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THE SYNTHETIC CONTROL METHOD: A NEW FRONTIER IN PRIVATE EQUITY TRANSACTION ANALYSIS

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ABSTRACT

This paper explores the complex debate on the role of private equity (PE) in shaping corporate and economic landscapes and introduces an analytical framework to assess specific transaction outcomes. It aims to provide empirical evidence that supports or refutes various claims in the advocacy or criticism of PE practices. At the heart of this discourse is the PE industry's buy-to-sell strategy, where PE firms acquire, transform, and divest entities to realize substantial returns. While critics label these firms as "barbarians at the gate", engaging in predatory practices detrimental to various stakeholders, proponents argue that PE firms are instrumental in transforming underperforming entities into efficient and competitive companies, thereby fostering operational improvements, innovation, and growth. In order to assess the diversity in outcomes of PE transactions, this paper advocates for a deal-by-deal analytical approach, enabling a nuanced assessment of PE's actual impact on individual ventures. To this end, this study employs Synthetic Control Method (SCM), first proposed by Abadie & Gardeazabal (2003), to isolate the causal effects of PE interventions from other exogenous factors. By constructing a synthetic control unit, i.e., a weighted average of untreated control units, this methodology facilitates a data-driven causal inference of PE's contribution to the investee's financial and operational performance post-acquisition. In particular, the SCM is applied to assess PE interventions within the healthcare sector, examining Proa Capital's 2015 acquisition of Avizor, a Spanish manufacturer and provider of eye care products. Through this analysis, the paper aims to contribute to the discourse on PE, illustrating its potential for corporate transformation and economic efficiency under certain conditions.

KEY WORDS

Private equity, synthetic control method, healthcare sector, deal-by-deal, Avizor

RESUMEN

El presente trabajo explora el complejo debate en torno al papel del capital riesgo (*private equity,* PE) en la configuración del panorama empresarial y económico y propone un enfoque analítico para evaluar los resultados de operaciones concretas. El objetivo es proporcionar pruebas empíricas que apoyen o refuten diversas afirmaciones en defensa o crítica de las prácticas de los fondos de capital riesgo (FCR). En el centro de este debate se encuentra la estrategia de *buy-to-sell*, según la cual las empresas de PE adquieren, transforman y desinvierten entidades para obtener beneficios. Mientras los críticos etiquetan a estas firmas como "*barbarians at the gate*", que realizan prácticas abusivas en detrimento de diversos *stakeholders*, sus proponentes sostienen que las empresas de PE son instrumentales en transformar entidades con bajo rendimiento en compañías eficientes, fomentando así mejoras operativas, innovación y crecimiento. Al objeto de evaluar los diferentes resultados de las operaciones de PE, el trabajo aboga por un enfoque analítico caso por caso, que permita una evaluación del impacto real de las operaciones de PE en cada participada. Con este fin, este estudio emplea el Método de Control Sintético (MCS), propuesto por primera vez por Abadie y Gardeazabal (2003), para aislar los efectos causales de las intervenciones de PE de otros factores exógenos. Mediante la construcción de una unidad de control sintético, es decir, una media ponderada de unidades de control no tratadas, esta metodología facilita una inferencia causal de la contribución de PE al desempeño financiero y operacional del FCR. El MCS se aplica para evaluar las intervenciones en el sector sanitario, examinando la adquisición en 2015 por Proa Capital de Avizor, un proveedor español de productos oftalmológicos. A través de este análisis, se pretende contribuir al debate en torno al papel del capital riesgo, ilustrando su potencial para la transformación empresarial y la eficiencia bajo determinadas condiciones.

PALABRAS CLAVE

Capital riesgo, método de control sintético, sector sanitario, operación a operación, Avizor

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ABBREVIATIONS

EBITDA	Earnings before interest, taxes, depreciation and amortization
GP	General partner
IPO	Initial public offering
LBO	Leveraged buyout
LP	Limited partner
LPA	Limited Partnership Agreement
MBI	Management buy-in
MBO	Management buy-out
PE	Private equity
ROI	Return on investment
SCM	Synthetic control method
VC	Venture capital

INTRODUCTION

1. CONTEXTUAL OVERVIEW. STATE OF THE ART

The narrative surrounding the impact of private equity (PE) on the corporate and broader economic landscape is both complex and multifaceted, characterized by an array of perspectives that range from staunch advocacy to critical skepticism. Central to the discourse on PE's role in the modern economy is its foundational strategy of buy-to-sell, a seemingly straightforward paradigm wherein PE firms acquire, transform, and ultimately divest underperforming or undervalued entities, aiming to realize a substantial return on investment (McGrath & Nerkar, 2023; Barber & Good, 2007). This strategy posits these firms as catalysts for significant corporate transformation and economic efficiency. Yet, the value proposition of PE is not without its controversies and criticisms (McGrath & Nerkar, 2023).

Detractors have cast PE firms in a less favorable light, drawing on narratives that depict these entities as "barbarians at the gate", a term coined by Burrough & Helyar (1990) to characterize PE investors as predatory entities engaged in practices detrimental to the broader ecosystem (Dodd, 2980; Shleifer & Summers, 1988; Palepu, 1990; Agrawal et al. 1992). Such practices include asset stripping, opportunistic market timing, aggressive tax avoidance strategies, and the pursuit of rapid exits from investments, often termed "quick flips" (Morrell and Clark, 2010; Morris & Phalippou, 2019). These actions are argued to prioritize exorbitant returns for the PE firms themselves at the expense of employees, taxpayers, and other stakeholders, potentially leading to value destruction and undermining the long-term health and sustainability of investee companies.

Despite these criticisms, proponents of PE maintain a more positive outlook, arguing that PE firms play a pivotal role in driving operational improvements, fostering innovation, and providing essential capital for growth and expansion. According to advocates like Jensen (1989) and Kaplan & Strömberg (2009), PE investments, through a combination of financial, governance, and operational engineering, can transform underperforming entities into more efficient and competitive companies, contributing positively to the broader economy.

However, while the arguments supporting and opposing private equity (PE) involvement are valid, it may be beneficial to evaluate the particular outcomes of individual deals, gaining insights into the efficacy and impact of PE interventions under various specific business scenarios. Adopting a case-by-case approach allows for a detailed assessment of the actual value that PE contributes to, or detracts from, different ventures. This method can provide a clearer understanding of the specific impact of a given combination of management practices, strategic decisions, and market conditions on a PE transaction.

2. OBJECTIVES AND METHODOLOGY

Critically assessing the true value created by PE firms requires a methodological approach capable of isolating the effects of their intervention from other variables that could influence the outcome of a deal. One such approach, is the synthetic control method (SCM), first proposed by Abadie & Gardeazabal (2003) and expanded upon by Abadie et al. (2010). This method offers a way to evaluate the performance of a PE-backed company against a synthetic counterfactual, i.e., a synthetic version of the investee company that approximates how it would have performed in absence PE intervention.

By constructing a synthetic control unit as a weighted average of control units that match the treated unit (i.e., the PE-acquired company) on a set of predictor variables, but did not undergo PE intervention, it is possible to infer the causal impact of PE ownership on the investee firm's performance. Thus, the SCM allows for a more accurate attribution of capital gains (or losses) to the actions taken by a PE firm, isolating the effects of financial restructuring, governance changes, and operational improvements implemented post-acquisition. Consequently, applying the SCM to PE deals can yield valuable insights into the conditions under which PE investments are likely to produce positive outcomes or result in value destruction.

In the context of target selection, evidence suggests that the effectiveness of PE interventions is not uniform across all economic sectors and industries. Certain industries are naturally more receptive to the changes implemented by PE firms, leading to more salient positive outcomes following acquisition. The healthcare sector, with its sensitivity to demographic trends and demonstrated resilience in the face of economic downturns (as exemplified by the COVID-19 pandemic) presents a compelling case for in-depth deal-by-deal analysis of PE intervention.

By leveraging methodologies like the SCM, it will be possible to isolate the effects of PE ownership from other exogenous factors and inherent growth trends in the healthcare sector and gain insights into the conditions under which PE investments in healthcare are most beneficial. Ultimately, without prejudice to the analysis being carried out in parallel for various potential treated units, the analysis will focus on the acquisition of Avizor, a manufacturer and provider of contact lenses and eye care products, by Proa Capital in 2015.

More specifically, this study aims to measure the causal effect of Proa Capital's interventions following its 2015 acquisition of Avizor by quantifying and isolating the direct impact of Proa Capital's strategic decisions on Avizor's gross revenue performance post-acquisition.

3. CHAPTER STRUCTURE

In order to approach the SCM analysis, the paper is structured into four chapters. Chapter I sets the stage by introducing the foundations and historical perspectives of the PE industry. It aims to provide the necessary background for understanding the organizational structure, strategic approaches, and broader economic implications of PE.

The narrative then transitions to exploring the core value proposition of PE. This section examines the various mechanisms PE firms employ to generate value, alongside presenting the debates and controversies that surround their practices.

Chapter II introduces the synthetic control method from a theoretical standpoint and provides insights into the possible applications, advantages and formal aspects of the method. This chapter serves as a bridge to the empirical application of SCM, which is provided in Chapter III.

Building upon the theoretical and methodological groundwork laid in earlier chapters, Chapter III focuses on the application of the SCM to a specific PE transaction involving a healthcare provider, in particular, the acquisition of Avizor by Proa Capital in 2015. This case study showcases the practical utility of SCM in evaluating the impact of PE investments with various tools.

Concluding the analysis, Chapter IV synthesizes the main empirical results obtained from this application. It provides a detailed examination of the strategies and actions implemented by Proa Capital during the acquisition process, providing insight into how these initiatives directly influenced Avizor's operational performance and financial results.

CHAPTER I. THEORETICAL FRAMEWORK. THE PRIVATE EQUITY INDUSTRY. FUNDAMENTALS AND CONTROVERSIES

1. INTRODUCTION. THE FUNDAMENTALS OF PRIVATE EQUITY

1.1 A definition of private equity and historical perspectives into equity financing

The concept of "private equity" (PE) encompasses the investment paradigm in which a PE firm raises equity through a fund and channels said private capital and managerial expertise toward investee companies with the objective of creating value and realizing capital gains upon divestment. This configuration allows for strategic, long-term investments aimed at operational restructuring, facilitated by the collaboration between the investment fund and the management of the investee entities (Kaplan & Strömberg, 2009; Caselli & Negri, 2021).

The origins of this structured PE investment model can be traced back to a landmark transaction in 1901, when J.P. Morgan acquired Carnegie Steel Co. from Andrew Carnegie and Henry Phipps. This model, characterized by its structured investment approach and strategic capital deployment, was further developed in the 1940s. This period marked the beginning of the PE role in facilitating corporate development (Caselli & Negri, 2021).

The establishment of the first modern PE partnership agreement in 1976 by Jerome Kohlberg, Henry Kravis, and George Roberts, which led to the creation of Kohlberg Kravis Roberts & Co. (KKR) in 1980, stands as a foundational milestone for the PE industry. Since then, the significance of corporate financing through private equity has been on the rise, becoming increasingly important, both strategically and financially (Lerner & Leamon, 2023; Caselli & Negri, 2021).

The evolution of the business over recent decades has led to a variety of interpretations regarding what constitutes PE. For the purposes of this analysis, PE will refer to investment firms engaging in leveraged buyouts (LBOs) of businesses using private capital raised from investors and pooled into funds, in line with definitions found in academic literature (McGrath & Nerkar, 2023; Axelson et al., 2009; Gompers et al., 2016; Hoskisson et al., 2013; Morris & Phalippou, 2020).

1.2 The economic importance of private equity financing: an eclipse of public ownership

At its core, PE is characterized by its emphasis on investments made by financial institutions into the equity of privately held companies which are not publicly traded on stock exchanges. As such, it primarily pertains to the acquisition of assets and securities transacted outside the scope of public markets. This investment model underscores a targeted approach toward leveraging equity positions in private companies to drive value creation, in contrast to the conventional public equity market strategies (Caselli & Negri, 2021; Demaria & Tarradellas, 2016).

Since its establishment in the 1980s, the PE industry has evolved into a constituent of the global financial landscape, becoming increasingly entrenched as a major player in the economy to the point where it is beginning to displace public equity (Lerner & Leamon, 2023; McGrath & Nerkar, 2023).

From a quantitative standpoint, recent data reveal a remarkable expansion of private equity funds[1]. According to McKinsey & Co. (2022), in the U.S. alone these funds increased from USD 5 billion in 1980 to slightly more than USD 3.9 trillion in 2021. On an international level, research by Bernstein et al. (2017) covering 20 industries across 26 OECD countries reveals that, on average, 4% of each industry is under private equity ownership, for a median duration exceeding five years. These statistics underscore the sector's significant influence on M&A deal-making activity, accounting for 30% of all global M&A volume (McGrath & Nerkar, 2023; Metrick & Yasuda, 2010).

These market dynamics indicate a potential shift toward private equity as the favored form of ownership, underscored by the progressive decline in the number of publicly listed companies. This trend aligns with the prescient argument made by Jensen (1989), suggesting that private equity ownership would "eclipse" the public corporation, particularly within specific sectors. The three decades since have witnessed substantial expansion within the private equity industry, accompanied by a significant reduction in the number of publicly traded entities (Morris & Phalippou, 2020). As a matter of fact, PE appears to have emerged as a financing and capital allocation method that channels private capital directly into target companies, bypassing public markets and the regulatory burdens associated with them.

On this matter, McGrath & Nerkar (2023) and Karsh & Robertson (2020) report that the proliferation of private equity-backed enterprises has notably outstripped the number of publicly listed companies in the United States, escalating from around 4,000 entities in 2006 to over 8,000 by 2020, nearly double that of quoted firms. Conversely, the number of publicly traded U.S. companies has experienced a marked contraction over recent decades: in 1996, the number of U.S. listed companies peaked at 8,090, but by the first quarter of 2023, this number had dramatically dwindled to 4,572, representing a gradual decline of 43% (Blue Trust, 2023).

Within the EU, the decline in listings mirrors the global downturn in public equity markets (TESG, 2021). In particular, the EU witnessed a significant reduction in the number of annual Initial Public Offerings (IPOs), with averages falling from 380 per year in the period of 1997 to 2007 to just 220 per year between 2008 and 2018. A worrying aspect of this trend is the pronounced reduction in IPOs by smaller, growth-oriented companies (IPOs raising less than €100 million) (FESE, 2020).

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[1] i.e., partnerships specializing in investment strategies including venture capital, LBOs, growth financing, mezzanine investments, build-up ventures or distressed asset acquisitions (Lerner & Leamon, 2023).

Concurrently, there has been a gradual increase in delistings over recent decades, with nearly 450 firms withdrawing from European multilateral trading facilities (MTFs) alone, further signaling a shift in the dynamics of public equity participation (FESE, 2020).

