. After 1992 it covers all deals. We restrict the sample to completed deals and if the acquirer is not a financial sponsor (ie an investment group or a mutual fund). Furthermore, we keep mergers, acquisitions and acquisitions of assets, leaving us with 224,692 deals.[8]

[7]From the raw Compustat dataset we drop observations where sales are missing or equal to zero. We also drop 20 observations where R&D expenses and 6 observations where acquired intangibles are negative.

[8]This means that we exclude deals classified as going private transaction, leverage buyout, liquidation, privatization, repurchase, reverse takeover, or restructuring.

We merge SDC data with Compustat and CRSP datasets. For the SDC-Compustat merge, we apply the mapping provided by Ewens, Peters, and Wang (2024), which assigns the unique Compustat firm identifier (`gvkey`) to both acquirers and targets if they are publicly listed. We merge on the completion year which is when changes in financial statements from acquisitions appear. We match 12,534 unique acquirers, 11,434 targets and 73,050 deals. Before merging SDC with CRSP, we further restrict our SDC sample following empirical M&A literature on cumulative abnormal returns (CAR). Given limited coverage before 1985, we exclude those observations. We follow Masulis, Reza, and Guo (2023) and select all deals where the acquirer owns less than 50% of the target before the announcement and 100% after the transaction, with deal values of at least $1 million, and the acquirer being a publicly listed U.S. firm covered by both CRSP and Compustat. This selection yields 35,642 deals. We exclude 1,350 deals where the acquirer announced multiple deals (with different targets) on the same date, leaving 34,292 deals.

For the SDC-CRSP merge we use the unique 6-digit security public identifier `CUSIP6` (identifying the issuer) and the deal announcement date. We match 26,027 deals from SDC with CRSP securities, leaving 9,615 unmatched deals. In the final steps we further drop observations with missing excess returns and keep securities with at least 500 days of information.[9] Finally, we discard securities who never are involved in an M&A and this leaves our SDC-CRSP merged dataset with 32,873,698 observations.

2.3.2 Recovering Intangibles From Business Accounts

Using Compustat, we recover intangible assets from business accounts. Business accounting distinguishes between two main categories of intangibles: those produced in-house and those acquired externally. We consider in-house intangibles to be R&D expenditures which are costs related to the development of new products or services and is $\texttt{xrd}_t$ in Compustat. Importantly, R&D also includes internal software development costs, which are treated as development expenses under ASC 350-40. Software expenses are reported regardless of whether the software is intended for internal use or to be sold externally.[10] Businesses are required to report R&D expenditures which are treated as expenses and are included in the total operational expenses reported in the income statement.[11] R&D expenses are generally reported in Selling, General and Administrative expenses (SG&A), but may be reported in Cost of Goods Sold (COGS) (ASC 730-10).[12]

[9] We keep `PERMNO` observations with at least 500 days of information. `PERMNO` is CRSP's unique security issuer identifier which differs with the public issuer identifier `CUSIP6`. When compute CAR, we center the event window around `PERMNO` instead of `CUSIP6`. There are frequent changes to CUSIP identifiers for the same security over time, especially around an M&A event. This that we may not have pre and post security information for the same security. The identifier `PERMNO` is invariant to changes in CUSIP. Note that we merge SDC with `CUSIP6` because it is available in both datasets, while `PERMNO` is specific to CRSP.

[10] We consider in-house intangibles to be be either R&D or software expenditures. However, there are other intangible investment like organizational capital which we do not consider. Ewens et al. (2024) estimates that 27% of SG&A expenses reported in Compustat not attributed to R&D are in-house organizational capital expenditures.

[11] Under certain circumstances, some R&D costs may be capitalized (ASC 730). Expenditures on materials, equipment, and facilities purchased or constructed for R&D activities with alternative future uses are allowed to be capitalized. There are also specific rules for software development (ASC 9085). Costs must be expensed until the product reaches technological feasibility; subsequent costs may then be capitalized and amortized, ending when the product is ready for general release.

[12] Cost of goods sold (COGS) are expenses directly tied to the production of goods and services, such as the wage bill of production workers and materials. Selling, General and Administrative (SG&A) expenses not directly

In Compustat, the acquired intangible capital is captured by the variable $\texttt{intan}_t$ which consists of the recognized acquired intangible in the balance sheet, $k^{acc}_{a,t}$. The amortization of this recognized acquired intangible capital, captured by variable $\texttt{am}_t$, appears in the income statement. Since the investment on recognized acquired intangible at the time of the purchase is the actual value paid for the acquired intangible, we can recover the investment on recognized acquired intangibles using the using the perpetuary inventory method and isolating $x^{acc}_{a,t}$

$$k^{acc}_{a,t} = \frac{x_{a,t} + k^{acc}_{a,t-1}}{1 + \delta^{acc}_{a,t}} \tag{2.2}$$

$$x_{a,t} = k^{acc}_{a,t} - k^{acc}_{a,t-1} + \delta^{acc}_{a,t} k^{acc}_{a,t} \tag{2.3}$$

where $k^{acc}_{a,t} = \texttt{intan}_t$ and $\delta^{acc}_{a,t} k^{acc}_{a,t} = \texttt{am}_t$ for all t. The timing of the law of motion differs with a one typically used in macroeconomics (ie $x_t = k_{t+1} - k_t(1 - \delta_t)$) where there is time to build. Our law of motion reflects accounting standards where both investment and depreciation in period t impacts capital on the balance in the same period. In contrast when assuming time to build, these factors affect capital in $t + 1$.

The recognized acquired intangibles ($\texttt{intan}_t$) is the sum of goodwill ($\texttt{gdwl}_t$) and identifiable acquired intangibles ($\texttt{intanID}_t$), which we can recover from the balance sheet as:

$$\texttt{intanID}_t = \texttt{intan}_t - \texttt{gdwl}_t \tag{2.4}$$

$$k^{acc}_{ID,t} = k^{acc}_{a,t} - k^{acc}_{g,t} \tag{2.5}$$

where $k^{acc}_{ID,t} = \texttt{intanID}_t$, $\texttt{intan}_t = k^{acc}_{a,t}$ and $k^{acc}_{g,t} = \texttt{gdwl}_t$. The variable $\texttt{intanID}_t$ is exactly the same as the variable $\texttt{intano}_t$ reported in compustat.

2.3.3 Evidence of Unrecognized Acquired Intangible

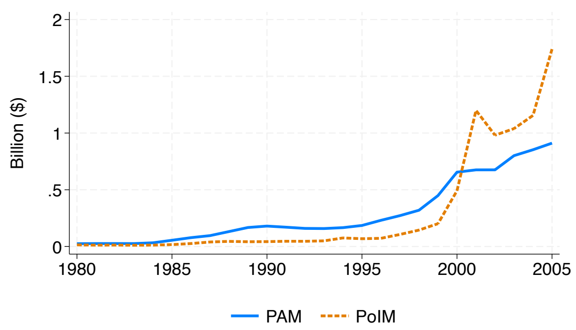
The 2001 accounting change had a significant impact on the balance sheet accounting of intangibles for firms that predominantly used the pooling-of-interest (PoIM) method. To illustrate this, we classify firms into PoIM and purchase accounting method (PAM) types based on their historical usage. Using COMPUSTAT's `ACQMETH` variable, which records the accounting method firms used for acquisitions (PoIM, PAM, or both), we determine the type of each firm by the frequency at which it reported using PoIM and PAM between 1980-2000. Firms are classified as PoIM types if they reported using PoIM more often than PAM during this period, and vice versa. For example, a firm is categorized as PoIM type if it reported using PoIM 10 times and PAM 5 times. Figure 2.1 compares some average metrics of these types with PAM denoted by the blue line and orange for pooling. Subfigure (a) shows the average value of acquired intangibles $k^{acc}_{a,t}$. Before 2001, the average value for PoIM types was relatively small but began to increase in 1999, coinciding with the rise in M&A activity during the dot-com bubble. The effect of the 2001 accounting change is evident: the average balance sheet value of acquired intangibles for PoIM types more than doubled between 2000 and 2001, rising from \$0.5 billion to \$1.2 billion, and continued to grow

tied to production, and include items like the wage bill for managers and office utilities.

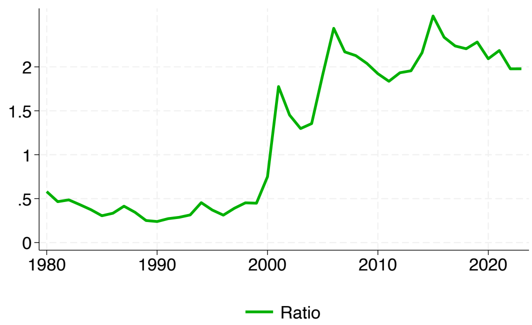
thereafter. Subfigure (c) shows that PoIM types also exhibited higher average business accounting profits (EBIT).

Figure 2.1: PoIM vs. PAM

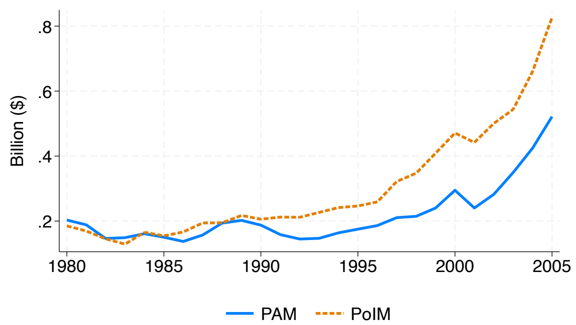
(a) Avg. k_a^{acc}



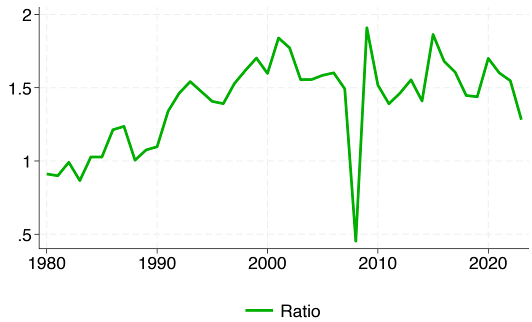
(b) Avg. $k_{a,PoIM}^{acc}$/Avg. $k_{a,PAM}^{acc}$



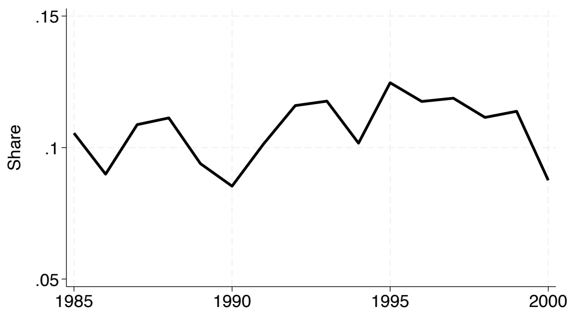
(c) Avg. π^{acc}



(d) Avg. π_{PoIM}^{acc}/Avg. π_{PAM}^{acc}



(e) Share of Deals that are PoIM



Notes: The figures depict the averages for PAM and PoIM types. We consider a firm to be a PAM type it reported using the PAM method more frequently than the PoIM method between 1980-2000 and vice versa. Subfigure (a) is the average balance sheet value of acquired intangibles (identifiable plus goodwill). Subfigure (c) depicts average reported earnings (EBIT). Subfigures (b) and (d) plot the ratios of the two series in subfigures (a) and (c). Subfigure (e) is the share of deals that are PoIM.
Source: Authors' calculations using COMPUSTAT.

2.3.4 Increased Bargaining Power of the Acquirer After 2001

The measurement of acquired intangibles is still unsolved after 2001. In this section, we show that before 2001, targets leveraged pooling to increase the deal premium. However, after 2001, this leverage was taken away and increased the bargaining power of acquirer relative to the target.

We document this shift in two different ways. First, we use cumulative abnormal returns (CAR) which is the market reaction to the M&A announcement and is commonly used in the M&A finance literature (Betton, Eckbo, & Thorburn, 2008). Larger CARs in the years after 2001 indicate that acquirers experience greater gains in firm value from M&A deals when pooling is no longer an option. Second, the literature also links the relative size of the acquirer to the target as a determinant of bargaining power in M&A negotiations (Ahern, 2012). Larger acquirers relative to their targets are often in a stronger position to negotiate favorable terms. We show that the relative size of acquirers has increased over time, reflecting an increase in bargaining power.

To formalize ideas, let $V_A(1)$ be the value of the acquirer if an M&A occurs and $V_A(0)$ and $V_T(0)$ be the values of acquirer and target if the M&A does not occur. We set the following bargaining protocol for M&As as

$$\left(\underbrace{V_A(1) - p_A - V_A(0)}_{\text{Surplus of the Acquirer}}\right)^{1-\alpha} \left(\underbrace{p_A - V_T(0)}_{\text{Surplus of the Target}}\right)^{\alpha}$$

where p_A is the acquisition price and α is the bargaining power of the target. The total surplus of the M&A is

$$S = V_A(1) - p_A - V_A(0) + p_A - V_T(0)$$

$$S = \left(\underbrace{\frac{V_A(1) - p_a - V_A(0)}{V_A(0)}}_{\text{Abnormal Returns from M\&A}}\right) V_A(0) + \underbrace{p_A - V_T(0)}_{\text{Surplus of Target}}$$

The bargaining power of the target determines how close the acquisition price is to the full marginal benefit of the acquisition. In the extreme case where the target holds all the bargaining power ($\alpha = 1$), the acquisition price equals the competitive market price

$$p_A^{CM} = V_A(1) - V_A(0)$$

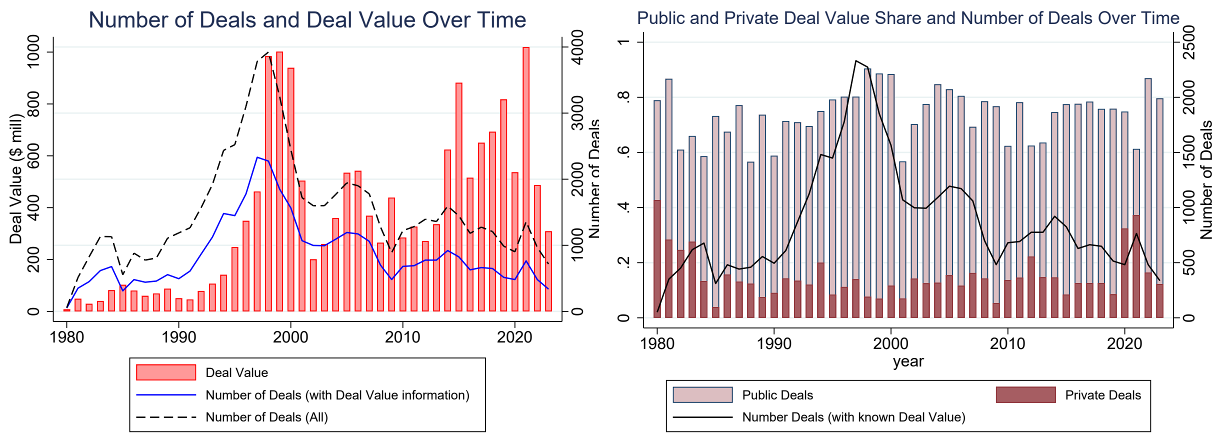
which implies that the target captures the entire marginal benefit (total surplus)

$$\frac{S_T}{S} = \frac{p_A^{CM} - V_T(0)}{V_A(1) - V_A(1) - V_T(0)} = 1$$

In what follows, we show that after the removal of the pooling-of-interests method in 2001, the acquirer surplus experienced a relative increase as targets lost the leverage they once used to drive up the deal premium. In other words, post-2001, acquirers negotiated from a stronger position, leading to a reallocation of the surplus in their favor.

Figure 2.2: Deal Activity Through Time

(a) (b)



Notes: Panel (a) shows the annual number of transactions and the aggregate dollar value. Panel (b) shows the annual number of transactions with deal value and the share of public and private aggregate dollar value. Shares do not add up to one because other target types: Govt.,J.V., Mutual, Priv., Public and Sub. are excluded.

2.3.4.1 Cumulative Abnormal Returns

The number of U.S. domestic deals peaked in 1999 at the height of the dot-com bubble and has been in decline ever since. Panel (a) of Figure 2.2 shows that by 2023, the number of deals was about the same as in 1988, just before the M&A boom of the 1990s. However, acquisition prices have followed a different trajectory and have steadily risen, reaching levels comparable to those observed during the dot-com era by the late 2010s.

The majority of acquirers are publicly traded firms, something which has remained relatively stable since the 1980s (Panel (b) in Figure 2.2). This allows us to directly observe firm value for most acquirers and the variation in their cumulative abnormal stock returns around the deal window. To measure cumulative abnormal returns, we use daily stock data from our CRSP-SDC merged dataset. We define abnormal returns as

$$AR_{i,t} = R_{i,t} - \mathbb{E}(R_{i,t}) \tag{2.6}$$

where $R_{i,t}$ is the actual return for firm i on day t and $\mathbb{E}(R_{i,t})$ is expected return. An abnormal return represents any deviation from the expected return on a given day. While the actual return $R_{i,t}$ is observable, the expected return $\mathbb{E}(R_{i,t})$ is not and must be estimated. We use two different models to do this: the capital asset pricing model (CAPM) and the Fama-French 3-Factor model (FF3). We estimate the following OLS regressions for each model

$$\texttt{EXRET}_{i,t} = \alpha^{CAPM} + \beta_1^{CAPM}\texttt{MKTRF}_{m,t} + \varepsilon_{i,t}^{FF3} \tag{2.7}$$

$$\texttt{EXRET}_{i,t} = \alpha^{FF3} + \beta_1^{FF3}\texttt{MKTRF}_{m,t} + \beta_2^{FF3}\texttt{SMB}_{m,t} + \beta_3^{FF3}\texttt{HML}_{m,t} + \varepsilon_{i,t}^{FF3} \tag{2.8}$$

where the only difference between the regressions is that the FF3 model has two additional regressors. The excess return $\texttt{EXRET}_{i,t}$ and the the market risk premium $\texttt{MKTRF}_{m,t}$ are defined as follows

$$\texttt{EXRET}_{i,t} = R_{i,t} - R_{f,t} \qquad\qquad \texttt{MKTRF}_{m,t} = R_{m,t} - R_{f,t}.$$

Here, $R_{f,t}$ is the risk-free rate and is measured with US treasury bills while $R_{m,t}$ is the overall market return. A higher value of $\texttt{MKTRF}_{m,t}$ indicates a greater return for taking on market risk. The FF3 includes two additional regressors compared to the CAPM. The regressor $\texttt{SMB}_{m,t}$ is "small minus big" and measures the size effect, representing the excess return of small-cap stocks over large-cap stocks. A positive value for $\texttt{SMB}_{m,t}$ implies that small-cap stocks outperform large-cap stocks. The other regressor $\texttt{HML}_{m,t}$ measures value by taking the difference between high book-to-market (value) stocks and low book-to-market (growth) stocks. A positive value for $\texttt{HML}_{m,t}$ means that value stocks outperform growth stocks. These regressors are defined as

$$\texttt{SMB}_{m,t} = R_{\text{small stocks},t} - R_{\text{big stocks},t} \qquad\qquad \texttt{HML}_{m,t} = R_{\text{value stocks},t} - R_{\text{growth stocks},t}.$$

We estimate the coefficients using an estimation window of -250 and -30 days before the M&A event. With the estimates, we compute the expected return using the CAPM equation

$$\mathbb{E}(R_{it}) = R_{f,t} + \beta_1(R_{m,t} - R_{f,t}). \tag{2.9}$$

We winsorize the predicted expected returns from both models at the 1st and 99th percentiles. The abnoromal returns for both models are then calculated as

$$AR^S_{i,t} = R_{i,t} - (R_{f,t} + \beta^S_1(R_{m,t} - R_{f,t}) \qquad\qquad \text{where } S \in \{CAPM, FF3\}. \tag{2.10}$$

Finally, we compute the cumulative abnormal returns by taking the cumulative product of abnormal returns. For any period from 1 to t:[13]

$$CAR^S_{1,t} = \left(\prod_{i=1}^{t}(1 + AR^S_{i,t})\right) - 1 \qquad\qquad \text{where } S \in \{CAPM, FF3\}. \tag{2.11}$$

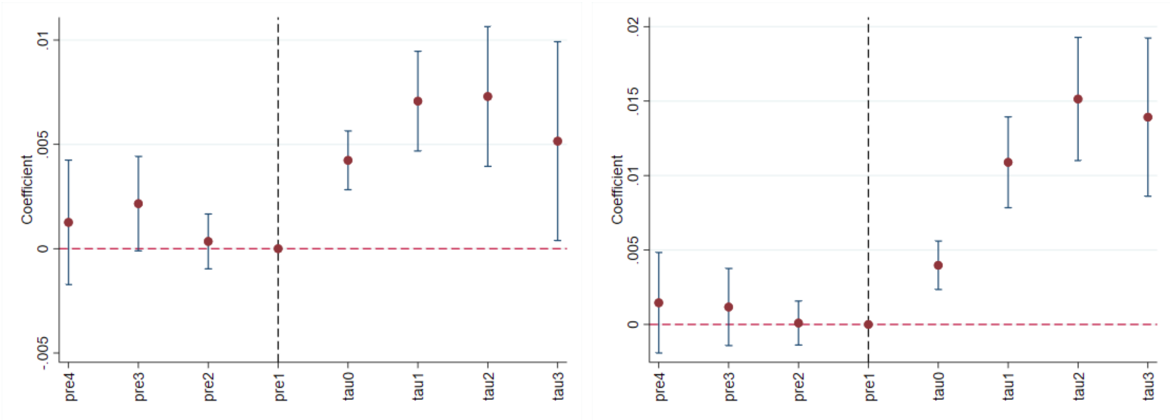
We use a local projections difference-in-differences event study estimator (LP DID) from Dube, Girardi, Jorda, and Taylor (2023) to examine how CARs change following the M&A announcement. The estimator is well-suited to our analysis as it allows for a flexible treatment of acquirers that undergo treatment (M&A) at different times and when treatment is non-absorbing, where in our case firms can undergo multiple M&A announcements over time. We run the following event

[13] For a sequence of abnormal returns $AR^S_{i,1}, AR^S_{i,2}, AR^S_{i,3}, ..., AR^S_{i,t}$, the cumulative abnormal returns over different periods are calculated as:

$$\begin{aligned} CAR^S_{1,2} &= (1 + AR^S_{i,1})(1 + AR^S_{i,2}) - 1 \\ CAR^S_{1,3} &= (1 + AR^S_{i,1})(1 + AR^S_{i,2})(1 + AR^S_{i,3}) - 1 \\ CAR^S_{1,4} &= (1 + AR^S_{i,1})(1 + AR^S_{i,2})(1 + AR^S_{i,3})(1 + AR^S_{i,4}) - 1. \end{aligned}$$

Figure 2.3: LP DID Event Study for Cumulative Abnormal Returns and M&A Announcements

(a) Without Post-2001 Interaction Term (b) With Post-2001 Interaction Term



Notes: Event study computed using the local projection diff-in-diff estimator from Dube et al. (2023). Cumulative abnormal returns are computed using the Fama-French 3 factor model. The control group is the not yet treated and the treatment is non-absorbing. The bands represent 95% confidence intervals with standard errors clustered at the firm level.

study regression where we examine the variation in CARs following an M&A announcement

$$CAR^S_{i,t+h} - CAR^S_{i,t-1} = \beta^{LP}_h D_{it} + \sum_{p=1}^{P} \gamma^h_p \Delta CAR^S_{i,t-p} + \delta^h_t + e^h_{it} \tag{2.12}$$

for $h = 0, \ldots, H$ periods after the event. We set $H = 3$. In this equation the dependent variable is the percentange change in CAR for firm i from date $t-1$ (the day before the M&A announcement) to date $t+h$ following the M&A event. The treatment indicator D_{it} is

$$\begin{array}{lr} (D_{it} = 1) \quad \& \quad (D_{i,t-j} = 0 \quad \text{for } -h \leq j \leq L;\; j \neq 0) & \text{treatment} \\ D_{i,t-j} = 0 \quad \text{for } -h \leq j \leq L & \text{clean control} \end{array}$$

where L is the maximum number of periods before the announcement time which we set $L = 4$. Here, $D_{it} = 1$ when firm i announces an M&A at date t and the second term, $D_{i,t-j} = 0 \quad \text{for } -h \leq j \leq L;\; j \neq 0$, ensures that the firm does not have any other M&A announcements within the window $t - h$ to $t + L$. This helps ensure that the observed changes in CAR are not confounded by the effect of another M&A announcement. On the other hand, the clean control group consists of firms that do not announce any M&A during the observation window for periods from $-h$ to L. The model also includes lagged values of the change in $\Delta CAR^S_{i,t-p}$ from earlier periods. The sum of these lags, $\sum_{p=1}^{P} \gamma^h_p \Delta CAR^S_{i,t-p}$ account for potential autocorrelation in CARs over time. Finally, the model includes time effects δ^h_t.

To determine whether CARs changed after the accounting change in 2001, we use the same model but include an interaction term $(D_{it} \times Post_t)$ where $Post_t = 1$ if the date t is in the year 2001 or after. The regression with the post-2001 interaction term is

Table 2.4: Acquirer and Target Sales by Period

Statistic	Acq.		Targ. Comp.		Targ. Hybrid	
	Before	After	Before	After	Before	After
Mean	3587.15	8332.57	4990.47	14627.61	368.39	642.45
Observations	6616	5184	466	381	6616	5184
Median	438.09	769.36	581.50	1976.00	41.09	55.94
p75	1990.41	3770.25	3935.90	10868.00	150.73	237.89
p90	8070.82	18274.10	14089.00	45188.00	534.24	1057.84

$$CAR^S_{i,t+h} - CAR^S_{i,t-1} = \beta^{LP}_h D_{it} + \theta_h (D_{it} \times Post_t) + \sum_{p=1}^{P} \gamma^h_p \Delta CAR^S_{i,t-p} + \delta^h_t + e^h_{it} \tag{2.13}$$

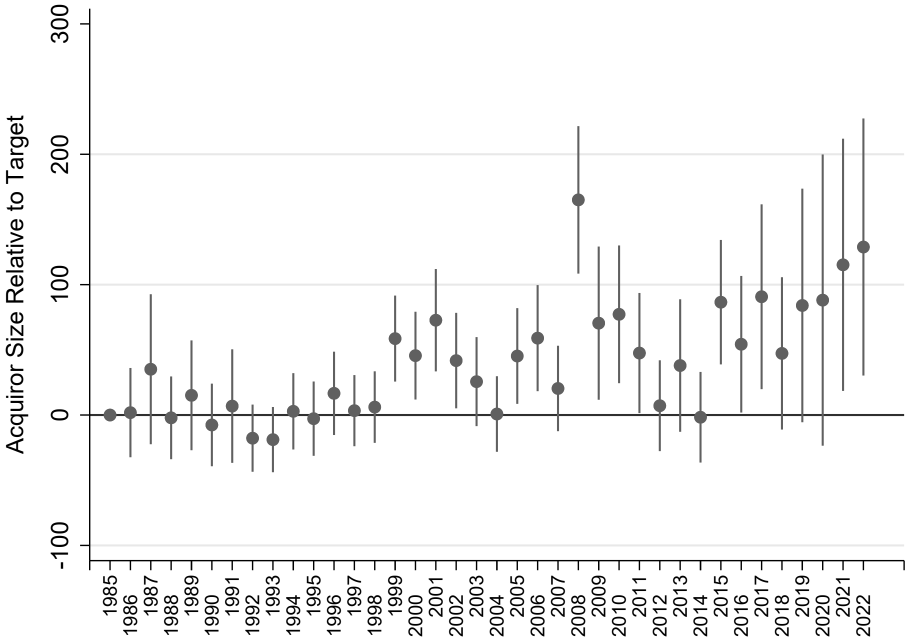
The inclusion of the interaction allows the model to test whether the announcement of an M&A is different for observations that fall after 2001 compared to before it. This is often called a triple difference and the interaction term measures how treatment varies specifically post-2001, compared any effects seen before 2001.

Panels (a) and (b) in Figure 2.3 plot the CAR using the LP DID estimator within a -4 to 3 day event window where the control group is the not yet treated. Panel (a) shows the following the M&A announcement CAR increases by almost 0.05% on the accouncement day and peaks at 0.07% two days later. Panel (b) includes the interaction term that distinguishes observations from the post-2001 period. The dynamics are similar but the effect is much more pronounced compared to panel (a). The estimated coefficient two days after the announcement is 1.5%, more than twice from model without an interaction term. By including the interaction term for post-2001 observations, these estimates reflect how the CAR differs specifically for this subgroup. The more pronounced post-event coefficients imply that the the impact of M&As on CARs is larger in the post-2001 period, suggesting that acquirers experience larger market value gains following an M&A announcement. As a robustness check, we re-estimate the model from equation (2.12) separately for observations before and after 2001. The results are consistent with the findings presented here (Figure B.2.1).

2.3.4.2 Increase in Relative Size

We now examine how the relative size of acquirers has changed over time, measuring firm size in terms of sales revenue. Acquirer sales are obtained from our merged SDC-Compustat dataset. For targets, sales data are available from the same source if the target is publicly listed. In Table 2.4, the first two column blocks present summary statistics on sales for acquirers (Acq.) and publicly listed targets (Targ. Comp.) for the periods before and after 2001. Most targets are private and therefore not in Compustat. This helps explain the relatively low number of observations in the Targ. Comp. block. SDC includes information on sales for targets during the fiscal year

Figure 2.4: Relative Size Comparisons (Compustat.-Hybrid Sales Size)



preceding the deal. When we incorporate this additional SDC data, we are able to obtain sales figures for all acquirer-target pairs (note the same number of observations). The statistics are reported in the Targ. Hybrid block. They are noticeably smaller than those for publicly listed targets in Compustat, reflecting the smaller scale of most private firms.

We use the Acquirer Compustat and Target Hybrid sample to estimate how the relative size as changed over time. We estimate and plot the year coefficients from the following regression

$$\text{relsize}_{dt} = \alpha + \sum_{t=1984}^{2022} \beta_t \cdot \mathbf{1}\{fyear\_ann = t\}_t + \varepsilon_{dt} \tag{2.14}$$

where relsize_{dt} is the ratio of acquirer sales to target sales for deal d in year t ($fyear\_ann$).

Figure 2.4 plots the estimated year coefficients from the regression of the acquirer-to-target sales ratio on year indicators. There is an upward trend over time, indicating that acquirers have become increasingly larger relative to their targets. In the mid-1980s, the relative size ratio was around 10, but by the late 2010s it was around 90. The pronounced increase over time reflects the greater prominence of acquirers.

To test whether there is a structural shift in relative acquirer size after the accounting change, we estimate a set of regressions that compare the pre- and post-2001 periods. Specifically, we regress the acquirer-to-target sales ratio on an indicator for the post-2001 period ($Post_t$). We control for whether the deal was paid entirely in cash ($Cash_{dt}$) and their interaction which are contained in the vector X_{dt}. We run three different regressions where each model differs by fixed effect. We include year fixed effects (η_t, equation (2.15)), 2-digit SIC industry effects (δ_j, equation (2.16))

Table 2.5: Regression Results for Relative Size

	(1)	(2)	(3)	(4)	(5)
$Post_t = 1$	32.571***	32.599***	30.840**	19.110***	33.454***
	(5.332)	(5.465)	(11.999)	(5.949)	(12.536)
$Cash_{dt} = 1$				22.797***	26.858**
				(7.961)	(10.489)
$Post_t \times Cash_{dt}$				27.665**	-15.848
				(12.581)	(16.857)
Constant	62.385***	62.382***	71.414***	57.009***	64.782***
	(3.003)	(3.035)	(5.775)	(3.243)	(5.865)
Observations	15,273	15,271	12,393	15,271	12,393
R-squared	0.003	0.029	0.310	0.032	0.311
FE	Year	Industry	Acquirer	Industry	Acquirer

Notes: *p<0.10; **p<0.05; ***p<0.01. Standard errors are in parentheses and are clustered at deal level in the model with industry fixed effects and at acquirer level in the model with acquirer fixed effects.

and includes acquirer fixed effects (θ_a, equation (2.17)).

$$\text{relsize}_{dt} = \alpha + \beta \cdot Post_t + \gamma X_{dt} + \eta_t + \varepsilon_{dt} \tag{2.15}$$

$$\text{relsize}_{dt} = \alpha + \beta \cdot Post_t + \gamma X_{dt} + \delta_j + \varepsilon_{dt} \tag{2.16}$$

$$\text{relsize}_{dt} = \alpha + \beta \cdot Post_t + \gamma X_{dt} + \theta_a + \varepsilon_{dt} \tag{2.17}$$

where the unit of observations is the d. Table 2.4 presents the results. In column 1 with year fixed effects, the coefficient on the post-2001 indicator is positive and statistically significant, confirming that relative size increased meaningfully after 2001. Acquirers are, on average, 32.6 units larger relative to targets post-2001. This effect remains virtually unchanged when controlling for industry fixed effects (Column 2), and is only slightly attenuated when including acquirer fixed effects (Column 3).

Columns 4 and 5 include cash deal control and interaction term. In Column 4, deals that are fully paid in cash are associated with a 22.8-unit higher relative size ratio on average. The interaction term ($Post_t \times Cash_{dt}$) is positive and statistically significant, suggesting that the post-2001 increase in relative size is especially pronounced for all-cash transactions. However, when acquirer fixed effects are included (Column 5), the interaction term turns negative and loses significance. Despite the inclusion of the control, the relative average size is significantly larger post-2001. Overall, the evidence found here supports the descriptive findings in Figure 2.4 in that the size gap between acquirers and targets has widened substantially in the post-2001 period. This shift remains robust across multiple fixed effects specifications.

2.3.5 An Unsatisfactory Solution from Deals Data

Given the differences in business accounting methods, it is clear that unrecognized goodwill existed in business accounts prior to 2001. As a result, unrecognized goodwill from the pooling accounting treatment is not reflected in stock of acquired intangible capital, $k^{acc}_{a,t}$. A quick, though not entirely satisfactory, solution is to account for these unrecognized intangibles by directly using deal data from SDC and M&A expenditures recorded in the cash flow statement, $x^{acc-cf}_{a,t}$. We can then use this investment flow and equation (2.2) to reconstruct an acquired capital stock $k^{acc-cf}_{a,t}$.

This alternative measure of acquired intangibles can then be used to compute measures of economic profits accordingly by explicitly including any unrecognized goodwill in acquired intangible capital. In De Loecker et al. (2020) economic profits are

$$\pi_{i,t} = \texttt{Sale}_{i,t} - \texttt{cogs}_{i,t} - \texttt{xsga}_{i,t} - r^{DLEU}_t \texttt{PPEGT}_{i,t} \tag{2.18}$$

which is the difference between sales revenue ($\texttt{Sale}_{i,t}$) and total operational expenses ($\texttt{cogs}_{i,t} + \texttt{xsga}_{i,t}$) which includes the wage bill, overhead costs and intangible *expenses*. The user cost of capital is also subtracted from sales revenue where the balance sheet value of tangible capital ($\texttt{PPEGT}_t$) serves as the capital stock with a rate of return r^{DLEU}_t. In De Loecker et al. (2020) this rate of return is assumed to be

$$r^{DLEU}_t = (I_t - \Pi_t) + \delta_T \tag{2.19}$$

where I_t is the nominal interest rate, Π_t is the inflation rate and δ_T is the depreciation rate. The nominal interest rate is the federal funds rate and the inflation rate comes from the PCE price index. We obtain both series from FRED. De Loecker et al. (2020) assume that $\delta_T = 0.12$.

Equation (2.18) does not include any form of acquired intangibles. A quick solution could be to incorporate this measure of acquired intangibles, $k^{acc-cf}_{a,t}$, and assume that the intangible rate of the return equals that of tangible capital r^{DLEU}_t. Economic profits would then be

$$\widetilde{\pi}_{i,t} = \texttt{Sale}_{i,t} - \texttt{cogs}_{i,t} - \texttt{xsga}_{i,t} - r^{DLEU}_t \texttt{PPEGT}_{i,t} - r^{DLEU}_t k^{acc-cf}_{a,i,t}$$

In what follows we argue that this is an unsatisfactory solution.

2.3.5.1 Acquired Intangibles from Deal Values

To construct $k^{acc-cf}_{a,t}$ we start be constructing an alternative measure of acquired intangibles from SDC deals data and cash flow statements. When a firm acquires another company, the purchase price is allocated among the acquired assets and liabilities through the purchase price allocation process (ASC 805). The total purchase price reflects the consideration paid by the acquirer. The process involves identifying and measuring the fair value of the target firm's *already existing* net tangible and intangible assets already on the target's balance sheet.[14] Tangible assets are items on the balance sheet such as property and equipment while intangible assets are any intangibles on the balance sheet that target acquired prior to being acquired itself. Once the the fair value of

[14] Net assets are the difference between the fair value of assets and its liabilities

Table 2.6: Breakdown of $x^{acc-cf}_{a,t}$

Variable	Source	Pct. (%)
$\texttt{aqc}_t$	Compustat	84.79
0	–	9.29
$\texttt{deal\_value}_t$	SDC	4.41
$x^{SDC}_{g,t} \equiv \texttt{deal\_value}_t - \texttt{netass}_t$	SDC	1.50

net assets have been measured, any excess of the purchase price over this amount is allocated to identifiable intangible assets and goodwill. Identifiable intangible assets, such as patents, trademarks and client lists, are recognized if they meet the separability and contractual-legal criteria.[15] Any remaining residual amount that cannot be attributed to specific identifiable assets is classified as goodwill.

$$\text{Purchase Price} = \text{Fair Value of Net Assets} + \text{Excess Purchase Price},$$

$$\text{Fair Value of Net Assets} = \text{Tangible Assets} + \text{Pre-Acquired Intangible Assets} - \text{Liabilities},$$

$$\text{Excess Purchase Price} = \text{Identifiable Intangibles} + \text{Goodwill}.$$

Ultimately, acquired intangibles that are created from an M&A are the difference between the purchase price and net assets of the targets. This can be most directly obtained using data from SDC where for each firm in year t we take the sum of all deal values ($\texttt{dealvalue}_t$) and net assets ($\texttt{netass}_t$) and then take the difference to obtain acquired intangibles ($x^{SDC}_{a,t} = \texttt{dealvalue}_t - \texttt{netass}_t$). We call this variable $x^{SDC}_{a,t}$. We then start constructing our alternative measure of acquired intangibles $x^{acc-cf}_{a,t}$ by setting it equal to the value of acquired intangible flows $x^{SDC}_{a,t}$ obtained in SDC: $x^{acc-cf}_{a,t} = x^{SDC}_{a,t}$. However, the majority of deals in SDC do not report the deal value and even fewer report the net assets of the target. Consequently, there are few available observations and only 2.17% of the total observations for $x^{acc-cf}_{a,t}$ are non-missing.