The convergence of these trends signals a transformation within the corporate environment, reflecting of broader trends such as increased regulatory and compliance costs associated with public listings, and an increasing preference towards alternative, private financing avenues as is PE (TESG, 2021; FESE, 2020). Mainly, the initial costs associated with public offerings (IPOs) and the subsequent regulatory compliance have increased considerably in recent decades, exacerbating the regulatory disparities between public and private financing. This observation is particularly salient for SMEs, common targets for PE firms, which encounter disproportionately burdensome regulatory costs associated with the process of becoming listed (TESG, 2021; Zingales, 2009).

The evolving dynamics of capital markets and the regulatory frameworks, combined with the strategic benefits provided by private capital, collectively contribute to the growing appeal of PE as the preferred form of corporate finance and ownership (Morris & Phalippou, 2020; Zingales, 2009). By way of conclusion, this rising prominence of PE not only highlights its adeptness at driving value creation but also signals a transformative shift in corporate ownership structures, with investors progressively favoring the flexibility and minor regulatory scrutiny offered by private capital investment vehicles vis-à-vis public market alternatives.

1.2 Modalities of private equity financing: Venture Capital and Private Equity

Private equity firms engage in investments spanning the entire corporate lifecycle, targeting entities ranging from newly founded start-ups to financially distressed firms (i.e., distressed investing)[2]. When an investee company is in its incipient stages of development, the investment is referred to as "venture capital" (VC), a subset of PE. In modern finance, the concept of VC predates the broader private equity field. Consequently, many terminologies and concepts originally coined in the context of VC are now applied more broadly to encompass all forms of private equity investments, irrespective of the developmental stage of the target company (EVCA 2007; Caselli & Negri, 2021).

Against this background, venture capital and private equity represent two major vehicles of corporate finance, facilitating the deployment of capital into businesses at varying stages of their lifecycle (Cumming et al., 2023; Caselli & Negri, 2021).

[2] Lerner & Leamon (2023) highlight that entrepreneurial companies often require significant capital investment for their ventures, beyond what the founders themselves can finance. Consequently, these entrepreneurs are compelled to explore external financing options. However, start-up companies, particularly those with a high proportion of intangible assets, anticipated prolonged periods of negative earnings, and uncertain success trajectories, generally find it challenging to secure traditional bank loans or debt financing. This issue is similarly encountered by companies in distress, requiring restructuring, as their financial situation makes it difficult to attract external financing.

As mentioned, VC is traditionally defined in academia as the allocation of speculative, smaller-scale investments aimed at bolstering the operational capabilities of high-growth potential enterprises during their incipient phases (i.e., startups), frequently with a high technology aspect (Wright & Robbie, 1998; Fried & Hisrich, 1988). The return on investment of these ventures is generated from a minority of portfolio companies achieving exponential growth and subsequent exit events, such as IPOs or strategic acquisitions. Thus, the primary reward is an eventual capital gain, supplemented by dividend yields (Wright & Robbie, 1998). This investment model is characterized by its higher risk profile, attributable to the early-stage nature of the recipient firms and the speculative character of their success trajectories (Cumming et al., 2023; Hsu & Kenney, 2004).

Conversely, PE firms employ a more conservative investment strategy focused on established companies with proven business models and stable cash flows. In this sense, PE encompasses the allocation of large amounts of capital to a more reduced cohort of established entities, with the intention of driving business expansion and operational scaling (scale-up) (Cumming et al., 2023).

These firms often engage in leveraged buyouts (LBOs), where they acquire majority control of a company, streamline operations, and implement strategic initiatives aimed at enhancing profitability and operational efficiency. The objective is to increase the value of these entities before exiting through a sale or public offering, thereby realizing a substantial capital gain. This investment strategy is generally associated with a lower risk profile, stemming from the mature status of the target companies (Barber & Good, 2007).

In conclusion, VC and PE both serve instrumental roles within the global financial ecosystem, driving economic expansion and ensuring the effective allocation of capital throughout the various stages of corporate development. Their distinct investment approaches reflect divergent risk profiles, expected returns, and impacts on their portfolio companies.

1.3 Corporate structure of PE firms and conventional compensation arrangements

Legally, the organizational structure of PE funds predominantly takes the form of limited partnerships, wherein a PE firm act as general partner (GPs) overseeing the fund's operations and investment decisions, and capital contributions are made by large institutional investors and high net-worth individuals, as limited partners (LPs) (Chaplinsky, 2015). Accordingly, PE represents a segment within the broader alternative investment industry, distinguished by its use of an illiquid, closed-end fund structure[3] to raise capital (Ivashina, 2023).

[3] In a "closed-end" fund, investors cannot withdraw their funds until the fund is terminated. PE funds operate as closed-end investment vehicles, characterized by a fixed term during which capital can be raised. Once this fundraising window closes, the fund is precluded from soliciting or accepting additional capital contributions. This structural feature distinguishes closed-end funds from open-end funds (e.g., mutual funds or hedge funds), where capital can continuously flow in and out (Kaplan & Strömberg, 2009, Braendel & Chertok, 2010).

Within this structure, PE funds leverage the capital raised from LPs to acquire equity interests in target portfolio companies. LPs do not directly allocate capital to these portfolio entities. Instead, the operational framework typically involves the PE firm, acting as general partner (GP), i.e., the managing body of the venture, creating a fund vehicle as a separate legal entity. This investment vehicle serves as the conduit through which the capital from the LPs is invested into selected portfolio companies (Kaplan & Strömberg, 2009; Gupta & Howell, 2023). Accordingly, the operational dynamics of a conventional close-end fund involve capital calls to LPs up to the committed amounts and the subsequent distribution of returns over the fund's tenure[4] (Phalippou & Gottschalg, 2009).

Under the aforementioned framework, the GP (i.e., the PE firm) bears the responsibility for the day-to-day management and operational oversight of the PE fund. This entails making the relevant investment decisions, which encompass the identification and acquisition of potential investments, as well as the management and divestment of existing holdings in portfolio companies (Gompers et al., 2016; Chaplinsky, 2015).

The GP's role extends beyond securing the necessary financing; it also includes a governance function for the portfolio companies, exerting influence over the board of directors, appointing key management personnel, and structuring their remuneration schemes[5]. In its essence, the GP functions predominantly as a sponsor or fund manager (Phalippou & Morris, 2019).

Conversely, LPs represent the investment constituency of the PE fund, typically consisting of institutional investors[6] (such as pension funds, sovereign wealth funds, and university endowments) alongside affluent individuals. LPs provide the capital for the PE fund but do not partake in its management[7]. They are afforded limited liability, which restricts their potential financial loss to the extent of their contributions to the fund (Lerner & Leamon, 2023).

Upon the commitment of their capital, LPs yield control over the deployment of their capital contributions to the GP, provided the GP adheres to the basic covenants stipulated within the LPA.

[4] In the context of PE, this means that after the initial capital commitment phase is completed, the fund's capital is fixed, and the GPs must then focus on deploying these resources toward strategic investments in portfolio companies within the prescribed period, aiming to maximize returns for the LPs before the fund's termination (Kaplan & Strömberg, 2009).

[5] As underscored by Metrick & Yasuda (2010), the increasing presence of PE firms in the capital structure of companies, generally with a shareholding controlling interest (i.e., more than 50% of the company's voting rights), has led to an evolution of PE funds from traditional financial intermediaries to entities with significant influence on the management and operational oversight of portfolio companies.

[6] Large institutional investors frequently pursue illiquid, long-term investment opportunities such as private capital to diversify their portfolios. Tasked with managing assets over the longer term, these entities are capable of allocating a portion of their funds to investments with extended time horizons. However, typically these organizations lack the internal staff or specialized knowledge required to directly engage in such investment activities (Lerner & Leamon, 2023).

[7] Note, however, that in a conventional PE transaction (i.e., a leveraged buyout), the financing structure of the fund vehicle typically comprises approximately one-third equity contributed by the LPs and two-thirds debt, sourced from banks and other financial institutions, including specialized private credit funds (Phalippou & Morris, 2019).

Additionally, the initial LPA outlines how the PE firm or GP is compensated, commonly incorporating both fixed and performance-based (variable) compensation elements. A noteworthy aspect of these compensation arrangements is the provision of significant financial incentives for the management of portfolio companies (Sahlman, 1990 Metrick & Yasuda, 2010; Phalippou, 2009).

The prevailing compensation arrangements for GPs managing PE funds consists of annual management fees and the so-called carried interest. Management fees are usually a percentage of committed or deployed capital and are determined based on the investments within the fund's portfolio and/or the overall size of the fund. For buyout funds, the compensation structure exhibits additional compensatory elements such as transaction fees and monitoring fees (Choi et al., 2011).

The carried interest, or "carry," that GPs receive is generally contingent upon the exit timings and valuations of portfolio companies, making it highly sensitive to the fund's performance. Prior to the GP receiving its share of carry, LPs first have to recoup the initial capital they invested into the fund. Additionally, the fund may be required to meet a preferred return, or hurdle rate, which represents the minimum profit threshold the fund must surpass before the GP can begin to accrue carried interest. Under this framework, fund profits are mostly realized via capital gains upon exit, i.e., on the sale of portfolio businesses (Choi et al., 2011; Barber & Good, 2007).

2. FUNDAMENTALS OF THE BUY-TO-SELL APPROACH. LITERATURE REVIEW

2.1 Introduction. The fundamental value proposition of private equity

At the heart of PE's value creation paradigm is the buy-to-sell strategy. This fundamental value proposition of PE is fairly straightforward: through its fund vehicle, a PE firm undertakes the strategic acquisition and transformation of underperforming or undervalued target entities, irrespective of the target's ownership status[8]. These targets encompass both free-standing companies and specific corporate divisions within larger enterprises, which can be acquired through methods such as carve-outs or partial spin-offs (Barber & Good, 2007; McGrath & Nerkar, 2023).

Following acquisition, the PE firm, acting as GP, takes over management and operational oversight of the investee entities. The primary objective during this stewardship phase is to guide the portfolio companies through a phase of rapid performance improvement. Upon achieving improved operational metrics and performance benchmarks, the fund positions these entities for a strategic divestiture, aiming to exit at a premium that reflects the value added during its tenure.

[8] As outlined by Kaplan & Stromberg (2009), if a target company is publicly listed, the PE firm will typically offer a purchase price that includes a premium of 15 to 50 percent above the current stock price. This premium is a strategic component of the acquisition process, reflecting the value the PE firm anticipates it can create through its operational, strategic, and financial interventions post-acquisition. See also Kaplan (1989) and Bargeron et al. (2007).

Unlike conventional investment models that may prioritize long-term holdings or passive investment strategies, PE firms focus on achieving value realization within a short- to medium-term horizon. This approach leverages the capabilities of identifying undervalued or underperforming assets and actively engaging in their transformation through hands-on management and operational improvements (Barber & Good, 2007). Consequently, PE firms are able to not only accelerate the value creation process but also ensure the timely realization of capital gains through the strategic divestment of these assets.

2.2 Financial, governance, and operational engineering

The sustained success of PE firms can be attributed to their capability to increase the value of their investment portfolios. This ability in achieving superior returns is linked to a management strategy that implements three primary sets of measures to the investee companies, categorized as financial, governance, and operational engineering (Kaplan & Strömberg, 2009; Barber & Good, 2007).

Jensen (1989) and Kaplan (1989) describe the financial and governance engineering measures. As explained previously, PE firms must align the interests of portfolio managers and the operating managers of investee entities within their portfolio through compelling incentive schemes (Kaplan & Strömberg, 2009). These incentives are designed to drive performance and value creation by establishing compensation arrangements that are tied to the profitability and eventual sale of the business at the end of the investment cycle (e.g., the carry). PE firms also require management to make a meaningful investment in the company, so that management not only has a significant upside, but a significant downside as well (i.e., hold skin in the game) (Barber & Good, 2007).

The second, and perhaps most noteworthy, measure of financial engineering is the use of leverage, or borrowed capital, by PE firms. Leveraged financing not only facilitates the acquisition of target companies but also amplifies financial returns through leverage effects: the strategic use of leverage can enhance firm value due to the tax deductibility of interest expenses (i.e., the so-called interest tax shields), reducing the firm's taxable income (Kaplan & Strömberg, 2009)[9].

Governance engineering, on the other hand, refers to the strategic approach adopted by private equity firms for the management and supervision of their portfolio companies. This involves acquiring controlling stakes in investees, which allows them to directly control their boards of directors. This control is typically exercised through the appointment of directors or the creation of advisory committees, which guide the company's strategy, financial management and operational improvements (Barber & Good, 2007).

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[9] However, while leverage can serve as a powerful tool for value creation, excessive reliance on debt raises the risk of financial distress. The mandatory character of debt repayments can lead to inflexibility in financial planning and increase the vulnerability of the firm to economic downturns or operational setbacks (Kaplan & Strömberg, 2009).

Through governance engineering, PE firms are able to implement strategic, operational, and financial changes more swiftly and effectively, leveraging their authoritative positions on the boards to influence decision-making processes and drive value creation with a focus on long-term growth (Kaplan & Strömberg, 2009; Morris & Phalippou, 2020).

By the late 1980s, financial and governance engineering had become standard practices within the PE industry. In recent times, PE firms have incorporated an additional set of measures, known as "operational engineering", which refers to the application of sector-specific knowledge and operational expertise aimed at enhancing the performance and value of their investments. For this reason, many PE firms are now organized around specific industries. This strategy enables PE firms to offer targeted operational insights and strategic guidance, thereby significantly contributing to the sustained growth and competitiveness of their portfolio companies (Kaplan & Strömberg, 2009).

In sum, the success of PE is underpinned by a comprehensive strategy that combines financial engineering, operational improvement, and strategic management, executed within a framework designed to maximize investor returns through a disciplined buy-to-sell approach.

2.3 Controversy around the buy-to-sell strategy: Value creators or barbarians at the gate?

However, this value proposition has also been subject to debate, encountering criticism from those who view PE firms not as value creators but rather as "barbarians at the gate"[10], a term popularized by Burrough & Helyar (1990) to depict PE investors as predatory (McGrath & Nerkar, 2023).

Detractors contend that PE firms engage in certain practices detrimental to the broader ecosystem, including asset stripping, opportunistic market timing, aggressive tax avoidance strategies, and the pursuit of rapid, albeit suboptimal, exits from investments ("quick flips"). These strategies primarily serve to generate exorbitant returns for PE firms at the expense of buyout employees, taxpayers, and other stakeholders (see Shleifer & Summers, 1988; Palepu, 1990; Agrawal et al. 1992).

In line with the foregoing, other scholars such as Dodd (1980), Morrell & Clark (2010) and Morris & Phalippou (2019) argue that these strategies can lead to value destruction, undermining the long-term health and sustainability of target companies and, by extension, affecting the welfare of the economy at large. The focus on short-term gains and financial engineering by PE firms can overshadow the essential aspects of business growth and development, thereby raising concerns about the overall impact of PE on economic growth (McGrath & Nerkar, 2023).

[10] The phrase "Barbarians at the Gate" gained widespread recognition from the book titled "*Barbarians at the Gate: The Fall of RJR Nabisco*", authored by Burrough and Helyar. It describes the aggressive tactics employed by PE firms and corporate raiders during the 1980s to acquire companies, often against the will of the incumbent management.

Despite the criticisms, proponents of PE maintain that the model can indeed be a force for good, arguing that PE firms play a crucial role in driving operational improvements, fostering innovation, and providing the necessary capital for growth and expansion. Under this premise, PE firms are able to unlock value that was previously untapped, thereby not only transforming underperforming or stagnant entities but also contributing positively to the broader economy (Morrell & Clark, 2010).

Advocates, such as Jensen (1989) and Kaplan and Strömberg (2009), argue that PE investments, through the implementation of financial, governance, and operational engineering, can lead to the development of more efficient and competitive companies. Indeed, a significant volume of empirical research indicates that PE firms contribute to value creation within their portfolio companies (see Jensen, 1986, 1989; Kaplan, 1989; Kaplan & Schoar, 2005; Cressy et al., 2007). These studies have shown that companies backed by PE investments exhibit improvements in operational profitability and productivity. According to this perspective, although the methods employed by PE firms may appear aggressive or opportunistic, the ultimate outcome is the creation of better-performing businesses that add value to the economy in general (Halvorsen & Johansen, 2017; Wilson et al., 2022; Gohil & Vyas, 2016).

However, while the arguments supporting and opposing private equity (PE) involvement are valid, it may be beneficial to evaluate the particular outcomes of individual deals, gaining insights into the efficacy and impact of PE interventions under various specific business scenarios. Adopting a case-by-case approach allows for a detailed assessment of the actual value that PE contributes to, or detracts from, different ventures. This method can provide a clearer understanding of the specific impact of a given combination of management practices, strategic decisions, and market conditions on a PE transaction.

Critically assessing the value created by PE firms requires a methodological approach capable of isolating the effects of their intervention from other variables that could influence the outcome of a deal. One such approach, is the synthetic control method, first developed by Abadie and Gardeazabal (2003) and Abadie et al. (2011). This econometric method offers a way to evaluate the performance of a PE-backed company against a synthetic counterfactual, i.e., a synthetic version of the company that approximates how it would have performed without PE intervention. By comparing the actual post-acquisition performance of the company to its synthetic counterpart, it is possible to estimate the direct impact of PE intervention.

3. SECTOR-SPECIFIC DYNAMICS OF PRIVATE EQUITY TARGET SELECTION

3.1 Effectiveness of private equity intervention across different sectors

Existing research has predominantly focused on the post-investment performance outcomes of PE-backed buyouts, often overlooking the characteristics of target companies that PE firms pursue within the pool of potential investees (Wilson et al., 2022; Kaul et al., 2018; Alemany & Pellón, 2005).

One of these factors for target selection is, naturally, the sector or industry in which the investee operates. As previously noted, the selection of entities constitutes a determinant aspect of operational engineering. In fact, with the application of sector-specific knowledge and operational expertise, many PE firms are now organizing around specific industries (e.g., technology, retail, healthcare, etc.), demonstrating the strategic importance of target selection (Kaplan & Strömberg, 2009). In this context, the effectiveness of PE intervention may vary across different sectors or industries. Certain industries may be more conducive to the improvements and changes implemented by PE firms, leading to more salient positive outcomes post-acquisition. This variability underscores the importance of considering industry-specific dynamics when selecting target companies (Osborne et al.; 2012; Halvorsen & Johansen, 2017).

Wilson et al. (2022) show that PE investors predominantly target companies operating within well-defined markets, typically concentrating on single-product lines with short development cycles. This investment preference steers PE firms away from industries heavily reliant on intangible, knowledge-based assets. PE firms prioritize targets with measurable, tangible assets and business models over those in sectors where value is deeply rooted in innovation-centric processes. In these sectors, PE firms can leverage their expertise in operational restructuring and cost management to drive substantial improvements. Industries such as manufacturing or healthcare often fall into this category, where PE intervention can lead to enhanced operational efficiencies (Applebaum & Batt, 2020).

Conversely, in industries that are highly regulated or require significant long-term investments, the typical short- to medium-term horizon of PE investments may not align well with the industry's dynamics. In such cases, the value added by PE might be less pronounced or even null. Industries like pharmaceuticals, biotechnology, and certain segments of the energy sector may exemplify sectors where the PE model faces challenges in creating value due to the longer timelines required for product development and regulatory approvals (Wilson et al., 2022; Sorensen & Yasuda, 2022).

The asserted variance in PE outcomes across different sectors further supports the use of analytical methods, such as the synthetic control method, to assess the effectiveness of PE interventions. Accounting for industry-specific factors when designing the synthetic control will allow for the isolation of the effect of PE ownership from other external factors, leading to a clearer understanding of the conditions under which PE investments are most beneficial.

3.2 Sector-specific trends in private equity activity in Spain

Having established that the effectiveness of PE interventions varies across industries, it is fitting to briefly review the industries in which PE activity is most salient. Identifying these key sectors serves as the first stage of the individual deal analysis, as it allows us to center the forthcoming study on a particular industry. However, since this deal-by-deal analysis will be contingent upon the availability of sufficient financial data following the acquisition and intervention by the PE firm, the review of sectorial trends should focus on the market's dynamics observed over the recent years (i.e. the post-intervention period), without prejudice to a brief commentary on the current situation.

Furthermore, given that the transaction analysis centers on PE firm transactions in Spain, it is convenient to confine the assessment to the trends observed within the Spanish private equity markets. This geographical focus ensures that the analysis is relevant and accurately reflects the specific dynamics and conditions of Spain's investment landscape.

Over the last few years, PE activity has primarily been observed in sectors such as energy, finance, healthcare and life sciences, software and technology, industry and consumer goods (Baird, 2023). From 2015 to 2021, the e-commerce sector, despite some fluctuations, exhibited the most significant share of transactions, with a peak in the percentage of transactions in 2015 of 40% and showing a slight decline to 23.3% in 2021 (ASCRI, 2022).

The services sector saw a progressive increase in its share of deals, rising from 12% in 2015 to a peak of 16.4% in 2017, before declining slightly to 15.3% in 2021. The information and communication technologies (*TIC*) sector recorded remarkable growth, rising from 8% in 2015 to 14% in 2021, illustrating a steady upward trend. For its part, the share of operations in the industrial sector showed a significant increase, rising from 13% in 2015 to 16.6% in 2020, before experiencing a slight decline to 12.1% in 2021. In civil construction, the trajectory was mixed, with a decline to 7.3% in 2016, followed by a steady increase to 12.5% in 2021.

Investments in the energy sector showed considerable volatility, peaking at 11.2% in 2016 and diminishing to 7.7% by 2021. The research and development (*Investigación y Desarrollo*) sector presented a steady and promising growth from 6% in 2015 to 10.5% in 2021. Lastly, the agriculture, livestock, and fishing sector (*Agricultura, Ganadería y Pesca*) maintained a minimal presence throughout the years, with the lowest percentage being 0.2% in 2021 (ASCRI, 2022).

Overall, the total number of operations increased over the years, starting at 612 in 2015 and growing to 1,432 by 2021. This upward trend indicates a growing investment landscape with varying degrees of emphasis on different sectors, reflecting a dynamic economic environment and evolving investment priorities (ASCRI, 2022).

In more recent years, the transactional activity in 2022 led to a more diversified sector distribution of investments compared to previous years. With the pandemic's impact receding, the industry shifted its focus back to traditional sectors such as technology, renewables, healthcare, food, education, pharmaceuticals, and biotechnology, which have consistently attracted fund interest. Additionally, the investment spectrum expanded to reintegrate sectors like restaurants, leisure, retail, and tourism, previously sidelined. This resurgence was accompanied by investments in less typical segments, including sports, aeronautics, and construction materials, driven by major fund managers backing leading companies in these niches (Capital&Corporate, 2023).

Finally, the sector analysis for 2023 illustrates the challenges faced within the year, with the PE sector pivoting towards more traditional and strategic markets in response to less favorable conditions. These markets, including technology, renewable energy, healthcare, food, education, pharmaceuticals, and biotechnology, have attracted significant capital volumes, thanks to a robust number of transactions executed in the last twelve months. Additionally, emerging sectors presenting unique opportunities have come into focus, driven by market entrants with strong track records, leadership in niche areas, and promising prospects for international expansion and growth through consolidation (Capital&Corporate, 2024).

Conversely, sectors like restaurants, leisure, retail, and tourism, which are more cyclically sensitive and have faced considerable challenges since the Covid-19 pandemic, are now specially targeted by PE firms. Despite these trends, the year did not show a marked polarization of activity by sector, as seen in previous years. The scope of PE investment has broadened, encompassing operations in occasional markets such as furniture, printing and reprographics, and even funeral services, indicating a diversification of investment interests (Capital&Corporate, 2024).

The year's standout sector was healthcare, including health clinics, hospitals, and nursing homes, driven by significant investments like KKR's €3,000M deal value in IVI-RMA and the acquisition of Palex by Apax and Fremman. This enabled the healthcare sector to accumulate over €2,625.5M, accounting for 38.3% of the total invested and 7.2% of the deals (i.e. 35 transactions) (Capital&Corporate, 2024).

3.3 The healthcare sector: Analyzing private equity's controversial role

In line with the foregoing, a focus on the healthcare sector is particularly compelling for several reasons. The noted economic backdrop emphasizes the importance of individual deal analysis in understanding the nuanced impact of PE interventions. This approach is especially relevant in the healthcare sector, where recent trends and external factors, such as demographic shifts and global health crises, significantly influence the industry's dynamics and investment patterns.

Firstly, there has been a notable increase in PE activity surrounding the healthcare sector in recent years. This surge is not arbitrary but rather reflects broader economic and demographic trends that make healthcare an attractive investment target. For instance, Western countries like Spain are experiencing aging populations, a factor that naturally leads to an increased demand for healthcare services (e.g. clinics, hospitals, and nursing homes) and medical supplies (e.g., orthopedic implants, and surgical instruments). An aging population is more susceptible to chronic conditions and requires more frequent healthcare interventions, thus expanding the market for healthcare services and its growth prospects.

Additionally, the COVID-19 pandemic, while causing a downturn in many sectors, has underscored the resilience and essential nature of the healthcare industry. The pandemic heightened the demand for healthcare services, ranging from acute care for COVID-19 patients to the accelerated development and distribution of vaccines and therapeutics. Unlike many other sectors that faced severe disruptions, healthcare services remained in demand, reflecting the sector's robustness against broader economic volatility (Bain & Company, 2024).

Secondly, analyzing a transaction involving a PE investment in the healthcare sector is compelling because it allows us to dissect whether the gains observed post-investment are attributable to the PE firm's operational improvements or broader economic and sector-specific trends. Given the unique circumstances of the COVID-19 pandemic and the ongoing demographic shifts favoring increased healthcare consumption (Bain & Company, 2024), there is a valid question of whether the positive outcomes of some PE investments might be significantly buoyed by these external factors rather than the value-add of PE interventions alone.

Furthermore, the Spanish PE market dynamics, where healthcare has stood out as a leading sector for investment, offers a rich context for analysis. The sector-specific trends, highlighted by significant deals and the overall share of investments directed towards healthcare, underscore the strategic importance of this sector within the PE landscape. This context enables a nuanced exploration of how PE investments in the healthcare sector are positioned within broader economic and demographic trends, including the aging population and the impacts of the Covid-19 pandemic.

The proposed use of the SCM to analyze PE transactions on a deal-by-deal basis is particularly suited to this task. This method enables a nuanced comparison between the actual post-acquisition performance of a healthcare company and a constructed counterfactual that approximates how the company would have performed without PE intervention. Such analysis can isolate the effect of the PE firm's intervention from the broader economic and demographic trends impacting the sector.

In conclusion, focusing on the healthcare sector for PE investment analysis is justified by the sector's significant exposure to demographic trends and its resilience during economic downturns, as exemplified by the COVID-19 pandemic. By leveraging methodologies like the synthetic control method, it may be possible to isolate the effects of PE ownership from other factors and inherent growth trends in the healthcare sector and gain insights into the conditions under which PE investments in healthcare are most beneficial.

CHAPTER II. METHODOLOGY. THE SYNTHETIC CONTROL METHOD

1. A PRIMER ON SYNTHETIC CONTROL METHODS AND THEIR APPLICATION TO PRIVATE EQUITY TRANSACTIONS

Originally proposed by Abadie & Gardeazabal (2003) and expanded upon by Abadie et al. (2010), the synthetic control method (SCM) is a statistical technique employed across economics and social sciences to assess the causal effect of an intervention or treatment in observational studies, focusing primarily on comparative case studies. The method aims to evaluate the impact of a policy, event, or treatment on a specific unit (i.e., the treated unit) by approximating the unit's counterfactual outcomes with a weighted combination of control units that did not undergo the treatment, i.e. a "synthetic control" unit (Abadie et al. 2011; Abadie et al. 2021; Shi et al., 2022).

Consequently, the innovation of SCM lies in its construction of the synthetic control to infer casual effects. In greater detail, Abadie and Gardeazabal (2003) and Abadie et al. (2010) define this "synthetic control" unit as a weighted average of control units that closely approximates the key characteristics of the treated unit before the intervention. The SCM make explicit the relative contributions of each control unit and quantifies the degree of similarity between the treated unit and its synthetic counterpart prior to the intervention (Abadie et al. 2011). In essence, the aim is to create a composite unit that closely resembles the treated unit in terms of pre-treatment characteristics and outcomes, thus serving as a counterfactual to estimate the treatment effect.

Once the synthetic control is constructed, the treatment effect is estimated by comparing the post-intervention outcome of the treated unit to the outcome of the synthetic control unit. The difference in outcomes provides an estimate of the intervention's effect. This approach allows for a more precise assessment of the intervention's impact by ensuring that the synthetic control closely mirrors the pre-treatment state of the treated unit.

In the field of private equity, the SCM can be applied to evaluate the performance impact of PE investment on portfolio companies. This method would offer a framework to evaluate the performance of a PE-backed company (i.e., the treated unit) against a synthetic counterfactual, i.e., a synthetic version of the company that approximates how the investee entity would have performed without intervention.

Under this framework, the treated unit would be an investee company that has received PE intervention, encompassing financial, governance, and operational engineering. The specific analysis would assess how the company's performance metrics (such as revenue growth, profitability margins, or operational efficiency) change post-investment compared to a counterfactual scenario where the PE intervention did not occur.

The donor pool of untreated units would consist of companies that are similar to the treated unit but did not receive private equity investment. These companies should be comparable in terms of size, industry, market conditions, and pre-investment performance metrics. The aim is to find control units that mirror the treated unit's characteristics as closely as possible before the PE investment.

Once the donor pool is created, a synthetic control company (or a weighted combination of companies from the donor pool) would be constructed to serve as the counterfactual. This synthetic control would closely replicate the pre-investment characteristics of the treated company on a set of pre-treatment variables. The weights would be optimized to minimize pre-investment differences in performance metrics between the treated company and the synthetic control.