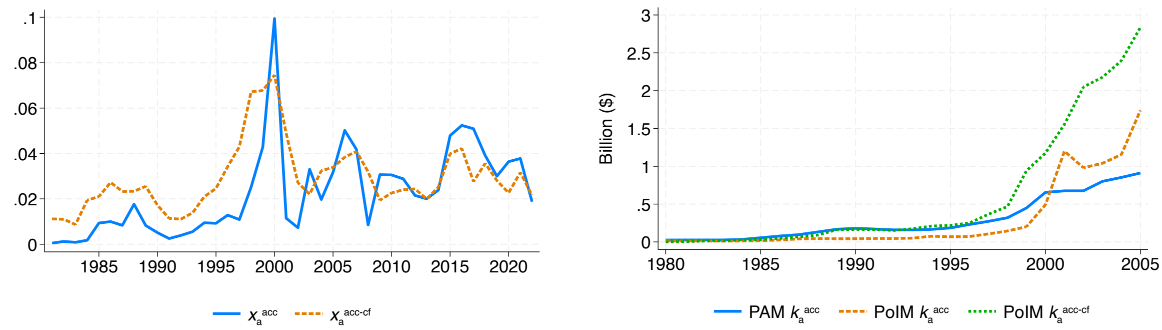
We then turn and compare $x^{SDC}_{a,t}$ to acquisition expenses that are reported in the cash flow statement which in Compustat is called $\texttt{aqc}_t$. This variable reports the total cash outflow for acquisitions made in the fiscal year. Most deals are paid in cash, and if the entire deal is in cash then $\texttt{aqc}_t$ coincides with the deal value. About a 30.67% of values $\texttt{aqc}_t$ reported in Compustat are greater than $x^{SDC}_{a,t}$. In such a scenario, greater cash expenditures on acquisitions indicates that either SDC is not recording the deal values for all deals in the fiscal year or it is missing deals entirely. Consequently, we replace $x^{acc-cf}_{a,t}$ for $\texttt{aqc}_t$ whenever $\texttt{aqc}_t > x^{SDC}_{a,t}$ resulting in about 0.67% ($\approx 0.3067\times$ 2.17%) of our observations are replaced.

Of the non-missing values of the target's net assets in SDC, most values are small relative to the

[15] The separability criterion states that the intangible assets can be sold independently of the entity. The contractual-legal criterion states that the control of the intangible asset's future economic benefits is established through contractual or legal rights.

Figure 2.5: A Quick Solution to Recover Acquired Intangible from Deal Values

(a) Avg. $x^{acc-cf}_{a,t}/\texttt{SALE}_t$ (Sales Weighted) (b) Acquired Intangibles by Pooling/PAM Type



Notes: In constant 2015 dollars. In panel (a) the solid line is acquired intangible investment $x^{acc}_{a,t}$ taken from financial statements while the dashed line is investment taken from deal values $x^{acc-cf}_{a,t}$. Panel (b) is the unweighted average of acquired intangible stocks by accounting method types.

deal value.[16] This means that the acquired intangibles calculated in SDC ($x^{SDC}_{a,t}$) is actually not too different from the deal value or cash expenditures for acquisitions. Because of this we argue that $\texttt{aqc}_t$ is a close measure of $x^{SDC}_{a,t}$ and we set $x^{acc-cf}_{a,t} = \texttt{aqc}_t$ whereever $x^{acc-cf}_{a,t}$ is missing. Doing this results in turning about 87.55% of missing $x^{acc-cf}_{a,t}$ observations into non-missing. Most deals are entirely paid in cash, but for those that are not then $\texttt{aqc}_t < \texttt{dealvalue}_t$. In such cases we set $x^{acc-cf}_{a,t} = \texttt{dealvalue}_t$ if $\texttt{dealvalue} > \texttt{aqc}_t$ and $x^{SDC}_{a,t}$ is missing. This replaces 3.42% of our observations. Finally, for observations where both $x^{SDC}_{a,t}$ and $\texttt{aqc}_t$ are missing we set $x^{acc-cf}_{a,t} = \texttt{dealvalue}_t$ which turns about 0.98% of our observations from missing into non-missing. All remaining observations where $x^{SDC}_{a,t}$, $\texttt{aqc}_t$ and $\texttt{dealvalue}_t$ are missing equal to zero (9.29% of observations). Table 2.6 provides a decomposition of $x^{acc-cf}_{a,t}$.

With the measure of $x^{acc-cf}_{a,t}$ we can then construct the capital stock as done in equation (2.2)

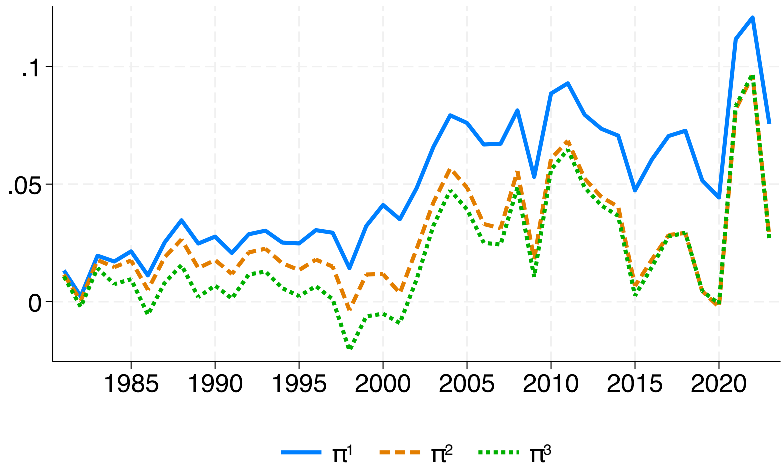
$$k^{acc-cf}_{a,t} = \frac{x^{acc-cf}_{a,t} + k^{acc-cf}_{a,t-1}}{1 + \delta^{acc}_{a,t}} \tag{2.20}$$

where we use the same firm level $\delta^{acc}_{a,t}$ from Compustat ($\texttt{am}_t/\texttt{intan}_t$ and assume that the initial stock $k^{acc-cf}_{a,0} = \texttt{intan}_t$.

Given our previous discussion regarding the existence of acquired intangible measures that can be recovered from M&A deal values and the cash flow statement. The left panel in Figure 2.5 compares the sales weighted average of acquired intangible investment from deal values over sales $x^{acc-cf}_{a,t}/\texttt{SALE}_t$ with that of recognized acquired intangible investment from financial statements $x^{acc}_{a,t}/\texttt{SALE}_t$. The corrected measure is considerably higher in the years prior to 2001 and both series closely follow each other after 2001. Panel (b) replots Figure 2.1 of the unweighted average $k^{acc}_{a,t}$ by pooling and PAM types. The implied measure $k^{acc}_{a,t}$ fills the missing acquired intangible stock of pooling firms as seen by the green line in the panel on the right.

[16] On average deal prices are more than five times greater than a target's net assets.

Figure 2.6: Avg. Economic Profit Rate (Sales Weighted)



2.3.5.2 Economic Profits and Acquired Intangibles

Having constructed an intangible capital that now contains unrecognized intangibles we now consider its impact on economic profits. We consider three different measures in equations (2.21)-(2.23). The first $\pi^1_{i,t}$ serves as the baseline measure of economic profits as in De Loecker et al. (2020). The second measure $\pi^2_{i,t}$ adds acquired intangibles $k^{acc}_{a,i,t}$ reported in firms' financial statements and the third measure $\pi^3_{i,t}$ instead adds acquired intangibles $k^{acc-cf}_{a,i,t}$ measured from deal values. In all three versions of economic profits we assume the same rate of return $r_{i,t}$ as in De Loecker et al. (2020) and apply it for both tangible and intangible capital.

De Loecker et al. (2020)

$$\pi^1_{i,t} = \texttt{Sale}_{i,t} - \texttt{cogs}_{i,t} - \texttt{xsga}_{i,t} - r^{DLEU}_t \texttt{PPEGT}_{i,t} \tag{2.21}$$

Acquired Intangibles from Financial Statements

$$\pi^2_{i,t} = \texttt{Sale}_{i,t} - \texttt{cogs}_{i,t} - \texttt{xsga}_{i,t} - r^{DLEU}_t (\texttt{PPEGT}_{i,t} + k^{acc}_{a,i,t}) \tag{2.22}$$

Acquired Intangibles from Deal Values

$$\pi^3_{i,t} = \texttt{Sale}_{i,t} - \texttt{cogs}_{i,t} - \texttt{xsga}_{i,t} - r^{DLEU}_t (\texttt{PPEGT}_{i,t} + k^{acc-cf}_{a,i,t}) \tag{2.23}$$

Figure 2.6 presents the sales-weighted average of the three economic profit rates ($\pi/\texttt{Sale}$). Incorporating acquired intangibles from financial statements lowers economic profits, and even more so when using acquired intangibles measured from deal values prior to 2001. As a result, including acquired intangibles dampens the stark upward trend of economic profits. ($\pi/\texttt{Sale}$).

This approach is unsatisfactory because the deal data from SDC and the M&A expenditures reported in the cash flow statement do not necessarily capture the competitive price of acquisition. Furthermore, it also fails to correct for the "excess" surplus that accrues to the acquirer after 2001 due to the loss of leverage by the target firms. While attaching a rate of return (user cost of capital) to acquired intangibles could, in principle, correct economic profits, determining the appropriate rate is not trivial. Consequently, we need to develop a model to accurately estimate the user cost of capital.

2.4 A Model of M&As and Strategic Business Accounting

We consider a three-period game ($t = 0, 1, 2$) involving two firms: an *acquirer* (A) and a *target* (T). The firms are managed by a CEO, invest in capital and face the possibility of merging with a probability p during period 1. The acquirer's CEO may have distorted incentives, who balances market value with accounting profits. Mergers can happen over alternative accounting standards (pooling (PoIM) vs PAM) which both parties must agree on. The decision to attempt to use pooling is strategic on the acquirer's part and targets potentially may block it.

2.4.1 Periods and Timeline

At the beginning ($t = 0$), each firm $i \in \{A, T\}$ possesses an initial capital stock denoted by $k_{i,0}$. The acquirer initiates the investment process, followed sequentially by the target, establishing a Stackelberg game in their initial investment decisions. Both firms determine their labor demand ($h_{i,0}$) and investment ($x_{i,0}$) for period 0. The production for each firm is modeled using a decreasing-returns CES function

$$y_{i,0} = \zeta_i \left(k_{i,0}^{\frac{\alpha-1}{\alpha}} + h_{i,0}^{\frac{\alpha-1}{\alpha}} \right)^{\frac{\gamma\alpha}{\alpha-1}},$$

where $0 < \gamma < 1$ is a span-of-control parameter, $\alpha > 0$ is a elasticity of substitution and ζ_i is total factor productivity (TFP). Labor is a variable input which firms hire for wage w_0. Investment is subject to a fixed cost c_i. Consequently, the profit for the firm i in period 0 is given by

$$\Pi_{i,0} = \zeta_i \left(k_{i,0}^{\frac{\alpha-1}{\alpha}} + h_{i,0}^{\frac{\alpha-1}{\alpha}} \right)^{\frac{\gamma\alpha}{\alpha-1}} - w_0 h_{i,0} - c_i x_{i,0} \tag{2.24}$$

Capital accumulates for each firm according to the following law of motion

$$k_{i,1} = (1 - \delta) k_{i,0} + z_i x_{i,0} \tag{2.25}$$

where $\delta \in (0, 1)$ represents the depreciation rate and $z_i > 0$ denotes the productivity of investment.

In period 1 ($t = 1$), the acquirer and target meet with probability p. If they agree to merge then the post-M&A production and capital for the acquirer is

$$y_{A,1}^{\text{merged}} = \zeta_A \left(\left(k_{A,1}^{\text{merged}} \right)^{\alpha} + h_{A,1}^{\alpha} \right)^{\gamma/\alpha} \qquad\qquad k_{A,1}^{\text{merged}} = \left(k_{A,1}^{\frac{\sigma-1}{\sigma}} + k_{T,1}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

The merged entity's capital $k_{A,1}^{\text{merged}}$ is aggregated using a CES aggregator where where $\sigma > 1$ is the elasticity of substitution in capital and determines the potential synergy. Note that $k_{A,1}$ is the acquirer's pre-M&A capital stock. If the firms do not meet with probability $(1-p)$ they continue to operate independently, making new labor $h_{i,1}$, investment decisions $x_{i,1}$ and produce $y_{i,1}$.

For firms that meet a strategic game unfolds over the merger and the accounting treatment of it. The sequence is as follows. The acquirer moves first and proposes a type of meger: PoIM or PAM. Suggesting the PoIM method entails a sunk cost c_{PoIM}^{A} for the acquirer. If PAM is proposed, then the two firms negotitate the acquisition price according to a Nash bargaining protocol where the acquirer has bargaining power $(1-\theta)$ and the target θ. The outside option of each firm is to operate independently.

If PoIM is proposed then the target moves next and decides whether to accept PoIM or to block it. Blocking PoIM entails a fixed cost c_{PoIM}^{T}. The outside option for each firm is to merge with PAM. The acquisition price is not recognized under PoIM which increases firm value and thus generates a larger surplus. This extra surplus is split between the two. If PoIM is not blocked then the two firms negotiate following the Nash bargaining protocol. If PoIM is blocked, then the two firms merge under PAM and split the surplus.

Finally, in period 2 ($t = 2$), regardless of whether the firms have merged, they engage in final production based on their accumulated capital stocks. While there is no further investment, firms decide on labor ($h_{i,2}$). In the *No Meet* scenario, both the acquirer and the target independently optimize their labor decisions based on their respective capital stocks $k_{A,1}$ and $k_{T,1}$. The final period's production and profits are directly influenced by these labor inputs. Conversely, in the *Meet* scenario, the merged entity determines its optimal labor decision $h_{A,2}^{\text{merged}}$ based on the aggregated capital stock $k_{A,2}^{\text{merged}}$. This decision directly impacts the final production and profits of the merged firm.

2.4.2 Firm Value

Firm value can either be its market value, the accounting value or the economic value. All three differ and impact how the CEO makes decisions for the firm. The market value of firm i is the present discounted value of its profits (dividends)

$$V_{i,t}^{\Pi} = \sum_{j=t}^{2} \beta^{j-t} \Pi_{i,j} \tag{2.26}$$

where $\Pi_{i,j}$ are dividends paid at time t and are given by the cash flow which are the net of total revenues minus total expenditures. For the acquirer $i = A$ in $t = 1$, (cash) expenditures include the price paid for acquisition p_A, investment $x_{A,1}$, labor costs $w_1 h_{A,1}$ and if proposed then the PoIM cost c^A_{PoIM}. For the target T in $t = 1$, we include as part of the revenues the price received in the case that they merge and as an expenditure the cost associated with blocking PoIM c^T_{PoIM} if they choose to do so.

The accounting value of the firm is the present discounted value of accounting profits

$$V^{acc}_{i,t} = \sum_{j=t}^{2} \beta^{j-t} \pi^{acc}_{i,j}$$

where accounting profits are given by

$$\pi^{acc}_{i,j} = y_{i,j} - w_t h_{i,j} - c_i x_{i,j} - \delta^{acc} p_A \cdot 1\{\text{merger in } j = 1 \text{ and } j \geq 1\}. \tag{2.27}$$

Accounting profits are the total revenues minus the variable costs and investment which are all expensed. In the case that acquirer $i = A$ ends up merging in $t = 1$ then the price it pays is amortized at rate δ^{acc}. The two accounting types PoIM and PAM come along with different δ^{acc}. When the accounting method used is PAM we set $\delta^{acc} = \delta^{PAM} = 0.5$ so that the acquisition is fully amortized over time. On the other hand with PoIM, $\delta^{acc} = \delta^{PoIM} = 0$, therefore the acquisition price does not impact accounting profits.

The CEO makes the decision to maximize a linear combination of market firm value and accounting profits,

$$V^{CEO}_{A,1} = (1 - \omega) V^{\Pi}_{A,1} + \omega V^{acc}_{A,1}. \tag{2.28}$$

where ω is a paramter that determines the size of the distortion. The larger ω, the more attractive the PoIM accounting method is for the acquirer.

The economic value is the net value created by the firm once the inputs are renumerated. In this case, it is the difference between revenues and the opportunity cost of production inputs. For the variable input this amounts to simply subtracting $w_t h_{i,t}$. On the other hand, for the use of capital we have to recover its opportunity or user cost. If we alternatively assumed that capital was rented competitively, then we would need to determine how large the income of the capital owner is. In a competitive market this would correspond to the marginal product of capital. The economic value is then

$$V^{econ}_{i,t} = \sum_{j=t} \beta^{j-t} \pi^{econ}_{i,j} \tag{2.29}$$

where

$$\pi^{econ}_{i,j} = y_{i,j} - MPH_{i,j} h_{i,j} - MPK_{i,j} k_{i,j}. \tag{2.30}$$

2.4.3 Bargaining Protocol and Acquirer's CEO Incentive

Traditionally, the acquirer maximizes *economic value* derived from the merger. However, this model introduces a *distorted CEO objective* for the acquirer's CEO where they place weight $(1-\omega)$ on market value and ω on value from accounting profits. This distortion alters the outcome of the Nash bargaining process and the final acquisition price.

In period $t = 1$ when two firms meet, the value of the acquirer's CEO if an M&A occurs $V_{A,1}^{CEO,merged}$ and $V_{A,1}^{CEO}$ is not. Let $V_{T,1}$ be the value of the target if the M&A does not occur. The objective function is

$$\left(\underbrace{V_{A,1}^{CEO,merged} - p_A - V_{A,1}^{CEO}}_{\text{Surplus of the Acquirer}}\right)^{1-\theta} \left(\underbrace{p_A - V_{T,1}}_{\text{Surplus of the Target}}\right)^{\theta}$$

Under Nash bargaining, the target's payoff from merging becomes the acquisition price p_A, where $V_{T,1}$ is the target's outside option if it remains independent. The acquirer surplus for the acquisition reflects the the CEO's objective. The surplus of the acquirer includes $V_{i,t}^{acc}$ which encapsulates the gradual recognition of acquisition cost when using the PAM accounting method or no recognition under PoIM. Regardless the accounting method, this distortion implies that a higher p_A is less burdensome from a short run accounting perspective. In contrast, were the CEO to maximize economic value the merger the surplus would then be $V_{A,1}^{econ,merged} - p_A - V_{A,1}^{econ}$. This altered objective function affects the Nash bargaining outcome, resulting in a different acquisition price p_A that reflects the CEO's preference structure.

2.4.4 Recursive Formulation

2.4.4.1 Period 0: Initial Capital Allocation and Production Decisions

We formulate the model recursively by defining each firm's value function at every point in time as a function of the relevant state variables. The state at time $t = 0$ is given by the pair $(k_{A,0}, k_{T,0})$ denoting the initial capital stocks of the acquirer and the target, respectively. Both firms simultaneously observe their capital endowments and proceed to make investment and labor allocation decisions. In this initial period, the acquirer moves first, choosing labor and investment $(h_{A,0}, x_{A,0})$. The target subsequently observes the acquirer's capital choice implied by the law of motion and chooses $(h_{T,0}, x_{T,0})$ accordingly. This interaction constitutes a Stackelberg game in capital accumulation.

Acquirer's Problem The acquirer solves:

$$V_{A,0}(k_{A,0}, k_{T,0}) = \max_{x_{A,0}, h_{A,0}} \{\Pi_{A,0}(k_{A,0}, h_{A,0}, x_{A,0}) + \beta \mathbb{E}_1 [V_{A,1}(k_{A,1}, k_{T,1})]\} \tag{2.31}$$

subject to:

$$k_{A,1} = (1-\delta)k_{A,0} + z_A x_{A,0}$$

where $\Pi_{A,0}$ is given by

$$\Pi_{i,0} = \zeta_i \left(k_{i,0}^{\frac{\alpha-1}{\alpha}} + h_{i,0}^{\frac{\alpha-1}{\alpha}} \right)^{\frac{\gamma\alpha}{\alpha-1}} - w_0 h_{i,0} - c_i x_{i,0} \tag{2.32}$$

and the continuation value $V_{A,1}(\cdot)$ will be defined in the next section as a function of capital stocks and the probabilistic merger outcome.

Target's Problem The target acts as the follower in the Stackelberg structure. It observes the acquirer's investment decision $x_{A,0}$ and infers $k_{A,1}$, then chooses $(h_{T,0}, x_{T,0})$ to maximize its own value:

$$V_{T,0}(k_{T,0}; k_{A,1}) = \max_{x_{T,0}, h_{T,0}} \left\{ \Pi_{T,0}(k_{T,0}, h_{T,0}, x_{T,0}) + \beta \mathbb{E}_1 \left[V_{T,1}(k_{T,1}; k_{A,1}) \right] \right\} \tag{2.33}$$

subject to:

$$k_{T,1} = (1-\delta) k_{T,0} + z_T x_{T,0}$$

Here, $V_{T,1}(k_{T,1}; k_{A,1})$ is the continuation value for the target in period 1, which depends on both firms' capital levels and on the realization of the merger process. The semicolon emphasizes that $k_{A,1}$ is treated as exogenous from the target's point of view due to the Stackelberg structure.

2.4.4.2 Period 1: Merger Possibility and Strategic Interaction

At the beginning of period $t = 1$, both firms observe their inherited capital stocks $(k_{A,1}, k_{T,1})$ resulting from the decisions taken in period 0. With probability p, the firms meet and negotiate a potential merger. With probability $(1-p)$, they remain independent and proceed with production and investment individually.

Overall Value Functions Before the realization of the merger opportunity, the value function for firm $i \in \{A, T\}$ is the expected value over the two possibilities:

$$V_{i,1}(k_{i,1}; k_{-i,1}) = p \cdot V_{i,1}^{\text{match}}(k_{A,1}, k_{T,1}) + (1-p) \cdot V_{i,1}^{\text{no match}}(k_{i,1}) \tag{2.34}$$

where $V_{i,1}^{\text{match}}$ corresponds to the value if a merger opportunity arises, and $V_{i,1}^{\text{no match}}$ corresponds to the scenario in which the firms continue to operate independently.

No-Match Scenario When no match occurs, firm i solves:

$$V_{i,1}^{\text{no match}}(k_{i,1}) = \max_{x_{i,1}, h_{i,1}} \left\{ \Pi_{i,1}(k_{i,1}, h_{i,1}, x_{i,1}) + \beta V_{i,2}(k_{i,2}) \right\} \tag{2.35}$$

subject to the capital law of motion:

$$k_{i,2} = (1-\delta) k_{i,1} + z_i x_{i,1}$$

Match Scenario If the firms meet, a strategic game unfolds over whether to merge and under which accounting standard. The acquirer chooses between proposing PoIM or PAM. The value function for the acquirer is:

$$V_{A,1}^{\text{match}}(k_{A,1}, k_{T,1}) = \max\left\{V_{A,1}^{\text{PoIM}}(k_{A,1}, k_{T,1}) - c_{PoIM}^{A},\ V_{A,1}^{\text{PAM}}(k_{A,1}, k_{T,1})\right\} \tag{2.36}$$

PAM Merger Proposal Under PAM, the acquisition price p_A is determined through a Nash bargaining problem over the total surplus generated by merging. The total surplus equals the difference between the value of the merged entity and the sum of the firms' values under independent operation.

The acquirer's surplus reflects the CEO's distorted preferences:

$$\text{Surplus}_A^{\text{PAM}} = V_{A,1}^{CEO,\text{merged}} - p_A - V_{A,1}^{CEO}$$

where

$$V_{A,1}^{CEO} := (1-\omega)V_{A,1}^{\Pi} + \omega V_{A,1}^{acc}$$

and similarly for the merged entity. The target's surplus is given by:

$$\text{Surplus}_T^{\text{PAM}} = p_A - V_{T,1}^{\text{no match}}(k_{T,1})$$

The Nash bargaining solution solves:

$$p_A^* = \arg\max_{p_A}\left(V_{A,1}^{CEO,\text{merged}} - p_A - V_{A,1}^{CEO}\right)^{1-\theta}\left(p_A - V_{T,1}^{\text{no match}}(k_{T,1})\right)^{\theta} \tag{2.37}$$

Given the equilibrium price p_A^*, the value function of each firm is:

$$V_{A,1}^{\text{PAM}}(k_{A,1}, k_{T,1}) = \Pi_{A,1}^{\text{merged}} - p_A^* + \beta V_{A,2}^{\text{merged}}(k_{A,2}^{\text{merged}}) \tag{2.38}$$

$$V_{T,1}^{\text{PAM}}(k_{T,1}; k_{A,1}) = p_A^* + \beta V_{T,2}^{\text{merged}}(k_{A,2}^{\text{merged}}) \tag{2.39}$$

PoIM Merger Proposal If the acquirer proposes PoIM, the target may choose to accept or block. Blocking incurs a cost c_{PoIM}^{T} and results in a fallback to a PAM merger. When PoIM is accepted, the acquisition price p_A^* remains the same as under PAM, but the firms negotiate an additional surplus stemming purely from accounting treatment: under PoIM, the amortization rate is zero, $\delta^{acc} = 0$, implying higher accounting profits for the acquirer and hence a larger $V_{A,1}^{acc}$. This surplus is purely accounting in nature.

Let Δ^{acc} denote the accounting surplus created by using PoIM instead of PAM. The additional surplus is split again via Nash bargaining. The target's outside option includes the cost of blocking PoIM and reverting to PAM:

$$\text{Surplus}_T^{\text{PoIM}} = \tilde{p}_A - p_A^* - c_{PoIM}^{T}$$

$$\text{Surplus}_A^{\text{PoIM}} = V_{A,1}^{CEO,\text{PoIM}} - \tilde{p}_A - V_{A,1}^{CEO,\text{PAM}}$$

Then the new price $\tilde{p}_A$ solves:

$$\tilde{p}_A = \arg\max_p \left(V_{A,1}^{CEO,\text{PoIM}} - p - V_{A,1}^{CEO,\text{PAM}}\right)^{1-\theta} \left(p - p_A^* - c_{PoIM}^T\right)^{\theta} \tag{2.40}$$

The final value functions are:

$$V_{A,1}^{\text{PoIM}}(k_{A,1}, k_{T,1}) = \max_{h_{A,1}, x_{A,1}} \left\{\Pi_{A,1}^{\text{merged}}(k_{A,1}^{\text{merged}}, h_{A,1}, x_{A,1}) - \tilde{p}_A + \beta V_{A,2}^{\text{merged}}(k_{A,2}^{\text{merged}})\right\} \tag{2.41}$$

$$V_{T,1}^{\text{PoIM}}(k_{T,1}; k_{A,1}) = \tilde{p}_A \tag{2.42}$$

where

$$k_{A,1}^{\text{merged}} = \left(k_{A,1}^{\frac{\sigma-1}{\sigma}} + k_{T,1}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

is the CES-aggregated capital stock immediately available after the merger,

$$k_{A,2}^{\text{merged}} = (1-\delta)k_{A,1}^{\text{merged}} + z_A x_{A,1}$$

is is the capital stock carried into period 2 and

$$\Pi_{A,1}^{\text{merged}}(k_{A,1}^{\text{merged}}, h_{A,1}, x_{A,1}) = \zeta_A \left(\left(k_{A,1}^{\text{merged}}\right)^{\alpha} + h_{A,1}^{\alpha}\right)^{\gamma/\alpha} - w_1 h_{A,1} - c_A x_{A,1}$$

2.4.5 Theoretical Biases

Existing studies often overlook the acquired intangibles. Specifically, they ignore the additional capital that the acquirer obtains from the target and the resulting synergies. This omission leads to biased measurements of total factor productivity (TFP), economic profits, and markups.

2.4.5.1 Total Factor Productivity

In the model when the acquirer that merges and obtains capital $k_{A,t}^{\text{merged}}$, the true production function of the merged entity incorporates the combined capital from both firms and any synergies between them

$$y_{A,t} = \zeta_A \left(\left(k_{A,t}^{\text{merged}}\right)^{\frac{\alpha-1}{\alpha}} + h_{A,t}^{\frac{\alpha-1}{\alpha}}\right)^{\frac{\gamma\alpha}{\alpha-1}}.$$

However, output is mismeasured by ignoring the combined capital $k_{A,t}^{\text{merged}}$ and using reported capital $k_{A,t}$ instead. The misspecified production function is

$$\widetilde{y}_{A,t} = \widetilde{\zeta}_A \left(k_{A,t}^{\frac{\alpha-1}{\alpha}} + h_{A,t}^{\frac{\alpha-1}{\alpha}}\right)^{\frac{\gamma\alpha}{\alpha-1}}.$$

While the production function is misspecified, output is still the same, $y_{A,t} = \widetilde{y}_{A,t}$, but, the true

TFP ζ_A of the merged firm is embedded in the production function

$$\widetilde{\zeta}_A = \frac{\widetilde{y}_{A,t}}{\left(k_{A,t}^{\frac{\alpha-1}{\alpha}} + h_{A,t}^{\frac{\alpha-1}{\alpha}}\right)^{\frac{\gamma\alpha}{\alpha-1}}} \tag{2.43}$$

$$\widetilde{\zeta}_A = \zeta_A \frac{\left(\left(k_{A,t}^{\text{merged}}\right)^{\frac{\alpha-1}{\alpha}} + h_{A,t}^{\frac{\alpha-1}{\alpha}}\right)^{\frac{\gamma\alpha}{\alpha-1}}}{\left(k_{A,t}^{\frac{\alpha-1}{\alpha}} + h_{A,t}^{\frac{\alpha-1}{\alpha}}\right)^{\frac{\gamma\alpha}{\alpha-1}}} \tag{2.44}$$

$$\widetilde{\zeta}_A = \zeta_A \left(\frac{\left(k_{A,t}^{\text{merged}}\right)^{\frac{\alpha-1}{\alpha}} + h_{A,t}^{\frac{\alpha-1}{\alpha}}}{k_{A,t}^{\frac{\alpha-1}{\alpha}} + h_{A,t}^{\frac{\alpha-1}{\alpha}}}\right)^{\frac{\gamma\alpha}{\alpha-1}} \tag{2.45}$$

$$\tag{2.46}$$

As long as $k_{A,t}^{\text{merged}} > k_{A,t}$, then the inferred TFP $\widetilde{\zeta}_A$ is biased upwards due to the ignored synergy.

2.4.5.2 Marginal Products

The biases extend to the marginal products. The marginal product of labor is

$$\frac{\partial y_{A,t}}{\partial h_{A,t}} = MPH_{A,t} = \gamma \frac{y_{A,t}/h_{A,t}}{\left(\left(\frac{k_{A,t}^{\text{merged}}}{h_{A,t}}\right)^{\frac{\alpha-1}{\alpha}} + 1\right)}.$$

and when the production function omits acquired intangibles

$$\frac{\partial \widetilde{y}_{A,1}}{\partial h_{A,t}} = \widetilde{MPH}_{A,t} = MPH_{A,t} \frac{\left(\left(\frac{k_{A,t}^{\text{merged}}}{h_{A,t}}\right)^{\frac{\alpha-1}{\alpha}} + 1\right)}{\left(\left(\frac{k_{A,t}}{h_{A,t}}\right)^{\frac{\alpha-1}{\alpha}} + 1\right)}$$

where again if $k_{A,t}^{\text{merged}} > k_{A,t}$ then the marginal product of labor $\widetilde{MPH}_{A,t}$ is overstated. For capital the marginal products clearly differ

$$\frac{\partial y_{A,t}}{\partial k_{A,t}^{\text{merged}}} = MPK_{A,t} = \gamma y_{A,t}^{\frac{\gamma\alpha}{\alpha-1}-1} \left(k_{A,t}^{\text{merged}}\right)^{\frac{\alpha-1}{\alpha}-1} \qquad \frac{\partial \widetilde{y}_{A,t}}{\partial k_{A,t}} = \widetilde{MPK}_{A,t} = \gamma \widetilde{y}_{A,t}^{\frac{\gamma\alpha}{\alpha-1}-1} k_{A,t}^{\frac{\alpha-1}{\alpha}-1}$$

where $MPK_{A,t} > \widetilde{MPK}_{A,t}$.

2.4.6 Implications of Mismeasurement Bias

The biases introduced by ignoring acquired capital and synergies have significant implications. As stated in equation (2.30), after accounting for payments to labor and capital, the residual

Table 2.7: Theoretical Biases From Omitting Acquired Intangibles (Acquirer Firm)

Variable	Economic Model	Misspecified Model (Omitting Intangibles)	Bias $(gr(\widetilde{x}_t) - gr(x_t))$
$y_{A,t}$:	$\zeta_A \left(\left(k^{\text{merged}}_{A,t} \right)^{\frac{\alpha-1}{\alpha}} + h_{A,t}^{\frac{\alpha-1}{\alpha}} \right)^{\frac{\gamma\alpha}{\alpha-1}}$	$\widetilde{\zeta}_A \left(k_{A,t}^{\frac{\alpha-1}{\alpha}} + h_{A,t}^{\frac{\alpha-1}{\alpha}} \right)^{\frac{\gamma\alpha}{\alpha-1}}$	0
$TFP_{A,t}$:	ζ_A	$\widetilde{\zeta}_A = \zeta_A \underbrace{\left(\frac{\left(k^{\text{merged}}_{A,t} \right)^{\frac{\alpha-1}{\alpha}} + h_{A,t}^{\frac{\alpha-1}{\alpha}}}{k_{A,t}^{\frac{\alpha-1}{\alpha}} + h_{A,t}^{\frac{\alpha-1}{\alpha}}} \right)^{\frac{\gamma\alpha}{\alpha-1}}}_{\text{Misspecification}}$	"Superstars"
$MPH_{A,t}$:	$\gamma \frac{y_{A,t}/h_{A,t}}{\left(\left(\frac{k^{\text{merged}}_{A,t}}{h_{A,t}} \right)^{\frac{\alpha-1}{\alpha}} +1 \right)}$	$\widetilde{MP}_h = MPH_{A,t} \underbrace{\frac{\left(\left(\frac{k^{\text{merged}}_{A,t}}{h_{A,t}} \right)^{\frac{\alpha-1}{\alpha}} + 1 \right)}{\left(\left(\frac{k_{A,t}}{h_{A,t}} \right)^{\frac{\alpha-1}{\alpha}} + 1 \right)}}_{\text{Misspecification}}$	Overestimated
Economic Profit Rate:	$\frac{\pi^{econ}_{A,t}}{y_{A,t}} = 1 - \frac{w_t h_{A,t}}{y_{A,t}} - \frac{r_{A,t} k^{\text{merged}}_{A,t}}{y_{A,t}}$ $= (1-\gamma)$	$\frac{\widetilde{\pi_{it}}}{Y_t} = 1 - \frac{w_t n_t}{Y_t} - \frac{\widetilde{r}_{A,t} k_{A,t}}{Y_t}$ $> (1-\gamma)$	Overestimated
Markups:	$\mu_{A,t} = \left(\frac{\partial y_{A,t}}{\partial h_{A,t}} \frac{h_{A,t}}{y_{A,t}} \right) \left(\frac{y_{A,t}}{w_t h_{A,t}} \right)$	$\tilde{\mu}_{A,t} = \mu_{A,t} \frac{\left(\left(\frac{k^{\text{merged}}_{A,t}}{h_{A,t}} \right)^{\frac{\sigma-1}{\sigma}} +1 \right)}{\left(\left(\frac{k_{A,t}}{h_{A,t}} \right)^{\frac{\sigma-1}{\sigma}} +1 \right)}$	Overestimated

profits constitute the economic rents of the firm. These rents reflect the firm's ability to generate profits beyond the necessary payments to its input factors

$$\pi^{econ}_{A,t} = y_{A,t} - MPH_{A,t} h_{A,t} - MPK_{A,t} k^{\text{merged}}_{A,t}.$$

When dividing by output it follows that $\frac{\pi^{econ}_{A,t}}{y_{A,t}} = 1 - \gamma$. If acquired intangibles are omitted, the marginal products are upward biased and economic profits are computed as

$$\widetilde{\pi}^{econ}_{A,t} = y_{A,t} - \widetilde{MPH}_{A,t} h_{A,t} - \widetilde{MPK}_{A,t} k_{A,t}.$$

where dividing by output results in $\frac{\pi^{econ}_{A,t}}{y_{A,t}} > 1 - \gamma$. Consequently, the mismeasured economic profits of the acquirer are overstated: $\widetilde{\pi}^{econ}_{A,t} > \pi^{econ}_{A,t}$.

The upward bias of the marginal products extended beyond profit measurement. The recent "superstar" literature argues that the firm distribution has shift toward toward highly productive firms, a phenomenon that explains the rising industrial concentration over recent decades (Autor et al., 2020). However, our model suggests that when acquired intangibles are omitted, the true level of TFP is overstated. In other words, the upward bias in marginal product estimates does not solely overstate profits; it also distorts the level of productivity across firms.

The implications extend to markups as well. Markups are an indicator of a firm's pricing power and are most commonly derived from cost minimization

$$\mu_{A,t} = \left(\frac{\partial y_{A,t}}{\partial h_{A,t}} \frac{h_{A,t}}{y_{A,t}}\right) \left(\frac{y_{A,t}}{w_t h_{A,t}}\right).$$

When $k_{A,t}^{\text{merged}} > k_{A,t}$ then labor productivity is overestimated and this leads to inflated estimated markups

$$\tilde{\mu}_{A,t} = \mu_{A,t} \frac{\left(\left(\frac{k_{A,t}^{\text{merged}}}{h_{A,t}}\right)^{\frac{\sigma-1}{\sigma}} + 1\right)}{\left(\left(\frac{k_{A,t}}{h_{A,t}}\right)^{\frac{\sigma-1}{\sigma}} + 1\right)} > \mu_{A,t}.$$

Thus, the markup is higher than its true value, with the bias increasing as the level of mismeasured capital $k_{A,t}^{\text{merged}}$ and $k_{A,t}$ grows.

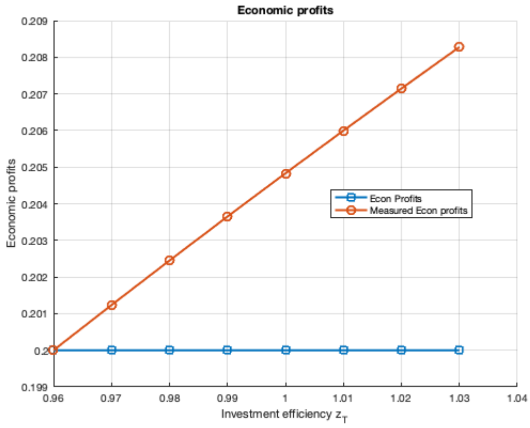
In a numerical exercise, we demonstrate how these theoretical biases emerge when the marginal efficiency of investment of the target, z_T, exogenously declines (see equation (2.25)). Intuitively, a lower z_T reduces the cost of capital investment for the target, enabling them to accumulate more capital. This in turn results in a greater stock of intangibles being acquired through M&A, leading to higher realized synergies. However, when these acquired intangibles are omitted from measurement, the resulting bias distorts metrics such as economic profits, markups and total factor productivity.

Figure 2.7 illustrates how these distortions grow as z_T increases. As targets become more productive at generating intangibles, the gap between the accounting and economic value of these assets widens. Panels (a) and (b) show that while the true economic profits and markups remain flat, their mismeasured counterparts appear to rise.[17] Although these distortions manifest in latent variables, they have observable consequences. Specifically, we show that the bias is tightly linked to cumulative abnormal returns (CAR), which are calculated by comparing the market value of a firm announcing an M&A against an otherwise identical firm that did not engage in a match. Since market value reflects the discounted stream of expected dividends (which is not distorted by mismeasurement) any divergence between CAR and accounting based performance indicators are driven by the omitted value of the acquired intangibles.

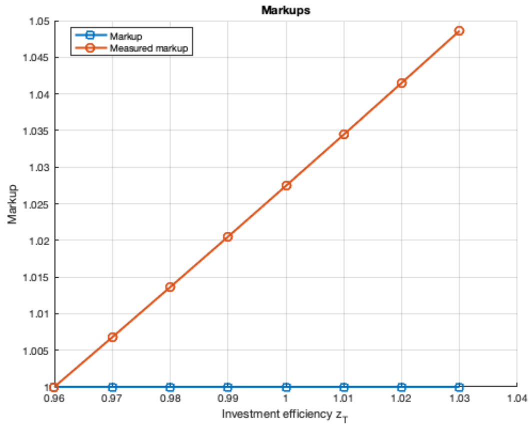
[17] The figures are the same for total factor productivity and the marginal product of labor.