The causal impact of the PE investment is then inferred by comparing the post-acquisition performance of the treated company to that of the synthetic counterpart. This comparison helps to isolate the effect of the PE investment from other factors. For instance, if the treated company outperforms the synthetic control in terms of revenue growth or profitability after the investment, this positive differential could be attributed to the value added by the private equity firm. In other words, SCM would allow for a more accurate attribution of capital gains (or losses) to the specific actions taken by the PE firm. Applying the SCM to PE deals can yield valuable insights into the conditions under which PE investments are likely to produce positive outcomes. Conversely, it can also help identify the characteristics of deals that tend to result in value destruction.

The proposition to study the impact of PE on a deal-by-deal basis, using statistical methods like the SCM, acknowledges the diversity of outcomes associated with PE investments and seeks to identify the specific factors that contribute to the success or failure of individual deals. Through such an analysis, the debate on the value proposition of PE can advance beyond generalizations, focusing instead on evidence-based assessments that can inform more effective practices.

2. LITERATURE REVIEW ON THE SYNTHETIC CONTROL METHOD

A methodological debate across various studies (Beck, 2010; Brady & Collier, 2010; George & Bennett, 2005; King et al., 1994; Ragin, 1987; Tarrow, 1995) has led to a broad consensus on the need to bridge the gap between quantitative and qualitative approaches in empirical research, especially within social sciences. Specifically, there have been calls for the development and application of quantitative methods that support qualitative analysis in comparative research (Gerring, 2007; Lieberman, 2005; Sekhon, 2004; Tarrow, 1995). Concurrently, a segment of the quantitative research community advocates for designs akin to Mill's Method of Difference, aiming to carefully select comparison units to mitigate biases in observational studies (Card & Krueger, 1994; Rosenbaum, 2005) (Abadie et al, 2014). One such method is the use of synthetic control estimators.

As previously noted, the SCM was originally proposed in Abadie & Gardeazabal (2003) with the aim to estimate the effects of aggregate interventions, that is, interventions that are implemented at an aggregate level affecting a small number of large units (such as a cities, regions, or countries), on some aggregate outcome of interest (Abadie et al. 2021). Their seminal paper, "*The Economic Costs of Conflict: A Case Study of the Basque Country*", applied SCM to evaluate the economic impact of terrorism on the Basque Country in Spain. By constructing a synthetic control unit with other Spanish regions, they isolated and quantified the adverse effects of terrorism on economic growth.

Following its initial application to the economic costs of conflict, SCM has been widely adopted and refined across various disciplines, including economics, political science, public policy, and health research, among others. Abadie et al. (2010) further expanded on the methodology in paper, "*Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program"*, showcasing its applicability to a broader range of contexts and solidifying its importance in empirical research (Abadie et al. 2011; Abadie et al. 2021).

As documented by Abadie et al. (2021), SCM has been applied to a wide array of policy studies, including the impacts of right-to-carry laws (Donohue et al., 2019), prostitution (Cunningham & Shah, 2018), immigration policies (Bohn et al., 2014), corporate political connections (Acemoglu et al., 2016), environmental policies (Rosado-Anastacio, 2018; Andersson et al.; 2019), taxation (Kleven et al., 2013) or organized crime (Pinotti, 2015). These methods have also become the main tool in data analysis for debates on issues such as immigration (Borjas 2017; Peri & Yasenov 2019) and minimum wage laws (Allegretto et al., 2017; Jardim et al, 2017; Neumark & Wascher 2017; Reich et al. 2017), showcasing SCM capabilities in assessing policy impacts across various domains.

3. ADVANTAGES AND SHORTCOMINGS OF THE SYNTHETIC CONTROL METHOD

Traditional regression analysis, which requires large samples and numerous observations of the event of interest, often proves inadequate for estimating the effects of infrequent events, such as policy interventions, on aggregate units. Analysts have approached the estimation of the effects of large-scale, infrequent interventions through comparative case studies and time series analysis (Abadie et al. 2021; Abadie et al. 2011). In social sciences, comparative case studies have long been applied to the evaluation of large-scale events or aggregate interventions. In comparative case studies, researchers compare outcomes between units affected by an event or intervention (i.e., the treated group) and those that are not (i.e., the control group) to approximate the outcome that would have been observed for the treated group in the absence of treatment (Abadie et al. 2011). This approach assumes that the evolution of the performance of the treated and control units is driven by common factors, resulting in considerable co-movement.

One inherent limitation of traditional comparative case studies is the lack of a formalized process for selecting comparison units, often depending on assessments of similarity between the treated unit and the potential set of comparison units (Abadie et al. 2021). Consequently, these methods often rely on the analyst's discretion for selecting control units, raising concerns about the arbitrariness of these choices and their ability to credibly represent the counterfactual outcomes of treated units.

Additionally, in studies where the units of observation are a small number of aggregate entities, such as countries or regions, it can be particularly difficult to find a single unexposed unit that approximates the most relevant characteristics for the one affected by the intervention. This complexity arises because no single unit may closely match the treated entity in all relevant pre-intervention characteristics (Abadie et al. 2011).

The SCM addresses these shortcomings by formalizing the selection of comparison units through a data-driven procedure, combining several unaffected units to create a "synthetic" control that more appropriately matches the treated unit[11]. This data-driven procedure for control group selection provides a structured framework for assessing the appropriateness of the selected control group, resulting in a more reliable comparison than with any unaffected unit alone, especially in the context of limited observational entities (Abadie et al. 2011; Abadie et al. 2021).

In this context, SCM also restricts the weights assigned to the units in the donor to be non-negative and to sum to one, ensuring that the synthetic control is a convex combination of the donor pool units. This constraint significantly reduces the risk of extrapolation (i.e., making predictions or inferences about data points or trends beyond the range of the observed data), thereby enhancing the reliability of the estimated causal effects.

For its part, single-unit time-series analysis serves as an effective tool for assessing the short-term effects of policy interventions, particularly when these effects are expected to be significant. However, employing time-series techniques to gauge medium and long-term effects is more challenging. This difficulty arises due to the potential for unpredicted variables that may influence the outcome of interest, making it difficult to isolate the effects attributable solely to the intervention.

By contrast, SCM is able to account for unobservable confounding factors that might affect the outcome. By ensuring the synthetic control closely matches the treated unit in pre-intervention outcomes and characteristics, SCM implicitly controls for unobserved heterogeneity that could bias the results. In fact, SCM accommodates the possibility that an intervention's effects may evolve over longer periods of time, acknowledging that these effects might not be immediate and could either

[11] Data-driven procedures limit discretion in selecting comparison control units, compelling researchers to validate the similarities between affected and unaffected units through observed, quantifiable characteristics. This approach ensures a more objective and transparent comparison (Abadie et al. 2011).

accumulate or diminish as time progresses. This flexibility allows to accurately assess the long-term impact of interventions (Abadie et al. 2021).

In sum, synthetic controls offer numerous practical benefits for the accurate estimation of the impact of policy interventions and other events of interest. However, while the SCM is undeniably a powerful tool for causal inference in observational studies, it is not without its limitations.

As with any statistical technique, particularly those designed to estimate causal effects, the credibility of the results is fundamentally dependent on the rigor applied in the method's implementation and the extent to which contextual and data requirements (see below) are satisfied in the specific empirical study (Abadie et al. 2021).

Furthermore, SCM is based on several ley assumptions to accurately estimate the causal effect of an intervention. First, it presumes a consistent relationship between pre-intervention characteristics and outcomes across both treated and control units, implying that the historical data can reliably predict future outcomes in the absence of the intervention. However, creating a synthetic control that accurately reflects the pre-intervention state of the treated unit can be difficult, especially when the control units or data available are limited or not closely comparable (Abadie et al. 2021).

Additionally, SCM's effectiveness is contingent on the assumption that the intervention's effects are confined to the treated unit, with no spillover effects influencing the control units. This assumption is crucial for ensuring that the synthetic control serves as a valid counterfactual. The method's ability to produce accurate and reliable estimates thus depends significantly on these underlying assumptions, and any deviation could affect the validity of its conclusions (Shi et al., 2022).

4. DATA REQUIREMENTS. QUANTITATIVE AND QUALITATIVE CONSIDERATIONS

In this regard, SCM requires the availability of data on outcomes and predictors of outcome on both the treated unit and a pool of potential control units over a significant pre-treatment period. High-quality, comparable data across these units are essential for constructing a reliable synthetic control. In scenarios where data are limited or of poor quality, the validity of the synthetic control and the resulting causal inference can be compromised.

Consequently, the outcomes of SCM are sensitive to the selection of units for the donor pool (both quantitatively and qualitatively) and the choice of predictor variables. For instance, the selection of pre-treatment periods and outcome variables can significantly influence the weights assigned to control units, thereby affecting the estimated impact of the intervention (Abadie et al. 2021).

From a quantitative point of view, the credibility of a synthetic control estimator depends in great part on its ability to steadily track the trajectory of the out- come variable for the affected unit before the intervention (Abadie et al. 2021). Therefore, when designing a synthetic control study, it is of crucial importance to collect information on the affected unit and the donor pool for a large pre-intervention window (Abadie et al. 2011). Furthermore, SCM requires sufficient post-intervention information. The evaluation data must include outcome measures that are possibly affected by the intervention and are relevant for the policy decision or scientific inquiry that is the object of the study. This may be problematic if the effect of an intervention is expected to arise gradually over time and if no forward-looking measures of the outcome are available (Abadie et al. 2021).

From a quantitative point of view, the credibility of a synthetic control estimator, as discussed by Abadie et al. (2021), significantly depends on its ability to accurately follow the pre-intervention trajectory of the outcome variable for the treated unit. This underscores the importance of gathering comprehensive data on the treated unit and potential control units within the donor pool over a substantial period before the intervention (Abadie et al. 2011).

Furthermore, SCM demands sufficient post-intervention information to assess the intervention's effects effectively. The collected data must cover outcome variables that could be influenced by the intervention and are pertinent to the policy decision or scientific question under investigation. This requirement poses challenges, especially if the intervention's effects are expected to manifest gradually over time (as might probably be the case with PE intervention) (Abadie et al. 2021).

5. FORMAL DESCRIPTION OF THE SYNTHETIC CONTROL METHOD

Formally, the SCM involves creating a synthetic control unit as a weighted average of control units from the untreated units that comprise the donor pool to serve as a comparison against the treated unit which has undergone the intervention. In a basic set, consider $j = 1, \dots, J + 1$ units (in this case, Spanish healthcare companies) observed over periods $t = 1, \dots, T$.

To this effect, the dataset consists of $J + 1$ units, where one unit, indexed as $j = 1$, is the treated unit[12]. The remaining J units, indexed from $j = 2$ to $j = J + 1$, make up the donor pool, i.e. the set of untreated units that serve as the control group (Abadie et al. 2011).

The analysis considers T time periods, which include both pre-intervention periods (T_0) and post-intervention periods (T_1), where $T_0 + T_1 = T$. Assume that there is no effect of the intervention during the pre-intervention periods. Accordingly, intervention occurs at time period T_0, so that $1, 2, \dots, T_0$ are pre-intervention periods and $T_0 + 1, T_0 + 2, \dots, T$ are the post-intervention periods.

[12] Without loss of generality, assume that only the first unit is subjected to the intervention, leaving J control units available to construct the synthetic control. In situations where several units are exposed to the intervention, data from these units can be aggregated prior to analysis (Abadie et al. 2011).

As previously mentioned, the pre-intervention characteristics of the treated unit are often more accurately approximated by a combination of untreated units rather than by any single untreated unit. Therefore, the synthetic control is constructed as a weighted average of the units in the donor pool. Mathematically, the synthetic control unit can be represented by a $(J \times 1)$ vector of weights $W = (w_2, \ldots, w_{J+1})$, with $0 \leq w_j \leq 1$ for $j = 2, \ldots J$ and $\sum_{j=2}^{J+1} w_j = 1$ (Abadie et al. 2014)[13 14].

Next, let X_1 be a $(k \times 1)$ vector that contains the values of the pre-intervention characteristics of the treated unit. Correspondingly, let X_0 be a $(k \times J)$ matrix that collect the same predictor variables for the untreated units in the donor pool. The pre-intervention characteristics in X_1 and X_0 may also include the pre-intervention values of the outcome variable (Abadie et al. 2014; Abadie, 2021).

The difference in pre-intervention characteristics between the treated unit and its synthetic control unit is given be the difference between vector X_1 and product of the matrix X_0 and the vector of weights W (see equation 1).

$$X_1 - X_0 W \tag{1}$$

The optimal synthetic control, denoted as W^*, is selected to minimize the magnitude of this difference. To operationalize this, the objective function for selecting the weights W is the following:

$$\sum_{m=1}^{k} v_m (X_{1m} - X_{0m} W)^2 \tag{2}$$

where, for each variable $m = 1, \ldots, k$, X_{1m} and X_{0m} represent the value of the m-th variable of the treated unit and the units of the donor pool (with $J \times 1$ dimension), respectively, and v_m denotes the weight that reflects the relative importance of the m -th variable in the pre-intervention period.

Regarding v_m, note that synthetic controls closely replicate the values of variables that have substantial predictive power on the outcome of interest for the unit affected by the intervention. Accordingly, such variables should be assigned larger v_m weights to reflect their importance in predicting the outcome (Abadie et al. 2014; Abadie, 2021).

[13] In order to avoid extrapolation (i.e. process of predicting or inferring data points or effect of the treatment beyond the range of the observed data) in SCM, the weights assigned to the units in the donor pool are restricted to be non-negative and to sum to one. Non-negative weights ($0 \leq w_j \leq 1$) prevents the synthetic control from being influenced by "negative amounts" of the control units, which would not make sense in a real-world context. By requiring that the weights sum to one ($\sum_{j=2}^{J+1} w_j = 1$ or $w_2 + \cdots + w_{J+1} = 1$) the method ensures that the synthetic control is a convex combination of the units in the donor pool. This constraint ensures that the synthetic control represents a point within the span of the observed data points in the donor pool, rather than outside of it. Together, these constraints ensure that the synthetic control represents a plausible scenario within the observed data's bounds, thus avoiding extrapolation.

[14] Selecting a specific set of weights (W) is tantamount to choosing a synthetic control. In line with Mill's Method of Difference, these weights should be chosen to ensure that the synthetic control closely resembles the treated unit in terms of its characteristics (Abadie et al. 2014).

As last step of the analysis, let Y_{jt} denote the outcome of interest for each unit j at each time t. Further, consider Y_1 as a $(T_1 \times 1)$ vector that aggregates the post-intervention outcome values for the treated unit, such that $Y_1 = \left(Y_{1T_0+1}, \dots, Y_{1T}\right)$. Correspondingly, let Y_0 be a matrix $(T_1 \times J)$, with each column j containing the post-intervention outcome values for unit $j + 1$ form the donor pool. The synthetic control estimator for the treatment effect is obtained by comparing post-intervention outcomes between the treated unit and the counterfactual synthetic control (Abadie et al. 2014):

(3) $$Y_1 - Y_0 W^*$$

Therefore, for a given post-intervention period t (where $t \geq T_0$), the synthetic control estimator of the treatment effect is calculated as the difference in outcomes between the treated unit and the synthetic control at time t. This comparison is expressed mathematically as the following:

(4) $$Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}$$

where w_j^* are the optimized weights from W^* (i.e., optimal synthetic control) that minimize the objective function in equation (4).

On a final note, inference about the treatment effect can be conducted using placebo tests or comparing the post-treatment differences for the treated unit to the distribution of post-treatment differences for units in a control group that did not receive the treatment but were subjected to the same synthetic control procedure (see section below) (Abadie et al. 2014).

CHAPTER III. DATA COLLECTION AND ANALYTICAL FRAMEWORK

1. DATA COLLECTION METHODOLOGY. DONOR POOL SELECTION

1.1 Selection of potential investee companies as treated unit

In the light of the reasons set out in the concluding sections of Chapter I, it follows to assess the causal effect of a private equity transaction in the Spanish healthcare industry. As established, the SCM presents itself as a suitable analytical tool, allowing for a sophisticated comparison between the invested firm and a synthetic counterpart, composed of a weighted average of peer companies that have not undergone to PE investment.

The first step in the analysis involves selecting a specific PE buyout within the healthcare sector. To achieve this, it is necessary to first examine the PE activity that has taken place in the Spanish healthcare industry, identifying specific sub-sectors where PE investment is particularly salient. According to Bain & Company (2024), the healthcare and life sciences sector encompasses five main sub-sectors: (i) provider and related services, (ii) biopharma and related services, (iii) med-tech and related services, (iv) payer and related services, and (v) life sciences tools and related services.

On a quantitative basis, PE activity is particularly pronounced in the healthcare providers and related services segment. Since 2001, this subsector has consistently accounted for 40-50% of the value of global healthcare buyout deals (Bain & Company, 2024). Given the demanding data requirements of the SCM (see above), an investee from this segment is particularly well suited for selection as a treated unit. The abundant number of transactions (and, consequently, financial information available) within this segments makes it a practical choice for applying the SCM analysis.

To identify suitable investee healthcare providers, a comprehensive review of deal activity was conducted using various reports. This included the annual report on private equity and venture capital in Spain published by Capital&Corporate for the years 2018 to 2023, as well as the Private Equity Yearbooks by the Private Equity Institute (*Instituto de Capital Riesgo*, INCARI). Following the initial identification of potential treated units, further information on the transactions was sought on the portfolio sites of the acquiring PE firms and in the coverage of the Spanish business press.

This first stage of the analysis identified a total of six healthcare providers as potential candidates for the treated unit. All six companies are classified under the same CNAE [15] code "3250 - Manufacture of medical and dental instruments and supplies (*Fabricación de instrumentos y suministros médicos y odontológicos*)". Namely, the identified investee entities are the following:

[15] The CNAE, or National Classification of Economic Activities, is a categorization system used in Spain to classify the economic activities of companies according to their corporate purpose. It facilitates the organization and statistical analysis of the Spanish economy, providing a standardized code for each type of economic activity (INE, n.d.).

Table 2: List of healthcare providers with PE intervention (potential treated units)[16]

Corporate name	NIF	Date of investment	Status	Type of investment	Acquiring PE firm
ORLIMAN, S.L.U.	B96122510	2015	Divested	MBO	MAGNUM INDUSTRIAL PARTNERS FUND III, F.C.R.
AVIZOR INTERNACIONAL, S.L.U.	B82434440	2015	Divested	Growth-LBO	PROA CAPITAL IBERIAN BUYOUT FUND II, F.C.R.
IMPLANT PROTESIS DENTAL 2004, S.L.	B63568513	2019	In portfolio	MBO	PROA CAPITAL IBERIAN BUYOUT FUND III, F.C.R.
TERRATS MEDICAL, S.L.	B64542285	2020	In portfolio	MBO	MIURA PARTNERS FUND III, F.C.R.
NEOS SURGERY, S.L.	B20822334	2020	Divested	Growth-LBO	SENDOGI CAPITAL, F.C.R.
AJL OPHTHALMIC, S.A.	A48464788	2021	In portfolio	Growth-LBO	TALDE PROMOCION Y DESARROLLO, S,C.R, S.A.

In this regard, note that investee entities were selected based on the availability of sufficient quantitative information, particularly focusing on entities with adequate pre-intervention and post-intervention data. This is because one of the data requirements of the SCM is the availability of sufficient pre-intervention and post-intervention information (see section above). To ensure sufficient pre-intervention data, transactions classified as VC deals involving relatively new entities (defined as those with less than 15 years of available annual accounts) were not considered. Additionally, entities

[16] See Magnum Industrial Partners (n.d.), MarketScreener (2018), Miura Partners (n.d.), PR Newswire (2024), Proa Capital (n.d.-a; n.d.-c) and Webcapitalriesgo (2015, 2021).

that underwent interventions within the last 3 years (up to 2021) were excluded to ensure the availability of sufficient post-intervention data for analysis.

Upon further consideration, it was decided to exclude the transactions relating to TERRATS MEDICAL, S.L. and NEOS SURGERY, S.L. from the analysis. In the case of the former, a pattern of staggered acquisitions and ownership changes (to Avista Capital Partners) was observed, with investments made in multiple stages in 2020, 2022 and 2023, (Miura Partners, n.d.). These multiple investment stages introduce potential volatility and non-linear effects on performance metrics. SCM typically assume that the pre-intervention period is unaffected by the treatment (Abadie et al., 2021). However, in this case, staggered investments create a series of "interventions", which makes the task of defining a clear pre-intervention period more complex. Additionally, each change in ownership could signal strategic shifts, making it difficult to attribute post-intervention outcomes solely to the initial venture capital transaction.

As for the latter, the venture is partially owned by Spanish public entities, notably following the authorization by Spanish authorities for Avançsa (a state-owned entity) to invest in its share capital. The involvement of public entities introduces an additional layer of complexity. Public investment often comes with different objectives compared to private equity, such as employment considerations, which might affect the firm's trajectory in ways that are not aligned with typical PE-driven objectives. This dual influence could confound the estimation of the PE transaction's causal effect. Also, the presence of public investment can imply regulatory and political considerations that may not be present in purely private transactions.

Once the set of potential treated units has been identified, the next step involves gathering the relevant financial data for each investee. The financial information was obtained by performing an individual search for each company in the SABI database[17].

The relevant information was abstracted from the available financial statements (balance sheet and income statement) and from the metrics provided by the platform. In compliance with the SCM's data requirements, financial data for at least the last 15 years were collected. The aim has been to obtain a timeframe that encompasses around 8 years of pre-intervention and 7 years of post-intervention data, depending on the point of entry of the PE firm. For the healthcare providers mentioned previously, the average span of available financial data extends to 22 years.

1.2 Selection of the donor pool for synthetic control unit

17 The SABI (*I*berian Balance Sheet Analysis System) database, managed by Bureau van Dijkes, is a financial information tool that provides detailed data on Spanish (9,600,000) and Portuguese (800,000) companies. It compiles financial information, management and shareholder information, merger and acquisition details, and other information from official sources and company registries. It is widely used for market analysis, risk assessment, business research, and academic studies, offering a wide range of information for business and financial decision making (IQS, n.d.).

The second phase of the analysis comprises the creation of the donor pool, through the selection of companies that resemble the key attributes of the treated units, but which have not received private equity intervention[18]. The selection of a suitable donor pool in both quantitative and qualitative terms is decisive, as it constitutes the basis for the subsequent construction of the synthetic control unit as a credible counterfactual.

For the creation of the donor pool, the untreated companies comprising the donor pool should be selected based on the same parameters as the potential treated units. Accordingly, the two fundamental criteria for selecting control units are: firstly, that the company operates within the same sector, specifically the manufacture of medical and dental instruments and supplies, as classified under the CNAE code 3250[19]; and secondly, that sufficient financial information is available, previously defined as those with at least 15 years of available annual accounts.

A search of the SABI database for comparable entities with the same CNAE code yielded a total of 261 companies (including the investees shown in Table 1). Following the same procedure as for the treated units, the financial information for all potential control units was gathered by performing an individual search for each company in the SABI database.

A preliminary filtering of these results based on the number of years available (setting as a minimum criterion the availability of data for every fiscal year between 2008 and 2022) reduced the results to 97 entities, excluding the ones identified as treated entities. In this context, despite many entities having a sufficient number of years of data in absolute terms, a notable issue was the presence of incomplete information for the period of interest (2008-2022). Please refer to the table in Annex 1 for a complete list of the entities that have been finally selected to form the donor group.

2. DATA ANALYSIS. APPLIED SYNTHETIC CONTROL WITH SYNTH R

2.1 Implementing synthetic control with Synth R package

The R package "Synth"[20] is designed to implement synthetic control methods in R (R Development Core Team, 2011) for comparative case studies, aimed at estimating the causal effects of policy interventions and various events of interest (Abadie et al., 2011).

[18] Since the control units are intended to approximate the counterfactual situation without the intervention, it is important to restrict the donor group to units exposed to the same underlying variables as the treated unit and that were not subject to structural changes in the outcome variable during the sampling period (Abadie et al., 2014).

[19] Note that it is particularly convenient to have previously obtained a set of various potential treated units with the same CNAE, as it will now be possible to create a donor pool adaptable for subsequent analysis with any of the candidate units.

[20] The Synth package can be accessed from the Comprehensive R Archive Network (CRAN) at http://CRAN.R-project.org/package=Synth (Abadie et al., 2011).

The core function of the Synth package is **'synth()'**, which constructs the synthetic control unit by solving the optimization problem detailed in equation (2). This function identifies a set of weights W that are assigned to the control units of the donor pool (see section above). Prior to the construction of the synthetic control unit, the **'dataprep()'** function organizes the available data (of the treated unit and the donor pool) into a standard (long) panel-data format required for executing the **'synth()'** function. Complementary functions like **'synth.tab()'**, **'path.plot()'**, and **'gaps.plot()'** are instrumental in generating tables and figures, which effectively summarize and visually represent the findings, aiding in the interpretation of results (Hainmueller & Diamond, 2023; Abadie et al., 2011) .

Accordingly, the standard sequence of instructions for implementing the SCM is to first call **'dataprep()'** to prepare the data to be loaded into **'synth()'**. Next, **'synth()'** is called to build the synthetic control group. Finally, the results are summarized using the **'synth.tab()'**, **'path.plot()'**, and **'gaps.plot()'** functions (Hainmueller & Diamond, 2023).

2.2 Defining relevant parameters, the outcome variable and predictor variables

Following the notation previously set out (see section above), the PE transaction synthetic control analysis considers $J + 1 = 98$ Spanish healthcare companies (with CNAE code "3250 - *Manufacture of medical and dental instruments and supplies*"), observed over periods T=15, specifically from the year 2008 to 2022. The company indexed as $j = 1$ will be the treated unit, while the remaining J units, indexed from $= 2$ to $j = 98$, make up the donor pool (i.e., the set of untreated healthcare providers that serve as the control group).

For the purpose of defining the other analysis parameters, and without prejudice to the analysis being carried out in parallel for each of the potential treated units (see Table 1 above), AVIZOR INTERNACIONAL, S.L.U. ("**Avizor**") has been selected as the treated unit of reference. Avizor is a manufacturer and provider of contact lenses and eye care products. Established in 1981 as a family business, the company has acquired global presence in the eye health industry. It stands out for its unique, proprietary products developed through extensive R&D over the years. This company was acquired by PROA CAPITAL IBERIAN BUYOUT FUND II, F.C.R. ("**Proa Capital**") in December 2015, for the purpose of executing a growth-LBO (Proa Capital, n.d.-a; El Confidencial, 2015).

Accordingly, intervention took place in the year 2015. However, given that the acquisition occurred in December and effects of the intervention are unlikely to be fully reflected in performance indicators within the same month, it may be appropriate to set the intervention point at the beginning of 2016, thereby including the year of 2015 in the pre-intervention timeframe. This would ensure that the analysis captures the complete performance data prior to any potential effects of the intervention. The pre-intervention period, denoted by T_0, includes the years from 2008 up to (and including) 2015, represented as the sequence $[2008, 2009, \dots, 2015]$. The post-intervention periods or T_1 comprise the sequence $[2016, 2017, \dots, 2022]$. The total number of time periods T is the sum of both pre-intervention periods (T_0) and post-intervention periods (T_1), such that $T = T_0 + T_1 = 8 + 7 = 15$.

The SCM analysis for assessing the impact of PE intervention was conducted using 15 predictor variables, with **`gross.revenue`** chosen as the outcome variable. This decision came after careful consideration of both gross revenue and EBITDA as potential outcome variables. In this regard, while the analysis was conducted with gross revenue as the outcome variable, attempts were also made to use EBITDA as the dependent variable. However, it was found that the SCM could not construct a synthetic control unit that closely mirrored Avizor's pre-intervention characteristics when using EBITDA. This difficulty in accurately replicating the treated unit's profile with EBITDA as the outcome variable prompted the selection of gross revenue instead.

The choice of gross revenue as the outcome variable is significant for several reasons. Firstly, gross revenue provides a direct measure of the company's top-line performance, reflecting the overall scale of its operations and its ability to generate sales. Thus, gross revenue is a good indicator of market position and growth potential, unaffected by the cost management and financial structuring that can influence net income figures like EBITDA. Secondly, gross revenue is less susceptible to accounting and financial engineering, making it a more straightforward metric for comparison across a set of diverse control units within the donor pool.

The table below summarizes the 15 predictor variables chosen for creating the synthetic control. Since the objective of this analysis is to understand the effect of PE intervention on a firm's financial and operating performance, the selected financial metrics are intended to provide information on the company's financial health, growth, and operating efficiency. The selection process of predictor variables has been guided by five broad indicators: (i) growth, (ii) profitability, (iii) operating efficiency, (iv) capital structure, and (v) liquidity.

Table 3: Summary and description of outcome and predictor variables[21]

Name	**Type**	**Description**
`gross.revenue`	Outcome	Gross revenue, sales (in millions of EUR)
`revenue.growth`	Growth	Percentage (%) change at which a company's revenue increases or decreases compared.
`ebitda.margin`	Profitability	EBITDA margin over gross revenues (%).

[21] Note that the dataset includes other variables that were considered for the analysis, but ultimately were excluded due to various factors. For instance, the variable **`ebitda.growth`** was excluded due to its significantly large negative sample mean, suggesting data issues or the presence of outliers. Other variables like **`debt.value, revenues.employees`** and **`assets.employees`** were also removed as they exhibited substantial differences between treated and synthetic units.