Figure 2.7: Theoretical Biases From Omitting Acquired Intangibles

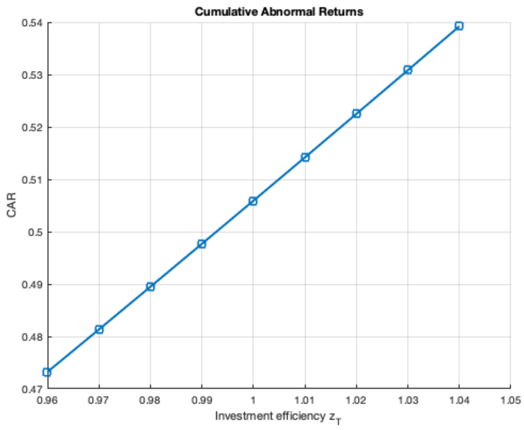
(a) Economic Profits



(b) Markups



(c) CAR As z_T Increases



2.4.7 Correcting the Bias with the User Cost

The value of acquired intangibles in business accounts understates its true economic value. This discrepancy arises because business accounts fail to incorporate the surplus generated during the transaction itself, namely the share of surplus accruing to the acquirer. As acquirers obtained more bargaining power after 2001, the gap between the true economic value of acquired intangibles and its accounting value has grown, further increasing the biases to economic profits. To correct for this measurement bias, we use the model to recover an economic user cost of capital and then use it to compute economic profits. The opportunity cost of acquiring capital is

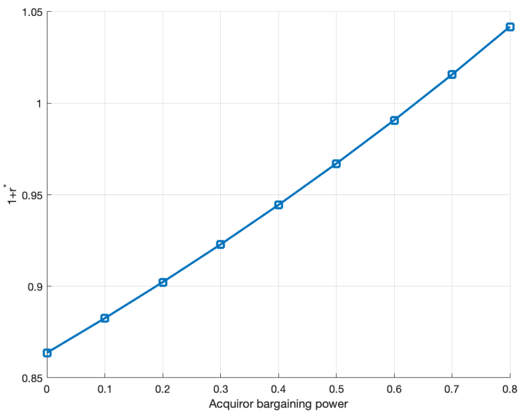
$$r_{A,t}p_{A,t} = MPK_{A,t}k_{A,t}^{\text{merged}} \tag{2.47}$$

$$r_{A,t} = \frac{MPK_{A,t}k_{A,t}^{\text{merged}}}{p_{A,t}} \tag{2.48}$$

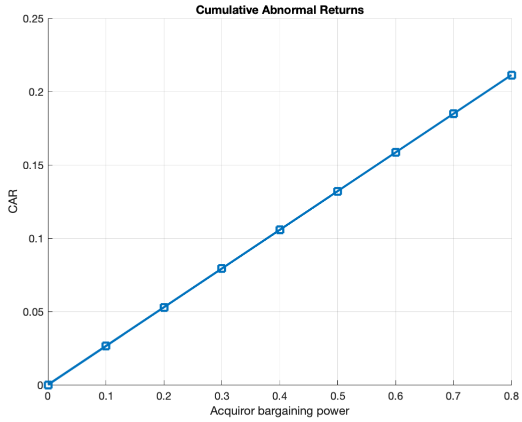
where $r_{A,t}$ is the user cost for the acquirer and p_A is the price paid in the M&A. The right hand side is the economic opportunity cost of acquiring capital where $k_{A,t}^{\text{merged}}$ incorporates the capital obtained from the target $k_{T,t}$ and the M&A synergies. This user cost of capital r_A is imputed

Figure 2.8: Increases in Acquirer Bargaining Power

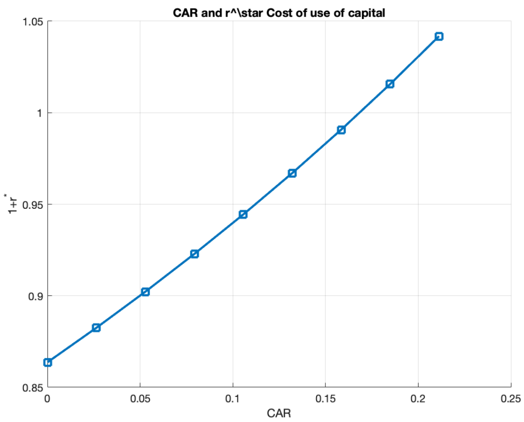
(a) User Cost r_A



(b) CAR



(c) CAR and r_A



through the model.

The user cost correction is closely linked to bargaining power in M&A transactions. When the acquirer has greater bargaining power, it pays a price that is low relative to the marginal product of capital. This implies a higher user cost. Conversely, when the target holds more bargaining power, the price rises and the implied user cost falls. This relationship is illustrated in Figure 2.8. Panel (a) shows that the user cost of capital increases with the acquirer's bargaining power. Panel (b) displays a parallel increase in cumulative abnormal returns (CARs) for acquiring firms. When the acquirer has no bargaining power, there are no abnormal returns, indicating that the acquirer captures no surplus from the deal. As bargaining power of the acquirer increases, so do CARs, reflecting the acquirer's growing ability to extract surplus from the transaction. Panel (c) makes this relationship explicit, plotting the model implied user cost against observed CARs where two series move in close alignment.

To identify this using the model, we exploit the observed increase in CAR for acquiring firms post-2001. The increased CAR that we document in Section 2.3 serve as evidence that acquirers have been capturing a larger share of the surplus in M&A transactions, consistent with a shift in bargaining power. By calibrating the model to match the observed distribution of CAR across deals, we can back out the corresponding user costs $r_{A,t}$. In essence, we use CAR as sufficient statistics for the degree of surplus capture by the acquirer, which in turn informs the economic cost of capital. This identification strategy provides a clear mapping from CAR to user costs: the higher the CAR observed in a given transaction (or period), the greater the implied upward adjustment in the user cost of capital. This allows us to systematically correct for the downward bias in accounting values and recover a user cost measure that reflects the true economic value.

2.5 Conclusion and Next Steps

We show that strategic accounting choices around the recognition of acquired intangibles have significant implications for the measurement of economic profits and labor share. Prior to the 2001 accounting reform, acquirer firms could use the pooling-of-interest accounting method that allowed them to not recognize acquired intangibles. This gave way to report higher accounting profits. Following the banning of the pooling method, we document a shift of bargaining power in favor of acquirers. The valuation of acquired intangibles is difficult, not only in that a portion is not reported in business accounts, but also that the accounting valuation differs from the economic one. This discrepancy arises because business accounts fail to incorporate the surplus generated by the deal. When bargaining power shifted in favor of acquirers after 2001, the gap between acquired intangibles in business accounts widened and the measurement bias of economic profits and markups grew.

We develop a dynamic model in which firms make strategic accounting decisions and search to acquire intangible capital. The model allows us to back out the user cost of acquired intangibles that reflects their true economic value, one that accounts for the surplus embedded in the deal but omitted from the financial statements. This user cost corrects the measurement bias in profits and markups. To identify it, we exploit the model's mapping between the user cost and the post-merger cumulative abnormal return (CAR), both of which depend on the underlying bargaining power in the transaction.

Moving forward, we are developing a full identification strategy for the structural parameters of the model. While we already have a method for recovering the user cost, this mapping is inherently dependent on other model parameters. Once the model is fully calibrated, we will apply the corrected user cost to the acquired intangibles reported in business accounts. We expect our resulting measure of economic profits to be trendless over time and will explore the implications for the long-run trend of the labor share.

Chapter 3

Evaluating the Effects of Mergers and Acquisitions on Firm Performance

with Xufeng Wang[1]

Abstract

Using a nationally representative dataset of Spanish firms we examine how firms that undergo an M&A change over time. We study how mergers and acquisitions (M&As) affect revenue total factor productivity (TFPR), markups, and input-output measures. Our results show that M&As lead to gradual increases in TFPR and markups, with significant gains observable only several years after the deal. Additionally, we find declines in sales, value added, number of employees, and total assets for the combined entities, suggesting a downsizing process post-M&A.

[1]KU Leuven

3.1 Introduction

Mergers and acquisitions (M&A) are a recurring dynamic in the economy and have far-reaching implications for productivity, market power, and consumer welfare. M&A may be beneficial by improving productivity and selection but also can increase concentration within industries by reducing competition and potentially harming consumers. In this paper we assess the effect that M&A has on productivity and markups at the firm level by using a nationally representative dataset for Spain that covers about 63% of the Spanish firm population over the span of 26 years. Through our empirical analysis we find that M&A is not only beneficial for revenue total factor productivity (TFPR), but also leads to higher markups.

The data that we use is administrative firm-level data for Spain from Orbis. Orbis Spain provides standard production-side data where we can observe revenue-based measures from financial statements. This dataset allows us to assess how the consolidation of an acquiring and target firm affects TFPR and markups.[2] Estimating TFPR and markups before and after an M&A is challenging. Unlike studying other firm-level activities such as R&D, trade, or investment where the firms remain distinct entities over time; M&A results in the combination of two firms into one by creating a single surviving entity. Tracking these firms over time is important not only for data consistency, but also for estimation.

The starting point of our analysis is by estimating firm-level value added production functions by NACE 2-digit industry where we assume the functional form to be Cobb-Douglas. Having estimated output elasticities by industry, we are able to obtain TFPR. We then examine how the consolidation of the acquirer and target affects TFPR before and after the merger. We focus on M&A deals occurring within the same two-digit industry (what we refer to as horizontal M&A), which account for approximately half of all M&A deals. By doing so both the acquirer and target share the same output elasticities.

When two firms merge, they consolidate their financial statements, and the newly merged entity reflects the pooled inputs and outputs of both the acquirer and target. A before and after comparison is complicated by the fact that, while two separate firms exist pre-M&A, only one entity remains afterward. A straightforward approach would be to compare the acquirer's TFPR before and after the M&A, as this allows for a direct within-firm comparison. However, we argue that this approach introduces a "merger bias," as it fails to account for the pre-M&A TFPR of the target firm. We show that under some basic assumptions, such as constant returns to scale, that conducting such an analysis would underestimate post-M&A TFPR.

To address this problem, we construct a counterfactual pre-M&A single firm by combining the outputs and inputs of both the acquirer and target. This allows us to obtain a pre-M&A TFPR level as if the two firms had already been merged before the deal. We then compare this counterfactual pre-M&A TFPR to the observed post-M&A TFPR of the merged entity.

[2] We do not have access to product-level information on quantities and prices. Therefore, we cannot track changes in product offerings or pricing strategies following an M&A, such as whether acquirers discontinue products of the target firm.

By consistently applying this method to acquirer-target pairs (treating them as a single firm both before and after the merger) we eliminate the merger bias that arises when the post-M&A acquirer pools its inputs and outputs.

Using difference-in-differences methods we find that the value-added production function-based TFPR starts to gradually increase after about four years and reaches about 10% within seven years of the M&A. We find a larger increase in markups. The changes in TFPR can either be attributed to changes in price or in quantity total factor productivty (TFPQ).[3] Since our dataset lacks product-level pricing information the magnitude and direction of either effect is ambiguous. That said, the rise in firm-level markups suggests that output prices likely increase. Additionally, we observe a decline in post-M&A sales and value added coinciding with a larger drop in employment and total assets. The decline in the latter reflects the elimination of redundant resources as two firms combine while the decline in production potentially indicates an increase in market power through a restriction of of quantity supplied. Despite these reductions, we find that both the average revenue products of labor (value added over employment) and capital (value added over total assets) increase.

Related Literature and Contribution There are few papers that study effects of M&A for productivity and market power (Asker & Nocke, 2021). For those that do, the effects of M&As on productivity and market power are mixed. Most existing work studies specific industries using price and quantity data. Braguinsky, Ohyama, Okazaki, and Syverson (2015) examine the the Japanese cotton spinning industry in the early 20th century and find that M&As led to both higher profitability and productivity. They attributed these gains to cost savings through better inventory management and higher capacity utilization. In a recent paper, Demirer and Karaduman (2024) study the the US electricity generation industry and find productivity gains. Both papers provide evidence for productivity gains from operational reorganization and acquisition of underperforming assets from less productive targets. While the previous papers find no evidence of price increases, some work does. Ashenfelter, Hosken, and Weinberg (2015) and Miller and Weinberg (2017) find price increases in the US brewing industry, but significantly smaller increases in regions that experienced greater cost declines after mergers. Kulick (2017), on the other hand, studies M&A within the ready-mix concrete industry and also finds increases in prices and productivity. He finds that price increases are larger than productivity gains.

An advantage of the aforementioned papers is that they use quantity based measures allowing them to disentangle price and productivity effects. However, such data are often difficult to obtain, whereas revenue-based measures from financial statements are more widely available. In these contexts, researchers typically rely on TFPR and markup estimates following Loecker and Warzynski (2012) where the latter is inferred as a measure of market power. The ambiguous effects of M&A on productivity, however, are further compounded as neither prices nor pure productivity improvements are directly observed. Blonigen and Pierce (2016) analyze US manufacturing plants and find that markups increase after acquisition but no significant change in TFPR. Similarly,

[3]See Foster, Haltiwanger, and Syverson (2008).

Stiebale and Szücs (2022) analyze European firms and find that that markups rise significantly after M&As, particularly in highly concentrated markets. They argue that these increases are unlikely to reflect productivity gains, as the increase coincides with declines in value added, investment, employment, and innovation.

Most of this literature focuses on narrow industry settings, with the broadest scope typically limited to the manufacturing sector. Our first contribution is to extend this analysis by using a nationally representative dataset to examine the dynamic effects of M&As. We find that M&As are associated with rising TFPR and markups, along with a downsizing of production. Second, a challenge in this literature is that most exisiting work relies on data sources that allow authors to observe the separate outcomes of acquirers and targets. We are unable to do this as targets disappear in Orbis and are consolidated into the financial statements of the acquirer. This is a common feature in other commonly used datasets like Compustat. To address this, we construct a pseudo pre-M&A firm to measure TFPR and markups prior to M&A's. To our knowledge, this is the first attempt to systematically correct for the consolidation-induced bias in large-scale financial datasets.

Outline The paper is organized as follows. Section 3.2 provides a description of the data. Section 3.3 outlines the production function estimation, challenges that we face in the data and our proposed method of identifying changes post-M&A. Section 3.4 presents the empirical results. Section 3.5 concludes.

3.2 Data

The main dataset used in this paper is from Orbis Global and Orbis M&A (previously known as Orbis Zephyr) both of which are databases maintained by Bureau van Dijk (BvD), a Moody's Analytics company. We exploit administrative firm-level data for Spain from Orbis Global (referred interchangeably as Orbis Global, Orbis Historical, or Orbis Spain in the paper). We specifically choose Spain because it is one of the countries with the best coverage in Orbis. The database includes public and private firms' balance sheets, income statements, and detailed information on firms' ownership, location, and industry. The data in Orbis Spain is obtained from financial statements that all firms in Spain are legally required to submit to the Commercial Registry (Registro Mercantil) every year.[4] While it does not cover the universe of firms, the coverage in Orbis Spain is quite large. Using this data, we are able to construct a representative sample of the aggregate economy between 1997-2022, covering an annual average of 63% of registered firms.[5]

[4]This information is highly reliable, as firms are bound by law to provide accurate information on their financial situation. Failure to do so can result in fines and even criminal charges. Furthermore, the tax administration routinely cross-checks the information provided in these financial statements with corporate income tax returns submitted by firms to ensure that they are consistent.

[5]We follow Kalemli-Özcan, Sørensen, Villegas-Sanchez, Volosovych, and Yeşiltaş (2024). Appendix C.2 provides details how the representative sample was constructed from the raw data. Appendix C.2 shows how the sample compares to aggregate data from Spanish National Accounts.

We use Orbis M&A to link M&A deals with Orbis Spain. The database contains information on M&A, IPO, Private Equity, Venture Capital operations and related rumors from around the world without limits on deal size. Orbis M&A is constantly updated and companies involved in the deals are easily linked to Orbis Spain. For the purposes of our analysis, we focus specifically on domestic M&A deals in Spain. In addition to deal characteristics, Orbis M&A records multiple dates for each deal, such as the announcement date, completion date and assumed completion date. For our analysis, we use the announcement year documented in Orbis M&A as the reference point for when a deal takes place. We do not differentiate between mergers and acquisitions and we refer to all deals collectively as M&A. Appendix C.1 contains more information regarding Orbis Spain and M&A. Finally, Orbis Spain offers firm-level financial data, including revenue-based metrics such as sales, value added, total assets, and employee count. However, it lacks product-level details on quantities and prices for its products and services. Consequently, our measures of productivity and markups are the the firm level rather than the product level. In addition, our M&A analysis is unable to assess explicit changes in product offerings or prices before and after a deal.

3.3 Methodology

3.3.1 Production Function

We examine the dynamics of firms involved in M&As both before and after the deals, focusing not only on changes in inputs and outputs but also for total factor productivity (TFP) and markups. To analyze these effects, we estimate production functions at the firm level. It is well known that estimating output elasticities is subject to several bias such as selection bias, measurement errors and most importantly, simultaneity bias. As a result, OLS estimates for output elasticities tend to be biased and consequently TFP and markups as well. We employ the control function approach, which allows us to obtain more accurate estimates of output elasticities.

In our benchmark production function estimation, we follow D. Ackerberg, Caves, and Frazer (2015), assuming a value added Cobb-Douglas production function with Hicks-neutral technology. Many studies differentiate between the concepts of TFPR (revenue-based total factor productivity) and TFPQ (quantity-based total factor productivity). The productivity measure that we observe is TFPR as our output variable is measured in monetary terms and we lack quantity and price data. Furthermore, we make no assumptions regarding the competitive environment in which firms operate; firms can charge different prices and have variable markups. The value-added production function is given by

$$Y_{it} = A_{it} K_{it}^{\beta_k} L_{it}^{\beta_l} e^{\epsilon_{it}} \tag{3.1}$$

where Y_{it} represents the value added of firm i at time t. The variable K_{it} denotes the capital input for firm i at time t, which is determined in the previous period. L_{it} refers to the number of employees employed in the production process. We assume that that labor is a dynamic variable as we believe it to be subject to adjustment costs making labor serially correlated over time.[6] The term A_{it} stands for productivity, which can be observed by firms when making their production

[6] Spain has particularly stringent firing costs and high structural unemployment.

decisions, while ϵ_{it} represents unobservable shocks to production that firms cannot foresee or predict when making input decisions at time t, or measurement errors in output. The term $A_{it}e^{\epsilon_{it}} \equiv Z_{it}$ represents total factor productivity (TFP), which can be obtained after estimating the output elasticities of labor (β_l) and capital (β_k).

When taking the logarithm of the value-added production function, the equation becomes

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \epsilon_{it}$$

where the lowercase letters (y, k, l) denote the logarithms of the corresponding variables (Y, K, L). In this equation, β_0 represents the average productivity level across firms, while ω_{it} captures productivity shocks that firms might be able to observe or anticipate when making their input decisions but are remain unobservable to the econometrician.

To identify productivity, it needs to satisfy the strict monotonicity assumption, i.e., the demand for materials must increase with productivity after controlling for labor, capital, and an additional variable vector E_{it} that can affect the demand for materials

$$m_{it} = f_t(k_{it}, l_{it}, \omega_{it}, E_{it}).$$

The vector E_{it} includes additional controls such as the market share of the firm, the location of the firm, and the type of the firm (e.g., whether the firm is a corporate or financial firm, and whether it is public or not). It is important to note that E_{it} does not include any M&A-related variables. In our estimation of production functions, we consider only firms that have never been involved in an M&A or prior to participating in one. Our rationale is as follows. Our estimation relies on the strict monotonicity of the materials proxy, which assumes that higher productivity leads to greater materials demand, holding other inputs constant. However, post-M&A firms may experience changes in market power that alter this relationship. Specifically, even if a merger increases TFPR, the newly merged firm may strategically reduce output due to increased market power, thereby lowering its demand for materials. This would break the expected positive relationship between productivity and materials demand, violating the strict monotonicity assumption. Thus, we can invert ω_{it} or firms not involved in M&As and for firms prior to an M&A, obtaining

$$\omega_{it} = g_t(k_{it}, m_{it}, l_{it}, E_{it}).$$

Nevertheless, excluding firms involved in M&As after the deal may introduce selection bias. For instance, conditional on capital and employment levels, firms involved in M&A may have higher relatively higher TFPR or are more profitable as pointed out in David (2021). To address this, we follow the approach of De Loecker, Goldberg, Khandelwal, and Pavcnik (2016), who apply the Olley and Pakes (1996) selection correction procedure to account for selection bias between single-product and multi-product firms. In our case, we adapt this procedure to correct for selection bias from using firms not involved in M&As and firms prior to engaging in M&A.

We define an indicator variable, χ_{t+1}, where $\chi_{t+1} = 1$ if a firm remains a non-M&A-involved firm at time $t+1$, and $\chi_{t+1} = 0$ if the firm becomes either an acquirer or a target in the next period. The probability of remaining a non-M&A firm is given by

$$\begin{aligned}
\Pr\{\chi_{it+1} =& 1 \mid \bar{\omega}_{it+1}(k_{it+1}, a_{it+1}), J_t\} \\
=& \Pr\{\omega_{it+1} \leq \bar{\omega}_{it+1}(k_{it+1}, l_{it+1}) \mid \bar{\omega}_{it+1}(k_{it+1}, l_{it+1}), \omega_{it}\} \\
=& \varphi_t\{\bar{\omega}_{it+1}(k_{it+1}, l_{it+1}), \omega_{it}\} \\
=& \varphi_t(m_{it}, k_{it}, l_{it}, i_{it}, E_{it}) \\
\equiv& P_{it}
\end{aligned}$$

where J_t represents the information set at time t, i_t is investment, and l_t is included as it is assumed to be a dynamic variable. This equation captures the selection process in which firms either continue operating independently or become involved in an M&A (as either an acquirer or a target). Firms face a threshold productivity level $\bar{\omega}_{it+1}$ above which they are more likely to engage in an M&A. If a firm's productivity ω_{it+1} exceeds the threshold then it may opt to be involved in an M&A, whereas firms below the threshold are more likely to continue operating independently. The selection function φ represents the probability of a firm remaining a non-M&A entity conditional on firm characteristics.

Finally, we assume that the evolution of productivity is

$$\omega_{it} = g(\omega_{it-1}, P_{it}) + \epsilon_{it}^{\omega}$$

where ϵ_{it}^{ω} represents the innovation to the productivity shock and is not correlated with pre-determined variables. The parameters (β_k, β_l) in the production function are estimated by NACE 2-digit industry using the standard GMM procedure. Appendix C.3 provides the estimates for when we use the capital input as total assets (our default) and fixed assets.

3.3.2 Data Challenges and Solutions for M&A Analysis

Having developed a method to estimate production function we turn to preparing our dataset for analyzing M&A. Our merged dataset of Spain Orbis and Orbis M&A provides a large representative firm-level sample of the Spanish economy. However, using this data directly for the empirical evaluation of M&A effects on firm-level outcomes comes with a number of challenges. One complication is tracking target firms after the M&A announcement as two firms merge into a single entity often resulting in the target firm disappearing from the dataset. In our dataset, more than 90% of target firms involved in M&As within the same NACE 2-digit industry disappear and are merged into their acquirer.[7] This leads to inconsistencies in the data, as the surviving firm's financial statements reflect the combined operations of both entities, thereby obscuring the change in individual pre to post-M&A characteristics and performance of the acquirer and

[7] If we to include deals that occur outside of the same NACE 2-digit industry then more than 60% of targets are merged into their acquirer.

target. As we demonstrate in the next section, conducting an analysis using unadjusted data risks introducing substantial bias for TFPR and markups.

Another issue that arises in our dataset is determining the accurate timing of M&A deals. In our dataset we use the year of the announcement date as the reference point when the deal occurs. However, we observe discrepancies in the timing of target firm disappearances relative to the M&A announcement date. Specifically, we find that 5,729 targets disappear one year before the announcement of the M&A, 2,194 targets disappear two years before, and 442 targets disappeared three years before (see Appendix Table C.1.3). We consider it reasonable for targets to disappear one period before the announcement date, but not two or three periods prior. To address this issue, we adjust the year of the deal announcement date based on the target firm's disappearance. Specifically, if the target firm disappeared two or three years before the M&A date and its latest status is recorded as "Dissolved (merger or take-over)" or "Dissolved (demerger),” we revise the M&A year to the year following the last year in which the firm appears in the data. As a robustness check we drop target firms that disappear two or more years prior to the announcement deal and obtain similar results.

Keeping track of acquirers and targets, as well as, the timing of the deal improves the accuracy of our results but is not without limitations. To further improve the precision of our results we impose two restrictions in our M&A analysis. First, we focus on firms that participate in only one M&A transaction during the sample period. Figure 3.1 shows the distribution of firms that repeatedly act as acquirers or targets where it is clear that most acquirers and targets engage in one deal. Fewer than 20% of firms are repeat acquirers, while fewer than 5% are repeat targets. While including firms with multiple M&A events and identifying changes in TFPR is theoretically possible, it is challenging to implement in practice. As a result, excluding repeat acquirers somewhat limits the generalizability of our findings, however, we view this as necessary to more accurately identify changes in TFPR. Second, we focus only on deals that occur within the same NACE 2-digit industry which we refer to as "horizontal M&A". Figure 3.1 depicts the NACE 2-digit industry information for acquirer-target pairs. Among these pairs, 46% of the deals involve an acquirer and target from the same industry while the rest of the deals include pairs from different industries. In section 3.3.3.3 we explain why acquirers and targets being from the same industry is important for the calculation of TFPR and markups in our analysis.

3.3.3 Measuring TFPR Changes Pre- and Post-M&A

In this section we outline the methodology for analyzing TFPR changes before and after M&A. While our discussion is tailored to our specific data and challenges, the approach is broadly applicable to any M&A analysis involving acquirers. Our research question is about how M&A affects the TFPR of transacting firms. Specifically, we want to examine how TFPR evolves post-M&A relative to its pre-M&A values. A before-and-after comparison is challenging because two separate firms exist before the M&A but merge into one afterward. A natural approach might be to compare the acquirer's TFPR before and after the M&A, as this allows for a direct within-firm comparison. However, we argue that this method leads to misleading results due to

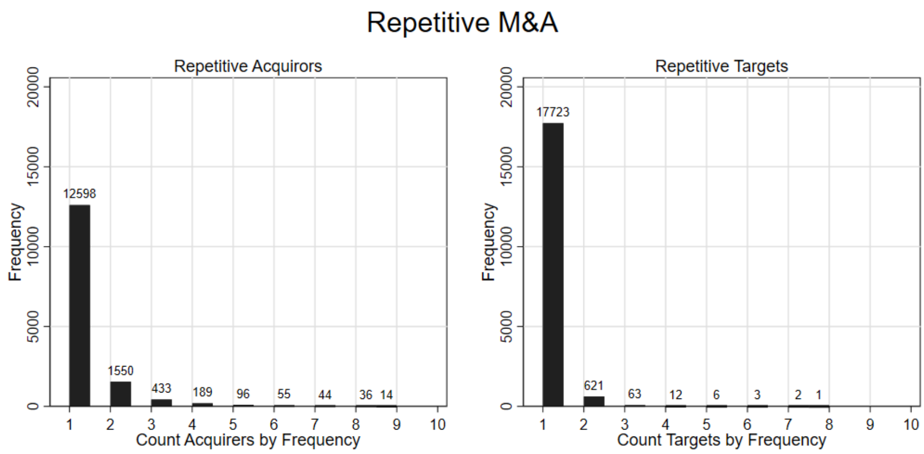


Figure 3.1

Note: This graph depicts the distribution of repetitive acquirers and targets in M&A transactions. The left chart represents the frequency distribution of firms by the number of times they have engaged in M&A transactions as acquirers. The right chart represents the frequency distribution of firms by the number of times they have been acquired in M&A transactions.
Source: Author's calculations using Orbis Spain and Orbis M&A.

what we call a "merger bias." This bias arises because it fails to fully account for the pre-M&A TFPR of the target firm.

To address this problem, we construct a counterfactual pre-M&A single firm by combining the outputs and inputs of the acquirer and target. This allows us to obtain a pre-M&A TFPR level as if the two firms had already been merged before the deal. We then compare this counterfactual pre-M&A TFPR to the observed post-M&A TFPR of the acquirer. By consistently applying this method to acquirer-target pairs (treating them as a single firm both before and after the merger) we eliminate the merger bias that arises when the post-M&A firm pools its inputs and outputs.

3.3.3.1 Merger Bias

We begin by demonstrating how the bias arises following an M&A within the same industry where an acquirer and target become one firm. Let $Y_{i,j} \equiv P_{i,j,t}Q_{i,j,t}$ be the value added produced where $P_{i,j,t}$ is its price and $Q_{i,j,t}$ is quantity. The subscript i denotes if a firm is an acquirer A or target T, j is an indicator for pre-M&A ($j = 0$) and post-M&A ($j = 1$). The subscript t denotes the time period. The value added production function is

$$Y_{i,j,t} = Z_{i,j,t}K_{i,j,t}^{\beta_k}L_{i,j,t}^{\beta_l}, \quad \text{for } i \in \{A, T\} \text{ and } j \in \{0, 1\}$$

where $Z_{i,j,t}$ is firm level TFPR. Post-M&A, we are unable to observe $Y_{i,1,t}$, $K_{i,1,t}$, and $L_{i,1,t}$ separately for the acquirer and target after the merger, as most targets disappear from the dataset and are fully absorbed into the acquirer. In our dataset, we only observe the financial statements of the acquirer post-M&A, which is the pooled variables of both acquirer and target:

$$Y_{A,1,t}^{\text{pooled}} \equiv Y_{A,1,t} + Y_{T,1,1}, \quad K_{A,1,t}^{\text{pooled}} \equiv K_{A,1,t} + K_{T,1,t}, \quad L_{A,1,t}^{\text{pooled}} \equiv L_{A,1,t} + L_{T,1,t}.$$

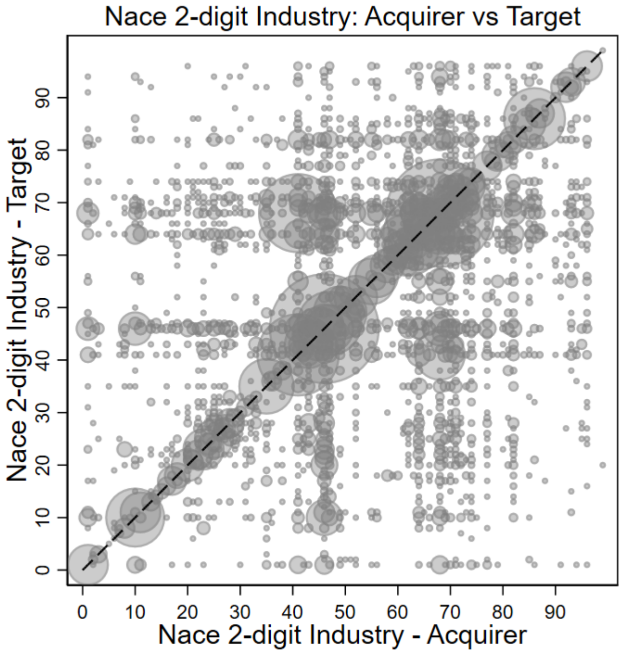


Figure 3.2

Note: This graph depicts the NACE-2 digit industry distribution of acquirer-target pairs. The x-axis represents the NACE-2 industry code of the acquirer, while the y-axis represents the NACE-2 industry code of the target. The size of each circle corresponds to the number of M&A deals that have occurred in the respective acquirer-target industry pairs. Larger circles indicate a higher frequency of deals between acquirers and targets occurring in those industry pairs, while smaller circles suggest fewer deals. The dashed line represents the diagonal, showing where acquirers and targets belong to the same industry (i.e., when the NACE-2 codes for both the acquirer and the target are identical).
Source: Author's calculations using Orbis Spain and Orbis M&A.

The pooled TFPR of the post-M&A acquirer is given by

$$Z^{\text{pooled}}_{A,1,t} = \frac{Y^{\text{pooled}}_{A,1,t}}{\left(K^{\text{pooled}}_{A,1,t}\right)^{\beta_k}\left(L^{\text{pooled}}_{A,1,t}\right)^{\beta_l}} = \frac{Z_{A,1,t}K^{\beta_k}_{A,1,t}L^{\beta_l}_{A,1,t} + Z_{T,1,t}K^{\beta_k}_{T,1,t}L^{\beta_l}_{T,1,t}}{(K_{A,1,t}+K_{T,1,t})^{\beta_k}(L_{A,1,t}+L_{T,1,t})^{\beta_l}} \tag{3.2}$$

where the output elasticities (β_k, β_l) in the production function are identical for all firms within their industry. Equation 3.2 highlights that acquirer's observable pooled post-M&A TFPR $Z^{\text{pooled}}_{A,1,t}$ depends on both the acquirer's individual post-M&A TFPR, $Z_{A,1,t}$ and the target's $Z_{T,1,t}$, neither of which is observable in the data.

To analyze the impact of M&A, we would ideally compare $Z_{A,1,t}$ with $Z_{A,0,t}$ for the acquirer and $Z_{T,1,t}$ with $Z_{T,0,t}$ for the target. Given our limited data on targets, we could compare the acquirer's post-M&A TFPR, $Z^{\text{pooled}}_{A,1,t}$, with its pre-M&A TFPR $Z_{A,0,t}$ by computing its change as

$$\Delta Z = Z^{\text{pooled}}_{A,1,t} - Z_{A,0,t}.$$

However, this approach introduces a bias because it fails to account for the target's pre-merger TFPR, $Z_{T,0,t}$. The comparison would only be unbiased if $Z^{\text{pooled}}_{A,1,t} = Z_{A,1,t}$, meaning that the pooled TFPR is identical to the acquirer's post-M&A TFPR.

In what follows, we demonstrate that under common assumptions for production functions, it is almost always the case that $Z^{\text{pooled}}_{A,1,t} \neq Z_{A,1,t}$. Specifically, we consider constant returns to scale in production ($\beta_k + \beta_l = 1$) and a constant input ratio (i.e., $\lambda \equiv \frac{K_{A,1,t}}{K_{T,1,t}} = \frac{L_{A,1,t}}{L_{T,1,t}}$).

Proposition 1. Let $Z_{A,1,t}$ be the post-M&A TFPR of the acquirer by itself, and $Z^{\text{pooled}}_{A,1,t}$ the TFPR obtained using the pooled data from the acquirer that is observed in the data. Consider two assumptions for production functions: constant returns to scale ($\beta_k + \beta_l = 1$) and constant input ratios ($\lambda \equiv \frac{K_{A,1,t}}{K_{T,1,t}} = \frac{L_{A,1,t}}{L_{T,1,t}}$).

1. Only constant returns to scale.

   (a) When $Z_{A,1,t} \neq Z_{T,1,t}$, then

   $$Z^{\text{pooled}}_{A,1,t} \leq Z_{A,1,t}(\beta_k s_{K_A} + (1-\beta_k)s_{L_A}) + Z_{T,1,t}(\beta_k s_{K_T} + (1-\beta_k)s_{L_T}),$$

   where $s_{X_i} = \frac{X_{i,1,t}}{X_{A,1,t}+X_{T,1,t}}$ for $X \in \{K, L\}$ and $i \in \{A, T\}$.

   (b) When $Z_{A,1,t} = Z_{T,1,t}$, then

   $$Z^{\text{pooled}}_{A,1,t} \leq Z_{A,1,t}.$$

   Proof. See Appendix C.6.1.1. ■

2. Only constant input ratios.

   (a) When $Z_{A,1,t} \neq Z_{T,1,t}$, then

   $$Z^{\text{pooled}}_{A,1,t} = \frac{Z_{A,1,t}\lambda^{\beta_k+\beta_l} + Z_{T,1,t}}{(\lambda+1)^{\beta_k+\beta_l}}.$$

   (b) When $Z_{A,1,t} = Z_{T,1,t}$, then

   $$Z^{\text{pooled}}_{A,1,t} = Z_{A,1,t}\frac{\lambda^{\beta_k+\beta_l}+1}{(\lambda+1)^{\beta_k+\beta_l}}.$$

   Proof. See Appendix C.6.1.2. ■

3. Both constant returns to scale and constant input ratios.

   (a) When $Z_{A,1,t} \neq Z_{T,1,t}$, then

   $$Z^{\text{pooled}}_{A,1,t} = \frac{Z_{A,1,t}\lambda + Z_{T,1,t}}{\lambda+1}.$$

   (b) When $Z_{A,1,t} = Z_{T,1,t}$, then

   $$Z^{\text{pooled}}_{A,1,t} = Z_{A,1,t}.$$

   Proof. See Appendix C.6.1.3. ■

Proposition 1 shows that under common assumptions, $Z^{\text{pooled}}_{A,1,t}$ always depends on the TFPR of both the acquirer $Z_{A,1,t}$ and the target $Z_{T,1,t}$, meaning that $Z^{\text{pooled}}_{A,1,t} \neq Z_{A,1,t}$. There is one exception, which is when both CRS and constant input ratios are assumed. If the TFPR of the acquirer and target are equal, $Z_{A,1,t} = Z_{T,1,t}$, then $Z^{\text{pooled}}_{A,1,t} = Z_{A,1,t}$.

3.3.3.2 Constructing a Pre-M&A Firm

Comparing an acquirer's pre-M&A TFPR $Z_{A,0,t}$ with its post-M&A TFPR $Z^{\text{pooled}}_{A,1,t}$ produces misleading results as it does not take into account the pre-M&A TFPR of the target $Z_{T,0,t}$. To address this, we construct a consolidated acquirer-target pair that aggregates the information of both acquirers and targets before the M&A. This approach ensures that the pre- and post-M&A performance of the involved firms can be accurately compared. Appendix C.1.5 provides details on how we generate these pairs. Once we pool together outputs and inputs of the counterfactual pre-M&A firm, we obtain its productivity level

$$Z^{\text{pooled}}_{A,0,t} = \frac{Y^{\text{pooled}}_{A,0,t}}{K^{\text{pooled},\beta_k}_{A,0,t} L^{\text{pooled},\beta_l}_{A,0,t}} = \frac{Y_{A,0,t} + Y_{T,0,t}}{(K_{A,0,t} + K_{T,0,t})^{\beta_k} (L_{A,0,t} + L_{T,0,t})^{\beta_l}} \tag{3.3}$$

In our analysis, we compare the post-M&A TFPR $Z^{\text{pooled}}_{A,1,t}$ of the acquirer/pooled firm with its pre-M&A counterfactual by computing its change as

$$\Delta Z \equiv Z^{\text{pooled}}_{A,1,t} - Z^{\text{pooled}}_{A,0,t}. \tag{3.4}$$

If $\Delta Z > 0$, we conclude that TFPR has increased after the M&A, where differences in TFPR can arise from three endogenous effects and a random productivity shock

$$\underbrace{\Delta Z}_{\text{productivity difference}} \equiv \underbrace{\underbrace{\Delta Z_{\text{resource reallocation}}}_{\text{internal reallocation}} + \underbrace{\Delta Z_{\text{synergy}}}_{\text{merger synergy}} + \underbrace{\Delta Z_{\text{market power}}}_{\text{price effects}}}_{\text{merger gain (endogenous)}} + \underbrace{\Delta Z_{\text{shock}}}_{\text{productivity shock}} . \tag{3.5}$$

The reallocation effect captures the internal restructuring of a firm's inputs and outputs following an M&A. In addition, merger synergies may arise from integrating assets, technologies, or processes, as well as from reductions in fixed costs. Any impact on returns to scale would also be captured here. Finally, changes in TFPR could stem from price effects; however, since we estimate TFPR rather than physical productivity, we cannot separately identify changes driven by price effects.

We refer to these three endogenous components—reallocation, synergy, and price effects—as the merger gain. Because we lack price and quantity data, we cannot disentangle their individual contributions. As a result, any increase in TFPR following an M&A remains ambiguous, as it could stem from genuine productivity improvements, market power effects, or a combination of both. The last term is a random productivity shock. If we compare TFPR directly before and after the M&A, we cannot eliminate the impact of productivity shocks. To account for these factors, we employ econometric techniques to isolate the endogenous components of productivity gains in our empirical analysis.

3.3.3.3 Extension to Vertical M&A

Up to this point, we have assumed that the acquirer and target operate within the same 2-digit industry, what we call a horizontal M&A. We now entertain the possibility of when the acquirer and target are from different industies (what we call a vertical M&A). We estimate production functions by 2-digit industry, meaning that in the vertical M&A case, acquirer target output elasticities differ, ie $\beta_{s,1} \neq \beta_{s,2}$ for $s \in \{k, l\}$. This complicates obtaining the pre-M&A TFPR $Z^{\text{pooled}}_{A,0,t}$ for an acquirer-target pair. Whereas for horizontal M&As $Z^{\text{pooled}}_{A,0,t}$ is obtained in a straightfoward manner (equation 3.3), the pre-M&A counterfactual firm for vertical M&As does not have a well-defined production function under a single set of output elasticities. This is because the acquirer and target initially operate under distinct production technologies. One possible way to address this issue is to construct a weighted average of the acquirer's and target's elasticities, based on their relative contributions to total output or inputs. However, this approach requires additional assumptions about the relative importance of each firm's technology. Furthermore, input complementarities in vertical M&As may alter production technology itself, making the estimation of TFPR changes even more complex. Given these challenges, we restrict our analysis to horizontal M&As.[8]

3.4 Empirical Analysis

3.4.1 Descriptives

Using our merged dataset, we categorize firms into three distinct groups. The first group, consists of firms that have never participated in any M&A activity. The second group, acquirers, includes Spanish firms that have acted as buyers in horizontal M&A transactions. The third group, targets, consists of Spanish firms that have been acquired in such transactions.

Table 3.1 shows the pooled average of acquirers and targets one year before their first M&A happened within the sample period (1997-2022). The non-M&A group is the pooled average for the entire sample period. The table shows that both acquirers and targets are much larger than firms in the non-M&A group. When comparing the number of employees of acquirers and targets to the national firm size distribution for Spain, as documented in Appendix C.2.3, we find that both acquirers and targets are among the largest firms and in the economy. Acquirers tend to be even larger than targets, with employment levels more than twice as high. They

[8]Nonetheless, we conducted the analysis despite the differing output elasticities where we assume that the pre-M&A firm has the output elasticities of the acquirer. We find similar results to those obtained for horizontal M&As and are available upon request.

Table 3.1: Descriptive Statistics: One Year before M&A

Varname	Non-M&A	Acquirers	Targets
Sales	1813.97	20 373.46	6615.39
Added Value	427.64	5302.46	1311.28
Ebitda	126.31	2450.39	351.59
Long Term Ddebt	1049.65	18 627.88	3808.02
Costs of Employees	309.23	2564.13	1075.17
Number of Employees	11.02	67.62	29.98
Total Assets	3561.09	56 409.52	18 506.68
Fixed Assets	1908.35	39 401.52	7436.23
Age	12.41	16.48	13.90

Notes: The table compares the pooled averages of sales, added value, cost of employment, and number of employees among the non-M&A group (firms not involved in M&A), acquirers, and targets. The information for acquirers and targets is taken from one period prior to their first involvement in M&A as acquirers or targets.
Source: Authors' calculations using Orbis Spain and Orbis M&A.

also are larger than targets in terms of value added, assets (by more than three times), and profitability/EBITDA (by over five times). Despite these differences, acquirers and targets have similar ages, differing by only three to four years on average. Table C.4.1 in Appendix C.4 shows the pooled averages for all three groups over the entire sample period, rather than just the year before a deal. We find the similar results.

We then turn to looking at the lifecycle of the three groups. Figure C.4.1 in Appendix C.4 shows how sales, value added, labor, and capital for these three groups by age grow between the year of birth (1) to 20 years of age (see the equivalent Table C.4.2 in the Appendix). We observe that both acquirers and targets are born large and continue to grow over time. Overall, we observe a positive trend between firm age and value added, as well as employment. For instance, in the non-M&A group, the average number of employees increases from approximately 6 at birth to 12.7 by age 20. Among acquirers, this figure rises from around 35 to 70, while for targets, it grows from 20 to 32. Acquirers tend to start with more assets, which stabilize in the early years of their lifecycle. In contrast, asset growth is more modest for both targets and firms in the non-M&A group.

3.4.2 Difference-in-Differences Discussion

In the previous subsection, we outlined the characteristics of each group. Here, we employ econometric tools to formally analyze how firms behave before and after an M&A deal, specifically examining variables like TFPR, markups and more. To identify the effect of M&A activities on firm-level outcomes and mitigate the issues discussed in Section 3.3.3, we use our constructed acquirer-target paired dataset. In our data 90% of merged firms post-M&A are already pooled, we pool together the remaining 10%. This results in an acquirer-target pair observed both before and after the M&A event. Since M&A activities occur in different years, the treatment in our analysis is staggered.

Recent advancements in the differences-in-differences (DID) methodology have highlighted that the treatment effect in staggered DID designs cannot be estimated in the same way as in classical DID, where all treatment groups receive the treatment simultaneously. The classical DID estimator[9], β^{fe} , which estimates the average treatment effect, is biased in the staggered setting and may not even estimate a convex combination of treatment effects (see Borusyak, Jaravel, and Spiess (2024), De Chaisemartin and d'Haultfoeuille (2020), de Chaisemartin and d'Haultfoeuille (2023)). Meanwhile, the commonly used Two-Way Fixed Effect Event Study Estimator (TWFE ES), β_l^{fe}, which estimates the cumulative effect of having been exposed to treatment for l periods is also biased and not robust to heterogeneous effects (even under parallel trends) when treatment is staggered (Sun & Abraham, 2021). The TWFE Event Study regression is specified as follows

$$Y_{it} = \alpha_i + \gamma_t + \sum_{l \neq -1} \beta_l^{fe} D_{it}^l + \epsilon_{it},$$

where $D_{it}^l = 1\{t - E_i = l\}$ is an indicator function and E_i represents the time when firm i (the acquirer-target pair) gets involved in a M&A transaction for the first time. Thus, D_{it}^l is a relative time indicator that equals 1 if acquirer-target pair i at time t has been exposed to the treatment for $l > 0$ periods. The event occurs when $l = 0$ which marks the period when acquirer-target pair i announce the M&A deal. Finally, D_{it}^l always equals 0 for the control group.[10] Y_{it} is the dependent variable which represents the logarithm of the variable we are interested in (ie, TFPR, markups, etc). Thus, the results from the regressions are to be interpreted as percentage deviations relative to the first year before M&A. In this model, α_i denotes the individual fixed effect, γ_t represents the time fixed effect and ϵ_{it} is the error term.[11] It is important to note that the ϵ_{it} in this regression is distinct from the error terms in other regressions (like in equation (3.1)).

To circumvent the issues mentioned above for the TWFE Event Study Estimator, there are a number of proposed heterogeneity-robust difference-in-differences estimators (see Callaway and Sant'Anna (2021), Sun and Abraham (2021), De Chaisemartin and d'Haultfoeuille (2024), and Borusyak et al. (2024)). The main intuition behind these estimators for staggered DID designs is similar, however, what makes them different is that they estimate cohort-specific or group-specific event-study effects and then aggregate them in a distinct manner.

For instance, in the design where treatment is staggered and binary (as is the case for us), the estimator from Sun and Abraham (2021), Callaway and Sant'Anna (2021), and De Chaisemartin and d'Haultfoeuille (2024) run the following regression, which estimates cohort-specific event-study

[9]The Classical DID regression is given by:

$$Y_{it} = \alpha_i + \gamma_t + \beta^{fe} D_{it} + \epsilon_{it},$$

where α_i is the individual fixed effect, γ_t is the time fixed effect, and D_{it} is an indicator that equals 1 when unit i has been treated at time t. Finally, ϵ_{it} represents the error term.

[10]We later consider two control groups. One being firms that are never involved in M&A deals and the other being treated firms before treatment.

[11]Our results are robust to industry-time fixed effects

treatment effects

$$Y_{it} = \alpha_i + \gamma_t + \sum_{c \in C} \sum_{l \neq -1} \beta^{fe}_{c,l} D^{c,l}_{it} + \epsilon_{it}$$

where $D^{c,l}_{it} = 1\{E_i = c \ \& \ t - E_i = l\}$, and E_i represents the year when the acquirer-target pair i is first involved in an M&A transaction. The term c represents the cohort, which is the year in which the M&A deal occurs for a firm. Thus, $D^{c,l}_{it}$ is a time-cohort indicator that equals 1 where if at time t acquirer-target pair i who belongs to cohort c has been exposed to treatment (M&A) for l periods. Like before, $l = 0$ marks the period when acquirer-target pair i announce the M&A deal and it equals 0 for all periods before the M&A deal, as well as, for all firms that are in the control group. The parameter $\beta^{fe}_{c,l}$ estimates the cohort-specific event-study effect for cohort c that has completed the M&A for l periods. The event-study average treatment effect for being exposed to M&A for l periods (which is equivalent to β^{fe}_{l} in the TWFE Event Study estimator) is a weighted average of the selected cohort-specific event-study effects.[12] We report the main results results using the estimator from Callaway and Sant'Anna (2021) and provide results from alternative estimators in the appendix.

3.4.3 Regression Results

3.4.3.1 Revenue Total Factor Productivity

This section examines the effect of M&A's on TFPR with an event study using the Callaway and Sant'Anna (2021) estimator. Results using different estimators are in Appendix C.5.1. Figure 3.3 presents the results where the treatment group is the matched acquirer-target pairs as described in Section 3.3.3.2. We only consider M&As that occur within the same NACE 2-digit industry and only firms involved in one M&A deal during the sample period.

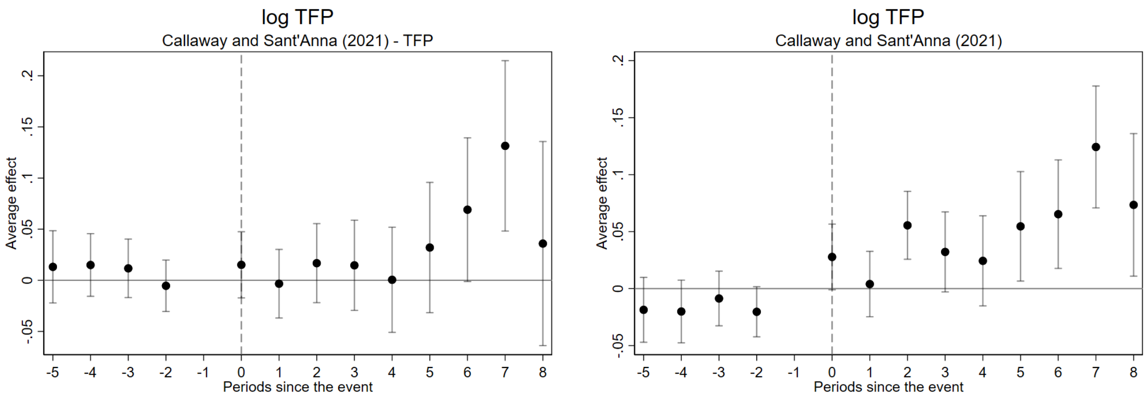
To identify the causal effect of M&As, we employ two different control groups. One control group consists of firms that are treated but have not yet undergone an M&A (Figure 3.3a). By comparing the treatment group with itself prior to treatment we potentially reduce any selection bias. However, this approach has certain limitations. Since the control group consists exclusively of firms that eventually undergo an M&A, we cannot fully account for potential confounding effects, such as ΔZ_{shock} in equation (3.5), even if the pre-trend assumption is satisfied. Furthermore, using this control group limits the number of observations as most firms in our sample are never involved in an M&A.

We consider an alternative control group by also including firms who are never involved in an

[12] When the data is balanced and the never-treated group is used as the controlled group, the event-study average treatment effect for being exposed to M&A for l periods, as defined by Sun and Abraham (2021) and Callaway and Sant'Anna (2021), is given by:

$$ATT_l = \sum_{c \in C} 1\{c + l \leq T\} \frac{N_c}{N_l} \beta^{fe}_{c,l},$$

where N_c denotes the number of firms in cohort c, N_l denotes the number of firms that reach their l-th period of exposure to M&A, and T indicates the last year in the data in which at least one firm has not been involved in M&A. The estimator from Borusyak et al. (2024) runs a different regression.



(a) Not Yet Treated (b) Never Involved and Not Yet Treated

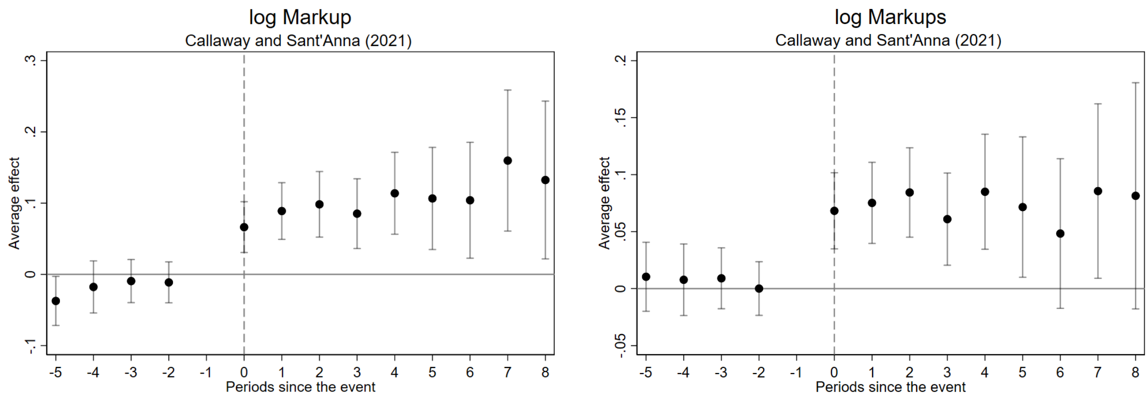
Figure 3.3: Effect of M&A on TFPR

Note: This figure presents the event study effect of M&A on TFPR using the Callaway and Sant'Anna (2021) estimator. The figure on the left is the regression using firms that have been involved in an M&A but not yet treated (ie, before the M&A deal occurs) as the control group. The figure on the right uses both firms that have never been involved in an M&A and firms not yet treated as the control group. The bands represent 95% confidence intervals with standard errors clustered at the firm level.
Source: Author's estimation using Orbis Spain and Orbis M&A.

M&A during the sample period (Figure 3.3b). This specification provides a broader comparison by comparing whether firms engaging in M&As experience systematically different TFPR trends compared to firms that remain independent. However, never-involved M&A firms are quite different from firms participating in M&A making the two groups somewhat less comparable. For the treatment group, we use the acquirer-target pairs for whom we have pooled the data consistently both before and after the M&A. Therefore, if the placebo test is satisfied (ie, the trends of acquirer-target pairs and the control group are parallel), any observed changes before and after the M&A can be attributed as the effect of M&As on TFPR.

When the not yet treated serve as the control group in Figure 3.3a we find limited TFPR gains in the first four years following the M&A. Beyond this period, we observe a gradual increase where TFPR reaches approximately 13% by year seven. On the other hand, Figure 3.3b also includes firms never involved in an M&A as the control group. We find that there is a more pronounced increase in TFPR. When using this control group, TFPR gains emerge earlier and continue to rise ultimately reaching approximately 12% by year seven similar to Figure 3.3a. The estimated average treatment effect on the treated is about 5%.

Both specifications suggest that the benefits of M&As take time to materialize as they gradually become apparent after four years. The choice of control group affects the interpretation of results. The not yet treated group isolates the within-firm effect of M&As and focuses on firms already on the path to acquisition. In contrast, the never involved plus the not yet treated control group includes firms that never merge which provides a broader comparison of whether M&A firms exhibit systematically different TFPR trajectories. While the similarity of findings across control groups suggests that our results are not solely driven by the choice of comparison group, we consider the never involved and not yet treated firms to be a more comprehensive control group.



(a) Not Yet Treated (b) Never Involved and Not Yet Treated

Figure 3.4

Note: This figure presents the event study effect of M&A on markups using the Callaway and Sant'Anna (2021) estimator. The figure on the left is the regression using firms that have been involved in an M&A but not yet treated (ie, before the M&A deal occurs) as the control group. The figure on the right uses both firms that have never been involved in an M&A and firms not yet treated as the control group. The bands represent 95% confidence intervals with standard errors clustered at the firm level.
Source: Author's estimation using Orbis Spain and Orbis M&A.

When using only the not yet treated as the control group we limit the number of observations because the never-involved in M&A firms account for a large proportion of the sample. We therefore prefer including the never involved as it increases the statistical precision.

3.4.3.2 Markups

In this section, we examine the effect of M&A on markups. In the estimation of the value added production we assumed capital and labor to both be dynamic inputs. Consequently, we can not construct markups at the firm level with our value added production. However, we can analyze markups for the gross output Cobb-Douglas production function assuming that the materials input is flexible. Because toutput elasticities are constant, we can measure variation in the markup using the deviation of the logarithm of the inverse of intermediates' share without explicitly estimating a the gross output production production function (Bils, Klenow, & Malin, 2018). Our regression is in logarithmic form and includes firm-level fixed effects, we estimate changes in the markup using the following regression

$$\ln\left(\frac{1}{\frac{p_m M}{\text{Sales}}}\right)_{it} = \alpha_i + \gamma_t + \sum_{c\in C}\sum_{l\neq -1} \beta^{fe}_{c,l} D^{c,l}_{it} + \epsilon_{it},$$

where $\frac{1}{\frac{p_m M}{\text{Sales}}}$ represents the inverse material share.

We find that for the not yet treated control group the markup increases by about 10% in the first five years and is around 12% around year eight. We find a similar pattern for the never involved and not yet treated group, though the increases are lower for year five and beyond. The increase in both regressions reflects a reduction in material costs relative to sales. This suggests that firms gain market power following M&As and that they do not fully pass these cost savings on to consumers. Appendix C.5.2 contains the results of the event study using the De Chaisemartin and d'Haultfoeuille (2024) estimator which are similar.

3.4.3.3 Inputs and Outputs

This section analyzes the impact of M&As on measures of output and input. As in the previous sections, we compare the combined inputs and outputs of acquirer-target pairs before and after the M&A. We present the results for sales, value added, number of employees and total assets here in the main text and report additional variables in Appendix C.5.3. Figure 3.5 shows the results using the estimator from Callaway and Sant'Anna (2021) using treated firms before treatment as the control group. In terms of output, we observe a decline in both sales and value added following an M&A with reductions ranging from 25% to 35% by year eight. The results do not necessarily imply that both the acquirer and the target separately are smaller following an M&A but rather they suggest that the combined production of the merged entity declines over time.

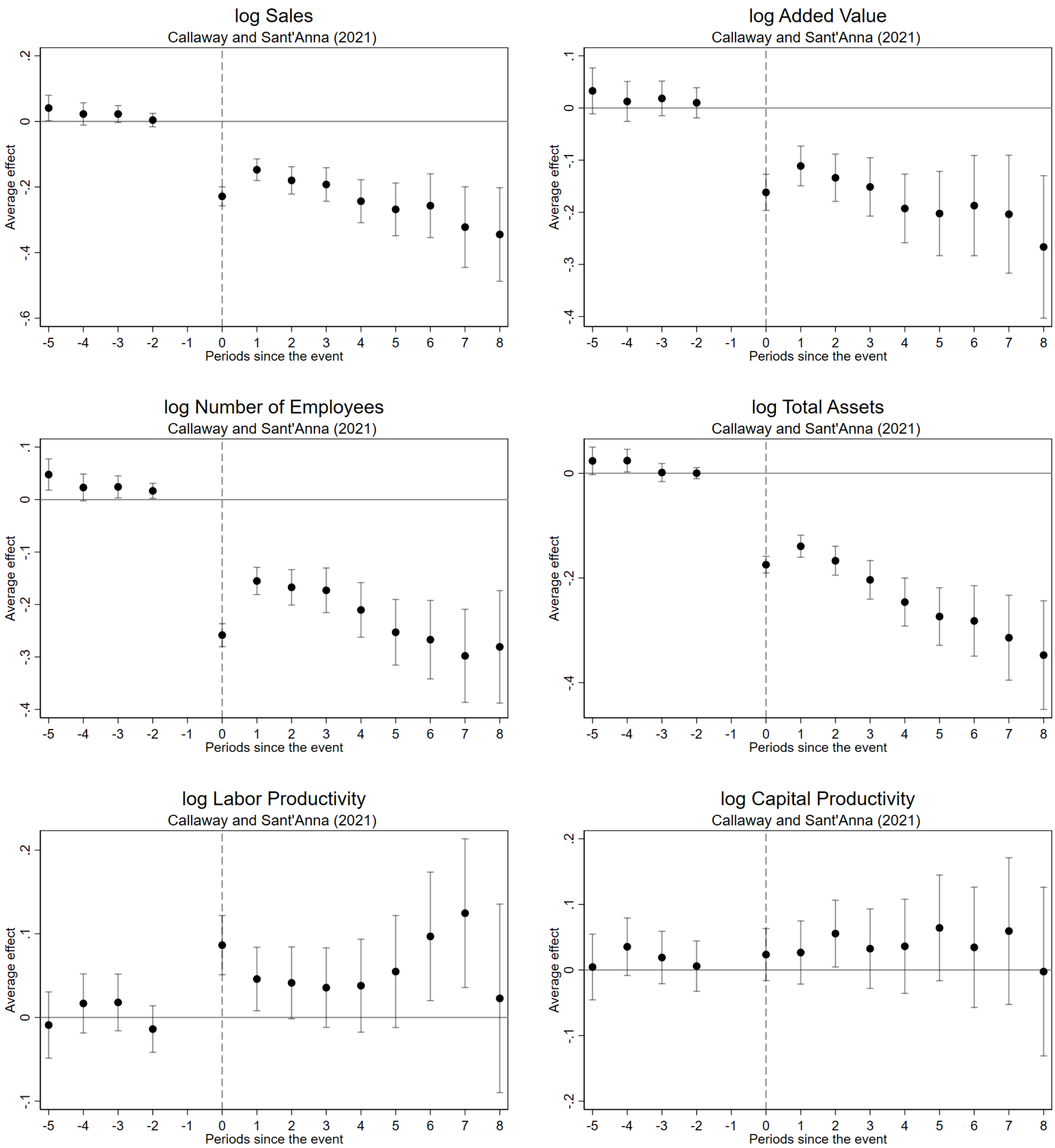


Figure 3.5: M&A Effect on Inputs and Outputs

Note: The figure presents the event study effect of M&A on sales, value added, number of employees and total assets for acquirer-target pairs (before and after the M&A) using the Callaway and Sant'Anna (2021) estimator. The regressions use firms that have been involved in M&A but not yet treated (i.e., before the M&A deal occurs) as the control group. The bands represent 95% confidence intervals with standard errors clustered at the firm level.
Source: Author's estimation using Orbis Spain and Orbis M&A.

We observe a similar pattern for the number of employees and total assets with declines in the range of 30% to 35% by year eight. However, we also observe a slight pre-existing downward trend in employment. In addition to the decline in overall input and output measures, we provide the results for the average revenue products of labor and capital, measured as value added per worker and value added per unit of capital in the bottom two subfigures titled labor and capital productivity. Following an M&A, we observe an increase in both the average revenue products with that of labor reaching a 10% increase by year seven. We also find that post-M&A firms generated more value added per unit of capital but we find this increase to be insignificant. The increases in the average revenue products are because the decline in the usage of workers and capital is greater than the decline in value added. In Appendix C.5.3, we report results using the De Chaisemartin and d'Haultfoeuille (2024) estimator. The pretrend from the estimation is slightly different in that it is declining for sales and assets in addition to number of employees, nevertheless, we find a similar post-M&A decrease across all variables at comparable rates.

One potential concern is that the observed decrease in input and output for acquirer-target pairs could be driven by the data matching process. When matching acquirer-target pairs, 90% of the targets disappear from Orbis Spain once the deal becomes effective as explained in Section 3.3. To alleviate any concern that the target firms are not consolidated in the acquirer's financial reports, we separately report the results for acquirers and for the 10% of targets that remain available in the data in Appendix C.5.3.1 and C.5.3.2.

For the acquirers we find that the both sales and value added initially increase following the years after the M&A (reflecting the consolidation of the acquirer's and target's accounts), but then begin to decline steadily. We observe the same pattern for number of employees and total assets. For target firms, sales and value added appear slightly higher after five years, though the change is not statistically significant. We find no significant post-M&A changes in the number of employees or total assets for targets. The standard errors are large which is likely due to the limited number of observations available for targets.

3.5 Conclusion

This paper examines the effects of mergers and acquisitions (M&As) on firm performance, focusing on TFPR, markups, and input-output dynamics using a nationally repersentative dataset of Spanish firms. Our results show that M&As lead to gradual increases in both TFPR and markups, with significant gains emerging only after several years. In terms of input-output measures, we observe declines in sales, value added, employees, and assets, indicating a process of downsizing post-merger.

In terms of future research we plan to build on the empirical findings of the simultaneous increases in both TFPR and markups at the firm level. We plan to develop a firm dynamics model with variable markups, capital investment and endogenous entry and exit to study the aggregate implications of M&As. Specifically, we aim to assess the effect of M&As on allocative efficiency. In doing so, we will quantify how M&As' impact on productivity and market power at the firm level affects aggregate dynamics. While M&As may enhance aggregate productivity through selection, they may also increase market power through consolidation, potentially discouraging entry and reducing investment. We expect to find that the gains to M&A for aggregate productivity and GDP are limited compared to a model without variable market power.

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Appendix A

Chapter 1 Appendix

A.1 Model Details

A.1.1 The Bargaining Problem

Let the foreign multinational f be the bidder and the domestic incumbent d the target. To simplify notation I write the value of the foreign subsidiary as $V_f \equiv V(a, k_I, k_T, f)$ and of the domestic target $V_d \equiv V(a, k_I, k_T, d)$. Let $S(a, k_I, k_T) \geq 0$ and p_d be the total surplus of acquisition and price at which the target is sold.

The bidder's surplus is

$$\Sigma_f(p_d) = V_f - \kappa_{ts} - p_d - \overbrace{V_f^x}^{=0}$$

The value of the target under foreign ownership is V_f. The foreign multinational's outside option V_f^x is no entry into the economy and is normalized to zero.

The target's surplus is

$$\Sigma_d(p_d) = p_d - V_d$$

where V_d is the value of the domestic target.

The total surplus of the acquisition is

$$S = \Sigma_f(p_d) + \Sigma_d(p_d)$$
$$S = V_f - V_d - \kappa_{ts}$$

By assumption the two firms have equal bargaining power and the price, p_d^*, solves the Nash bargaining problem.

$$p_d^* = \arg\max_{p_d \geq 0} \ \frac{1}{2} \ln\left(\Sigma_f(p_d)\right) + \frac{1}{2} \ln\left(\Sigma_d(p_d)\right)$$

subject to

$$\Sigma_f(p_d) \geq 0 \qquad\qquad \text{and} \qquad\qquad \Sigma_d(p_d) \geq 0$$

Note that if the price causes either of the surpluses to be negative then the objective function is undefined. Due to the strict concavity of the objective function there exists a unique interior solution p_d^* for a given negotiating pair. Taking the first order condition $\frac{d}{dp_d} = 0$:

$$\begin{aligned} -\frac{1}{2\Sigma_f(p_d)} + \frac{1}{2\Sigma_d(p_d)} &= 0 \\ \Sigma_f(p_d) &= \Sigma_d(p_d) \\ V_f - \kappa_{ts} - p_d &= p_d - V_d \\ V_f - \kappa_{ts} + V_d &= 2p_d \\ V_f - \kappa_{ts} + V_d - V_d &= 2p_d - V_d \\ \underbrace{V_f - V_d - \kappa_{ts}}_{=S} + 2V_d &= 2p_d \end{aligned}$$

The optimal acquisition price is

$$p_d^* = V_d + \frac{S}{2}$$

It follows then

$$\Sigma_f(p_d^*) = \Sigma_d(p_d^*) = \frac{S}{2} > 0$$

A.1.2 Stationary Equilibrium Formally Defined

To simplify the equilibrium exposition denote the states as $s = (a, k_I, k_T, o)$. Define the compact sets $a \in \mathbf{A} = [\underline{a}, \overline{a}]$, $k_I \in \mathbf{K_I} = [\underline{k}_I, \overline{k}_I]$, $k_T \in \mathbf{K_T} = [\underline{k}_T, \overline{k}_T]$ and the countable set $o \in \mathbf{O} = \{d, f\}$ as all possible values of TFP, intangible capital, tangible capital and ownership type. The state space $\mathbf{S}$ is the Cartesian product $\mathbf{A} \times \mathbf{K_I} \times \mathbf{K_T} \times \mathbf{O}$ and the σ-algebra $\Sigma_\mathbf{S}$ is defined as $\mathbf{B}(\mathbf{A}) \times \mathbf{B}(\mathbf{K_I}) \times \mathbf{B}(\mathbf{K_T}) \times \mathbf{P}(\mathbf{O})$ where $\mathbf{B}(\mathbf{Z})$, $\mathbf{B}(\mathbf{K_I})$ and $\mathbf{B}(\mathbf{K_T})$ are the Borel σ-algebras on $\mathbf{A}$, $\mathbf{K_I}$ and $\mathbf{K_T}$ and $\mathbf{P}(\mathbf{O})$ is the power set of $\mathbf{O}$. The space $(\mathbf{S}, \Sigma_\mathbf{S})$ is a measurable space. Let $\mathcal{S} = (\mathcal{A} \times \mathcal{K_I} \times \mathcal{K_T} \times \mathcal{O})$ be a typical subset of $\Sigma_\mathbf{S}$. For any element of the σ-algebra $\mathcal{S} \in \Sigma_\mathbf{S}$, $\lambda(\mathcal{S})$ is an invariant probability measure of firms in set $\mathcal{S}$.

Law of Motion Firms transit across states over time through a transition function; $Q : \mathbf{S} \times \Sigma_\mathbf{S} \longrightarrow [0,1]$ and

$$Q(s, \mathcal{S}) = (1-\xi)\,[1-\chi(s)] \int_{a' \in \mathcal{A}} \mathbb{1}_{k_I'(s) \in \mathcal{K_I}} \mathbb{1}_{k_T'(s) \in \mathcal{K_T}}\, d\Gamma(a'|a). \tag{A.1.1}$$

where $\mathbb{1}_{\{.\}}$ is an indicator function and $k_I'(s)$ and $k_T'(s)$ are the policy functions for intangible and tangible capital levels in the next period. As previously defined, ξ is an exogenous exit shock and $\chi(s)$ is the exit policy function. The conditional distribution a is $\Gamma(a'|a)$.

To distinguish between ownership states o I denote the state vectors for domestic and foreign ownership as $s_d = (a, k_I, k_T, d)$ and $s_f = (a, k_I, k_T, f)$. Abusing notation I denote the measures conditional on ownership as $\lambda(s_d) = \lambda(a, k_I, k_T \mid o = d)$ and $\lambda(s_f) = \lambda(a, k_I, k_T \mid o = d)$. Each period there are domestic firms that change ownership states (ie leaving $\lambda(s_d)$ and joining $\lambda(s_f)$). The measure of firms λ consists of three components which are defined as follows

$$\begin{gathered}\text{Matched Domestic Owned Firms}\\ P_M(s_d) \equiv \mu \int_{\mathbf{S}} \left[\mathbb{1}_{\{S(s_d)>0\}} + (1 - \mathbb{1}_{\{S(s_d)>0\}})\right] Q(s_d, \mathcal{S}) d\lambda(s_d)\end{gathered} \tag{A.1.2}$$

$$\begin{gathered}\text{Unmatched Domestic Owned Firms}\\ P_U(s_d) \equiv (1 - \mu) \int_{\mathbf{S}} Q(s_d, \mathcal{S}) d\lambda(s_d)\end{gathered} \tag{A.1.3}$$

$$\begin{gathered}\text{Foreign Owned Firms}\\ P_F(s_f) \equiv \int_{\mathbf{S}} Q(s_f, \mathcal{S}) d\lambda(s_f).\end{gathered} \tag{A.1.4}$$

Matched domestic owned firms in equation (A.1.2) is the measure of domestic firms that meet a foreign multinational entrant with probability μ. The first term are firms that get acquired and transit to the $\lambda(s_f)$ in the same period. The second term are matched firms that do not reach an agreement and remain in the measure $\lambda(s_d)$. Unmatched domestic firms in equation (A.1.3) do not meet a foreign multinational entrant and remain under domestic ownership. Finally, the measure of foreign owned firms in equation (A.1.4) consists of firms that were acquired in the past and have not exited.

For all $(\mathcal{A} \times \mathcal{K_I} \times \mathcal{K_T} \times \mathcal{O}) \in \Sigma_{\mathbf{S}}$ the invariant measure of firms λ satisfies the law of motion

$$\lambda(\mathcal{A} \times \mathcal{K_I} \times \mathcal{K_T} \times \mathcal{O}) = [P_M(s_d) + P_U(s_d) + P_F(s_f)] + M \int_{a' \in \mathcal{A}} dG(a'). \tag{A.1.5}$$

The firm term in brackets accounts for transiting incumbent firms that choose to continue operating. These incumbents may exit or operate at different states in the following period. The second term is the mass of entrants that enter in the next period and draw their initial TFP level from CDF $G(a')$, which is the stationary distribution of a.

SRCE Definition A stationary recursive competitive equilibrium (SRCE) consists of prices (w_s, w_u), an invariant measure of firms λ, a constant mass of potential entrants M, a value function for incumbent firm $V(s)$, a value function for the entrant firm V_e, policy functions for the incumbent firm $l_s(s)$, $l_u(s)$, $k'_I(s)$, $k'_T(s)$, $\chi(s)$, and for the entrant firm $k'_{I,e}$, $k'_{T,e}$ such that

1. Given prices, the policy functions $l_s(s)$, $l_u(s)$, $k'_I(s)$, $k'_T(s)$, $\chi(s)$ solve the incumbent firm's problem in equation (1.5) with the associated value function $V(s)$. The policy functions $k'_{I,e}$ and $k'_{T,e}$ solve the entrant firm's problem with the associated function V^e in equation (1.6).

2. Given prices, households of type $i \in \{s, u\}$ with mass N_i maximize utility in equation (1.12) subject to the budget constraint in equation (1.13). Aggregate labor supplied is $L_i = N_i h_i$.

3. Matched domestic firms transfer ownership only if the total acquisition surplus in equation (1.7) is strictly positive. The aggregate sale price is $P_d = \mu \int \mathbb{1}_{\{S(s_d)>0\}} p(s_d) d\lambda(s_d)$.

4. Markets clear

   (a) Skilled labor: $L_s = \int_{\mathbf{S}} l_s(s) d\lambda(s)$

   (b) Unskilled labor: $L_u = \int_{\mathbf{S}} l_u(s) d\lambda(s)$

   (c) Goods:[1] $C + X_I + X_T + \kappa_e M = \int_{\mathbf{S}} (\mathcal{F}(z, k_I, k_T, l_s(s), l_u(s)) - \kappa_{op}) d\lambda(s) + P_d - \Pi_f$

5. The invariant measure of firms λ satisfies equation (A.1.5).

6. The free entry condition is satisfied: $V_e = 0$.

A.1.3 Decomposition of Steady State Changes

This subsection explains how output Y, TFP Z and the wage skill premium are decomposed by ownership type. Starting with the decomposition of output, let aggregate output be $Y = Y_d + Y_f$ where the subscript denotes ownership type. The change between steady states is

$$g_y = \frac{Y_{\text{new}} - Y_{\text{initial}}}{Y_{\text{initial}}} \qquad g_{y,d} = \frac{Y_{d,\text{new}} - Y_{d,\text{initial}}}{Y_{\text{initial}}} \qquad g_{y,f} = \frac{Y_{f,\text{new}} - Y_{f\text{initial}}}{Y_{\text{initial}}} \tag{A.1.6}$$

where g_y is the aggregate change, while $g_{y,d}$ and $g_{y,f}$ are changes in output by domestic and foreign firms. Note that the denominator Y_{initial} is the same for all. It follows that $g_y = g_{y,d} + g_{y,f}$. Aggregate TFP Z is decomposed the same way.

Wage Skill Premium The decomposition of the wage skill premium is a bit more involved given that all firms pay the same each to each skill type i. I approximate the contribution by ownership to the change in the wage skill premium by log-linearizing the ratio of marginal products of labor. As firms are perfectly competitive, the wage skill premium is equal to the ratio of the marginal products of labor by skill type. The skill premium is as follows where aggregate variables can be separated by ownership type

[1]where

i. Aggregate profits by ownership type $o \in \{d, f\}$ are $\Pi_o = \int_{\mathbf{S}} \pi_o(s) d\lambda(s)$ and foreign dividends Π_f flow out the economy.

ii. Investment for capital type $j \in \{I, T\}$ is $X_j = p_j \int_{\mathbf{S}} (k_j'(s) - (1 - \delta_j) k_j) d\lambda(s)$.

$$\omega = \frac{MPL_s}{MPL_u}$$

$$\omega = \frac{\varsigma\varrho}{(1-\varsigma)} \left[(1-\varrho)\left(\frac{K_I}{L_s}\right)^{\rho} + \varrho\right]^{\frac{\sigma-\rho}{\rho}} \left(\frac{L_u}{L_s}\right)^{1-\sigma}$$

$$\omega = \frac{\varsigma\varrho}{(1-\varsigma)} \left[(1-\varrho)\left(\frac{\sum_{o\in\{d,f\}} K_{I,o}}{\sum_{o\in\{d,f\}} L_{s,o}}\right)^{\rho} + \varrho\right]^{\frac{\sigma-\rho}{\rho}} \left(\frac{\sum_{o\in\{d,f\}} L_{u,o}}{\sum_{o\in\{d,f\}} L_{s,o}}\right)^{1-\sigma}. \tag{A.1.7}$$

Log-linearizing this expression around the initial steady state approximates the between steady state change in wage skill premium

$$g_\omega \approx \underbrace{(\sigma-\rho)\sum_{o\in\{d,f\}} \Xi_o \left(g_{K_{I,o}} - g_{L_{s,o}}\right)}_{\text{Intangible-Skill Complementarity Effect}} + \underbrace{(1-\sigma)\sum_{o\in\{d,f\}} \left(g_{L_{u,o}} - g_{L_{s,o}}\right)}_{\text{Relative Quantity Effect}} \tag{A.1.8}$$

where

$$\Xi = \frac{(1-\varrho)\left(\frac{K_{I,o,\text{initial}}}{L_{s,o,\text{initial}}}\right)^{\rho}}{(1-\varrho)\left(\frac{K_{I,o,\text{initial}}}{L_{s,o,\text{initial}}}\right)^{\rho} + \varrho}.$$

Equation (A.1.8) consists of two additive terms that affect g_ω differently. The first term is the intangible-skill complementarity effect which is present when $\sigma - \rho > 0$. A larger increase in the aggregate intangible stock relative to skilled labor ($g_{K_I} > g_{L_s}$) increases the wage skill premium. The second component, the relative quantity effect, shows that relatively faster growth in skilled labor supply ($g_{L_u} < g_{L_s}$) reduces the skill premium.

Table A.1.1 displays the approximate wage skill premium change between the initial and new steady states broken down by ownership and the two effects. The second row shows the change in the wage skill premium. The approximate change is 3.7%, which coincides with the percentage point increase of the wage skill premium in Table 1.8. The final two columns decompose growth by ownership with foreign ownership accounting for approximately 24% (0.9/3.7). Domestic ownership contributes more to the change in the wage skill premium because its overall distributional mass is larger relative to foreign ownership. However, foreign ownership's impact on wages is particularly remarkable, despite the small number of foreign-owned firms. This is due to their significant scale, which magnifies their influence in the aggregate.

Table A.1.1: Decomposition of Wage Skill Premium Change (in pp.)