`roa`	Profitability	Return on Assets. Percentage (%) of net income over total assets. ROA = (EBT/ Total Assets) x 100
`roe`	Profitability	Return on Equity. Ratio (%) of net income over shareholders' equity. ROA = (EBT/ Equity) x 100
`current.ratio`	Liquidity	Ratio (x) that measures a company's ability to pay off its short-term liabilities with its short-term assets. Current Ratio = Current Assets / Current Liabilities
`quick.ratio`	Liquidity	Ratio (x) that measures a company's ability to pay off its short-term liabilities with its most liquid assets, excluding inventory. Quick Ratio = (Current Assets - Stock) / Current Liabilities.
`working.capital.over.assets`	Liquidity	Ratio (x) of working capital (current assets minus current liabilities) to total assets, indicating the proportion of a company's assets that are financed by short-term funds.
`total.assets`	Capital structure	Total value of all assets owned by a company (in ths. of EUR). Total Assets = Current Assets + Fixed (non-current) Assets
`debt`	Capital structure	Aggregate financial liabilities incurred by the company (in ths. Of EUR). Total Debt = Current Liabilities + Long-term Debt
`interest.coverage.ratio`	Capital structure	Ratio (x) that measures a company's ability to pay interest on its outstanding debt. Interest coverage ratio = EBIT / Financial expenses
`net.asset.turnover`	Operating efficiency	Ratio (x) that measures that measures how much revenue a company can generate per unit of assets. Net Asset Turnover = Gross Revenue / Total Assets.
`working.capital.employees`	Operating efficiency	Ratio that measures the amount of operational funds available per employee or efficiency of resource allocation to employees for operational activities, as the amount of working capital available per employee (EUR/Employee).

2.2 Dataset structure and reorganization into the appropriate format for the SCM

The dataset is organized in a standard (long) panel-data format, where the variables are laid out across columns, and rows are sequentially arranged first by company and then by time period (i.e., 2008-2022) (Hainmueller & Diamond, 2023). Each unit is assigned both a `corporate.name` (as a character string) and a numerical `id`. For the Synth package to proceed with the analysis, at least one of these types of unit identifiers is required (Abadie et al., 2011). By way of example, see below the output showing the data corresponding to the treated unit ($j = 1$), for the first five variables.

Code element 1: Output showing the standard panel-data format of the dataset

```
> datacompanies[1:15,2:7]

         corporate.name     date   gross.revenue revenue.growth  ebitda ebitda.growth
1  AVIZOR INTERNACIONAL SLU 2008      10.80644             NA 2152.374            NA
2  AVIZOR INTERNACIONAL SLU 2009      10.01077     -7.3629734 2675.938     24.324949
3  AVIZOR INTERNACIONAL SLU 2010      10.14087      1.2996104 2898.243      8.307554
4  AVIZOR INTERNACIONAL SLU 2011      10.45674      3.1148018 2990.276      3.175476
5  AVIZOR INTERNACIONAL SLU 2012      10.71945      2.5123896 2652.514    -11.295345
6  AVIZOR INTERNACIONAL SLU 2013      10.97346      2.3695614 2285.802    -13.825073
7  AVIZOR INTERNACIONAL SLU 2014      11.97002      9.0816330 2656.814     16.231152
8  AVIZOR INTERNACIONAL SLU 2015      10.94722     -8.5447524 1381.820    -47.989585
9  AVIZOR INTERNACIONAL SLU 2016      12.23087     11.7258397 2070.395     49.831020
10 AVIZOR INTERNACIONAL SLU 2017      15.61468     27.6661863 3969.212     91.712789
11 AVIZOR INTERNACIONAL SLU 2018      17.88377     14.5317190 4697.996     18.360924
12 AVIZOR INTERNACIONAL SLU 2019      23.27154     30.1266132 7998.599     70.255552
13 AVIZOR INTERNACIONAL SLU 2020      23.47969      0.8944316 6007.373    -24.894685
14 AVIZOR INTERNACIONAL SLU 2021      29.10832     23.9723298 5376.200    -10.506639
15 AVIZOR INTERNACIONAL SLU 2022      32.97883     13.2969394 9386.899     74.601001
```

The first step of the analysis involves restructuring the panel dataset into a format compatible with the function **'synth()'** function, the primary estimator of the SCM. This reorganization is facilitated by the **'dataprep()'** function, which converts a standard panel dataset into a list of data objects (X_1, X_0, Z_1 and Z_0) necessary for running **'synth()'**. **'synth()'**requires the following data matrices as inputs to construct a synthetic control unit (Abadie et al., 2011; Hainmueller & Diamond, 2023):

- X_1, which is the (15×1) vector with the treated unit's (Aviazor) predictors variables.
- X_0, which is the (15×97) matrix of values of the same predictor variables for the 97 control companies that comprise the donor pool.
- Z_1, which is the (8×1) vector with the values of the outcome variable **gross.revenue** for the treated unit (Aviazor) for the pre-intervention periods ($T_0 = 8$).
- Z_0, which is the (8×97) matrix of values of the outcome variable **gross.revenue** for the 97 control companies for the pre-intervention periods ($T_0 = 8$).

The code example below illustrates the use of the **'dataprep()'** function. To obtain X_1 and X_0 data objects it is necessary to define several parameters: the predictor variables, the operator (e.g. mean or median), the time-period applied to these variables (i.e., 2008:2015), the dependent variable (i.e., the outcome variable **gross.revenue**), the variables for unit names (i.e., **corporate.name**) and/or numbers (i.e., **id**), the variable identifying time-periods (i.e., year), the treated unit (i.e., **id=1**), the control units (i.e., `setdiff(unique(datacompanies$id),1)`), the time-period over which to optimize (i.e., 2008:2015), and the time-period over which outcome data should be plotted (i.e., 2008:2022) (Abadie et al., 2011).

Code element 2: Code for the **'dataprep()'** function

```
> dataprep.out <- dataprep(
    foo = datacompanies,
    predictors = c("ebitda.margin", "roa", "roe", "current.ratio",
                   "quick.ratio", "working.capital.over.assets",
                   "total.assets","debt", "net.asset.turnover",
                   "working.capital.employees"),
    predictors.op = "mean",
    time.predictors.prior = 2008:2015,
    special.predictors = list(
                   list("revenue.growth", 2009:2015, "mean"),
                   list("interest.coverage.ratio", 2010:2015, "median")
    ),
    dependent = "gross.revenue",
    unit.variable = "id",
    unit.names.variable = "corporate.name",
    time.variable = "date",
    treatment.identifier = 1,
    controls.identifier = setdiff(unique(datacompanies$id), 1),
    time.optimize.ssr = 2008:2015,
    time.plot = 2008:2022
)
```

The **'dataprep()'** function generates a list object `dataprep.out` that contains various data objects: **`dataprep.out$X0`** and **`dataprep.out$X1`**, which represent the matrices X_1 and X_0; and **`dataprep.out$Z0`** and **`dataprep.out$Z1`**, corresponding to the matrices Z_0 and Z_1, respectively (Abadie et al., 2011; Hainmueller & Diamond, 2023). See below how X_1 (i.e., a (15×1) vector with the treated unit's (Aviazor) predictors variables) and Z_1 (i.e., a (8×1) vector with the values of the outcome variable **`gross.revenue`** for the treated unit (Aviazor) for the pre-intervention periods ($T_0 = 8$)) have been stored in **`dataprep.out`**.

Code element 3: Output showing the data matrices X_1 and Z_1 corresponding to the treated unit

```
> X1_matrix <- dataprep.out$X1
> X1_matrix
                                                   1
ebitda.margin                           2.302723e-01
roa                                     3.720800e-01
roe                                     4.344650e-01
current.ratio                           7.613000e-02
quick.ratio                             7.613000e-02
working.capital.over.assets             3.614753e-01
total.assets                            1.082259e+04
debt                                    3.937380e+03
net.asset.turnover                      1.783000e-02
working.capital.employees               2.734484e+02
special.revenue.growth.2009.2015[22]     3.528958e-03
special.interest.coverage.ratio.2010.2015 3.730925e+00
```

[22] Notice how the list **`dataprep.out`** adds the date range associated with the names of the special variable labels.

```
> Z1_matrix <- dataprep.out$Z1
> Z1_matrix
            1
2008 10.80644
2009 10.01077
2010 10.14087
2011 10.45674
2012 10.71945
2013 10.97346
2014 11.97002
2015 10.94722
```

2.4 Construction of the synthetic control. Running `synth()`

Finally, the **'synth()'** function estimates the impact of a PE intervention by comparing the evolution of an aggregate outcome for the treated unit with that of a synthetic control unit. **'synth()'** constructs this synthetic control through an optimization process that identifies the vector of weights W^*, yielding a weighted combination of control units that best approximates the treated unit in terms of characteristics predictive of the outcome (Hainmueller & Diamond, 2023). The optimal synthetic control W^* is selected to minimize the magnitude of the difference in pre-intervention characteristics between the treated unit and its synthetic control (Abadie et al., 2011).

As demonstrated below, the **'synth()'** function knows how to extract its input arguments (X_1, X_0, Z_1 and Z_0) from the output of the list **data.prep** generated by the **'dataprep()'** function. No additional arguments are needed (Abadie et al., 2011).

The **optimxmethod** parameter is a vector of strings that designates the optimization algorithms to be employed in the analysis. It accepts any optimization algorithm currently supported by the **'optimx'** function. The available options include the following algorithms: **c("Nelder-Mead", "BFGS","CG","L-BFGS-B","nlm","nlminb","spg","ucminf").** If multiple algorithms are indicated, the synth function will execute the optimization using each specified method and ultimately select the result from the best-performing algorithm. The default setting for this parameter is **c("Nelder-Mead", "BFGS")**. Additionally, the option **'All'** prompts the **'synth()'** function to utilize every algorithm available in **'optimx'** (Hainmueller & Diamond, 2023).

The **'synth()'** function generates a list object, **synth.out**, which provides easy access to the optimization output. For instance, the (97×1) vector of optimal weights W^* is stored in **synth.out$solution**. This output can be readily combined with the data output from the **'dataprep()'** function to calculate additional relevant metrics (Abadie et al., 2011).

2.5 Obtaining final results using 'synth.tables()', 'path.plot()', and 'gaps.plot()'

Finally, The output from **'dataprep()'** and **'synth()'** can be given to other auxiliary functions like **'synth.tab()'**, **'path.plot()'**, and **'gaps.plot()'** to produce tables and figures that summarize and illustrate the results (Abadie et al., 2011).

Firstly, the **'synth.tab()'** function creates tables summarizing the results of the analysis. This function produces four different types of tables: **tab.pred, tab.v, tab.w** and **tab.loss**.

The **synth.tables$tab.pred** object generates a table that facilitates a comparative analysis of pre-treatment predictor values among the treated unit, the synthetic control unit, and all other units in the sample (with the sample mean). This table allows for a detailed examination of how closely the synthetic control unit approximates the treated unit before the intervention, in terms of the selected predictors (Abadie et al., 2011).

The **synth.tables$tab.w** object shows the optimal vector of weights W^* for each potential control unit. Given that the donor pool is made up of a large number of companies, it is common for a substantial number of these entities to receive a weight (w^*) of zero, indicating these units do not contribute to the synthetic control unit's construction. In order to improve the interpretability of the analysis, it is advisable to adjust the code so that the weights are displayed in descending order. See the code for the use of the **'synth.tab()'** function below.

Next, the **'path.plot()'** function plots the trajectories of the outcome variable **gross.revenue** for the treated unit and the synthetic control unit for the entire observation period T, including both pre-intervention periods (T_0) and post-intervention periods (T_1). For a compelling demonstration of a treatment effect, it is necessary that the outcome variable trajectories for both the treated unit and its synthetic control unit exhibit close similarity before the intervention. Then, at the time of the intervention, these trajectories should diverge sharply (Abadie et al., 2011). This pattern of convergence before the intervention and subsequent divergence provides clear evidence of the PE intervention's impact on the investee entity (Abadie et al., 2010).

The **'gaps.plot()'** function offers an alternative perspective by plotting the gaps in the trajectories of the outcome variable for the treated unit and the synthetic control unit. Rather than simply overlaying the two trajectories over time, this function depicts how the difference in outcomes evolves throughout the study period, effectively visualizing the changing disparity post-intervention (Hainmueller & Diamond, 2023; Abadie et al., 2011). A widening of gaps post-intervention signals a positive (or negative) effect of the intervention. Conversely, if the gaps approximate zero, no direct effect attributable to the intervention can be determined.

2.6 Implementing placebo tests

On a final note, a key benefit of the SCM is its suitability for conducting placebo tests. These tests replicate the SCM analysis on units and periods unaffected by the intervention, essentially reassigning the intervention within the dataset to where it did not actually occur (Abadie et al., 2011)[23]. Such an approach serves as a validity check, helping to ensure the observed effects are genuinely attributable to the intervention. It strengthens the analysis by comparing the treated unit's outcomes against those of the placebo units. If the treated unit displays a significant deviation in outcomes compared to placebo units, it underscores the intervention's effectiveness.

In the context of this study, conducting permutation tests is a fitting approach. This involves applying the SCM to each control unit within the donor pool (or a subsample, given the dimension of the donor pool), thereby generating a series of iterations. With each iteration, information on the gaps between the outcome trajectories of the control unit treated as "treated" in the permutation and its synthetic counterpart is collected. Following Abadie et al. (2010), these gaps across all iterations can then be plotted to visually assess whether the line associated with the true synthetic control unit (i.e., synthetic Avizor) differs from the rest with small gaps prior to treatment and large gaps afterward.

The approach is easily implemented by running a `for` loop to perform placebo tests on all control units in the donor pool and gathering data on the gaps in a separate data-frame (see the entire code in Annex 2) (Abadie et al., 2011). As recommended, companies with a poor fit for the pre-treatment period are excluded (i.e., control companies with a MSPE that is five time higher than for Avizor).

[23] Abadie & Gardeazabal (2003) demonstrated this approach by applying the SCM method to Catalonia. Upon running the `'path.plot()'` function for Catalonia, no noticeable treatment effect was found, underlining the validity of the SCM findings by demonstrating the absence of a treatment effect in a comparable but untreated region.

CHAPTER IV. MAIN FINDINGS

1. MAIN FINDINGS. AVIZOR'S SYNTHETIC CONTROL UNIT

1.1 Evaluation of the synthetic control unit pre-intervention similarity

The objective of this section is to assess the impact of Proa Capital's acquisition of Avizor in 2015 on the firm's financial and operating performance. The effectiveness of Proa Capital's intervention will be determined by analyzing the gross revenues (i.e., the outcome variable) of Avizor and comparing them to those of its synthetic control unit, as the outcomes that would hypothetically have been observed for the treated unit in the absence of the intervention. A successful intervention by Proa Capital would be evidenced by a widening gap in gross revenues between Avizor and its synthetic counterpart post-acquisition. Such a divergence, both statistically significant and persist over time, would indicate that the observed improvements in financial and operating performance are directly attributable to the management practices implemented by Proa Capital.

Prior to delving into the analysis of post-acquisition disparities, it is necessary to ensure that the synthetic control unit closely matches the pre-intervention characteristics of the treated unit. The implementation of the SCM, as outlined in the previous chapter, has allowed to adequately construct a synthetic control for Avizor, which closely approximates Avizor's pre-intervention characteristics.

In this regard, the **`synth.tables$tab.pred`** object has generated a table that facilitates a comparative analysis of pre-treatment predictor values among Avizor, it's synthetic control, and all other units in the donor pool. Code Element 4, in columns (1) and (2), reports pre-intervention values of the predictor variables for Avizor and its synthetic counterpart.

Code element 4: Output of **`'synth.tab()'`**. Mean values of pre-intervention predictor variables.

```
> synth.tables$tab.pred # Display predictor balance

                                          Treated Synthetic Sample Mean
ebitda.margin                               0.230     0.197       0.057
roa                                         0.372     0.282       0.060
roe                                         0.434     0.369       0.203
current.ratio                               0.076     0.044       0.035
quick.ratio                                 0.076     0.042       0.030
working.capital.over.assets                 0.361     0.262       0.312
total.assets                            10822.593 10641.023    3713.864
debt                                     3937.380  3903.273    1486.212
net.asset.turnover                          0.018     0.022       0.002
working.capital.employees                 273.448    41.949      33.891
special.revenue.growth.2009.2015            0.004     0.005       0.081
special.interest.coverage.ratio.2010.2015   3.731     4.723       0.418
```

In general terms, these results suggest that the constructed synthetic control serves as a suitable counterfactual for Avizor, effectively matching the company's profile across several key financial and operational metrics (i.e., the selected predictor variables).

The comparison of EBITDA margins (`ebitda.margin`) reveals a synthetic value of 0.197 against the treated company's value of 0.230, demonstrating similar profitability levels. This suggests that the synthetic control is well-aligned with the treated company's ability to generate profit. Furthermore, the return on assets (`roa`) and return on equity (`roe`) between the synthetic control and the treated company are closely matched, with synthetic figures of 0.282 and 0.369 compared to the treated values of 0.372 and 0.434, respectively. These metrics further support the conclusion that the synthetic control accurately mirrors the company's financial performance in terms of profitability.

Looking at operating efficiency, the net asset turnover ratio (`net.asset.turnover`) is reasonably close, with the synthetic control at 2.2% against the treated's 1.8%. This similarity suggests that the synthetic control mirrors the treated company's asset utilization efficiency closely, with a nearly equal capacity of utilizing assets to generate revenue. Working capital over assets (`working.capital.over.assets`) reports similar figures.

In terms of capital structure, the comparison of total assets (`total.assets`) and debt (`debt`) between the synthetic control and Avizor shows a minor discrepancy, suggesting that the synthetic control effectively reflects the treated company's financial structure. This close resemblance indicates that the synthetic control provides a reasonable approximation of the treated company's capital allocation and financial leverage. The interest coverage ratio (`interest.coverage.ratio`)[24] stands out as the sole variable where the synthetic control exhibits a higher value (4.72) compared to the treated company's 3.73. This discrepancy suggests that the synthetic control may have a marginally better capacity for debt servicing but still indicates that the synthetic control generally reflects Avizor's interest-bearing liability management.

Liquidity ratios (i.e., `current.ratio` and `quick.ratio`) for Avizor are slightly higher than those for the synthetic control, suggesting Avizor has a better liquidity position and ability to cover short-term obligations with its most liquid assets. However, the fact that these ratios for the synthetic control are closer to Avizor than the much lower donor pool mean suggests the synthetic control is still a reasonable proxy for Avizor's liquidity, albeit not perfectly matched.

Lastly, when evaluating growth prospects, Avizor demonstrates a revenue growth rate (`revenue.growth`) of 0.4%, similar to the 0.5% growth of its synthetic counterpart, but which stands in contrast with the sample mean of 8.5%. A noteworthy observation from these results is the comparative analysis of Avizor's growth prospects vis-à-vis its industry peers. The relatively modest revenue

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[24] Note that this variable was designated as a special variable in the **'dataprep()'** function. This decision was made in response to the dataset exhibiting a significant number of outliers, which arise from the division (EBIT / Financial expenses) involved in calculating the interest coverage ratio. To mitigate the impact of these outliers on the analysis, the median value (within each unit) was employed as the metric for analysis. The median is less sensitive to outliers than the mean, providing a more stable and representative measure for this variable.

growth exhibited by Avizor in the pre-intervention period, particularly when compared to the broader industry average, suggests a certain underperformance of the company and might have been a factor influencing Proa Capital's decision to acquire Avizor.

Overall, the synthetic control unit seems to provide a good approximation of Avizor across several key financial and operational metrics, thereby serving as a suitable counterfactual for assessing the impact of the Proa Capital's intervention.

1.2 Components of the synthetic control unit

As defined by Abadie and Gardeazabal (2003) and Abadie et al. (2010), the synthetic control unit is a weighted average of control units. As previously noted, the **`synth.tables$tab.w`** object displays the weights assigned to each of the 98 untreated control units in the donor pool, ordered by their weights in descending order. Based on the output code, among the 98 control units, only four control units were ultimately chosen to construct the synthetic control unit:

Code element 5: Output of **`synth.tables$tab.w`**. Synthetic control weights.

```
# Display synthetic control weights
> synth.tables$tab.w
# Order the table based on w.weights in descending order
> ordered_tab.w <- synth.tables$tab.w[order(-synth.tables$tab.w$w.weights), ]

   w.weights                                  unit.names unit.numbers
38     0.843                              CARLOS P BRO SL           38
5      0.107                   BIOTECHNOLOGY INSTITUTE SL            5
3      0.049                          B BRAUN SURGICAL SA            3
9      0.001             SERVICIO INTEGRAL HOSPITALARIO SL            9
2      0.000                        BECTON DICKINSON SAU            2
4      0.000                                  DENTAID SL            4
6      0.000                                LEVENTON SAU            6
7      0.000                            ANTONI CARLES SA            7
```

In particular, the composition and respective weights are as follows (see Code element 5 above):

1) CARLOS P BRO, S.L. carries the most significant weight in the synthetic control unit, with a weight of 84.3%, indicating that this company's characteristics closely align with those of the treated company and thus, it represents a large portion of the synthetic control. Despite the significant weight assigned to CARLOS P BRO, S.L. in the synthetic control unit, it is important to clarify that the company does not have any direct or indirect relationship with Avizor (nor its subsidiaries). The weight of 84.3% reflects its statistical similarity to the characteristics of the treated company in the context of the synthetic control model. This substantial weighting is based on the alignment of specific, measurable attributes that are deemed relevant for the analysis, rather than indicating any form of business association, partnership, or similarity in operational activities with Avizor.

2) BIOTECHNOLOGY INSTITUTE, S.L. is the second most significant component with a weight of 10.7%, contributing to the synthetic control to a lesser but still meaningful extent.

3) BRAUN SURGICAL, S.A. has a smaller weight of 4.9%, suggesting its characteristics are relevant but less representative compared to the first two companies.

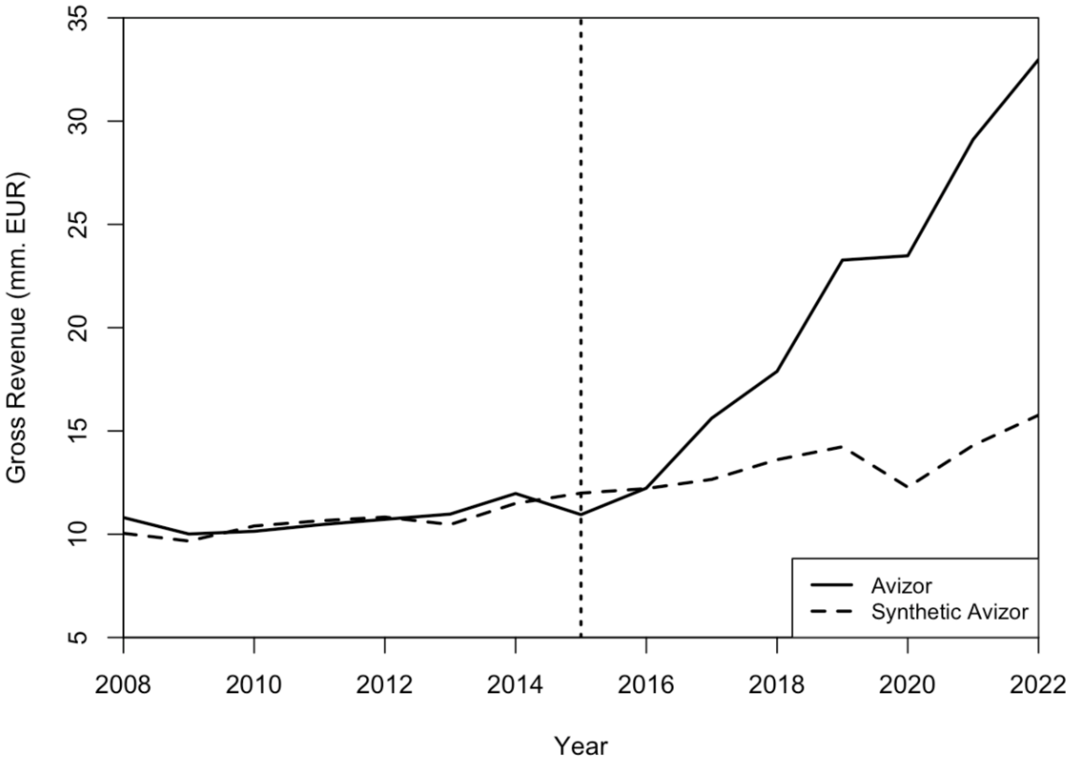
4) SERVICIO INTEGRAL HOSPITALARIO, S.L. carries the smallest weight among the contributing units, with a weight of 0.1%.

Other units within the donor pool, such as BECTON DICKINSON, S.A.U., DENTAID, S.L., and LEVENTON, S.A.U., have been assigned a weight of 0.00%, meaning that these companies do not contribute to the synthetic control unit.

1.3 Plotting the effect of the PE intervention on gross revenues

Next, the use of this synthetic control allows for a nuanced understanding of the acquisition's effects, providing insights into how Avizor's financial and operating performance might have developed in the absence of the PE fund's intervention. The **`'path.plot()'`** function plots the trajectories of **`gross.revenue`** for Avizor and its synthetic control for the observation period T, including both pre-intervention periods (T_0) and post-intervention periods (T_1).

Figure 1: Output of `path.plot()`. Trajectories of Gross Revenue for Avizor and synthetic Avizor



Prior to the intervention (T_0), indicated by the vertical dotted line around 2015, the gross revenue paths of Avizor and the synthetic Avizor run closely together, implying a strong similarity in performance. In line with the analysis of Code element 4, this close tracking further suggests that the synthetic control unit is a well-matched counterfactual for Avizor, as it captures the firm's revenue trajectory accurately in the absence of treatment.

Post-intervention (T_1), there is a marked divergence between the two paths. Avizor's actual gross revenues appear to increase significantly while the synthetic control remains relatively flat. This sharp divergence is consistent with the expected outcome if the PE intervention had a positive impact.

The fact that the gross revenues for Avizor depart upwards from the trend established by the synthetic control indicates that the treatment, in this case the acquisition by Proa Capital, has been a catalyst for growth in gross revenues. As a limitation to this assessment, note that this analysis assumes that no other events coincided with the timing of the intervention that could have influenced Avizor's performance, and that the synthetic control was properly constructed to mirror the treated unit in the pre-intervention period.

The SMC's strength lies in its ability to isolate the effect of specific interventions by accounting for external factors that equally affect both the treated unit and the control group. In the case of Avizor, since the synthetic control is comprised of other healthcare providers, it is reasonable to assume these controls were subject to the same external influences as Avizor, including the COVID-19 pandemic and demographic shifts driving healthcare consumption outlined in chapter one.

Given that the synthetic Avizor did not experience the same growth as the actual Avizor post-intervention, it suggests that the observed rapid growth in Avizor's gross revenues is not merely a reflection of industry-wide uplifts due to the pandemic or demographic trends. Instead, it indicates that the PE intervention has had a distinct and positive impact on Avizor's financial performance.

The fact that the synthetic control, which should theoretically track sectoral and broader economic trends, did not show the same revenue increases reinforces the notion that the growth observed in Avizor is directly attributable to the operational improvements implemented by Proa Capital, rather than external environmental factors. This comparative analysis helps bolster the argument that the PE firm's intervention was the key driver behind Avizor's growth during this period.

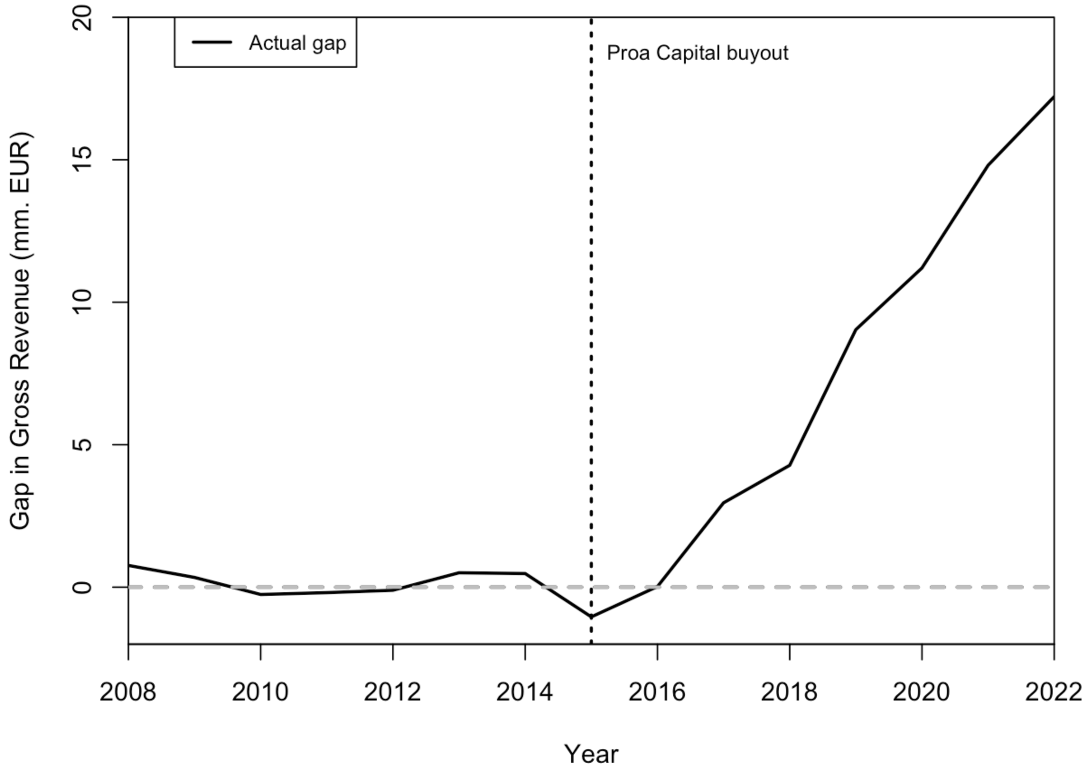
1.4 Quantifying differences in the trajectories of the outcome variable

Alternatively, the **'`gaps.plot()`'** function visualizes the difference in gross revenues between Avizor and its synthetic control over time, highlighting the effect of the Proa Capital buyout. As seen in Figure 2 below, prior to the buyout, indicated by the vertical dashed line around the year 2015, the actual gap fluctuates around zero, suggesting no significant difference between Avizor's performance and that of its synthetic control. This implies that any differences in gross revenue are nominal, reinforcing the synthetic control's validity as a proxy for Avizor in absence of the PE intervention.