	Total g_ω	Domestic $g_{\omega,d}$	Foreign $g_{\omega,f}$
Wage Skill Premium Change	+3.7	+2.8	+0.9
Intangible-Skill Complementarity Effect	+4.5	+3.1	+1.4
Relative Quantity Effect	-0.8	-0.3	-0.5

Notes: The table displays the decomposition of the approximated wage skill premium change between the initial (2002-2006) and new (2013-2017) steady states. The second column is the approximated total change. The third and fourth columns are growth by ownership type and when added together equal the total change. The final two rows displays the two additive terms in equation A.1.8.

The final two rows present the two effects. The intangible-skill complementarity effect is larger for domestic firms. This is because its increase in skilled labor $g_{L_{s,d}}$ is relatively lower than that from foreign $g_{L_{s,f}}$. While the supply of skilled labor increased, both in terms of hours and overall number of workers, it is higher for foreign-owned firms as more labor (of both types) is reallocated to them due to increased acquisitions ($g_{L_{s,d}} < g_{L_{s,f}}$). Consequently, this weighs down the intangible-skill complementarity effect for foreign-owned firms. The relative quantity effect embodies the change on the extensive margin of skill (more skilled workers relative to unskilled) and the intensive margin of hours supplied. This effect is ultimately weaker than the intangible-skill effect. In terms of ownership, the effect experiences a smaller decrease of 0.3 for domestic firms while the decrease is greater for foreign ones at 0.5. The difference is again due to the larger amount of skilled workers reallocated to foreign firms ($g_{L_{s,d}} < g_{L_{s,f}}$).

A.2 Firm-Level Data

The firm-level data used in the paper is from the Survey on Business Strategies (ESEE in Spanish). It is a representative survey of Spanish manufacturing firms with 10 or more employees. Section 1.2.3 provides a description of the survey. Section A.2.1 contains variable definitions and Section A.2.2 explains how firm-level TFP is estimated. Summary statistics are in Table A.6.1.

A.2.1 ESEE Variable Definitions

This subsection describes the variables from the ESEE used in the paper. Unless stated otherwise, all variables are deflated by the manufacturing sector gross output price index with base year 2015 provided by INE.

- **Sales**. The sales of goods, the sales of transformed products (finished and half-finished), the provision of services and other sales (packages, packaging, byproducts and waste).
- **Value Added**. The sum of sales, the variation in stocks and other management income, minus intermediates.

- **Employment**. Number of personnel.
- **Wage Bill**. All gross salaries and wages, compensations, social security contributions paid by the company, the contributions made to supplementary pension systems and other social expenses.
- **Skilled and Unskilled Employment**. Skilled employment is the number of personnel with a tertiary education or higher. Unskilled employment is personal without a tertiary education.
- **Labor Hours**. Total effective hours worked. Determined by multiplying number of personal by effective hours worked per employee. Hours effectively worked during the year per worker is equal to the sum of the normal work time and overtime minus the non-worked hours.
- **Intermediate Expenditures**. The sum of purchases of intermediate goods (raw materials, components, energy) and external services, minus the variation in the stock of purchases.
- **Tangible Fixed Assets**. The gross value of property, plant and equipment (PP&E). This includes, land, buildings, technical facilities, machinery, tools, other facilities, furniture, information processing equipment and rolling stock. This variable is deflated by the manufacturing capital goods price index with base year 2015 provided by INE.
- **Intangible Fixed Assets**. The gross value of identifiable non-monetary asset without physical substance. According to the International Financial Reporting Standards Foundation (whose standards Spain follows), such an asset is identifiable when it is separable, or when it arises from contractual or other legal rights. Separable assets can be sold, transferred, licensed, etc. Examples of intangible assets include computer software, licenses, trademarks, patents, films, copyrights and import quotas. Goodwill acquired in a business combination is also accounted. Development expenditure that meets specified criteria is recognized as the cost of an intangible asset. This variable is deflated by the manufacturing capital goods price index with base year 2015 provided by INE.
- **Total R&D**. Total research and development expenditures that include the cost of intramural R&D activities that occurs on site (in-house R&D) and extramural activities, ie payments to outside R&D laboratories and research centers.
- **Tangible Investment**. The net difference between the purchase and sale of tangible fixed assets or property, plant and equipment (PP&E). These assets are defined as acquisitions of lands and natural goods, buildings, equipment for information processing, technical facilities, machinery and tools, rolling stock and furniture, office equipment. This variable is deflated by the manufacturing capital goods price index with base year 2015 provided by INE.
- **Patent Stock**. The ESEE records registered patents registered annually. In cases of foreign ownership the patent is registered with the foreign subsidiary. A patent can either be registered internationally (EU or US) and those registered with the national Spanish

patent office. Most patents are registered with the former. I construct a patent stock by calculating the cumulative sum of all registered patents through time for each firm.

- **Exports**. Value in euros.

A.2.2 Firm-Level TFP Estimation

This appendix section describes how TFP reported in the empirical Section 3.4 is estimated. Let f denote a firm and t denote time. I follow the foreign ownership literature and assume that that the production function is Cobb-Douglas. Assuming a translog production function generates similar results. To estimate firm-level production functions, one needs to control for the simultaneity and selection bias, which is inherently present. I follow the procedure developed by D. A. Ackerberg et al. (2015) who rely on an observable proxy variable being a function of the unobserved productivity level (aka control function approach) paired with a law of motion for productivity. This method builds on standard control function methods by taking into account the fact that the variable factor of production adjusts in response to a productivity shock, whereas the fixed factor does not react to contemporaneous shocks to productivity, but it is correlated with the persistent productivity term. The observable proxy variable that I use expenditures on materials. The production function in logs is

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \epsilon_{it}$$

where y_{it} is real value added, l_{it} is labor hours, k_{it} is the book value of tangible fixed assets and TFP is ω_{it}. The term ϵ_{it} is the measurement error an i.i.d. unanticipated shock to production. Firms do not observe ϵ_{it} when making optimal input decisions. Value added is deflated by an industry-specific price index. I estimate productivity over time using a rolling window of 10 years. Production functions are estimated by sector and year and the TFP distribution is winsorized at the 1st and 99th percentiles. As an extension I estimate TFP where the labor input l_{it} is the wage bill and also where value added is deflated by a firm-specific price index.[2] The results can be found in Table A.6.6 are very similar. The two-step estimation is as follows

[2]Firms are asked to report average transaction price changes introduced from the previous to the reporting year in percentage points in up to five markets in which the firm operates. Most firms report 2-3 markets. The ESEE computes a global percentage change of prices of firm f across markets for each year using a Paasche type formula (current quantities, changing prices)

$$\%\text{price variation}_{ft} = \left(\frac{1}{\sum_k \frac{WEIGHT_{ftm}}{100+\%\text{ price variation }_{ftm}}} - 1 \right) \times 100$$

where m is the market and $WEIGHT_{ftm}$ is the share of sales of market m in total sales of firm f at time t. More precisely the variable $WEIGHT_{ftm}$ is the percentage which sales in market m represent on sales of all the markets identified and covered by the company. I compute recursively a price index for each firm f using $\%price\ variation_{ft}$:

$$p_{ft} = p_{ft-1} \left(1 + \frac{\%price\ variation_{ft}}{100} \right).$$

When t is the first year that firm f is observed I set p_{ft} equal to industry-specific price index of that year. Alternatively, if period t is the first time a firm is observed I could set p_{ft} equal to 1, calculate the price index over time and then normalize p_{ft} by the average value for each firm. Both methods produce similar indices.

Stage One

- Get expected output

$$y_{it} = \phi_t(l_{it}, k_{it}, m_{it}) + \epsilon_{it}$$
$$y_{it} = \underbrace{\beta_l l_{it} + \beta_k k_{it} + h_{it}(m_{it}, k_{it}, l_{it})}_{=\phi_t} + \epsilon_{it}$$

- Run OLS y_{it} on a higher-order polynomial in (l_{it}, k_{it}, m_{it}) to obtain $\widehat{\phi}(l_{it}, k_{it}, m_{it})$.
- We now have expected output $\widehat{\phi}_{it}$ where ϵ_{it} is netted out.

Stage Two

- Estimate the coefficients β_l and β_k using a standard GMM techniques. Use block bootstrapping to get the standard errors.
- Guess the coefficients β_l and β_k. Get productivity:

$$\omega_{it}(\beta_k, \beta_l) = \widehat{\phi}_{it} - \beta_k k_{it} - \beta_l l_{it}$$

- Non-parametrically regress and take the innovations $\xi_{it}(\beta_k, \beta_l)$

$$\omega_{it}(\beta_k, \beta_l) = \overbrace{\omega_{it-1}(\beta_k, \beta_l) + \omega^2_{it-1}(\beta_k, \beta_l) + \omega^3_{it-1}(\beta_k, \beta_l)}^{\mathbb{E}(\omega_{it}(\beta_k, \beta_l)|\omega_{it-1}(\beta_k, \beta_l))} + \xi_{it}(\beta_k, \beta_l)$$

- There are two parameters and two moment conditions. Check if conditions are satisfied.

$$\mathbb{E}\left(\xi_{it}(\beta_k, \beta_l)\begin{pmatrix} l_{it-1} \\ k_{it} \end{pmatrix}\right) = 0$$
$$T^{-1}N^{-1}\sum_t \sum_i \left(\xi_{it}(\beta_k, \beta_l)\begin{pmatrix} l_{it-1} \\ k_{it} \end{pmatrix}\right) = 0$$

A.3 Data Series From EUKLEMS-INTANProd

This section describes how both the wage skill premium (Section A.3.1) and the income shares are calculated (Section A.3.2). Furthermore, it explains how the elasticities of the production functions from the model are estimated at the sector level (Section A.3.3). All three sections use data for Spain from EUKLEMS-INTANProd Database.[3]

[3] 2023 release. See description in 1.2.1. Further information https://euklems-intanprod-llee.luiss.it/

A.3.1 Wage Skill Premium

To calculate the wage skill premium I use data from the labor accounts of EUKLEMS-INTANProd which provide the share of hours worked and share of labor compensation by three skill groups at the the 2-digit sector level. The skill groups are low skill (lower secondary education or lower), medium skill (upper secondary education and post-secondary non-tertiary) and high skill (tertiary degree).[4] I define skilled workers (denoted with subscript s) as those with tertiary education and I combine the low and medium skill groups to form unskilled workers which I denote with subscript u.

Denoting that share of labor compensation that goes to skilled workers as $\mathfrak{W}_t$ and share of hours worked by skilled workers as $\mathfrak{L}_t$, labor compensation and hours worked by skill type is

$$\text{Skilled Compensation} = \mathfrak{W}_t w_t L_t = w_{s,t} L_{s,t} \qquad \text{Skilled Hours} = \mathfrak{L}_t L_t = L_{s,t} \tag{A.3.1}$$

$$\text{Unskilled Compensation} = (1 - \mathfrak{W}_t) w_t L_t = w_{u,t} L_{u,t} \qquad \text{Unskilled Hours} = (1 - \mathfrak{L}_t) L_t = L_{u,t} \tag{A.3.2}$$

The skill premium is then calculated by dividing the ratios of labor compensation to hours worked for skilled and unskilled workers

$$\text{Wage Skill Premium} = \frac{\text{skilled workers' wage}}{\text{unskilled workers' wage}} = \frac{\frac{w_{s,t} L_{s,t}}{L_{s,t}}}{\frac{w_{u,t} L_{u,t}}{L_{u,t}}} = \frac{w_{s,t}}{w_{u,t}} = \omega_t. \tag{A.3.3}$$

A.3.2 Income Shares

This section describes how the labor income share by skill type and the capital income share by capital type are calculated. The income share is the proportion of gross value added Y_t, which is the sum of labor and capital income.

A.3.2.1 Labor Share

I define the labor income share in year t as labor compensation $w_t L_t$ divided by gross value added Y_t

$$\text{Labor Share} = \frac{w_t L_t}{Y_t}. \tag{A.3.4}$$

As defined in the previous subsection, $\mathfrak{W}_t$ is the share of labor compensation that goes to skilled types. The labor share by skill type is

$$\text{Skilled Labor Share} = \frac{\mathfrak{W}_t w_t L_t}{Y_t} = \frac{w_{s,t} L_{s,t}}{Y_t} \tag{A.3.5}$$

$$\text{Unskilled Labor Share} = \frac{(1 - \mathfrak{W}_t) w_t L_t}{Y_t} = \frac{w_{u,t} L_{u,t}}{Y_t} \tag{A.3.6}$$

[4]KLEMS aggregates education levels according to the International Standard Classification of Education (IECED). Low skill: IECED 0-2. Medium Skill IECED 3-4. High Skill IECED 5-8.

and $w_t L_t = w_{s,t} L_{s,t} + w_{u,t} L_{u,t}$.

A.3.2.2 Capital Share

The capital income share is the ratio of tangible and intangible investment to gross value added

$$\frac{R_{T,t} X_{T,t} + R_{I,t} X_{I,t}}{Y} = 1 - \frac{w_t L_t}{Y_t}. \quad \text{(A.3.7)}$$

As is commonly assumed in national accounting, all rents generated by intangibles goes to capital income. Investment of each capital type is gross fixed capital formation (GFCF) and is defined as resident producers' expenditures on new or acquisitions of existing fixed assets minus disposals. Tangible investment $X_{T,t}$ includes equipment, buildings and structures. It does not include land. Intangible investment $X_{I,t}$ includes R&D, software, artistic originals, design, brand, organizational capital and training.

To determine capital income, it is necessary to estimate the gross rate of return for each type of capital. I assume that the gross return R_j for capital type $j = \{T, I\}$ satisfies the no-arbitrage condition

$$R_{j,t} = (1 + r_t) p_{j,t-1} + (1 - \delta_{j,t}) p_{j,t} \quad \text{(A.3.8)}$$

where r_t is the net rate of return, $p_{j,t}$ is the price of capital j relative to final goods, and $\delta_{t,j}$ is the depreciation rate for capital type j. I calculate $p_{j,t}$ using the capital type j price index relative the price index for final output goods. I compute the depreciation rate using the net capital stock and investment

$$\delta_{j,t} = \frac{K_{j,t-1}\left(\frac{p_{j,t}}{p_{j,t-1}}\right) - K_{j,t} + X_{j,t}}{K_{j,t-1}\left(\frac{p_{j,t}}{p_{j,t-1}}\right)} \quad \text{(A.3.9)}$$

where $K_{j,t}$ is the nominal net capital stock for type j and is constructed by EUKLEMS-INTANProd.

The only unknown in equation (A.3.8) is the net return r_t where all other series $w_t L_t$, Y_t, $X_{j,t}$, $K_{j,t}$, $\delta_{j,t}$ and $p_{j,t}$ are taken from the data. Once r_t is found, so is $R_{j,t}$. I back out r_t from the rearranged equation (A.3.7)

$$\frac{w_t L_t}{Y_t} = 1 - \frac{R_{T,t}(p_{T,t}, \delta_{T,t}, r_t) X_{T,t} + R_{I,t}(p_{I,t}, \delta_{I,t}, r_t) X_{I,t}}{Y_t}. \quad \text{(A.3.10)}$$

Note that by calculating the capital income share I did not need to impose any functional form on the production function.

Figures 1.1 and A.5.5-A.5.6 display the shares of investment and labor compensation. That is, the intangible share (green lines) is $\frac{R_{I,t} X_{I,t}}{R_{T,t} X_{T,t} + R_{I,t} X_{I,t}}$ and tangible (red lines) $\frac{R_{T,t} X_{T,t}}{R_{T,t} X_{T,t} + R_{I,t} X_{I,t}}$. Similarly, the skilled share of labor compensation (yellow lines) is $\frac{w_{s,t} L_{s,t}}{w_{s,t} L_{s,t} + w_{u,t} L_{u,t}}$ and unskilled share (purple lines) is $\frac{w_{u,t} L_{u,t}}{w_{s,t} L_{s,t} + w_{u,t} L_{u,t}}$.

A.3.3 Sector Level Production Function Estimation

As described in the main text, I am unable to credibly identify the production function elasticity parameters (σ, ρ) at the firm-level due to data limitations. However, given the assumptions in the model the elasticities can be estimated at the sector or aggregate level. Similar to the firm level production function from equation (3.1) in the model, the sector level production function with intangible-skill complementary is

$$Y_t = Z_t K_{T,t}^{\alpha} \left[(1-\varsigma)\, L_{u,t}^{\sigma} + \varsigma\, \left(\varrho L_{s,t}^{\rho} + (1-\varrho) K_{I,t}^{\rho} \right)^{\frac{\sigma}{\rho}} \right]^{\frac{(1-\alpha)\nu}{\sigma}} \tag{A.3.11}$$

where $K_{j,t}$ is the nominal net capital stock for type $j = \{T, I\}$, which is constructed by EUKLEMS-INTANProd and $L_{i,t}$ are labor hours by skill type $i = \{s, u\}$, gross value added is Y_t and Z_t is total factor productivity. The production function in real terms is

$$\widetilde{Y}_t = \widetilde{Z}_t \widetilde{K}_{T,t}^{\alpha} \left[(1-\varsigma)\, L_{u,t}^{\sigma} + \varsigma\, \left(\varrho L_{s,t}^{\rho} + (1-\varrho) \widetilde{K}_{I,t}^{\rho} \right)^{\frac{\sigma}{\rho}} \right]^{\frac{(1-\alpha)\nu}{\sigma}} \tag{A.3.12}$$

where output $\widetilde{Y}_t$ is deflated by the final output goods index and both j types of capital $\widetilde{K}_{j,t}$ are deflated by their respective capital price indices.

I first estimate the elasticity of substitution between intangible capital and skilled labor using the ratio of the first order conditions of $K_{I,t}$ and $L_{s,t}$

$$\ln\left(\frac{\widetilde{R_{I,t}K_{I,t}}}{\widetilde{w_{s,t}L_{s,t}}}\right) = \ln\left(\frac{1-\varrho}{\varrho}\right) + \rho \ln\left(\frac{\widetilde{K}_{I,t}}{L_{s,t}}\right) \tag{A.3.13}$$

where the gross return $R_{I,t}$ is found in the previous section. Real skilled labor compensation $\widetilde{w_{s,t}L_{s,t}}$ is deflated by the final output good index. Running OLS returns an estimate for ρ and the elasticity of substitution between intangible capital and skilled labor is $1/(1-\rho)$.

I proceed to the elasticity of substitution between unskilled labor and skilled labor. To do so, I rewrite the production function

$$\widetilde{Z}_t \widetilde{K}_{T,t}^{\alpha} \left[(1-\varsigma)\, L_{u,t}^{\sigma} + \varsigma\, (b_t L_{s,t})^{\sigma} \right]^{\frac{\nu(1-\alpha)}{\sigma}} \qquad \text{where } \; b_t = \varrho \left(\left(\frac{(1-\varrho)\widetilde{K}_{I,t}}{\varrho L_{s,t}} \right)^{\rho} + 1 \right)^{\frac{1}{\rho}} \tag{A.3.14}$$

Plugging in the estimate ρ into b, I can estimate the elasticity of substitution between unskilled and skilled labor using the first order conditions

$$\ln\left(\frac{\widetilde{R_{I,t}K_{I,t}} + \widetilde{w_{s,t}L_{s,t}}}{\widetilde{w_{u,t}L_{u,t}}}\right) = \ln\left(\frac{\varsigma}{1-\varsigma}\right) + \sigma \ln\left(\frac{b_t L_{s,t}}{L_{u,t}}\right) \tag{A.3.15}$$

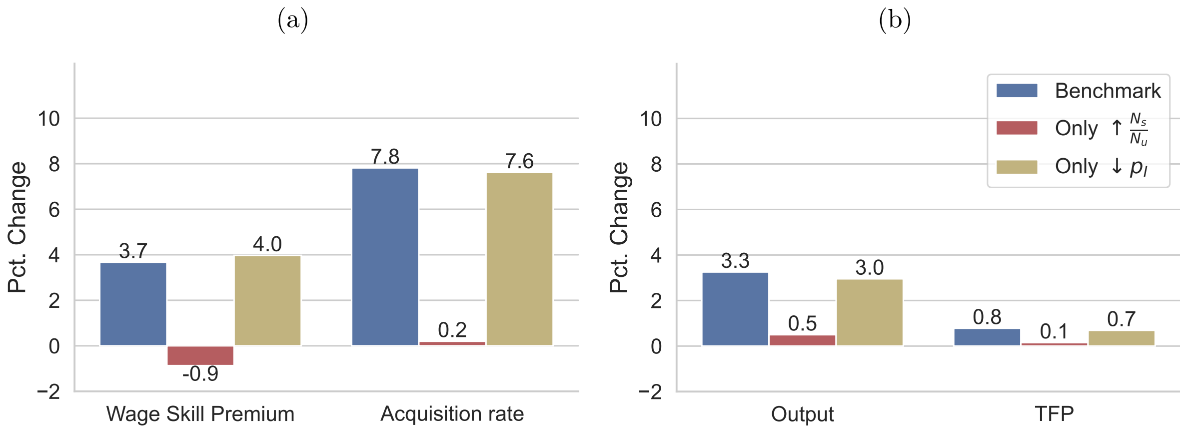
where $R_{T,t}$ is found in the previous section and $\widetilde{w_{u,t}L_{u,t}}$ is unskilled labor compensation deflated by the final output goods index. Running OLS returns an estimate for σ and the elasticity of substitution between unskilled and skilled labor is $1/(1-\sigma)$.

A.4 Additional Counterfactuals

A.4.1 Steady State Comparison and Isolated Changes

The steady state comparison in Section 1.5 compares the calibrated model to a new steady state where the relative intangible investment price p_I is lowered and the skill ratio of the labor force $\mathfrak{s} = \frac{N_s}{N_u}$ is increased to their 2013-2017 average levels. This section examines how the wage skill premium, acquisition rate, output and TFP are affected by these two changes in isolation. Figure A.4.1 depicts the percentage point change between steady states. The blue bars are for the benchmark model from Section 1.5. The red bars depict the percentage point change when only the skill ratio is increased and the yellow when only the relative intangible investment price is lowered. When increasing the relative supply of labor to its 2013-2017 level but holding fixed the intangible investment price to its 2002-2006 level, the wage skill premium decreases; there are small increases for output and TFP due to the relative cheapening of skilled labor. The isolated change of the skill ratio has a negligible effect on foreign ownership as evident by virtually no change in the acquisition rate. The effects are similar to that in the benchmark model when only the intangible investment price is lowered to its 2013-2017 level. The wage skill premium increases more because the relative supply of skilled labor is held fixed. The increases for the acquisition rate, output and TFP are slightly lower as the skilled wage is higher than in the benchmark economy.

Figure A.4.1: Steady State Comparison with Isolated Changes (in pp.)



Notes: This figure compares the percentage point change of steady state values relative to their levels in the calibrated model. Subfigure (a) contains the wage skill premium and foreign acquisition rate while subfigure (b) has aggregate output and TFP. The blue bars depict the percentage point change in the benchmark model in Section 1.5 of the paper where in the new steady state the relative intangible investment price p_I is lowered and the skill ratio of the labor force $\mathfrak{s} = \frac{N_s}{N_u}$ is increased to their 2013-2017 average levels. The red bars show the results for the new steady state when only the skill ratio $\mathfrak{s} = \frac{N_s}{N_u}$ is increased to its 2013-2017 average level and the relative intangible investment price is unchanged. The yellow bars depict the results if only the relative intangible investment price is lowered to its 2013-2017 average level and the skill ratio is unchanged.

A.4.2 An Economy Without Foreign Ownership

This section conducts a counterfactual exercise where the economy is closed to foreign ownership. This is done by setting the matching rate to zero ($\mu = 0$) which shuts down the foreign acquisition channel. Table A.4.1 presents aggregate variables of the closed economy model relative to the initial steady state (2002-2006) in the benchmark model. Aggregate output and TFP experience modest decreases of 3.5% and 2.9%. Equilibrium wages and the skill premium are left mostly unchanged, though there is a slight increase in the latter. There is a large change in the number of firms operating in the economy, which increases by 25.4%. The absence of more productive foreign-owned firms lowers the entry/exit threshold in the new equilibrium leading to increased domestic firm entry. As domestic incumbents and many of the new entrants are generally less productive, a much larger number of them are needed to operate in the place of foreign-owned firms.

Table A.4.1: Steady State Comparison - No Foreign Ownership Rel. to Benchmark (in pp.)

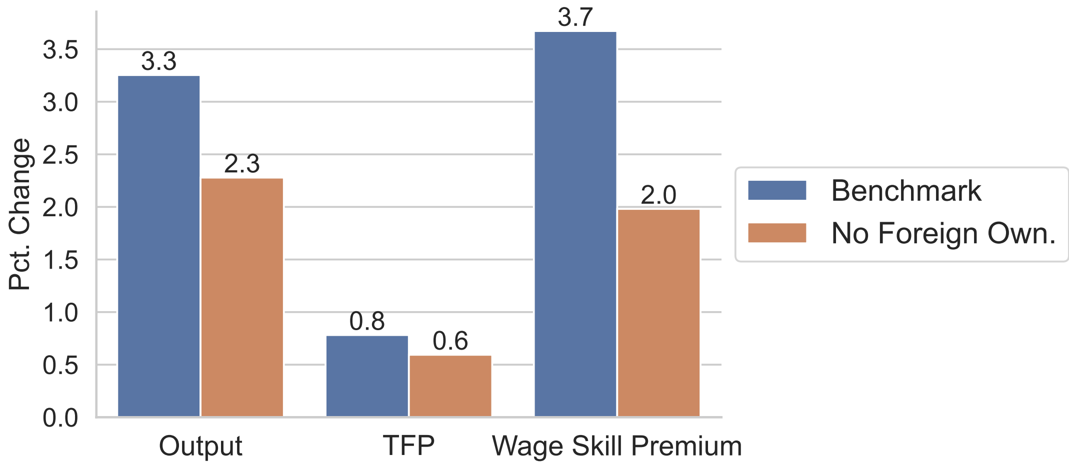
Output Y	TFP Z	Wage Skill Premium $\frac{w_s}{w_u}$	Mass of Incumbents
-3.5	-2.9	+0.2	+25.4

Notes: This table shows the percentage change of values in the model without foreign ownership ($\mu = 0$) relative to the initial steady state (2002-2006) in the benchmark model.

A.4.2.1 Amplifying Effect of Foreign Ownership

Foreign ownership amplifies the effects of intangible-skill complementarity for the wage skill premium and other aggregate variables. I demonstrate this by conducting the same steady state comparison as in Section 1.5 but where the initial steady state is the model without foreign ownership (Table A.4.1). As in Section 1.5, in the new steady state the relative intangible investment price p_I is lowered and the skill ratio of the labor force $\mathfrak{s} = \frac{N_s}{N_u}$ is increased to their average 2013-2017 average levels. Figure A.4.2 compares the percentage change of aggregate output, TFP and the wage skill premium relative to their initial steady state values. The blue bars represent the benchmark model where the percentage point changes are those found in Tables 1.8 and 1.9 in the paper. The orange bars are for the model without foreign ownership where the percentage point increases for all are lower than the benchmark model.

Figure A.4.2: Steady State Comparison With and Without Foreign Ownership



Notes: The figure depicts the percentage change of values in the new state state relative to their initial state steady state level. The blue bars are for the benchmark model in the paper. The orange bars are the model without foreign ownership ($\mu = 0$). In the new steady state for both models the relative intangible investment price is lowered and the skill ratio is increased to their 2013-2017 levels.

A.4.3 An Alternative Production Function

Table 1.8 demonstrates that the benchmark model accounts for the long-term increase in the wage skill premium and changes in income shares. This section considers an alternative production function that assumes tangible-skill complementarity in production, rather than intangible-skill complementarity. The benchmark production function with intangible skill complementarity is

$$\mathcal{F} = z{k_T}^{\alpha}\left[(1-\varsigma)\, l_u^{\sigma} + \varsigma\, (\varrho l_s^{\rho} + (1-\varrho){k_I}^{\rho})^{\frac{\sigma}{\rho}}\right]^{\frac{(1-\alpha)\nu}{\sigma}} \tag{A.4.1}$$

where the substitution parameters are estimated to be $\sigma = 0.579$ and $\rho = -0.322$. In the main counterfactual of the paper the new steady state is where the relative intangible investment price p_I is lowered and the skill ratio of the labor force $\mathfrak{s} = \frac{N_s}{N_u}$ is increased to their average 2013-2017 average levels. The relative intangible price declined by 8.5%.

I consider an alternative production function where intangible and tangible capital are swapped within the nested CES structure

$$\mathcal{F} = z{k_I}^{\alpha}\left[(1-\varsigma)\, l_u^{\sigma} + \varsigma\, (\varrho l_s^{\rho} + (1-\varrho){k_T}^{\rho})^{\frac{\sigma}{\rho}}\right]^{\frac{(1-\alpha)\nu}{\sigma}}. \tag{A.4.2}$$

I estimate the production function and find that $\sigma = 0.675$ and $\rho = -1.251$. Here $\sigma > \rho$ indicates that there is tangible-skill complementarity. I recalibrate the model and conduct the same counterfactual but this time I lower the relative tangible investment price p_T, which declined by 5.1%. Table A.4.2 compares the percentage point changes in data with those from the benchmark model (intangible-skill complementarity) and the alternative model (tangible-skill complementarity).

Table A.4.2: Steady State Comparison - Change in Percentage Points

	Data	Intangible-Skill Complementarity	Tangible-Skill Complementarity
Wage Skill Premium	+9.4	+3.7	+2.9
Intangible Share	+36.7	+8.2	-2.6
Tangible Share	-2.2	-2.0	+7.2

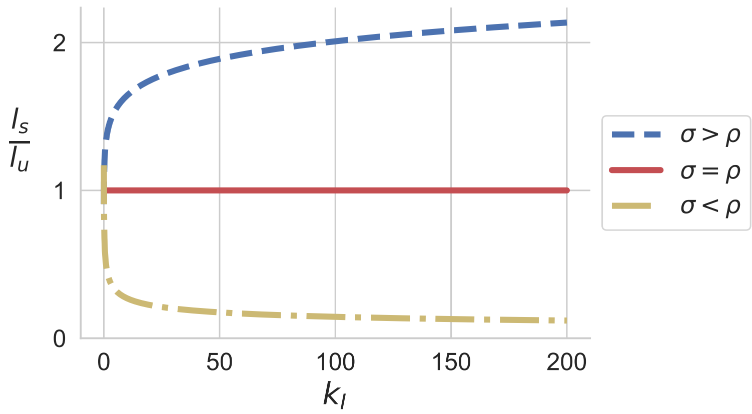
Notes: This table compares the percentage changes of values in the new steady state relative to their initial steady state level for two different models. The third column is the benchmark model with intangible-skill complementarity in production and the fourth column is the the alternative model with tangible-skill complementarity. Values reported in the second and third columns are the same as those reported in Table 1.8 in the paper.

The model with tangible-skill complementarity is able to account for some of the increase in the skill premium, though less than the benchmark model. This is due to the decline in the relative tangible investment price being smaller than the intangible price decline. However, the tangible-skill complementarity model cannot account for the change in the composition of the capital income share. It incorrectly predicts a decline in the intangible share and a rise in tangible capital, contrary to what is observed in data.

A.4.4 Cobb-Douglas in Production

In this section, I disentangle the effects of intangible-skill complementarity and foreign ownership following the decline in the relative price of intangible investment. Specifically, I assess how much of the change in the skill premium is attributable to intangible-skill complementarity versus foreign ownership. In the production function, when $\sigma > \rho$, skilled labor is more complementary with intangible capital than unskilled labor, so the relative demand for skilled labor (l_s/l_u) increases with intangible capital k_I. In the baseline counterfactual, a decline in the price of intangible investment raises intangible capital accumulation, leading to increased relative demand for skilled labor and, consequently, a higher wage skill premium. Figure A.4.3 illustrates how the optimal skilled-to-unskilled labor demand ratio varies with intangible capital under different substitution parameters. When $\sigma < \rho$, there is intangible-skill substitutability in production, and the relative demand for skilled labor declines with k_I. When $\sigma = \rho$, the ratio remains constant, implying proportional shifts in labor demand across skill types.

Figure A.4.3: Skilled to Unskilled Labor Ratios By Intangible Capital and Substitution Elasticities



Notes: Share parameters: $\varsigma = 0.8$ and $\varrho = 0.5$. Substitution parameters: $\sigma > \rho : 0.25 > 0.05$; $\sigma = \rho : 0.25 = 0.25$; $\sigma < \rho : 0.25 < 0.45$. The parameters have been set such that when $\sigma = \rho$ the labor demand ratio equals one.

To isolate the role of intangible-skill complementarity, I consider a counterfactual in which both substitution parameters are set to zero: $\rho = \sigma = 0$. This yields Cobb-Douglas functional forms in both the inner and outer nests of the production function, implying unit elasticity of substitution and fixed expenditure shares across inputs. As a result, changes in relative input prices lead to proportional changes in their relative demand. Intangible capital no longer boosts the marginal productivity of skilled labor more than that of unskilled labor when there is intangible-skill complementarity. Consequently, a decline in the price of intangible investment raises the demand for both skill types equally, leaving the skill premium unchanged. Moreover, because Cobb-Douglas implies constant income shares, the expansion in intangible capital does not alter the distribution of income across inputs—output grows, but income shares remain fixed.

Table A.4.3: Cobb-Douglas in Production and No Foreign Ownership

	Benchmark	$\sigma = \rho = 0$	$\sigma = \rho = 0$ and $\mu = 0$
Wage Skill Premium	+3.7	0	0
Output	+3.3	+2.1	+1.1
TFP	+0.8	+0.5	+0.2
Acquisition Rate	+7.8	+5.1	0

Notes: Percentage point changes in steady-state outcomes following a decline in the relative price of intangible capital. The second column imposes a Cobb-Douglas production structure ($\sigma = \rho = 0$), eliminating intangible-skill complementarity. The third column combines Cobb-Douglas production with a counterfactual in which foreign acquisitions are shut down ($\mu = 0$)

Table A.4.3 summarizes the outcomes of this scenario, including the case with and without foreign ownership. Output and total factor productivity (TFP) increase by less than in the benchmark. The attenuated gains stem from the absence of input substitution and complementarity effects. In the benchmark model, a decline in the price of intangible capital raises output through two channels: a capital deepening effect, as firms accumulate more intangible capital, and a reallocation effect, as intangible-skill complementarity induces firms to substitute toward skilled labor, whose marginal productivity increases disproportionately. This reallocation enhances aggregate productivity by shifting resources toward more productive input combinations. In contrast, when the production function nests are Cobb–Douglas, input shares are fixed and no substitution is possible. As a result, firms respond to the price decline by proportionally increasing all inputs, but cannot reoptimize their input mix to exploit complementarities. Consequently, the economy forgoes the productivity gains from reallocation, and both output and TFP rise by less than in the benchmark scenario. These effects are even more pronounced when foreign ownership is removed, as the economy no longer benefits from the inflow foreign ownership and technology transfer associated with post-acquisition activity. The acquisition rate is lower where there is Cobb-Douglas in production. Foreign firms acquire domestic firms based on expected gains in firm value. Under Cobb-Douglas, intangible intensity is fixed leading meaning that firms scale up proportionately. Since these gains are smaller under Cobb–Douglas, fewer firms surpass the value threshold for acquisition, resulting in a lower acquisition rate compared to the benchmark.

A.4.5 Optimal Policy and Labor Supply Elasticity χ

To better understand the distributional effects of the foreign intangible investment subsidy, consider the implications of relaxing the assumption that skilled and unskilled households have identical labor supply elasticities. In the benchmark model, both types face the same Frisch elasticity, $\chi = 0.5$, a standard assumption in the macro-labor literature. However, some more recent work suggests that unskilled workers may exhibit higher labor supply elasticities than their skilled counterparts (Attanasio, Levell, Low, & Sánchez-Marcos, 2018; Keane & Rogerson, 2015). If unskilled households indeed have a more elastic labor supply, the welfare effects of the subsidy would change. A higher elasticity among unskilled households implies a stronger increase in hours worked in response to the wage incentive created by the subsidy. This leads to a larger increase in total unskilled labor supply, which puts downward pressure on unskilled wages relative to skilled wages, thereby amplifying the increase in the wage skill premium. As a result, skilled households, whose elasticity remains unchanged, benefit from a greater increase in relative wages and hence enjoy larger consumption gains, even if their hours response is muted. Meanwhile, unskilled households gain from the higher income associated with increased hours worked, but this is partly offset by their declining relative wage.

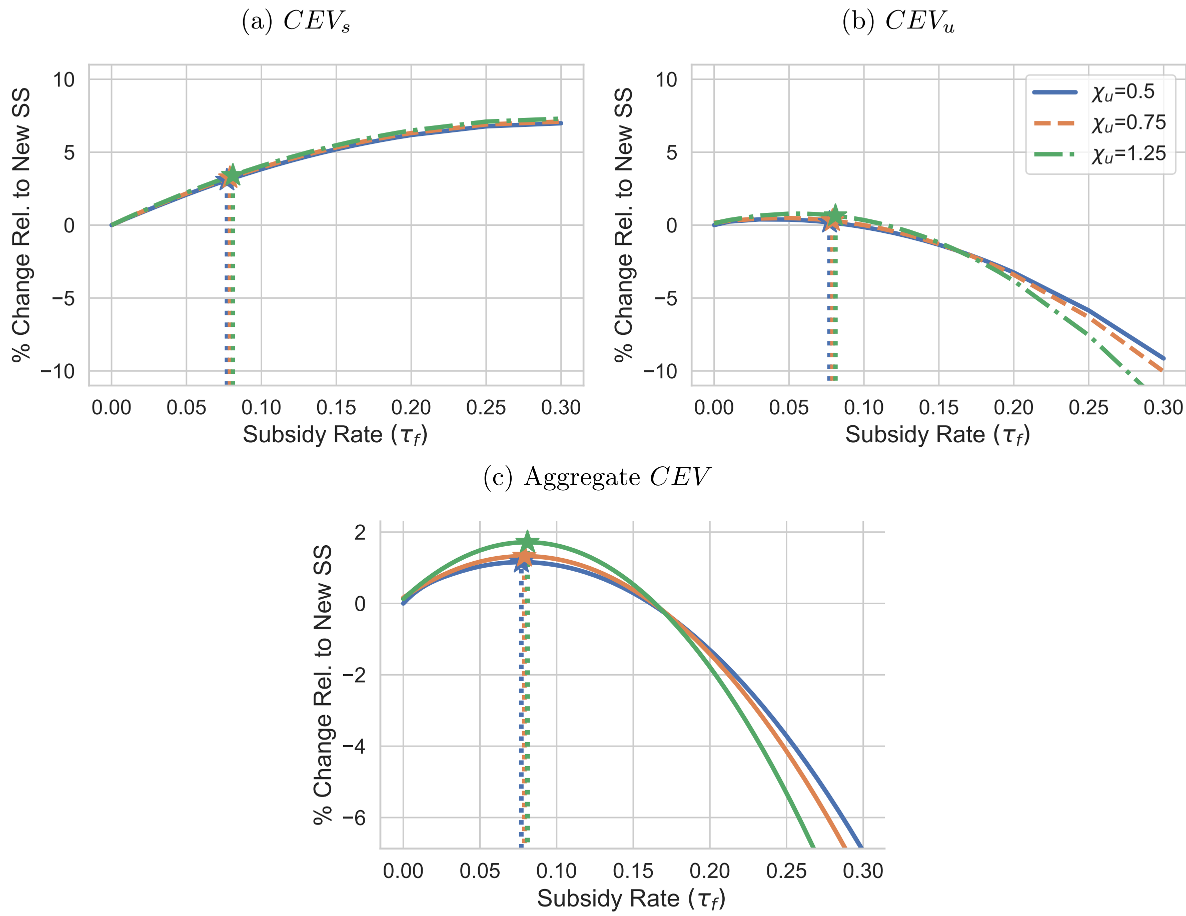
Table A.4.4 and Figure A.4.4 show the consumption equivalent variation (CEV) by skill type for different labor supply elasticities for unskilled types. When $\chi_u > \chi_s$, the CEV for unskilled households shifts upwards more for lower values of the subsidy, reflecting the stronger labor supply response, but it tilts downward more sharply as τ increases. This is due to the increase in labor hours supplied by the unskilled household eventually erodes its consumption gains. For skilled households, the steeper increase in the skill premium raises their welfare further compared to the benchmark case, despite no change in their labor supply elasticity.

Table A.4.4: Optimal Subsidy and Labor Supply Elasticities

	Benchmark	$\chi_u = 0.75$	$\chi_u = 1.25$
Optimal Subsidy τ	7.7	7.9	8.1
Aggregate CEV	+1.16	+1.33	+1.72
Skilled CEV	+3.08	+3.25	+3.34
Unskilled CEV	+0.19	+0.30	+0.66

Notes: This table reports the optimal subsidy rate and associated welfare gains, measured as consumption equivalent variation (CEV). The benchmark assumes identical elasticities for skilled and unskilled households ($\chi_s = \chi_u = 0.5$). The second and third columns hold the skilled labor elasticity fixed $\chi_s = 0.5$ and increase the elasticity of labor supply for unskilled households χ_u.

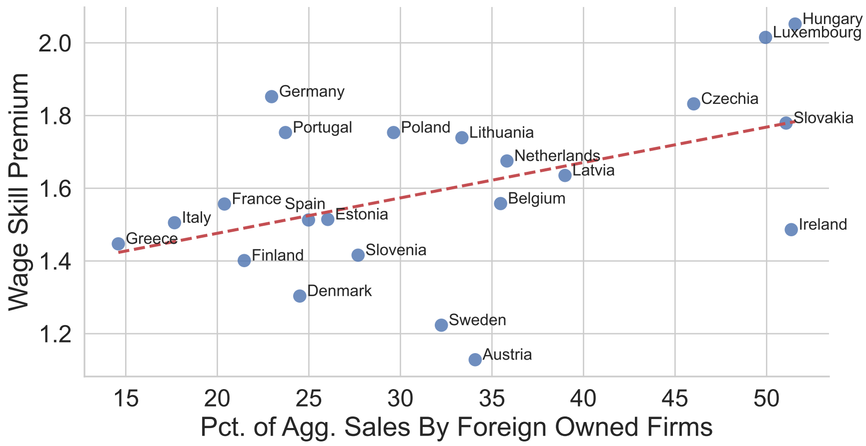
Figure A.4.4: Welfare and Foreign Intangible Investment Subsidy Under Different χ_u



Notes: The figure shows consumption equivalent variation (CEV) for skilled workers (CEV_s), unskilled workers (CEV_u) under different values of the foreign intangible investment subsidy τ. The blue line denote the benchmark model which assumes identical elasticities for skilled and unskilled households ($\chi_s = \chi_u = 0.5$). The orange and green lines are the CEVs when the skilled labor elasticity held fixed $\chi_s = 0.5$ the elasticity of labor supply for unskilled households χ_u increases. The stars are the optimal subsidy rate.

A.5 Additional Figures

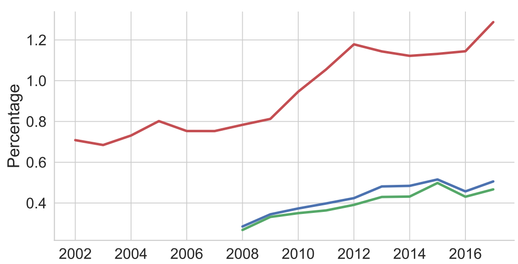
Figure A.5.1: Wage Skill Premium and Foreign Ownership in the EU (Avg. 2008-2019)



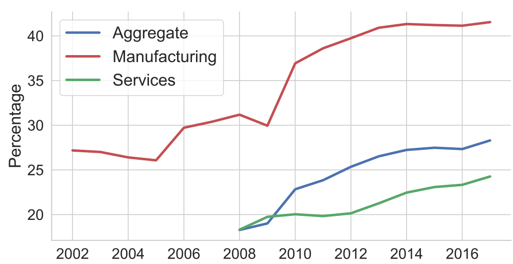
Notes: Click here to go back to introduction. The scatterplot displays the wage skill premium and share of aggregate sales revenue by foreign subsidies averaged between 2008 and 2019. The countries of Bulgaria, Cyprus, Malta and Romania do not report foreign ownership. Croatia does not appear as it joined the EU in 2013. A similar slope coefficient is found for the growth rates during this time.
Source: Author's calculations using EUKLEMS-INTANProd and OECD AMNE and SDBS Databases.

Figure A.5.2: Foreign Ownership in Spain

(a) % of Foreign Owned Firms



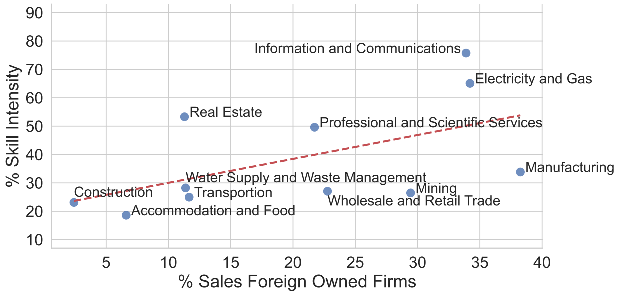
(b) % of Total Sales By Foreign Owned Firms



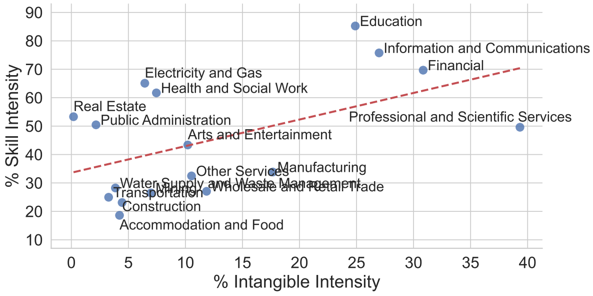
Notes: A firm is considered to be foreign owned if it is a subsidiary or at least 50% or more of its capital is owned by a foreign entity. Both figures depict time series at the aggregate, manufacturing (ISIC Rev. sector code C) and business services (ISIC Rev. 4 sector codes $G-N$) levels. Data collection for the aggregate and all sectors starts in 2008, except for manufacturing. The left figure is the series of the percentage of foreign owned firms. Figure A.5.8 in Appendix A.5 shows how the number of both domestic and foreign firms changed over time. By 2017 the total number of foreign subsidiaries in Spain was about 13,300. Among them, the majority are found in the business services sectors (9,700) and manufacturing (2,100). The right figure displays the percentage of aggregate sales revenue that is done by foreign owned firms.
Source: Author's calculations using OECD AMNE and SDBS Databases.

Figure A.5.3: Additional Figures for Section 1.2.2

(a) % Foreign Sales and Skill Intensity



(b) Skill and Intangible Intensity

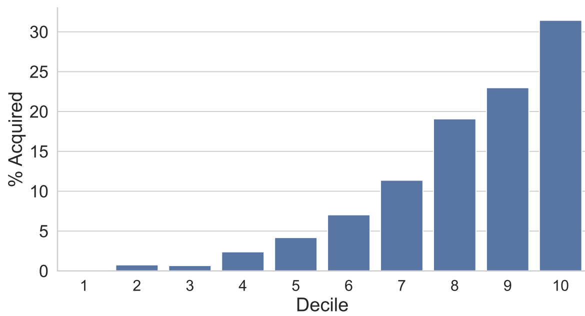


Notes: A firm is considered to be foreign owned if it is a subsidiary or at least 50% or more of its capital is owned by a foreign entity. The left subfigure has skill intensity (labors hours of skilled workers over total labor hours) and percentage of aggregate sales revenue done by foreign owned firms. The right subfigure plots skill intensity and intangible intensity (intangible capital over total capital). All points are for one-digit sector and averaged between the years 2008-2017.

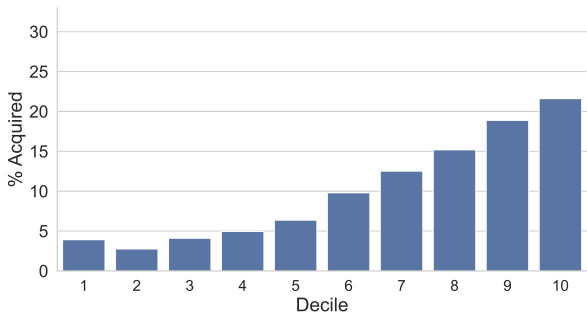
Source: Author's calculations using OECD AMNE and SDBS Databases.

Figure A.5.4: Marginal Distributions of Acquired Firms (Prior to Acquisition)

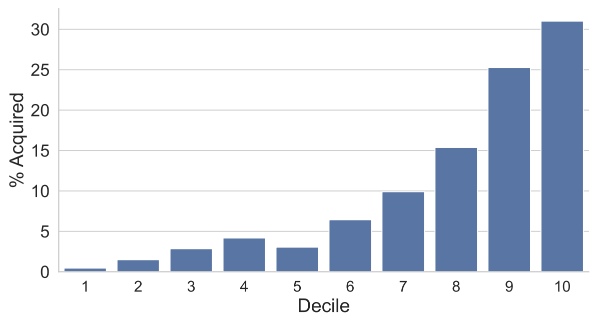
(a) Sales



(b) Labor Productivity



(c) Employment

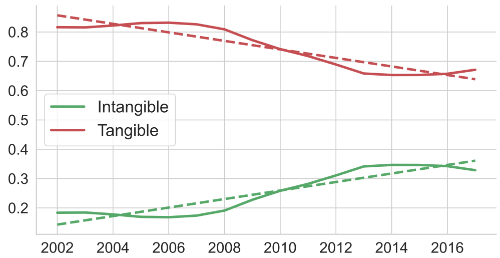


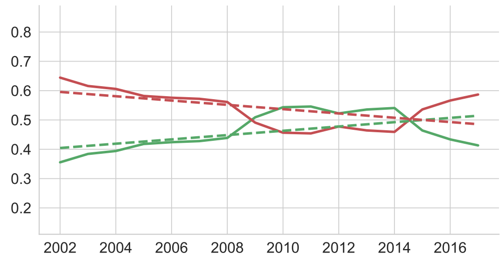
Notes: Author's calculations using ESEE. Figure displays the proportion of acquired firms that fall into each decile of its respective distribution: real sales, real value added (real value added over employment) and employment. Distributions exclude observations of firms under foreign ownership. I calculate the deciles of each distribution measured across all firms in each sector and year and count the proportion of acquired firms into each decile. The purpose of the figure is to emphasize the presence of positive selection in acquisition. If acquired firms were randomly selected then they would be distributed according to the population of firms (in their sector) and 10% of acquired firms would fall into each decile. This is clearly not the case as more than half of target firms at the time of acquisition are above the 70th percentile in their respective distributions suggesting foreign multinationals "cherry-pick" the best domestic firms.

Figure A.5.5: Share of Capital Investment in Spain

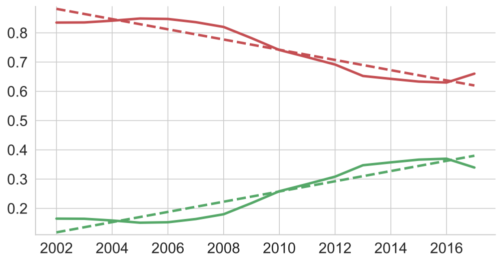
(a) Aggregate

(b) Manufacturing





(c) Services

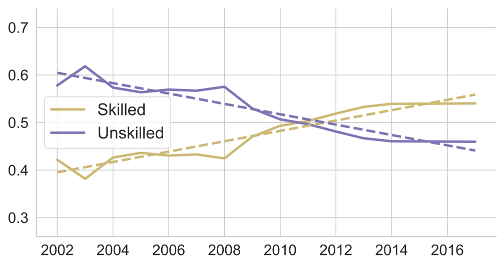


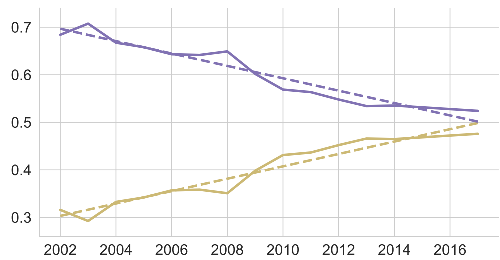
Notes: The figure displays the series of the investment share by capital type in Spain between 2002 to 2017. Intangible investment is expenditures of R&D, software, artistic originals, design, brand, organizational capital and training. Tangible investment is expenditures on traditional forms of physical capital: equipment, non-residential buildings and structures. Subfigure (a) is the aggregate share. Subfigure (b) contains the shares for manufacturing (ISIC Rev. 4 sector C). Subfigure (c) contains the share for business services (ISIC Rev. 4 sectors G-N). Details regarding how the shares are calculated are in Appendix A.3.2.
Source: Author's calculations using EUKLEMS-INTANProd database.

Figure A.5.6: Skill and Unskill Labor Share in Spain

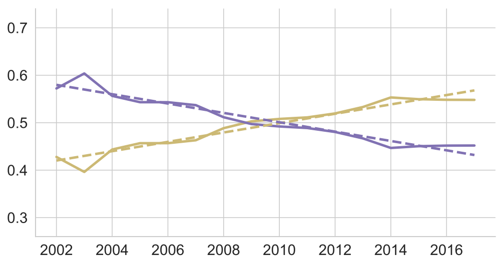
(a) Aggregate

(b) Manufacturing





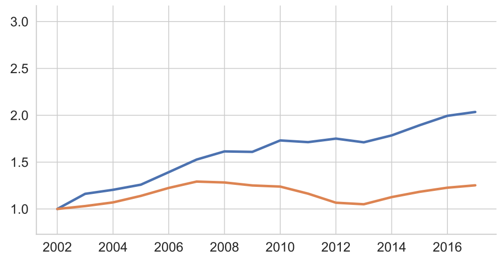
(c) Services



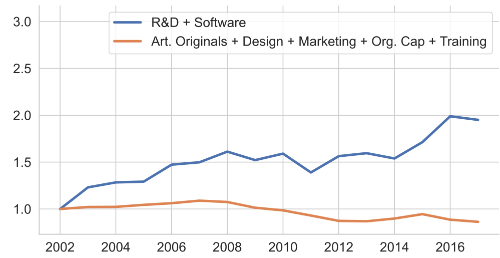
Notes: The figure displays the series of the labor compensation share in Spain by skill type between 2002 to 2017. The skilled share is the share of total labor compensation paid to workers with a tertiary degree or higher and unskilled are those with no tertiary degree. Subfigure (a) is the aggregate share. Subfigure (b) contains the shares for manufacturing (ISIC Rev. 4 sector C). Subfigure (c) contains the shares for business services (ISIC Rev. 4 sectors G-N). Details regarding how the shares are calculated are in Appendix A.3.2.
Source: Author's calculations using EUKLEMS-INTANProd database.

Figure A.5.7: Growth of Intangible Investment In Spain

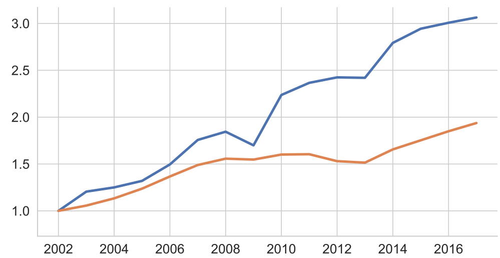
(a) Aggregate



(b) Manufacturing



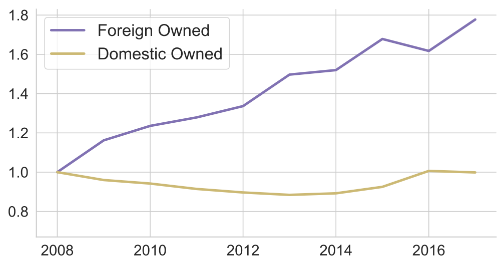
(c) Services



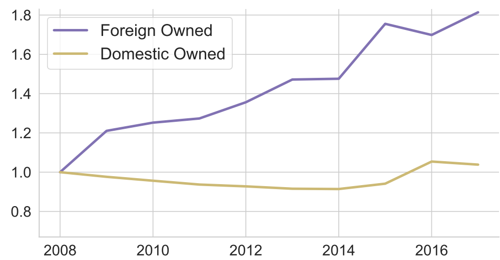
Notes: Intangible investment is expenditures of R&D, software, artistic originals, design, brand, organizational capital and training. This figures shows that much of the change in the intangible share of investment comes from R&D and software. The figures depict the investment levels normalized to 2002. Subfigure (a) is the aggregate. Subfigure (b) is manufacturing (ISIC Rev. 4 sector C). Subfigure (c) is business services (ISIC Rev. 4 sectors G-N).
Source: Author's calculations using EUKLEMS-INTANProd database.

Figure A.5.8: Nbr. of Firms By Ownership Relative To Reference Year

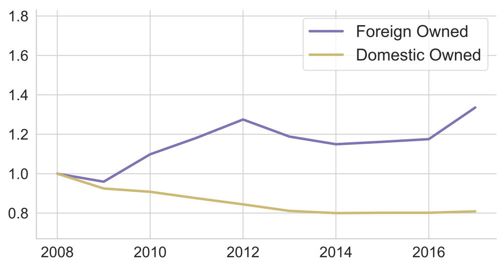
(a) Aggregate (Relative to 2008)



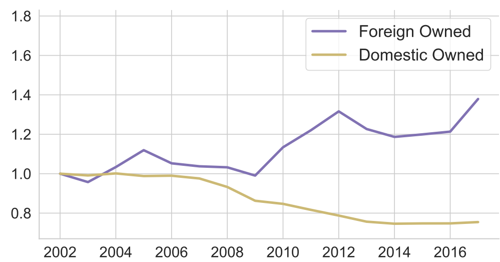
(b) Services (Relative to 2008)



(c) Manufacturing (Relative to 2008)

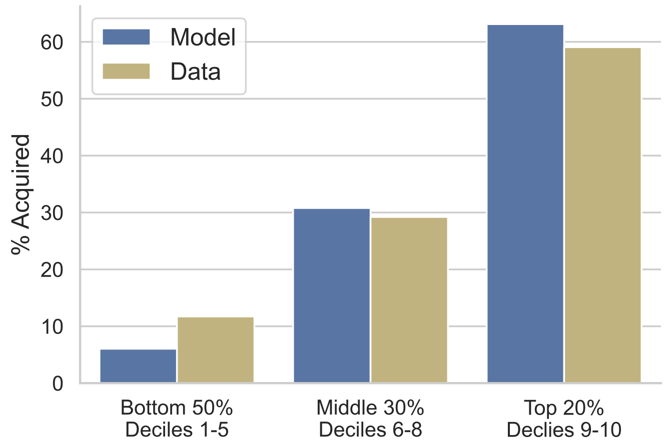


(d) Manufacturing (Relative to 2002)



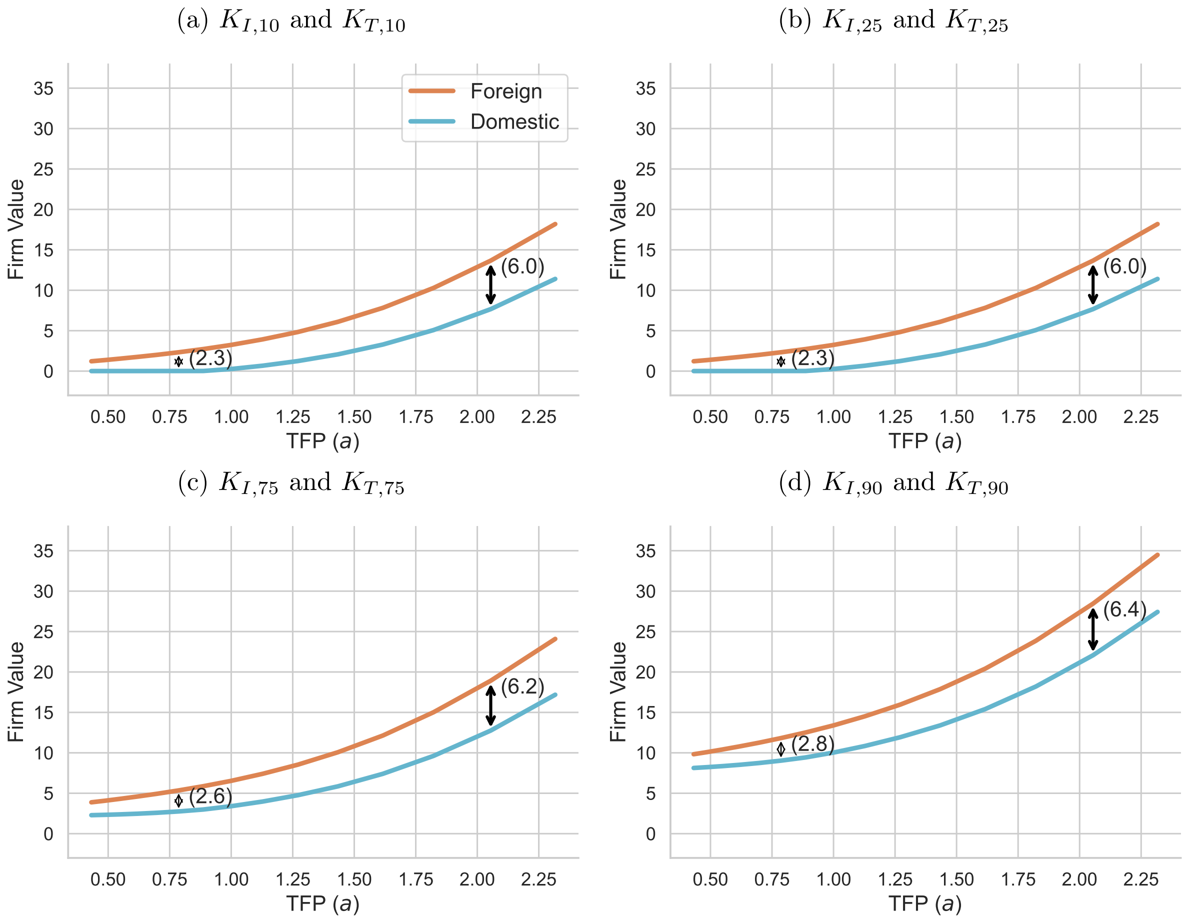
Notes: Figure is the relative number of firms classified by ownership relative to a reference year (2008 in subfigures (a)-(c) and 2002 in (d)). The purple line depicts foreign subsidiaries while the yellow is domestically owned firms. A firm is foreign owned if it is a subsidiary or at least 50% or more of its capital is owned by a foreign entity. Both figures depict time series at the aggregate, manufacturing (ISIC Rev. sector code C) and business services (ISIC Rev. 4 sector codes $G-N$) levels. Data collection for the aggregate and all sectors starts in 2008, except for manufacturing.
Source: Author's calculations using OECD AMNE and SDBS Databases.

Figure A.5.9: Marginal Distribution of Acquired Firms



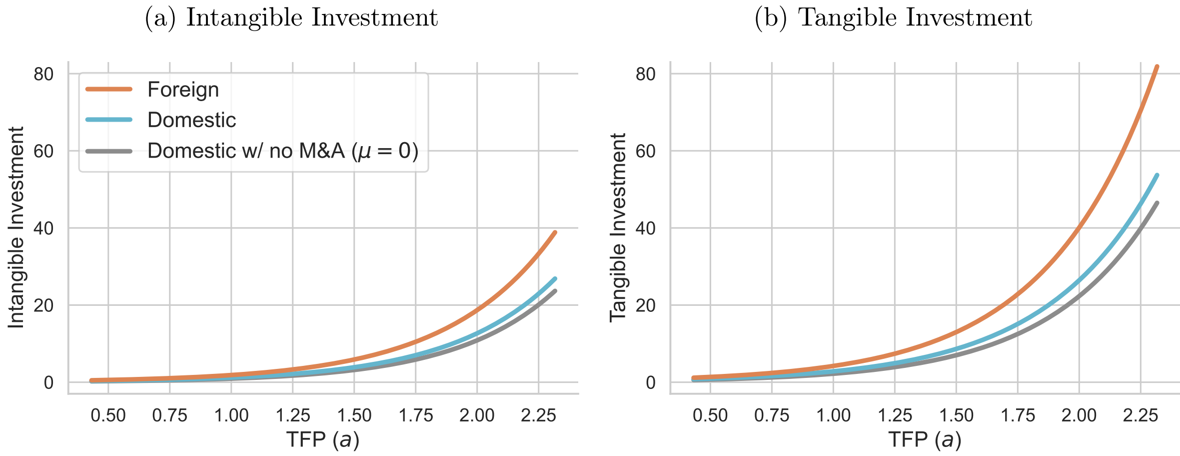
Notes: The figure displays the proportion of acquired domestic firms that fall into each decile of the firm size distribution (measured by employment). The empirical distribution (in yellow) is from the ESEE where I calculate the deciles of the marginal employment distribution across all firms in each sector and year and count the proportion of acquired firms that fall into each decile. The top 20% is the share of acquired firms (in pp.) that are in the 9th and 10th deciles. The middle 30% is the share of acquired firms that are in the 5th, 6th, and 7th deciles. The bottom 50% is the share of acquired firms below the median firm size. The firm size distribution is only of domestic firms prior to acquisition. The shares generated by the model are the blue bars. The top 20% and middle 30% shares are targeted moments.

Figure A.5.10: Firm Value $V(a, k_{I,p}, k_{T,p}, o)$ At Different Capital Percentiles p



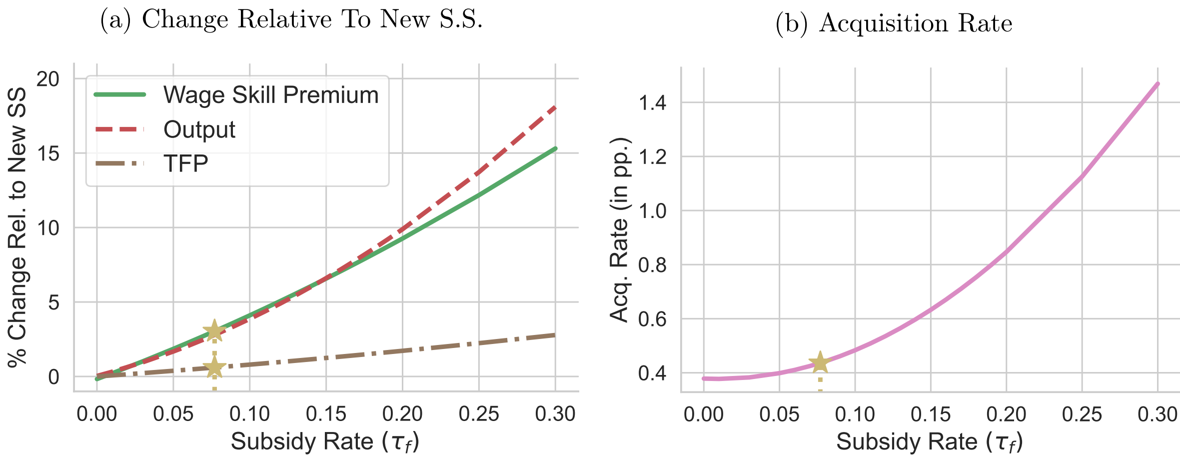
Notes: The figure displays firm value as a function of TFP at the percentile values $p = \{10, 25, 75, 90\}$ of intangible and tangible capital from the stationary distribution: $V(a, k_{I,p}, k_{T,p}, o)$. Domestic firm value is the teal line and foreign is the orange. The black arrows marked the difference in parenthesis between the two at a given TFP level. Firm value is convex in TFP and the figure shows that the absolute difference is larger for higher TFP levels.

Figure A.5.11: Capital Investment $x_j(a, k_{I,p}, k_{T,p}, o)$



Notes: The figure displays investment function of TFP at the median values of capital from the stationary distribution: $x_j(a, med(k_I), med(k_T), o)$ for both capital types $j = \{I, T\}$. Domestic firm value is the teal line and foreign is the orange. The gray line indicates the investment level of a domestic incumbent in a model without acquisitions and no foreign ownership.

Figure A.5.12: Changes and Foreign Intangible Investment Subsidy



Notes: Subfigure (a) plots the percentage change of aggregate equilibrium objects relative to the new steady state at different intangible investment subsidy τ_f levels. Subfigure (b) is the acquisition rate in percentage points where it equals 0.378% when $\tau_f = 0$, its value in the new steady state. The gold stars are the values at the optimal policy rate.

A.6 Additional Tables

Table A.6.1: Extended ESEE Summary Statistics (1990-2017)

Avg. Variable (in logs)	Domestic Never Acquired	Foreign *Before*	Foreign *After*	Obs.
Sales	15.40	17.57	17.96	39,011 / 2,271 / 1,727
Value Added	14.33	16.38	16.72	38,456 / 2,231 / 1,711
Employment	3.78	5.40	5.66	39,011 / 2,271 / 1,727
Wage Bill	14.03	16.00	16.36	39,011 / 2,271 / 1,727
Labor Hours	4.34	5.94	6.20	39,011 / 2,271 / 1,727
Labor Productivity (Value Added/Emp.)	10.54	10.97	11.06	38,456 / 2,231 / 1,711
Total Factor Productivity (TFP)	-0.051	0.027	0.039	32,791 / 1,853 / 1,640
Tangible Fixed Assets (Gross Value)	14.61	16.97	17.39	36,691 / 2,067 / 1,712
Intangible Fixed Assets (Gross Value)	12.10	14.67	15.11	27,603 / 1,730 / 1,576
Intangibility (Intangible Assets/Tangible+Intangible Assets)	-3.10	-2.64	-2.63	27,427 / 1,710 / 1,563
Total R&D	12.08	13.15	13.29	10,640 / 1,343 / 1,076
In-House R&D	11.99	13.02	13.15	9,241 / 1,198 / 970
Patent Stock	1.38	1.75	2.11	7,290 / 714 / 685
Tangible Inv.	11.86	13.87	14.18	27,593 / 1,988 / 1,485
Skilled Emp.	1.44	2.54	3.00	12,580 / 681 / 504
Unskilled Emp.	3.71	5.30	5.51	12,580 / 681 / 504
Exports	14.07	16.00	16.51	21,214 / 1,890 / 1,561

Notes: Variables in constant 2015 prices.

Source: Author's calculations using ESEE.

Table A.6.2: Wage Skill Premium Change in Spain (2002-2017)

	Avg. 2002-2006	Avg. 2013-2017	Change (in pp.)
Aggregate	1.489	1.523	2.299
Manufacturing	1.426	1.560	9.419
Services	1.414	1.479	4.607
Other	1.618	1.579	-2.427

Notes: The table contains the beginning (2002-2006) and end of sample (2013-2017) averages of the wage skill premium. The final column is the change in percentage points. Aggregate includes all sectors except "Other Services" S and "Employed by Household" T due to inconsistent data. Manufacturing is ISIC Rev. 4 sector code C and business services are ISIC Rev. 4 sector codes $G - N$. Other consists of remaining sectors (ISIC Rev. 4 sector codes $A - B, D - F, O - R$) like agriculture, construction, public administration and more. The wage skill premium broken down by sector is in Table A.6.3.
Source: Author's calculations using EUKLEMS-INTANProd database.

Table A.6.3: Wage Skill Premium Change in Spain By Sector (2002-2017)

		Avg. 2002-2006	Avg. 2013-2017	Change (in pp.)
Manufacturing	Manufacturing (C)	1.426	1.560	9.419
Services	Retail (G)	1.370	1.554	13.426
	Transportation and Storage (H)	1.410	1.416	0.413
	Accomodation (I)	1.296	1.378	6.339
	Information and Communication, Real Estate, Professional and Support Services (J,L,M,N)	1.588	1.536	-3.295
	Financial Services (K)	1.017	1.131	11.237
Other	Agriculture (A)	1.673	1.724	3.037
	Mining (B)	1.310	1.912	45.896
	Utilities (D-E)	1.326	1.298	-2.092
	Construction (F)	1.412	1.676	18.715
	Public Administration (O)	1.640	1.269	-22.635
	Education (P)	1.849	1.692	-8.455
	Health and Social Work (Q)	1.948	1.870	-4.005
	Arts and Entertainment (R)	1.678	1.310	-21.929

Notes: The table contains the beginning (2002-2006) and end of sample (2013-2017) averages of the wage skill premium by sector (ISIC Rev. 4 sector codes $A - R$). The table does not contain sectors "Other Services" S and "Employed by Household" T due to inconsistent data.
Source: Author's calculations using EUKLEMS-INTANProd database.

Table A.6.4: Determinants of Foreign Acquisitions (Logit)

	(1) Foreign Ownership Indictator
Lag Logged Sales	0.490***
	(0.115)
Lag Logged Labor Productivity	-0.353**
	(0.142)
Lag Sales Growth	-0.202
	(0.124)
Lag Labor Productivity Growth	0.108
	(0.078)
Lag Logged Average Wage	1.988***
	(0.332)
Lag Logged Total Assets	0.093
	(0.095)
Lag R&D Status	-0.174
	(0.170)
Obs.	29710
Psuedo R-squared	.252

Notes: * p<0.10; ** p<0.05; *** p<0.01. Standard errors clustered by firm in parentheses.

Table A.6.5: P.S. Reweighted Regressions: Additional Variables

	(1) Value Added	(2) Labor Prod.	(3) Total R&D	(4) Patent Stock
Lag Foreign	0.153***	0.079**	0.216**	0.170*
	(0.049)	(0.031)	(0.103)	(0.088)
Obs.	32892	32892	10523	7616
R-squared	.914	.643	.166	.454

Notes: * p<0.10; ** p<0.05; *** p<0.01. Standard errors clustered by firm in parentheses. All regressions include firm and industry-year effects. All dependent variables are in logs. Lag foreign is a dummy variable for foreign ownership in previous period (equal to one if at least 50% the firm's capital is foreign owned by and zero otherwise). The characteristics used to obtain the propensity score are log sales, log labor productivity (value added over employment), sales growth, labor productivity growth, log average wage, log total fixed assets (tangible plus intangible), R&D status, and a year trend. All the previously mentioned variables are lagged one period relative to acquisition. I allow for this relationship to vary across industries by estimating the propensity score separately for each industry. I ensured that only observations within the region of common support are included. I performed the standard tests to check that the balancing hypothesis holds within each industry and found that all covariates are balanced between treated and control observations for all blocks in all industries.

Table A.6.6: P.S. Reweighted Regressions: Different TFP Measures

	Hours as Labor Input		Wage Bill as Labor Input	
	(1) TFP	(2) TFP (Firm Price Index)	(3) TFP	(4) TFP (Firm Price Index)
Lag Foreign	0.039***	0.043***	0.020***	0.026***
	(0.012)	(0.014)	(0.008)	(0.009)
Obs.	32064	27508	32558	27879
R-squared	.659	.689	.818	.696

Notes: * p<0.10; ** p<0.05; *** p<0.01. Standard errors clustered by firm in parentheses. The table shows total factor productivity (TFP) estimates using different labor inputs in the production function: hours and the wage bill. Details regarding firm-level TFP estimation are in Appendix A.2.2. The columns labeled TFP are estimated TFP when value added is deflated by an sector-specific price index. This measure is sometimes referred to as revenue total factor productivity. Column (1) is the TFP that appears in Table 1.2 in the main text. The columns TFP (Firm Price Index) display estimated TFP when value added is deflated by a firm-specific price index. All regressions include firm and industry-year effects. All dependent variables are in logs. Lag foreign is a dummy variable for foreign ownership in previous period (equal to one if at least 50% the firm's capital is foreign owned by and zero otherwise). The characteristics used to obtain the propensity score are log sales, log labor productivity (value added over employment), sales growth, labor productivity growth, log average wage, log total fixed assets (tangible plus intangible), R&D status, and a year trend. All the previously mentioned variables are lagged one period relative to acquisition. I allow for this relationship to vary across industries by estimating the propensity score separately for each industry. I ensured that only observations within the region of common support are included. I performed the standard tests to check that the balancing hypothesis holds within each industry and found that all covariates are balanced between treated and control observations for all blocks in all industries.

Appendix B

Chapter 2 Appendix

B.1 The Pooling-of-Interest Accounting Method

Mergers and acquisitions received different accounting treatments prior to 2001. A merger is defined as the joining of two or more companies to form a single entity. Typically, the assets of the target company are merged into those of the acquirer, and the target's shareholders are either bought out or become shareholders in the acquiring company. A merger usually requires approval from the shareholders of both the acquirer and the target. An acquisition, on the other hand, involves the purchase of more than 50% of the voting shares in a target firm. After an acquisition, the acquirer and target may operate as a single entity or continue as separate legal entities, where the acquirer is referred to as the parent and the target as a subsidiary. In contrast to a merger, the acquirer can negotiate which assets to purchase and which liabilities to assume.

The purchase acquisition method was typically used for acquisitions, while the pooling-of-interest method applied to mergers. To qualify for pooling-of-interests treatment, a "merger" must satisfy 12 specific criteria, grouped into three categories outlined below. APB Opinion No. 16 mandated that these conditions must be met for a combination to be treated as a pooling.

B.1.1 Twelve Criteria for Pooling-of-Interest Accounting

1. **Attributes of Combining Companies**

    (a) Autonomous - Combining companies must be autonomous and not have been a subsidiary or division of another corporation within two years before the plan of combination is initiated. This ensures that the combination is indeed "the union of previously separable groups of stockholders."

    (b) Independent - Prior to the combination, each combining company must have been independent of the other. Intercorporate investment of ten percent or less of the total outstanding voting common stock of any combining company is acceptable and will not impair independence.

2. **Manner of Combining Interest**

   (a) Single Transaction - The combination must be completed within one year after the plan is initiated or completed in a single transaction.

   (b) Exchange of Common Stock - The combination must be effected through the exchange of voting common stock. The acquiring company must acquire no less than 90% of the combining company's voting common stock.

   (c) No Equity Changes in Contemplation - No changes in the equity interests of the voting common stock of any combining company may be made in contemplation of a pooling of interests for a period beginning two years prior to the initiation date of the plan of combination.

   (d) No Shares Reacquired for Purposes of Combination - The reacquisition of voting common stock by any combining company is allowed except for purposes of business combination.

   (e) No Change in Proportionate Equity Interest - The ownership ratios of the stockholders of the combining companies must be preserved.

   (f) Voting Rights Immediately Exercisable - The common stockholders must receive the voting rights they are entitled to and may not be restricted in any way from exercising those rights.

   (g) Combination Resolved at Consummation - The entire plan of combination must be effected on the date of consummation. There may not be any pending provisions for contingent shares to be issued at a later date.

3. **Absence of Planned Transactions**

   (a) No Reacquisition or Retirement of Stock - The combining company may not agree to reacquire or retire any of the stock issued to effect the combination.

   (b) No Special Agreements for Former Shareholders - The combined company may not enter into any agreement for the benefit of former shareholders of the combining companies.

   (c) No Planned Disposal of Substantial Assets - The combined company may not plan to dispose of substantial amounts of assets of the combining companies within two years of the combination. However, disposals in the ordinary course of business of the formerly separate companies and to eliminate duplicate facilities or excess capacity is permitted.

B.1.2 Case Study: The AT&T Acquisition of NCR (Barth & Coxe, 1995)

In 1991, AT&T pursued NCR in a hostile takeover, beginning with an unsolicited bid of $85 per share in November 1990 and eventually closing the deal at $110 per share in September 1991. AT&T aimed to strengthen its position in the computer networking market by integrating NCR's expertise and products. A key priority for AT&T was ensuring the acquisition qualified for pooling-of-interests accounting. NCR, however, resisted the takeover by deliberately creating obstacles to disrupt AT&T's ability to meet the pooling criteria by focusing its efforts on violating the criteria against changes in equity interests.

There three actions to disrupt AT&T's ability to meet the 12 pooling criteria The first was that it repurchased its stock throughout 1991 which is prohibited under criterion 2d. Pooling-of-interests is based on the idea of a "merger of equals" without significant alterations to the equity structure. Such repurchases were prohibited because it disrupts the proportional equity interests of the combining companies' shareholders. The second was that in February 2001, it adopted a qualified employee stock ownership program (ESOP) that held just under 10% of NCR's voting stock. While this technically complied with Criterion 1b, which allows intercorporate investments of 10% or less, the ESOP was a defensive tactic designed to consolidate voting power within NCR and resist AT&T's bid. The third was that NCR issued a $1.00 special dividend in March 1991, violating Criterion 2c, which prohibits changes in equity interests, such as special dividends, when made in contemplation of a business combination. The issuing of special dividends reduced the retained earnings of NCR and thus changed NCR's equity structure.

NCR eventually agreed to the deal and a major part of the negociations was to undo the obstacles that it had constructed. While a federal court invalidated NCR's ESOP program in March 1991, the share repurchases and special $1.00 dividends remained. To remedy the stock repurchaes, NCR reissued 6.3 million shares of its treasury stock before the merger was finalized, reversing the impact of the repurchases. To resolve the special dividends violation, NCR eliminated its next two quarterly dividends, effectively nullifying the special dividend's impact on equity. AT&T compensated NCR shareholders for the forgone dividends by increasing the acquisition price to $110.74 per share. The deal was completed in September 1991 and AT&T was able to use pooling for the acquisition.

Timeline AT&T Acquisition of NCR

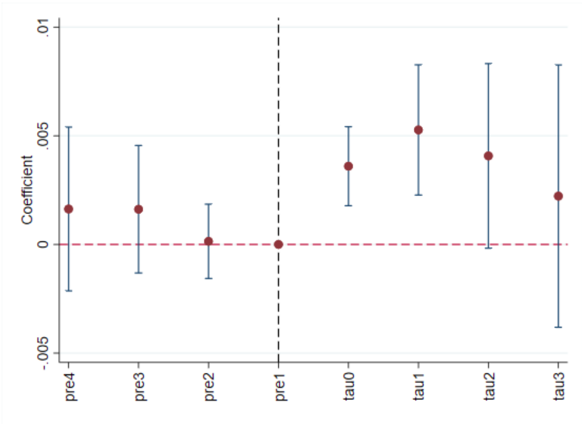
- November, 1990: AT&T's unsolicited bid of $85/share.
- December, 1990: AT&T raises the bid to $90/share.
- January-March, 1991: NCR repurchases stocks.
- February, 1991: NCR issues preferred stock.
- February, 1991: AT&T raises the bid to $100/share.
- March, 1991: NCR distributes special dividends.

- March, 1991: AT&T secures four seats on NCR's board unseating NCR's chairman and CEO, but fails to replace the entire board.
- April, 1991: AT&T raises the bid to \$110/share.
- May, 1991: NCR accepts the \$110/share bid.
- September, 1991: Accounting obstacles are removed and acquisition completed.

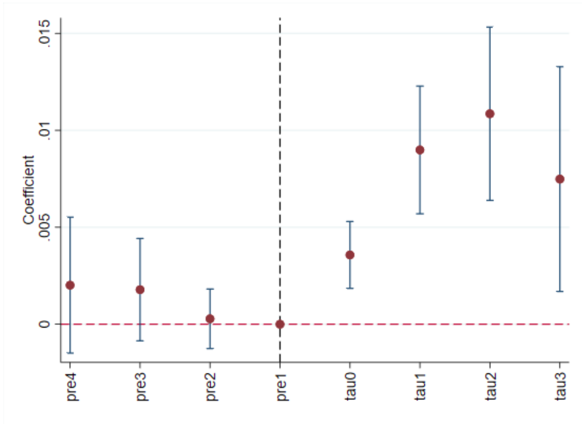
B.2 Additional Figures

Figure B.2.1: LP DID Event Study Pre and Post 2001

(a) Pre-2001



(b) Post-2001



Appendix C

Chapter 3 Appendix

C.1 Data Cleaning

C.1.1 Orbis Historical data

The Orbis Historical data was downloaded in August 2024 from Moody's DataHub.

The preliminary data selection is conducted through the following steps:

1. We construct the year following the suggestion of Kalemli-Özcan et al. (2024). If the closing date is on or after June 1st, the current year is assigned as the operating year. If the closing date is before June 1st, the previous year is assigned as the operating year of the firm. The bvd_id_number and year serve as unique identifiers in the Orbis dataset.

2. We dropped observations with the consolidated code "C2", which denotes a "Statement of a legal entity integrating the statements of its controlled subsidiaries or branches. An unconsolidated statement (U2) is available for this legal entity from the same or a different information provider on Orbis." These firms have two accounts: one for the entire enterprise (headquarters and all branches) and one for the headquarters. We choose to drop the consolidated account of the entire enterprise (C2) and keep the unconsolidated headquarters account (U2) when both accounts exist.

3. To make the values comparable, furthermore, we only keep the data where "number_of_months" is equal to 12 months.

4. After completing the above steps, we found that the Orbis dataset still contains a small portion (0.029%) of observations that exist as duplicates concerning the bvd_id_number and year unique identifiers. These duplicates are mainly due to reporting on different closing dates or through different filing types—local registry filings or/and annual reports. In these cases, we keep the record with the latest date for the reporting year.

5. We drop the years before 1997 because M&A data starts from 1997, as well as the year 2023, which has only 10 observations after the cleaning mentioned above.

Table C.1.1: Missing Observations Analysis - Preliminary

Cause	# Obs Lost	Proportion of Total %	Remaining
# ObS in Raw Data			19,131,872
Step 2: Drop consolidated code C2	62,668	0.325	19,069,204
Step 2: Drop consolidated code C1	5,008	0.026	19,064,196
Step 3: Drop number_of_months $\neq$ 12	712,195	3.723	18,352,001
Step 4: Drop duplicates - keeping latest	2,063	0.011	18,349,938
Step 5: Drop years	698,974	3.665	17,650,964
N. Remaining in Sample	1,480,908	7.741	17,650,964

C.1.2 Orbis M&A data

The merger and acquisition (M&A) data were downloaded from Orbis M&A (formerly known as Orbis Zephyr) provided by Bureau van Dijk, a Moody's Analytics company, in August 2024. As noted earlier, Orbis M&A contains detailed information on mergers and acquisitions starting from 1997. Consequently, our analysis is limited to deals that occurred after 1997.

In the raw data for Spain downloaded from Orbis M&A, we initially identified a total of 40,636 deals. Out of these, 40,180 deals were classified as acquisitions, while 456 were mergers. Since mergers accounted for only about 1% of the total deals, we chose not to differentiate between mergers and acquisitions in our analysis. Instead, we refer to all deals collectively as M&A in this study. The Orbis M&A dataset included deals of various statuses, such as "rumored," "pending," and "withdrawn." To focus on finalized deals, we retained only deals with a status of "completed" or "completed assumed." This filtering process resulted in the exclusion of 5,651 M&A deals.

Our analysis focuses on domestic M&A transactions where both the acquirer and target are Spanish firms. Therefore, we removed deals involving foreign entities. After applying this filter, 26,484 deals remained in our dataset. Additionally, we excluded deals involving more than one acquirer or target, leaving only deals with a single acquirer and a single target. This step reduced the dataset by 4,016 cases. Since our analysis cannot be applied to cross industry M&As, we keep the cases where acquirer and targats from the same industry, this drops 10,604 cases. After this final step, we retained a total of 10,727 deals in the M&A dataset, covering the period from 1997 to 2022.

Table C.1.2: M&A Deals Selection Analysis

Cause	# Deals Lost	Proportion of Total %	Remaining
# Deals in Raw Data			40,636
Layer 1: keep if deal status are completed or completed assumed	5,651	13.9	34,985
Layer 2: keep if acquirers and targets are all Spanish firms	8,501	20.9	26,484
Layer 3: keep if only one acquirer and one target in one deal	4,016	9.88	22,468
Layer 4: keep if deals happened within 1997 - 2022 (included)	2,163	5.32	21,327

Finally, we used information from Orbis Historical to correct the M&A years (defined as the year the deal was announced) in the Orbis M&A data. The reason for this adjustment is that the status date of deals might be documented late in Orbis M&A. Table C.1.3 shows the time difference between the last year the target firm appears in Orbis Spain and the year of the M&A for the corresponding firm recorded as a target in Orbis M&A. For cases where the target firm disappeared one, two, or three years before the recorded M&A year, we adjusted the M&A year to be the year after the last year the firm appeared in the data.

Table C.1.3: Time Difference of M&A between Orbis Spain and Orbis M&A

Relative Disappear Year to M&A	Obs
-5	153
-4	235
-3	442
-2	2,194
-1	5,729
0	286
1	99
2	92
3	73
4	68
5	60
6	49
7	36
8	36
Total Obs	10,144

Note: Table C.1.3 shows the Relative Disappear Year to M&A, defined as the time difference between the last year the target firm appears in Orbis Spain and the year of the the M&A announcement year for the corresponding firm recorded as a target in Orbis M&A. For instance, if the Relative Time to M&A Date equals -1, it means that the last year the target firm existed in the Orbis Global database was one year before the announcement of the M&A documented in Orbis M&A. To address the concern that targets may disappear from the data because the final year of our dataset is 2022, we exclude cases where the last year target firms appear in Orbis Spain data is 2022.
Source: Author's calculation using Orbis Spain and Orbis M&A.

Figure C.1.1 compares the number of deals of Layer 4 in Orbis M&A and our sample with SDC Platinum, another popular source of M&A deals. Prior to 2012, Orbis M&A documents fewer domestic deals per year than SDC Platinum After 2012, the number of deals increases for Orbis M&A. In addition, the figure also demonstrates that our sample (after merging the Orbis Historical and Orbis M&A) contains almost all of the deals from Orbis M&A.

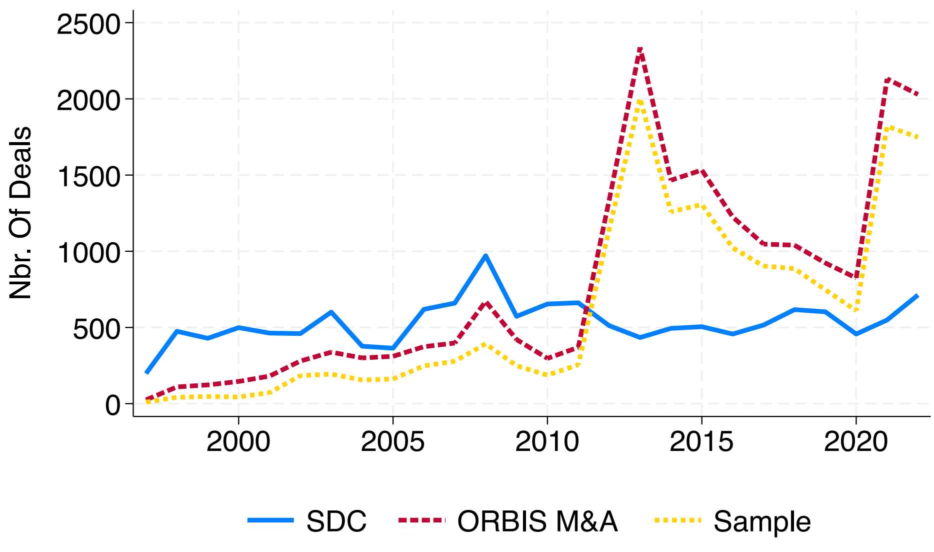


Figure C.1.1

Note: This graph depicts the number of M&A deal observations in SDC Platinum, Orbis M&A, and those used in our analysis.

Source: Author's calculations using SDC Platinum and Orbis M&A.

C.1.3 Merging Orbis historical and Orbis M&A

After the above data cleaning process, we obtained a refined list of M&A deals containing detailed information, including the corresponding Bureau van Dijk (BvD) ID numbers for both the acquirers and the targets. However, it is worth noting that among the 21,427 deals in the final dataset (Layer 4 of Table C.1.2), 2,558 cases were missing either the acquirer ID or the target ID. Additionally, there were instances where some acquirers and targets were involved in multiple M&A deals during the sample period.

We merged the cleaned Orbis Historical dataset with the information from Orbis M&A. Since we do not want our analysis to be influenced by cases outside the focus of our study, we dropped the firms involved in M&A deals that do not satisfy the criterion of involving one Spanish acquirer and one Spanish target. Finally, the merged dataset contains the relevant observations. After the further cleaning described in the section below, this will be the dataset used for the descriptive analysis of the control group, acquirers, and targets, as well as for estimating the production function.

We merged the cleaned Orbis Historical dataset with the information from Orbis M&A. To ensure the analysis focuses on cases within the scope of our study, we excluded firms involved in M&A deals that do not meet the criteria of one Spanish acquirer to one Spanish target. This filtering step ensures that our analysis remains relevant and unaffected by cases outside the intended scope. Following further cleaning procedures outlined in the subsequent sections, this dataset serves as the foundation for our descriptive analysis for the categories of the controlled group, acquirers, and targets. Additionally, this dataset will be used for estimating the production function in later stages of the analysis.

Table C.1.4: Missing Observations Analysis - Further

Cause	# Obs Lost	Proportion of Total %	Remaining
# ObS from last			17,650,964
Drop other cases of M&A	231,619	1.31	17,419,345

C.1.4 Further Data Cleaning

After merging the Orbis M&A data, we performed data cleaning based on the guidelines in Appendix 5.3 of Kalemli-Özcan et al. (2024), customized for our research objectives. Specifically, we implemented the following steps:

1. We removed company-years that lacked simultaneous data for total assets, operating revenue, sales, and employment.

2. Companies were excluded entirely if they reported negative values for total assets, materials, fixed assets, or depreciation/amortization in any year.

3. Firms were dropped if employment or wage bills were negative in any year.

4. Firms reporting negative costs of goods sold, sales, or tangible fixed assets (e.g., buildings, machinery) in any year were removed from the dataset.

5. Companies were excluded if their employment per million of total assets fell below 0.1 or exceeded the 99.9th percentile. Firms with employment per million of sales or sales-to-total-assets ratios exceeding the 99.9th percentile were also removed.

This is the dataset we used to estimate the output elasticities of the production function.

C.1.5 Generating Acquirer-Target Paired Firms

The data we cleaned up to the last step can be used for descriptive statistics of M&A deals, the control group, acquirers, and targets. However, since many observations of firms no longer exist in the dataset after the M&A, the data is subject to selection bias in further regression analyses. To circumvent this problem, we create a virtual acquirer-target paired dataset by combining the information of both acquirers and targets. This virtually constructed dataset can be used more credibly for pre- and post-M&A performance comparisons.

Ideally, if we had firm-year level information for all acquirers and targets in our data, we could build a acquirer-target paired dataset with the variables of interest and the number of mergers or acquisitions that occurred in each year. However, this is difficult to implement in practice, as it is common for observations from some years or firms to be missing.

Thus, when creating this acquirer-target paired data, we include only firms that acted as acquirers or targets once during the sample period. Specifically, we first correct the M&A dates. Orbis M&A reports various dates for M&A events, including the announcement date, completion date, and assumed completion date. Although we do not have a specific definition of the dates used in Orbis M&A, by comparing the data, we observe that many reported dates appear to have been delayed. Since the effects of M&A may also occur between the announcement date and the completion date, we define the year of M&A as the announcement date. We then use historical information from Orbis Historical to correct inconsistencies in M&A dates between Orbis M&A and Orbis Historical.

Next, we merge the information of both acquirers and targets if data is available for both before and after the M&A. In cases where only acquirer information is available after the M&A, we use the acquirer data as the post-M&A information, assuming that the target has been integrated into the acquirer during the post-M&A period. After constructing this virtual dataset, we conduce the similar data cleaning steps like Appendix C.1.4 then merge it with the previously cleaned dataset. Finally, we use the control group (firms not involved during the sample period) and this virtual acquirer-target paired dataset to conduct the event study differences-in-differences design.

After generating all these acquirer-target pairs, we only keep the case where both then acquirers and targets are from the same industry.

C.1.6 Observations used in empirical

Information about the total observations and distinct observations of controlled is described in the following tables.

Table C.1.5: Summary of Observations

Variable	Total Observations	Distinct Observations
Non-M&A firms	17,432,390	1,939,304
Acquirer-Target Paired firms (Horizontal M&A)	63,885	5,147

Notes: The table presents the number of observations in the main data (Orbis Historical) after merging it with Orbis M&A and virtually consolidated firms. 'Non-M&A firm' represents the firms that were not involved in mergers and acquisitions during the sample period. The column 'Total Observations' reports the total number of observations exists in the merged data. The 'Distinct Observations' column provides a count of distinct firms within the corresponding total observations.
Source: Authors' calculations using Orbis Spain and Orbis M&A.

C.1.7 GDP Deflator

The GDP deflator we used was downloaded from the World Bank's World Development Indicators.[1]

C.2 Representativeness of Orbis Spain

We evaluate the coverage and representativeness of Orbis Spain by comparing it to statistics from Eurostat and the National Institute of Statistics (INE), the Spanish national accounts provider.

[1]https://databank.worldbank.org/source/world-development-indicators

We first compare value added, labor compensation, employment and number of firms. Table C.2.1 compares Orbis to Eurostat for value added and labor compensation. It also includes a comparison where exclude Public Services (NACE Rev. 2 sectors > 82) and a smaller time frame (2002-2021). Table C.2.2 does the same comparison but for total number of employment and employment excluding the self-employed. Self-employed individuals account for about a sixth of total employment. Orbis by construction does not contain self-employed individuals, only registered companies. Overall, our sample covers more than half the aggregate economy.

We compare the number of firms for the years 1999 to 2002. We obtain the aggregate number of firms from INE.[2] The first year available from INE is 1999 which is where the comparison begins, however our sample extends further back to 1997. We first examine the sample coverage over time (Figure C.2.1). Coverage stabalizes after 2002. There is a significant drop in 2022 because not all firms have been updated in Orbis as of August 2024. Table C.2.3 shows the averages for number of firms (1999-2022). Our sample covers about 63% of firms in the economy. The table also compares the representativeness of the firm size distribution in terms of employment, averaged over the years 1999 to 2022. The distribution is quite similar. Tables C.2.4-C.2.6) confirms that there is a similar pattern in the cross-section afor the years 2000, 2010 and 2020. The distribution is similar and stable in all three years.

Finally, tables C.2.7-C.2.9 compare value added, labor compensation and employment for some one-digit sector levels and groupings. Coverage in public service sectors (Nace 2-digit codes greater than 82) is limited. The values for some sectors in Orbis exceed that of Eurostat (ie share coverage is greater than 100%). These higher figures in certain sectors reported by Orbis may be due to different NACE codes by Eurostat/INE. A firm can operate across multiple sectors and therefore may be associated with more than one NACE code. In our analysis, we opted to retain only the core NACE code for each firm.

[2]We use INE instead of Eurostat because the latter only provides aggregate number of firms starting in 2005.

C.2.1 Main Tables

Table C.2.1: Representativeness Value Added and Labor Compensation (1997-2022)

	Orbis	Eurostat	Share (%)
Value Added (bil.)	537.7	938.5	57.3
Value Added (bil.) - NACE Rev. 2 $\leq$ 82	511.6	732.6	69.8
Value Added (bil.) - NACE Rev. 2 $\leq$ 82 (2002-2021)	559.3	758.0	73.8
Labor Compensation (bil.)	291.5	489.1	59.6
Labor Compensation (bil.) - NACE Rev. 2 $\leq$ 82	271.7	330.4	82.3
Labor Compensation (bil.) - NACE Rev. 2 $\leq$ 82 (2002-2021)	297.8	339.3	87.8

Notes: The table compares averages (in billions) from Orbis Spain and Eurostat averaged over the years 1999 to 2022. All variables are in constant 2015 prices. Value added and labor compensation from Orbis are the unweighted sums by year and averaged over the time period, whereas the aggregate variables are taken from the national accounts in Eurostat (table code: nama_10_a10).
Source: Authors' calculations using Orbis Spain and Eurostat.

Table C.2.2: Representiveness of Employment (1997-2022)

	Total			No Self-Employed	
	Orbis	Eurostat	Share (%)	Eurostat	Share (%)
Emp. (mil.)	8.2	18.7	43.8	15.9	51.6
Emp. (mil.) NACE Rev. 2 $\leq$ 82	7.6	13.3	57.2	10.9	70.2
Emp. (mil.) NACE Rev. 2 $\leq$ 82 (2002-2021)	8.3	13.7	60.5	11.2	73.8

Notes: The table compares total number of employees (in millions) from Orbis Spain and Eurostat (table code: nama_10_a10_e) averaged over the years 1999 to 2022. The second, third and forth columns compare Orbis employment to the total number of individuals employed. Orbis by construction does not contain self-employed individuals. Columns 4 and 5 show total employment when the self-employed are excluded.
Source: Authors' calculations using Orbis Spain and Eurostat.

(a) Number of Firms

(b) Pct. Share of All Spanish Firms

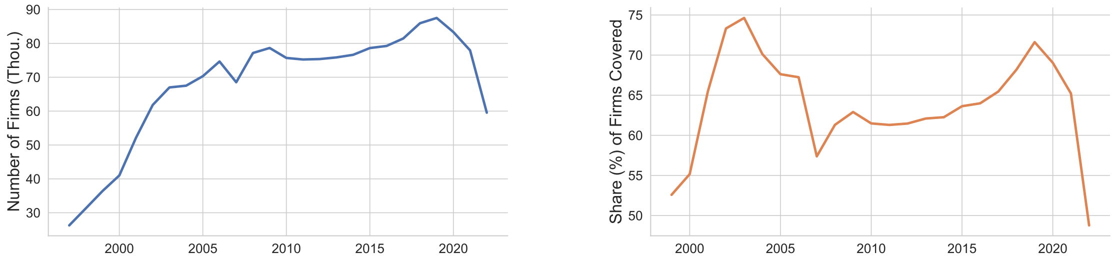


Figure C.2.1

Notes: The graph depicts the coverage of firms in Orbis Spain. Subfigure (a) is the number of firms that appear in Orbis Spain by year. Subfigure (b) is the percentage share of the universe of firms that is covered by Orbis Spain. The aggregate number of firms is obtained from the National Statistics Institute (INE). Data from INE is only available between 1999 and 2022. Self-employed persons are not included.
Source: Authors' calculations using Orbis Spain and National Statistics Institute.

Table C.2.3: Representativeness Number of Firms and Disitribtion (1999-2022)

	Orbis		INE	
Employees	Nbr	Share (%)	Nbr	Share (%)
0 to 9	590,200.9	83.0	978,853.8	87.8
10 to 19	63,382.7	8.9	72,800.7	6.5
20 to 49	39,227.3	5.5	41,898.6	3.8
50 to 199	14,776.2	2.1	16,634.1	1.5
200+	3,910.5	0.5	4,365.4	0.4
Total	711,497.6	100.0	1,114,552.7	100.0

Notes: The table compares the coverage of the firm size distribution by employment of Orbis Spain with the aggregate number of firms from the Central Business Register in INE. Number of firms consists of those either publicaly listed or are limited liability. The distributions are averaged over the years 1999-2022. Self-employed are not included.
Source: Authors' calculations using Orbis and National Statistics Institute.

C.2.1.1 Firm Size Distributions by Year

Table C.2.4: Representativeness of Firm Disitribtion 2000

	Orbis		INE	
Employees	Nbr	Share (%)	Nbr	Share (%)
0 to 9	316,989	77.3	610,626	82.1
10 to 19	47,258	11.5	69,861	9.4
20 to 49	31,569	7.7	43,578	5.9
50 to 199	11,490	2.8	15,822	2.1
200+	2,784	0.7	3,566	0.5
Total	410,090	100.0	743,453	100.0

Notes: The table compares the coverage for the year 2000 of Orbis Spain with the aggregate number of firms from the Central Business Register in INE. It also compares the distribution of firm size. Self-employed are not included.
Source: Authors' calculations using Orbis Spain and National Statistics Institute.

Table C.2.5: Representativeness of Firm Disitribtion 2010

	Orbis		INE	
Employees	Nbr	Share (%)	Nbr	Share (%)
0 to 9	633,549	83.7	1,091,949	88.7
10 to 19	65,542	8.7	75,394	6.1
20 to 49	39,325	5.2	42,448	3.4
50 to 199	14,652	1.9	17,291	1.4
200+	3,943	0.5	4,111	0.3
Total	757,011	100.0	1,231,193	100.0

Notes: The table compares the coverage for the year 2010 of Orbis Spain with the aggregate number of firms from the Central Business Register in INE. It also compares the distribution of firm size. Self-employed are not included.
Source: Authors' calculations using Orbis Spain and National Statistics Institute.

Table C.2.6: Representativeness of Firm Disitribtion 2020

	Orbis		INE	
Employees	Nbr	Share (%)	Nbr	Share (%)
0 to 9	706,546	84.8	1,077,446	89.3
10 to 19	65,702	7.9	68,235	5.7
20 to 49	40,170	4.8	39,815	3.3
50 to 199	16,374	2.0	16,590	1.4
200+	4,662	0.6	4,995	0.4
Total	833,454	100.0	1,207,081	100.0

Notes: The table compares the coverage for the year 2020 of Orbis Spain with the aggregate number of firms from the Central Business Register in INE. It also compares the distribution of firm size. Self-employed are not included.
Source: Authors' calculations using Orbis Spain and National Statistics Institute.

C.2.2 Tables by Sector

Table C.2.7: Representativeness Value Added By Sector (1997-2022)

	Orbis	Eurostat	Share (%)
(A) Agriculture	5.1	29.5	17.2
(B-E) Industry (except construction)	155.8	164.9	94.5
(F) Construction	52.6	78.6	67.0
(G-I) Wholesale and retail trade, transport, accommodation and food service activities	122.0	215.7	56.5
(J) Information and communication	44.5	37.9	117.1
(K) Financial and insurance activities	44.8	40.8	109.7
(L) Real estate activities	16.0	93.1	17.1
(M-N) Professional, scientific and technical activities; administrative and support service activities	52.3	72.1	72.5
(O-Q) Public administration, defence, education, human health and social work activities	12.4	164.5	7.6
(R-U) Arts, entertainment and recreation; other service activities; activities of household and extra-territorial organizations and bodies	8.8	41.4	21.2

Notes: The table compares value added (in billions) of one-digit NACE sectors from Orbis Spain and Eurostat averaged over the years 1999 to 2022. All variables are in constant 2015 prices. Value added and labor compensation from Orbis are the unweighted sums by year and averaged over the time period, whereas the aggregate variables are taken from the national accounts in Eurostat (table code: nama_10_a10).
Source: Authors' calculations using Orbis and Eurostat

Table C.2.8: Representativeness Labor Compensation By Sector (1997-2022)

	Orbis	Eurostat	Share (%)
(A) Agriculture	3.0	5.0	59.4
(B-E) Industry (except construction)	76.0	83.9	90.5
(F) Construction	34.1	40.8	83.5
(G-I) Wholesale and retail trade, transport, accommodation and food service activities	80.4	111.0	72.4
(J) Information and communication	21.6	20.1	107.5
(K) Financial and insurance activities	6.1	20.7	29.6
(L) Real estate activities	4.8	3.5	135.0
(M-N) Professional, scientific and technical activities; administrative and support service activities	35.6	45.3	78.6
(O-Q) Public administration, defence, education, human health and social work activities	10.3	132.9	7.8
(R-U) Arts, entertainment and recreation; other service activities; activities of household and extra-territorial organizations and bodies	5.3	25.9	20.3

Notes: The table compares labor compensation (in billions) of one-digit NACE sectors from Orbis Spain and Eurostat averaged over the years 1999 to 2022. All variables are in constant 2015 prices. Value added and labor compensation from Orbis are the unweighted sums by year and averaged over the time period, whereas the aggregate variables are taken from the national accounts in Eurostat (table code: nama_10_a10).

Source: Authors' calculations using Orbis and Eurostat

Table C.2.9: Representativeness Employment By Sector (1997-2022)

	Total			No Self-Employed	
	Orbis	Eurostat	Share (%)	Eurostat	Share (%)
(A) Agriculture	0.1	0.8	16.1	0.5	30.3
(B-E) Industry (except construction)	1.9	2.6	74.3	2.4	78.5
(F) Construction	1.1	1.7	64.2	1.4	75.3
(G-I) Wholesale and retail trade, transport, accommodation and food service activities	2.7	5.3	51.1	4.1	67.3
(J) Information and communication	0.5	0.4	107.1	0.4	116.3
(K) Financial and insurance activities	0.2	0.4	52.2	0.3	56.0
(L) Real estate activities	0.2	0.2	89.9	0.1	136.4
(M-N) Professional, scientific and technical activities; administrative and support service activities	1.3	1.9	66.7	1.7	78.5
(O-Q) Public administration, defence, education, human health and social work activities	0.4	3.8	9.6	3.7	9.9
(R-U) Arts, entertainment and recreation; other service activities; activities of household and extra-territorial organizations and bodies	0.2	1.6	11.6	1.3	13.7

Notes: The table compares total number of employees (in millions) of one-digit NACE sectors from Orbis Spain and Eurostat (table code: nama_10_a10_e) averaged over the years 1999 to 2022. The second, third and forth columns compare Orbis employment to the total number of individuals employed. Orbis by construction does not contain self-employed individuals. Columns 4 and 5 show total employment when the self-employed are excluded.

Source: Authors' calculations using Orbis Spain and Eurostat.

C.3 Production Function Output Elasticity Estimates

Table C.3.1: Estimated Output Elasticity of Capital and Labor Results

		ACF(2015) Total Assets		ACF(2015) Fixed Assets	
NACE-2	NACE Description	β_k	β_l	β_k	β_l
1	Crop and animal production, hunting and related service activities	0.261	0.710	0.120	0.823
2	Forestry and logging	0.215	0.769	0.081	0.884
3	Fishing and aquaculture	0.475	0.229	0.224	0.314
5	Mining of coal and lignite	0.311	0.766	0.030	1.046
6	Extraction of crude petroleum and natural gas	0.523	0.657	0.255	0.830
7	Mining of metal ores	0.254	0.764	0.111	0.861
8	Other mining and quarrying	0.270	0.776	0.123	0.907
9	Mining support service activities	0.414	0.280	0.071	1.089
10	Manufacture of food products	0.355	0.447	0.076	0.979
11	Manufacture of beverages	0.307	0.732	0.123	0.905
12	Manufacture of tobacco products	0.479	0.573	0.204	0.856
13	Manufacture of textiles	0.202	0.840	0.059	0.983
14	Manufacture of wearing apparel	0.146	0.911	0.043	1.015
15	Manufacture of leather and related products	0.335	0.414	0.159	0.301
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	0.169	0.897	0.051	1.015
17	Manufacture of paper and paper products	0.400	0.440	0.185	0.451
18	Printing and reproduction of recorded media	0.209	0.834	0.061	0.976
19	Manufacture of coke and refined petroleum products	0.469	0.595	0.026	0.370
20	Manufacture of chemicals and chemical products	0.289	0.754	0.070	0.986
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	0.324	0.712	0.076	0.969
22	Manufacture of rubber and plastic products	0.243	0.794	0.201	0.427
23	Manufacture of other non-metallic mineral products	0.412	0.441	0.214	0.421
24	Manufacture of basic metals	0.316	0.569	0.164	0.528
25	Manufacture of fabricated metal products, except machinery and equipment	0.177	0.875	0.049	0.998
26	Manufacture of computer, electronic and optical products	0.212	0.807	0.048	0.971
27	Manufacture of electrical equipment	0.218	0.812	0.044	0.990
28	Manufacture of machinery and equipment n.e.c.	0.195	0.822	0.048	0.970

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NACE-2	NACE Description	ACF(2015) Total Assets β_k	β_l	ACF(2015) Fixed Assets β_k	β_l
29	Manufacture of motor vehicles, trailers and semi-trailers	0.366	0.460	0.187	0.391
30	Manufacture of other transport equipment	0.179	0.845	0.045	0.988
31	Manufacture of furniture	0.120	0.947	0.037	1.023
32	Other manufacturing	0.158	0.883	0.048	0.996
33	Repair and installation of machinery and equipment	0.174	0.860	0.037	0.982
35	Electricity, gas, steam and air conditioning supply	0.542	0.480	0.299	0.738
36	Water collection, treatment and supply	0.331	0.674	0.136	0.862
37	Sewerage	0.277	0.728	0.096	0.940
38	Waste collection, treatment and disposal activities; materials recovery	0.283	0.737	0.110	0.902
39	Remediation activities and other waste management services	0.311	0.698	0.094	0.934
41	Construction of buildings	0.295	0.713	0.122	0.841
42	Civil engineering	0.252	0.750	0.086	0.927
43	Specialised construction activities	0.163	0.872	0.042	0.983
45	Wholesale and retail trade and repair of motor vehicles and motorcycles	0.170	0.883	0.038	1.027
46	Wholesale trade, except of motor vehicles and motorcycles	0.265	0.763	0.054	0.980
47	Retail trade, except of motor vehicles and motorcycles	0.165	0.901	0.047	1.011
49	Land transport and transport via pipelines	0.232	0.793	0.197	0.420
50	Water transport	0.230	0.865	0.071	1.045
51	Air transport	0.271	0.718	−0.002	0.976
52	Warehousing and support activities for transportation	0.272	0.785	0.083	0.964
53	Postal and courier activities	0.170	0.870	0.033	1.008
55	Accommodation	0.197	0.819	0.110	0.894
56	Food and beverage service activities	0.111	0.929	0.039	0.994
58	Publishing activities	0.234	0.780	0.045	0.954
59	Motion picture, video and television programme production, sound recording and music publishing activities	0.348	0.665	0.136	0.861
60	Programming and broadcasting activities	0.230	0.801	0.039	0.990
61	Telecommunications	0.413	0.383	0.078	0.991
62	Computer programming, consultancy and related activities	0.347	0.456	0.040	0.955

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NACE-2	NACE Description	ACF(2015) Total Assets β_k	ACF(2015) Total Assets β_l	ACF(2015) Fixed Assets β_k	ACF(2015) Fixed Assets β_l
63	Information service activities	0.241	0.780	0.059	0.944
64	Financial service activities, except insurance and pension funding	0.351	0.664	0.212	0.801
65	Insurance, reinsurance and pension funding, except compulsory social security	0.257	0.741	0.102	0.936
66	Activities auxiliary to financial services and insurance activities	0.245	0.765	0.069	0.946
68	Real estate activities	0.355	0.672	0.200	0.788
69	Legal and accounting activities	0.209	0.798	0.072	0.918
70	Activities of head offices; management consultancy activities	0.276	0.742	0.106	0.894
71	Architectural and engineering activities; technical testing and analysis	0.267	0.730	0.082	0.884
72	Scientific research and development	0.187	0.814	0.031	0.978
73	Advertising and market research	0.251	0.762	0.062	0.936
74	Other professional, scientific and technical activities	0.251	0.776	0.074	0.930
75	Veterinary activities	0.188	0.836	0.059	0.932
77	Rental and leasing activities	0.403	0.644	0.194	0.847
78	Employment activities	0.160	0.854	−0.101	2.062
79	Travel agency, tour operator and other reservation service and related activities	0.221	0.809	0.025	1.008
80	Security and investigation activities	0.159	0.863	0.025	0.970
81	Services to buildings and landscape activities	0.125	0.897	0.029	0.982
82	Office administrative, office support and other business support activities	0.232	0.793	0.085	0.923

Note: The "ACF(2015) Total Asset" columns display the estimation results using the procedure described in the main text with total assets as the measure of capital used in estimation. The "ACF(2015) Fixed Asset" columns display the estimation results using the same procedure, with fixed assets as the measure of capital used in estimation. Our preferred results are those from the first approach, and our findings are robust to the second approach. The second result is similar to the labor productivity results, as the output elasticity of capital is relatively small, which is a common finding not only in the Spanish data. Regression results for labor productivity are also reported in the appendix.

Source: Author's estimations using Orbis Spain and Orbis M&A.

C.4 Additional Descriptives

C.4.1 Never-Involved, Targets and Acquirers

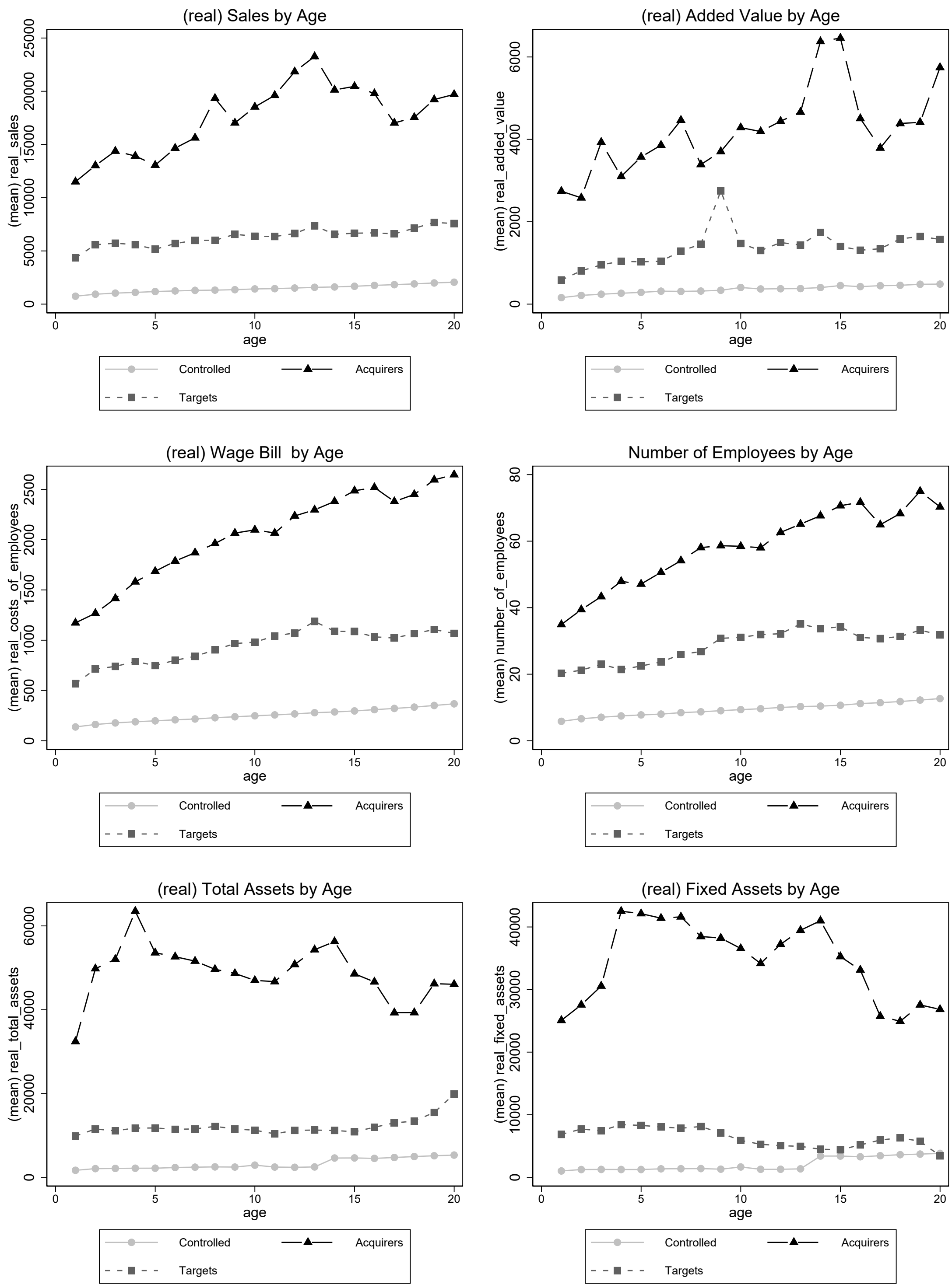

Figure C.4.1

Note: This graph depicts the trends in sales, value added, labor, and capital by ages for the control group (firms that have never been involved in any M&A), acquirers, and targets.

Source: Author's calculations using Orbis Spain and Orbis M&A.

Table C.4.1: Descriptive Statistics

Varname	Non-M&A	Acquirers	Targets
Sales	1813.97	23423.72	7404.48
Added Value	427.64	5616.37	1574.69
Ebitda	126.31	2289.74	453.57
Long Term Debt	1049.65	13395.64	3628.50
Costs of Employees	309.23	2870.79	1140.35
Number of Employees	11.02	83.88	33.35
Total Assets	3561.09	56170.46	13594.48
Fixed Assets	1908.35	33421.13	6495.26
Age	12.41	16.46	12.64

Notes: The table compares the pooled averages of sales, added value, cost of employment, and number of employees among the non-M&A group (firms not involved in M&A), acquirers, and targets. Acquirers (and targets) also only include firms that acted as acquirers (or targets) once.
Source: Authors' calculations using Orbis Spain and Eurostat.

Table C.4.2: Descriptive Statistics By Ages

Age	Group	Sales	Added Value	Wage	Employees	Total Assets	Fixed Assets
1	Acquirers	11499.87	2741.43	1172.46	34.94	32410.67	25073.63
1	Targets	4351.74	587.94	568.58	20.30	9860.92	6854.78
1	Non-M&A	747.02	158.28	137.31	5.84	1673.82	1021.87
2	Acquirers	13027.67	2580.47	1267.96	39.42	49796.71	27559.51
2	Non-M&A	934.11	213.00	161.94	6.62	2078.68	1243.36
2	Targets	5578.83	808.70	713.31	21.20	11527.28	7715.72
3	Acquirers	14376.89	3931.05	1416.05	43.33	52034.22	30567.41
3	Targets	5729.36	954.10	739.40	22.99	11127.78	7438.48
3	Non-M&A	1035.77	241.32	177.35	7.07	2129.88	1262.96
4	Non-M&A	1106.23	264.76	188.87	7.46	2173.43	1249.40
4	Targets	5587.61	1041.21	788.08	21.43	11754.75	8429.42
4	Acquirers	13918.69	3099.95	1580.63	47.92	63510.52	42515.82
5	Targets	5161.01	1027.32	748.41	22.46	11777.59	8299.76
5	Acquirers	13057.51	3572.69	1685.36	47.11	53599.39	42133.81
5	Non-M&A	1184.02	286.79	197.93	7.77	2182.88	1253.95
6	Acquirers	14658.03	3859.81	1787.09	50.63	52653.55	41410.50
6	Non-M&A	1242.09	314.73	208.17	8.01	2347.39	1361.98
6	Targets	5696.15	1042.69	800.35	23.70	11452.36	8045.47
7	Targets	5985.95	1288.00	839.13	25.93	11555.09	7850.69
7	Non-M&A	1295.04	310.12	216.55	8.45	2427.17	1381.63
7	Acquirers	15623.33	4465.24	1869.64	54.13	51614.81	41620.00
8	Targets	6005.34	1456.55	904.13	26.81	12153.61	8112.68
8	Acquirers	19342.45	3389.05	1962.20	58.07	49651.66	38480.27
8	Non-M&A	1320.63	317.80	229.07	8.70	2490.76	1397.09

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Age	Group	Sales	Added Value	Wage	Employees	Total Assets	Fixed Assets
9	Non-M&A	1360.07	336.57	238.42	9.04	2451.75	1306.64
9	Targets	6561.98	2748.20	966.75	30.79	11555.03	7072.45
9	Acquirers	17027.39	3705.06	2065.46	58.64	48658.92	38230.14
10	Non-M&A	1431.25	404.38	248.22	9.36	2910.21	1659.92
10	Acquirers	18528.49	4285.06	2097.63	58.46	47005.02	36568.28
10	Targets	6381.27	1473.02	980.53	31.09	11246.04	5904.16
11	Acquirers	19619.91	4191.15	2066.44	58.02	46714.37	34173.65
11	Non-M&A	1456.39	368.32	256.99	9.62	2456.52	1288.21
11	Targets	6353.16	1302.22	1042.60	31.92	10390.80	5282.85
12	Non-M&A	1512.91	374.48	267.19	10.00	2391.53	1293.84
12	Targets	6633.79	1495.65	1072.03	32.17	11205.42	5057.00
12	Acquirers	21840.17	4440.44	2236.12	62.64	50806.24	37243.64
13	Acquirers	23267.69	4661.65	2296.50	65.13	54329.62	39471.14
13	Targets	7369.34	1435.68	1186.43	35.10	11271.84	4952.01
13	Non-M&A	1582.26	379.16	279.04	10.28	2485.05	1354.46
14	Targets	6562.00	1742.36	1089.10	33.71	11194.10	4490.17
14	Non-M&A	1615.94	402.46	286.56	10.41	4606.98	3404.48
14	Acquirers	20131.63	6375.25	2380.05	67.66	56271.14	41001.79
15	Targets	6669.34	1402.19	1086.68	34.26	10874.10	4400.16
15	Non-M&A	1680.69	451.84	296.47	10.67	4628.87	3401.68
15	Acquirers	20457.95	6459.88	2486.41	70.67	48585.09	35271.47
16	Acquirers	19784.54	4506.55	2519.07	71.69	46651.23	33124.13
16	Targets	6700.84	1309.63	1033.29	31.06	11963.05	5181.89
16	Non-M&A	1763.82	425.67	308.96	11.18	4529.44	3286.90
17	Acquirers	17023.70	3790.70	2379.01	64.93	39300.05	25742.34
17	Non-M&A	1832.24	448.79	321.31	11.45	4737.73	3458.94
17	Targets	6606.67	1344.27	1022.04	30.72	12994.06	5959.88
18	Targets	7127.61	1584.41	1066.14	31.35	13432.96	6308.10
18	Acquirers	17546.26	4386.02	2449.93	68.31	39315.96	24931.64
18	Non-M&A	1903.27	458.05	334.35	11.79	4963.88	3621.44
19	Acquirers	19226.24	4414.24	2595.00	75.02	46214.68	27550.83
19	Non-M&A	1991.34	482.69	350.86	12.23	5156.54	3711.76
19	Targets	7672.10	1642.74	1105.71	33.25	15488.08	5758.76
20	Acquirers	19706.91	5745.94	2646.71	70.29	46075.12	26837.61
20	Targets	7576.63	1573.21	1067.73	31.82	19838.89	3427.26
20	Non-M&A	2062.47	487.21	367.39	12.68	5318.09	3829.77

Note: This table presents sales, value added, labor, and capital by age for the non-M&A group (firms that have never been involved in any M&A), acquirers, and targets.
Source: Author's calculations using Orbis Spain and Orbis M&A.

C.4.2 Acquirer-Target Pairs

Table C.4.3: Descriptive Statistics for Acquirer-Target Pairs (time to treat: -5 to 8)

Time to Treat	Sales	Added Value	Wage Bill	N. Employees	Total Assets	Fixed Assets
-5	30242	10457	4005	113	107648	73748
-4	29433	12114	4179	116	104150	77400
-3	27525	7293	4288	110	103197	76349
-2	28714	8810	4760	123	100818	68917
-1	27815	6756	4739	121	99755	69592
0	23268	7260	3920	97	94090	62773
1	25535	7625	4218	100	90402	61010
2	26296	7095	4142	103	89712	61022
3	26899	6630	4255	104	88759	59469
4	27296	7963	4168	103	88274	58816
5	27573	8380	4168	102	91011	61031
6	28072	9031	4318	107	88765	60608
7	27557	8359	4315	109	87386	58643
8	27671	6726	4328	109	83311	55436

Notes: Number of Unique Acquirer-Target Pairs = 456. The table compares the pooled averages of sales, added value, labor, and capital for the acquirer-target pairs that exist at all time points from *time to treat* == -5 to *time to treat* == 8.
Source: Authors' calculations using Orbis Spain and Eurostat.

Table C.4.4: Descriptive Statistics for Acquirer-Target Pairs (time to treat: -1 to 8)

Time to Treat	Sales	Added Value	Wage Bill	N. Employees	Total Assets	Fixed Assets
-1	25937	7404	3997	103	101680	54012
0	22593	6256	3348	79	97322	48942
1	23163	7546	3438	83	89841	49756
2	23457	6604	3410	87	90544	49607
3	24505	6555	3643	86	90098	48631
4	25214	7332	3542	88	89666	46896
5	25719	8018	3613	89	90421	46902
6	25993	8154	3755	95	90997	46277
7	26678	8193	3849	97	93732	45103
8	26898	7605	3869	99	89796	41492

Notes: Number of Unique Acquirer-Target Pairs = 858. The table compares the pooled averages of sales, added value, labor, and capital for the acquirer-target pairs that exist at all time points from *time to treat* == -1 to *time to treat* == 8.
Source: Authors' calculations using Orbis Spain and Eurostat.

Table C.4.5: Descriptive Statistics for Acquirer-Target Pairs (time to treat: -1 to 3)

Time to Treat	Sales	Added Value	Wage Bill	N. Employees	Total Assets	Fixed Assets
-1	24899	7181	4056	114	90609	57776
0	23328	6396	3628	96	89204	56277
1	24471	7399	3794	101	87323	56850
2	25508	6790	3771	104	87350	50399
3	30251	7978	3926	108	86508	46652

Notes: Number of Unique Acquirer-Target Pairs = 2,571. The table compares the pooled averages of sales, added value, labor, and capital for the acquirer-target pairs that exist at all time points from *time to treat* == -1 to *time to treat* == 3.
Source: Authors' calculations using Orbis Spain and Eurostat.

C.5 Additional Regresson Results

C.5.1 Additional TFPR Results

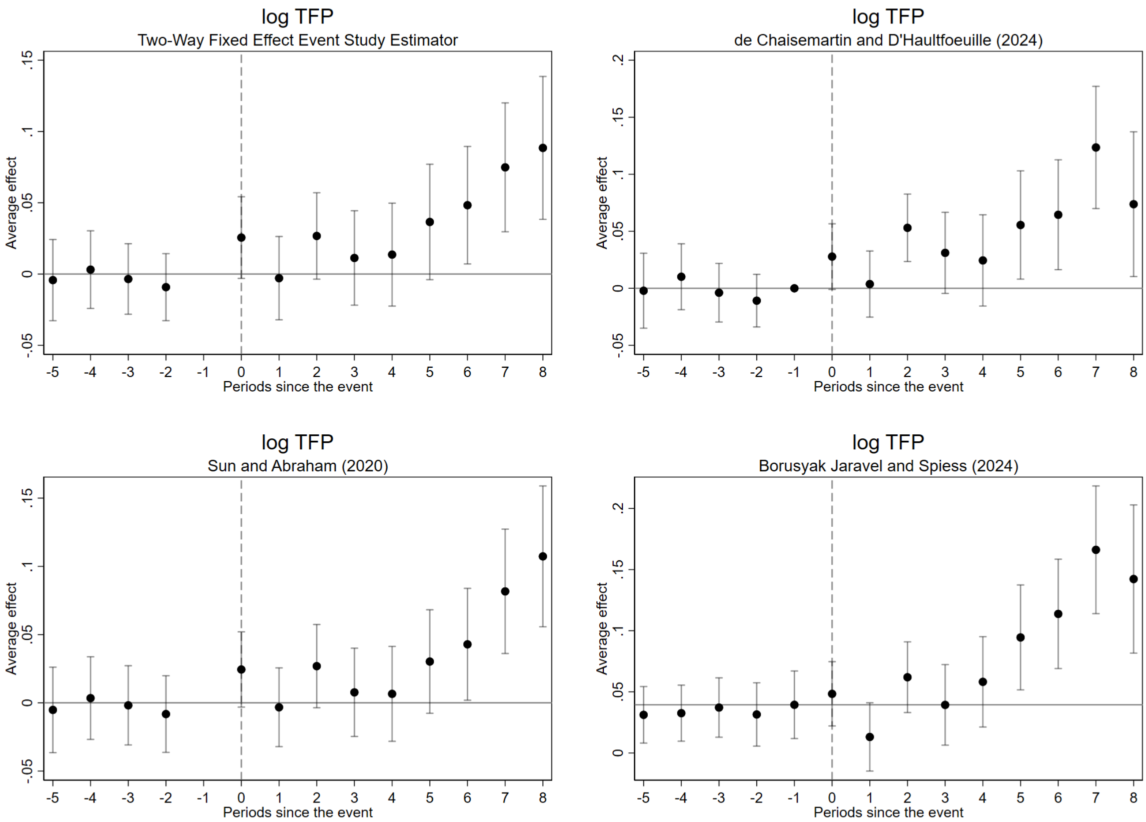
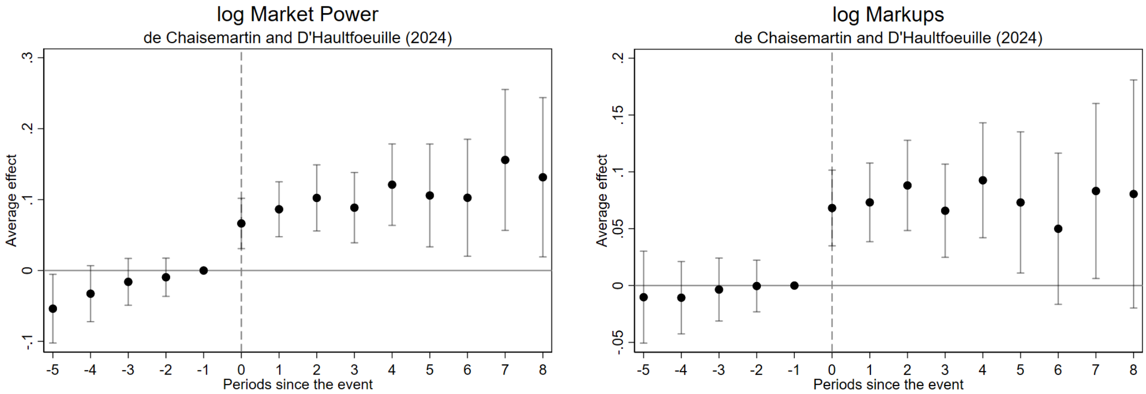


Figure C.5.1: Effect of M&A on TFPR – Different Estimators

Note: This figure presents the event study effect of M&A on TFPR using the Two-Way Fixed effect estimator and estimators from De Chaisemartin and d'Haultfoeuille (2024), Sun and Abraham (2021) and Borusyak et al. (2024). The two way fixed effect and estimators from Sun and Abraham (2021) and Borusyak et al. (2024) use firms that have never been involved in M&A as the control group, while the estimators from De Chaisemartin and d'Haultfoeuille (2024) use both firms that have never been involved in M&A and firms that have been involved in M&A but not yet treated as the control group. The bands represent 95% confidence intervals with standard errors clustered at the firm level.

Source: Author's estimation using Orbis Spain and Orbis M&A.

C.5.2 Additional Markup Results



(a) Not Yet Treated (b) Never Involved and Not Yet Treated

Figure C.5.2: M&A Effect on Markups with Different Estimator

Note: This figure presents the event study effect of M&A on markups using the De Chaisemartin and d'Haultfoeuille (2024) estimator. The figure on the left is the regression using firms that have been involved in an M&A but not yet treated (ie, before the M&A deal occurs) as the control group. The figure on the right uses both firms that have never been involved in an M&A and firms not yet treated as the control group. The bands represent 95% confidence intervals with standard errors clustered at the firm level.

Source: Author's estimation using Orbis Spain and Orbis M&A.

C.5.3 Additional Results for Inputs and Outputs

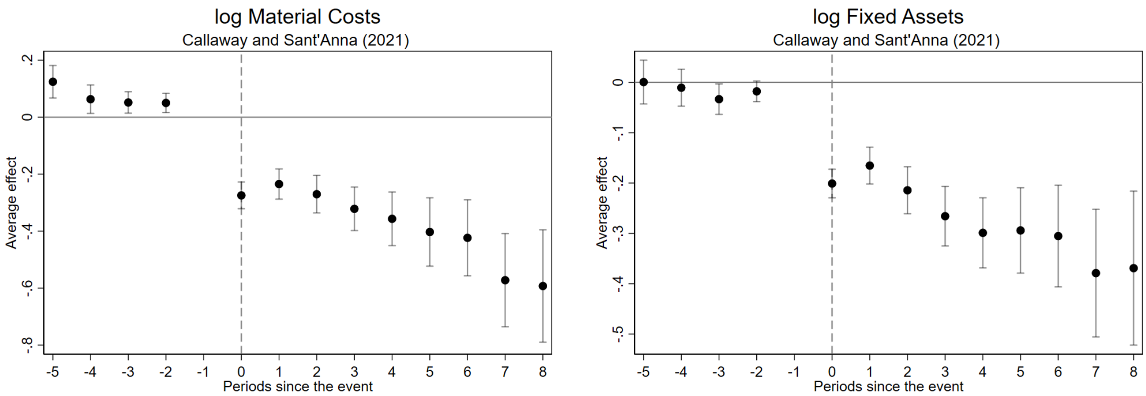


Figure C.5.3: M&A Effect on Inputs and Outputs – Additional Variables

Note: The figure presents the event study effect of M&A on materials and fixed assets for acquirer-target pairs (before and after the M&A) using the Callaway and Sant'Anna (2021) estimator. The regressions use firms that have been involved in M&A but not yet treated (i.e., before the M&A deal occurs) as the control group. The bands represent 95% confidence intervals with standard errors clustered at the firm level.

Source: Author's estimation using Orbis Spain and Orbis M&A.

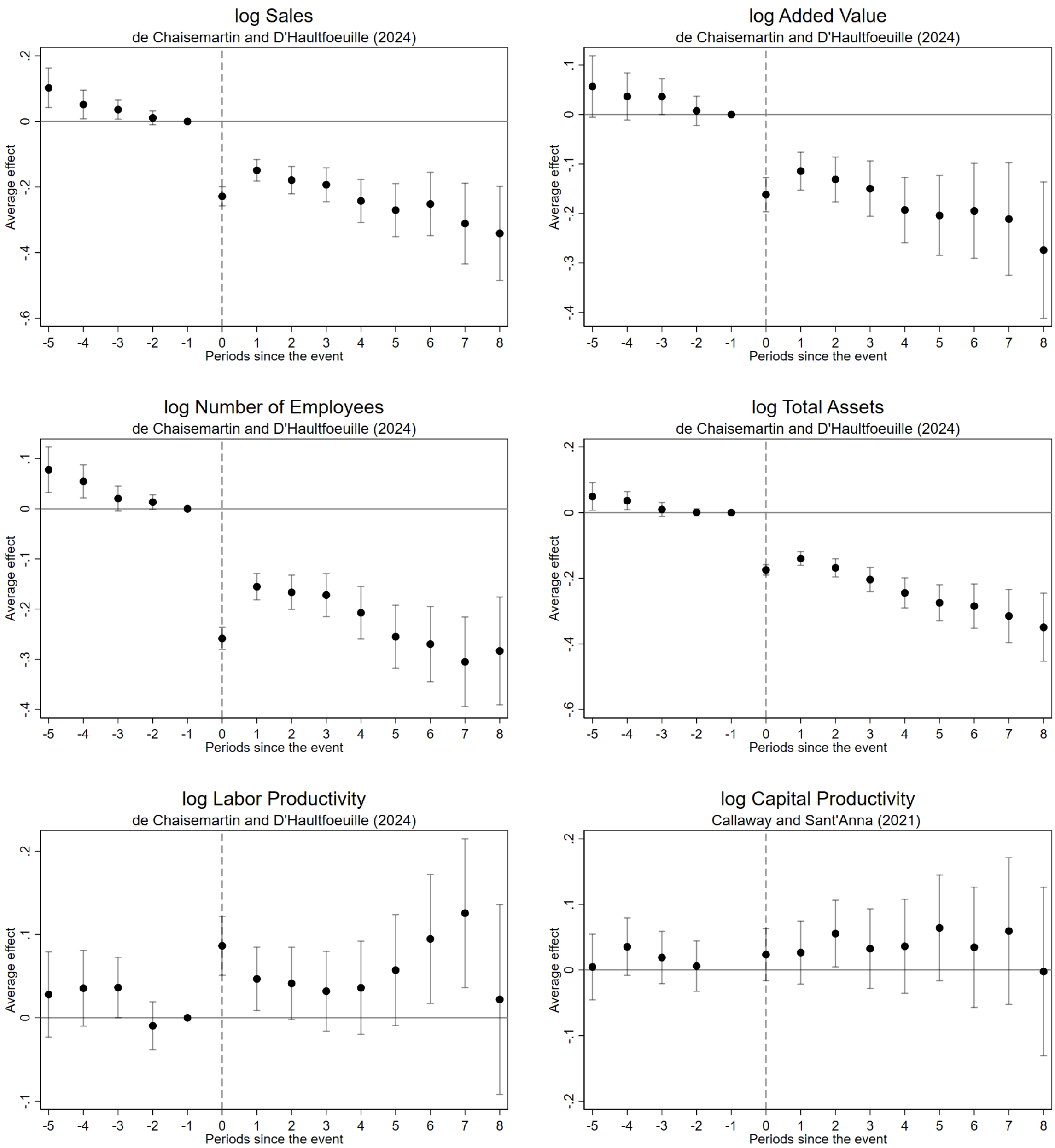


Figure C.5.4: M&A Effect on Inputs and Outputs – Different Estimators

Note: The figure presents the event study effect of M&A on sales, value added, number of employees and total assets for acquirer-target pairs (before and after the M&A) using the De Chaisemartin and d'Haultfoeuille (2024) estimator. The regressions use firms that have been involved in M&A but not yet treated (i.e., before the M&A deal occurs) as the control group. The bands represent 95% confidence intervals with standard errors clustered at the firm level.

Source: Author's estimation using Orbis Spain and Orbis M&A.

C.5.3.1 Acquirers

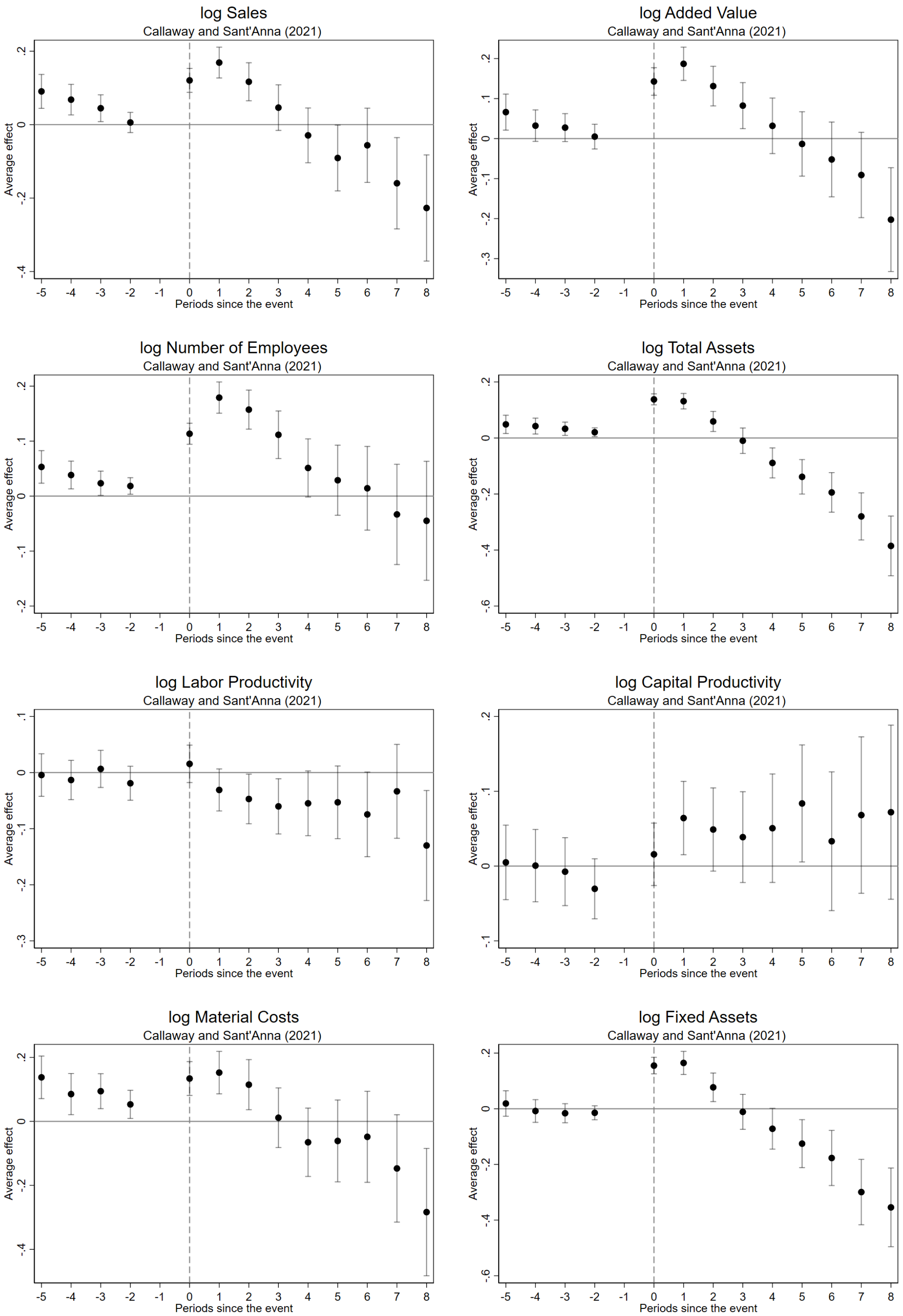


Figure C.5.5: M&A Effect on Inputs and Outputs – Acquirers

Note: The figure presents the event study effect of M&A on sales, value added, number of employees, total assets, material costs and fixed assets for acquirers (before and after the M&A) using the Callaway and Sant'Anna (2021) estimator. The regressions use firms that have been involved in M&A but not yet treated (i.e., before the M&A deal occurs) as the control group. The bands represent 95% confidence intervals with standard errors clustered at the firm level.

Source: Author's estimation using Orbis Spain and Orbis M&A.

C.5.3.2 Targets

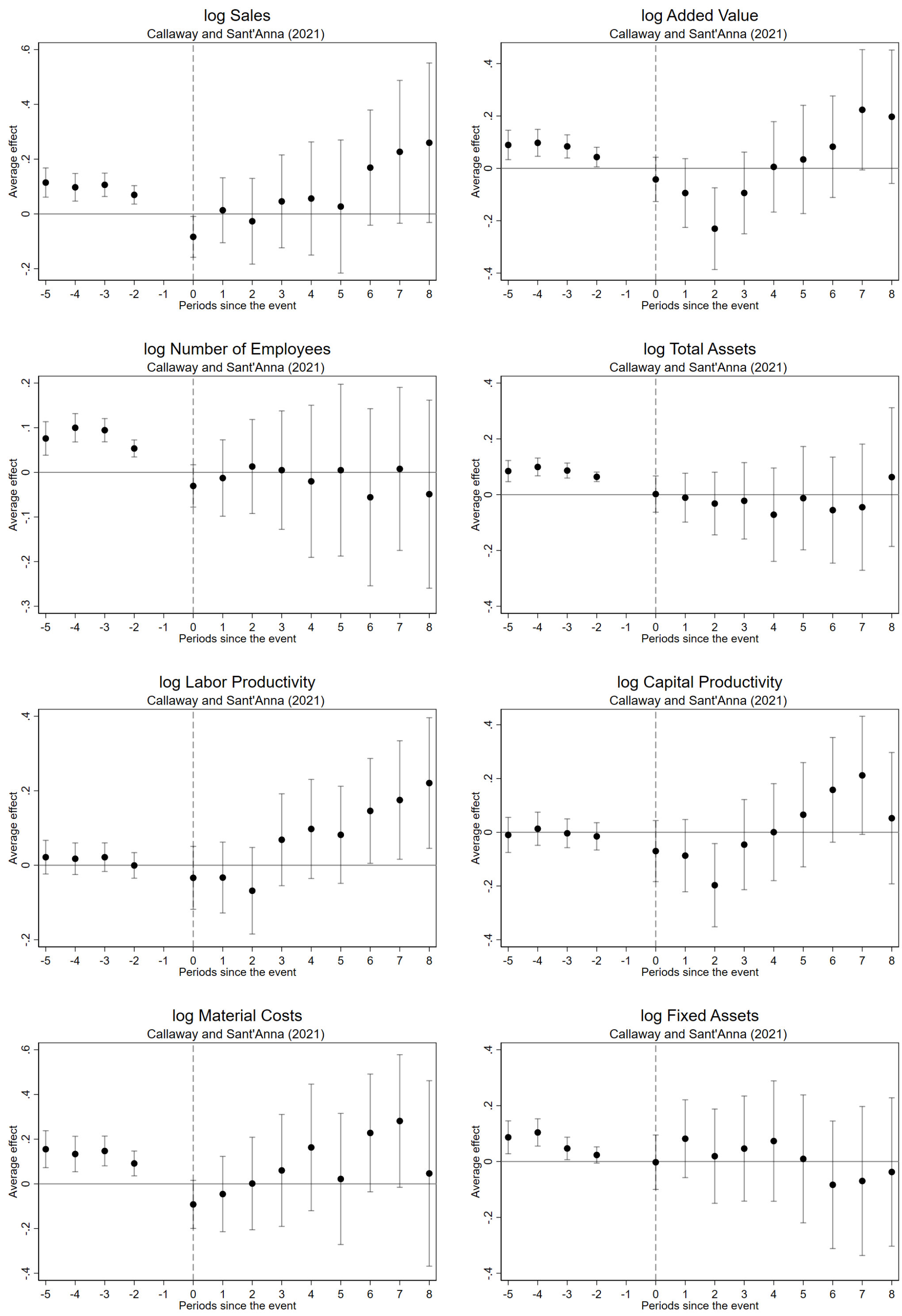


Figure C.5.6: M&A Effect on Inputs and Outputs – Targets

Note: The figure presents the event study effect of M&A on sales, value added, number of employees, total assets, material costs and fixed assets for targets (before and after the M&A) using the Callaway and Sant'Anna (2021) estimator. The regressions use firms that have been involved in M&A but not yet treated (i.e., before the M&A deal occurs) as the control group. The bands represent 95% confidence intervals with standard errors clustered at the firm level.

Source: Author's estimation using Orbis Spain and Orbis M&A.

C.6 Math Appendix

C.6.1 Productivity

$$
\begin{aligned}
Z^{\text{pooled}}_{A,1,t} =& \frac{Y^{\text{pooled}}_{A,1,t}}{K^{\beta_k}_{A,1,t} L^{\beta_l}_{A,1,t}} \\
=& \frac{Y_{A,1,t} + Y_{T,1,t}}{(K_{A,1,t} + K_{T,1,t})^{\beta_k} (L_{A,1,t} + L_{T,1,t})^{\beta_l}} \\
=& \frac{Z_{A,1,t} K^{\beta_k}_{A,1,t} L^{\beta_l}_{A,1,t} + Z_{T,1,t} K^{\beta_k}_{T,1,t} L^{\beta_l}_{T,1,t}}{(K_{A,1,t} + K_{T,1,t})^{\beta_k} (L_{A,1,t} + L_{T,1,t})^{\beta_l}} \\
=& Z_{A,1,t} \frac{K^{\beta_k}_{A,1,t} L^{\beta_l}_{A,1,t}}{(K_{A,1,t} + K_{T,1,t})^{\beta_k} (L_{A,1,t} + L_{T,1,t})^{\beta_l}} + Z_{T,1,t} \frac{K^{\beta_k}_{T,1,t} L^{\beta_l}_{T,1,t}}{(K_{A,1,t} + K_{T,1,t})^{\beta_k} (L_{A,1,t} + L_{T,1,t})^{\beta_l}} \\
=& Z_{A,1,t} \left(\frac{K_{A,1,t}}{K_{A,1,t} + K_{T,1,t}} \right)^{\beta_k} \left(\frac{L_{A,1,t}}{L_{A,1,t} + L_{T,1,t}} \right)^{\beta_l} + Z_{T,1,t} \left(\frac{K_{T,1,t}}{K_{A,1,t} + K_{T,1,t}} \right)^{\beta_k} \left(\frac{L_{T,1,t}}{L_{A,1,t} + L_{T,1,t}} \right)^{\beta_l}
\end{aligned}
$$

C.6.1.1 Under Constant Returns to Scale

Define input shares:

$$
s_{K_A} = \frac{K_{A,1,t}}{K_{A,1,t} + K_{T,1,t}}, \quad s_{K_T} = \frac{K_{T,1,t}}{K_{A,1,t} + K_{T,1,t}}, \quad s_{L_A} = \frac{L_{A,1,t}}{L_{A,1,t} + L_{T,1,t}}, \quad s_{L_T} = \frac{L_{T,1,t}}{L_{A,1,t} + L_{T,1,t}}.
$$

The pooled productivity becomes

$$
Z^{\text{pooled}}_{A,1,t} = Z_{A,1,t} s^{\beta_k}_{K_A} s^{\beta_l}_{L_A} + Z_{T,1,t} s^{\beta_k}_{K_T} s^{\beta_l}_{L_T}
$$

By the concavity of the logarithm (Jensen's inequality), we have

$$
s^{\beta_k}_{K_i} s^{1-\beta_k}_{L_i} \leq \beta_k s_{K_i} + (1 - \beta_k) s_{L_i}
$$

When $Z_{A,1,t}$ and $Z_{T,1,t}$ are different:

$$
\begin{aligned}
Z^{\text{pooled}}_{A,1,t} =& Z_{A,1,t} s^{\beta_k}_{K_A} s^{\beta_l}_{L_A} + Z_{T,1,t} s^{\beta_k}_{K_T} s^{\beta_l}_{L_T} \\
\leq& Z_{A,1,t} (\beta_k s_{K_A} + (1 - \beta_k) s_{L_A}) + Z_{T,1,t} (\beta_k s_{K_T} + (1 - \beta_k) s_{L_T}) \\
Z^{\text{pooled}}_{A,1,t} \leq& \beta_k s_{K_A} Z_{A,1,t} + (1 - \beta_k) s_{L_A} Z_{A,1,t} + \beta_k s_{K_T} Z_{T,1,t} + (1 - \beta_k) s_{L_T} Z_{T,1,t}
\end{aligned}
$$

When $Z_{A,1,t} = Z_{T,1,t}$:

The pooled productivity becomes

$$
Z^{\text{pooled}}_{A,1,t} = Z_{A,1,t} \cdot \left[s^{\beta_k}_{K_A} s^{\beta_l}_{L_A} + s^{\beta_k}_{K_T} s^{\beta_l}_{L_T} \right]
$$

$$
Z_{A,1,t} s^{\beta_k}_{K_A} s^{\beta_l}_{L_A} + Z_{T,1,t} s^{\beta_k}_{K_T} s^{\beta_l}_{L_T} \leq \beta_k (s_{K_A} + s_{K_T}) + (1 - \beta_k)(s_{L_A} + s_{L_T}) = \beta_k + (1 - \beta_k) = 1
$$

Thus,

$$
Z^{\text{pooled}}_{A,1,t} \leq Z_{A,1,t}
$$

C.6.1.2 Under Constant Ratio Input Use

Simplify the numerator and denominator:

Numerator:

$$Z_{A,1,t}\lambda^{\beta_K+\beta_L}K_{T,1,t}^{\beta_K}L_{T,1,t}^{\beta_L}+Z_{T,1,t}K_{T,1,t}^{\beta_K}L_{T,1,t}^{\beta_L}=(Z_{A,1,t}\lambda^{\beta_K+\beta_L}+Z_{T,1,t})K_{T,1,t}^{\beta_K}L_{T,1,t}^{\beta_L}.$$

Denominator:

$$(\lambda K_{T,1,t}+K_{T,1,t})^{\beta_K}(\lambda L_{T,1,t}+L_{T,1,t})^{\beta_L}=(\lambda+1)^{\beta_K+\beta_L}K_{T,1,t}^{\beta_K}L_{T,1,t}^{\beta_L}.$$

Combine numerator and denominator:

When $Z_{A,1,t}$ and $Z_{T,1,t}$ are different:

$$Z_{A,1,t}^{\text{pooled}}=\frac{(Z_{A,1,t}\lambda^{\beta_K+\beta_L}+Z_{T,1,t})K_{T,1,t}^{\beta_K}L_{T,1,t}^{\beta_L}}{(\lambda+1)^{\beta_K+\beta_L}K_{T,1,t}^{\beta_K}L_{T,1,t}^{\beta_L}}=\frac{(Z_{A,1,t}\lambda^{\beta_K+\beta_L}+Z_{T,1,t})}{(\lambda+1)^{\beta_K+\beta_L}}.$$

When $Z_{A,1,t}=Z_{T,1,t}$:

$$Z_{A,1,t}^{\text{pooled}}=Z_{A,1,t}\frac{(\lambda^{\beta_K+\beta_L}+1)}{(\lambda+1)^{\beta_K+\beta_L}}.$$

C.6.1.3 Under CRS and Constant Ratio Input Use Assumption

$$Z_{A,1,t}^{\text{pooled}}=\frac{Z_{A,1,t}K_{A,1,t}^{\beta_K}L_{A,1,t}^{\beta_L}+Z_{T,1,t}K_{T,1,t}^{\beta_K}L_{T,1,t}^{\beta_L}}{(K_{A,1,t}+K_{T,1,t})^{\beta_K}(L_{A,1,t}+L_{T,1,t})^{\beta_L}}.$$

Assume both constant ratio input use $\frac{K_{A,1,t}}{K_{T,1,t}}=\frac{L_{A,1,t}}{L_{T,1,t}}\equiv\lambda$ and constant returns to scale $\beta_K+\beta_L=1$.

Simplify the numerator and denominator

Numerator:

$$Z_{A,1,t}(\lambda K_{T,1,t})^{\beta_K}(\lambda L_{T,1,t})^{\beta_L}+Z_{T,1,t}K_{T,1,t}^{\beta_K}L_{T,1,t}^{\beta_L}.$$

Using $\beta_K+\beta_L=1$, this becomes:

$$Z_{A,1,t}\lambda^{\beta_K+\beta_L}K_{T,1,t}^{\beta_K}L_{T,1,t}^{\beta_L}+Z_{T,1,t}K_{T,1,t}^{\beta_K}L_{T,1,t}^{\beta_L}=(Z_{A,1,t}\lambda+Z_{T,1,t})K_{T,1,t}^{\beta_K}L_{T,1,t}^{\beta_L}.$$

Denominator:

$$(\lambda K_{T,1,t}+K_{T,1,t})^{\beta_K}(\lambda L_{T,1,t}+L_{T,1,t})^{\beta_L}=(\lambda+1)^{\beta_K+\beta_L}K_{T,1,t}^{\beta_K}L_{T,1,t}^{\beta_L}.$$

Using $\beta_K+\beta_L=1$, this simplifies to:

$$(\lambda+1)K_{T,1,t}^{\beta_K}L_{T,1,t}^{\beta_L}.$$

Combine the numerator and denominator

When $Z_{A,1,t}\neq Z_{T,1,t}$:

$$Z_{A,1,t}^{\text{pooled}}=\frac{(Z_{A,1,t}\lambda+Z_{T,1,t})K_{T,1,t}^{\beta_K}L_{T,1,t}^{\beta_L}}{(\lambda+1)K_{T,1,t}^{\beta_K}L_{T,1,t}^{\beta_L}}=\frac{Z_{A,1,t}\lambda+Z_{T,1,t}}{\lambda+1}.$$

When $Z_{A,1,t}=Z_{T,1,t}$:

$$Z_{A,1,t}^{\text{pooled}}=Z_{A,1,t}.$$