Post-intervention, the gap widens significantly, with the actual gross revenue of Avizor increasingly exceeding that of the synthetic control. This growing divergence suggests that the Proa Capital buyout has had a substantial positive impact on Avizor's revenue generating capacity. In this sense, notice that the gap continues to grow over the following years, suggesting that the effects of the buyout are not only immediate but also sustained in timed.

In line with the foregoing, the lack of a similar increase in the synthetic counterpart indicates that this growth is likely not due to external factors such as the pandemic or demographic trends that would have affected all entities in the healthcare sector similarly. Instead, the data suggest that the positive outcomes are attributable to the PE firm's intervention, distinguishing the treated unit's performance from its synthetic counterpart.

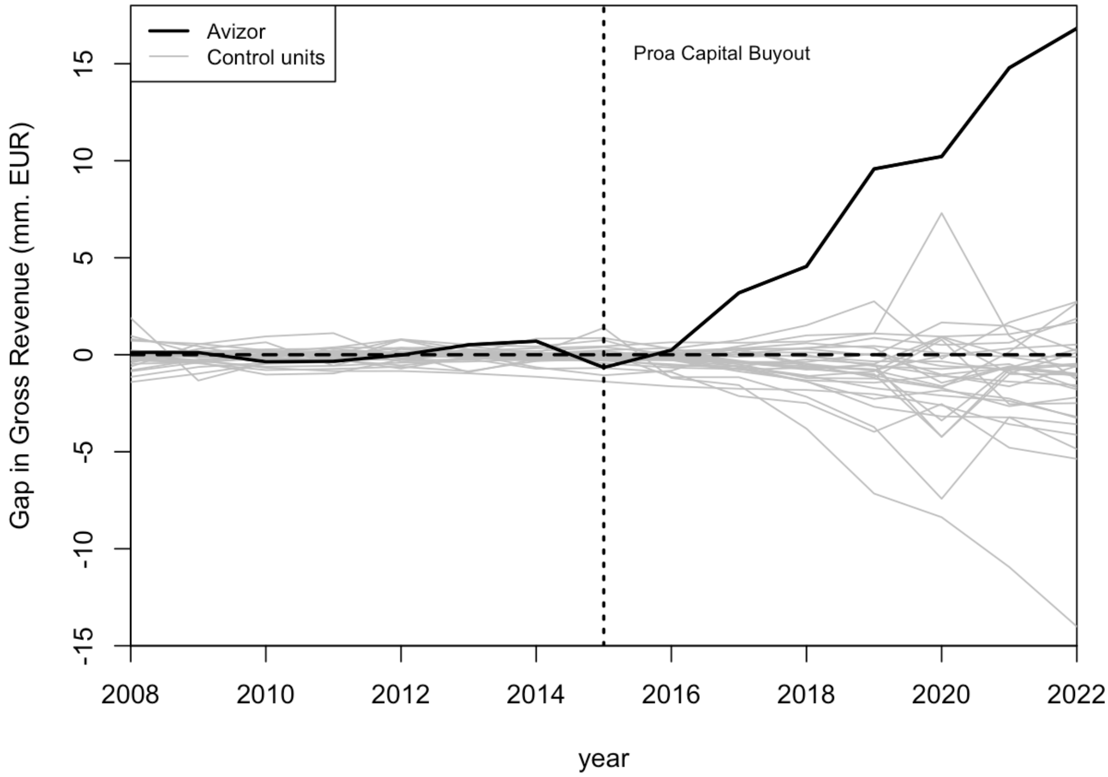
Figure 2: Output of `gaps.plot()`. Gross Revenue Gap between Avizor and synthetic Avizor



<u>1.3 Performing placebo tests</u>

In order to conclude the analysis, a placebo test was conducted by iterating over s subsample of 30 control units in the donor pool. This involved applying the SCM individually to each control unit and collecting data on the outcome gaps for each iteration. These collected gaps allow for a comprehensive visual comparison (see Figure 3 below). By plotting these gaps, one can visually assess the distinction of the true synthetic control unit (i.e., synthetic Avizor) from the rest. Specifically, smaller gaps before the intervention and significantly larger gaps afterward would indicate a meaningful divergence attributable to Proa Capital's intervention.

Figure 3: Placebo study: Gross Revenue Gap in Avizor and 35 control companies



The placebo test plot provides a powerful visualization to assess the effect of the Proa Capital buyout on Avizor against a set of control units in the donor pool. Each light gray line represents the gaps in `gross.revenue` for a control unit from the donor pool treated as "treated" in the permutation test, with its own synthetic control constructed similarly to Avizor's.

Before the intervention in late 2015, the gaps for both Avizor and the control units hover around zero with minor fluctuations, indicating that any deviations are not significant. This suggests that the synthetic control units are accurately capturing the gross revenue trajectories of their respective placebo-treated units during the pre-intervention period.

Post-intervention, the gap associated with the actual Avizor (i.e., the black line) significantly diverges from zero, soaring above all the placebo gaps. This stark divergence indicates that the post-intervention performance of Avizor is not only better than its own synthetic control but is also an outlier when compared to the placebo units' performance. The fact that the gaps for the control units largely remain near zero post-intervention reinforces that the impact observed in Avizor's revenue is not a common pattern across the control units and is thus unlikely to be due to chance or to sector-wide trends alone.

The marked difference between Avizor's trajectory and the placebo trajectories post-intervention supports the conclusion that the Proa Capital buyout had a distinct and substantial impact on Avizor's financial performance, beyond what could be expected from normal fluctuations or industry-wide effects during that time.

2. ANALYSING PROA CAPITAL'S INTERVENTION

2.1 Proa Capital's investment model

Proa Capital's investment strategy is focused on acquiring majority stakes in non-listed mid-market companies, typically valued between €30 million and €500 million (Proa Capital, n.d.-b). Their investment limit per operation is up to €100 million, which can be extended with additional funds from co-investors.

Proa Capital takes a generalist approach, investing across various sectors, with the exception of purely real estate ventures. Geographically, while they have a strong focus on Spain, their strategy also seeks international investment opportunities. Proa Capital is particularly focused on deals where the management team has or will obtain an equity stake, engaging in a variety of transaction types such as management buyouts (MBOs), management buy-ins (MBIs), and leveraged buyouts (LBOs), as well as supporting growth and build-up strategies (Proa Capital, n.d.-b).

The acquisition of Avizor was articulated as a Growth-Leveraged Buyout (Growth-LBO) (Proa Capital, n.d.-a). In a traditional LBO, the emphasis is often on financial restructuring and operational efficiency to improve margins and cash flows, leading to an increased company valuation over time. However, in a Growth-LBO, the strategy extends beyond financial engineering. While leveraging is still a key component, providing the necessary capital for the buyout, the private equity firm also actively supports the expansion of the business. This might include investing in new product lines, entering new markets, scaling operations, or even pursuing strategic acquisitions that can complement the existing business (i.e. acquisitions that drive organic growth).

In Avizor's case, labeling the transaction as a Growth-LBO implies that Proa Capital's intervention was instrumental in providing the necessary capital and strategic oversight to help the company expand and grow its operations substantially post-acquisition. This aligns with the observable impact of the buyout, where Avizor's gross revenue significantly diverged from its synthetic control, underscoring the effectiveness of this growth-oriented approach.

Furthermore, their deal origination prioritizes proprietary operations. Proa Capital focuses on sourcing investment opportunities that are exclusive or proprietary (i.e., deals that are not broadly auctioned or marketed to multiple potential buyers). By prioritizing proprietary deals, they aim to avoid highly competitive bid situations, which can drive up the price, and instead seek unique opportunities that might provide better investment terms (Proa Capital, n.d.-b).

Post-acquisition, Proa Capital maintains a high level of collaboration, involvement and commitment, aiming to maximize investment returns while seeking the best outcome for the company during the exit phase (Proa Capital, n.d.-b).

2.2 Proa Capital's financial and operational engineering on Avizor

Although detailed information on the specific measures Proa Capital implemented to improve Avizor's financial and operational performance is not publicly available, educated inferences about these strategies can be drawn by examining the company's annual accounts since the acquisition, obtained from the SABI database (see the table in Annex 3). This analysis of the financial records can provide valuable insights on the types of actions implemented post-acquisition.

Avizor has undergone a significant transformation since its acquisition by Proa Capital in 2015. The financial data up to 2022 show total assets expanding from €41,356,633 in 2015 to €255,791,578 by 2022, a clear indicator of significant capital deployment. In particular, fixed assets increased from €36.26 million to €241.59 million over the seven-year period. Within this category, intangible assets (*Inmovilizado inmaterial*) alone climbed from €421,475 to over €92.62 million. This growth pattern is indicative of major investments in intellectual property, which could be attributed to intensive research and development advancements or the acquisition of new proprietary products or technologies in the eye care industry.

The company has also substantially increased its holdings in other fixed assets (*Otros activos fijos*), which rose from €35,833,365 to €148,959,707, suggesting considerable capital expenditures. These substantial capital deployments into long-term assets, such as manufacturing facilities and machinery could suggest a ramp-up in production capabilities.

Moreover, an examination of the company's current assets (*Activo circulante*) reveals an increase to €14,203,810 in 2022 from €5,096,305 in 2015, alongside a notable enhancement in cash reserves from €1,062,924 to €4,707,102, which indicates improved liquidity conditions. Such liquidity is paramount to the company's ongoing operations and its capacity to finance further growth initiatives.

Avizor's capital structure also reflects significant developments. The equity position increased notably through retained earnings or additional capital contributions, rising from €15,488,710 in 2015 to €161,561,626 in 2022. Concurrently, the increase in long-term debt from €22,899,981 to €73,039,483 signifies a strategic leverage of debt to facilitate the expansion of the asset base.

While Avizor's operating income has grown substantially, the company faced a setback in 2022 with an operating loss, a pivot from the profit witnessed in the preceding years. This downturn was mirrored in the net results with a loss reported for the year. Such financial results could denote a period of large investment whose benefits are yet to be realized in the form of future returns. Cash flow and EBITDA figures, despite fluctuations, generally followed an upward trend, ending significantly higher in 2022 than in 2015, which suggests that operationally, the company maintains a sound performance base before financial and accounting effects are considered.

In terms of profitability, notable growth in operating income and net sales underscores a successful expansion of Avizor's core business activities, suggesting effective market expansion and possibly, the introduction of new eye care products. However, losses in both operating and net results for 2022 introduces a note of caution into this narrative of growth. These losses could potentially indicate significant capital investments or operational expansions that have yet to mature into profitable ventures. Such financial dynamics are not uncommon in growth phases, where upfront costs and investments precede the realization of financial benefits. The fluctuation in cash flow, with a notable peak in 2020 followed by a downturn in 2022, may further signify the cyclical nature of investments and the impact of external market conditions on the company's liquidity.

Furthermore, analyzing the evolution of the EBITDA margin is pivotal in this extrapolation. Even with increases in revenue, if the EBITDA margin is not maintained or improved, it signals that the additional revenue is being consumed by proportional (or greater) increases in operating expenses or cost of goods sold. Thus, maintaining a healthy EBITDA margin is essential to back the revenue growth and ensure that it translates into actual profitability.

Regarding the SCM analysis, it was found that the synthetic control method could not construct a synthetic control unit that adequately mirrored Avizor's pre-intervention characteristics when using EBITDA. However, with gross revenue as the outcome variable, the SCM analysis indicates that Proa Capital's intervention can be linked to the increase in gross revenues with a high degree of certainty. This strong causal relationship suggests that the changes implemented post-acquisition have been successful in driving top-line growth. The next step is to extrapolate these findings to understand the effects on EBITDA.

In the context of Avizor, EBITDA margin for Avizor has shown a positive trajectory since the acquisition. The increase from 12.62% in 2015 to a high of 34.37% in subsequent years, before adjusting to 28.46% in 2022, signals that Avizor has enhanced its operational efficiency over time. This improvement suggests that the company has effectively managed its core operational costs relative to its revenue growth. Avizor is generating more operational profit from each euro of revenue than it did prior to the acquisition. However, the fluctuations in this margin indicate that Avizor's profitability is sensitive to various factors, possibly including the scaling of operations.

In essence, Avizor's financial performance reveals a company in the midst of strategic growth and transformation. The investment in expanding the business, whether through R&D, market expansion, or operational scaling, appears to be a key driver behind the observed financial patterns. While the immediate financial results show a mix of sensible growth and temporary setbacks, the overall trend towards improved operational efficiency and the substantial increase in EBITDA suggest that Avizor is positioning itself for sustained profitability in the future.

Lastly, complementing these financial indicators is the expansion of Avizor’s human resources, with the number of employees expanding from 10 to 42 over the seven-year period. The increase in the workforce likely supports an increased production output and a broader operational scope.

In summary, the financial data indicates that following the acquisition by Proa Capital, Avizor has embarked on a phase of strategic asset growth, underpinned by considerable capital deployments in both tangible and intangible assets. The significant increase in intangible assets underlines a dedicated investment in innovation and intellectual property, necessary for maintaining a competitive advantage in the eye care industry. Concurrently, the increase in other fixed assets indicates a broadened production capacity, aligning with the company's growth trajectory.

Overall, the augmented asset base, coupled with an increased workforce, aligns with Avizor’s strategic objectives of innovation and market expansion. This asset expansion has been underpinned by a strengthened capital structure, that utilizes both equity and long-term debt to sustain the company's upward trajectory. The adept use of debt leverage, as seen in the rise of long-term liabilities, suggests a strategic approach to financing the company's growth. By employing leverage, Avizor has been able to amplify its asset acquisition and expansion efforts without diluting ownership.

CONCLUSIONS

This paper has provided a comprehensive examination of the role and impact of PE in the corporate and broader economic landscape. At the heart of discussions about the PE's value creation propositions is its fundamental buy-to-sell strategy. This approach appears straightforward at first: PE firms acquire, transform, and eventually sell off underperforming or undervalued entities, aiming to realize a substantial return on investment. However, a literature review on the buy-to-sell strategy has revealed an array of perspectives that diverge between proponents and critics of the approach. The debate surrounding PE's value proposition is both complex and multifaceted, reflecting a dichotomy of views that position PE firms both as catalysts for transformation and growth, and as entities engaging in practices detrimental to long-term corporate health and stakeholder welfare.

On one hand, the literature underscores the potential of PE firms to act as catalysts for transformative growth and operational efficiency in their target companies (Jensen, 1986, 1989; Kaplan, 1989; Kaplan & Schoar; 2005 and Cressy et al; 2005). Proponents argue that by leveraging financial, governance, and operational engineering, PE firms can significantly enhance the value of underperforming or undervalued entities (Kaplan & Strömberg, 2009; Barber & Good, 2007). Under this premise, PE firms are able to unlock value that was previously untapped, thereby not only transforming underperforming or stagnant entities but also contributing positively to the broader economy (Morrell & Clark, 2010). Conversely, naysaying literature presents a more critical view of the PE buy-to-sell strategy, highlighting its potential drawbacks and negative externalities (Dodd, 1980; Shleifer & Summers, 1988; Palepu, 1990; Agrawal et al. 1992). Detractors contend that PE firms engage in practices detrimental to the long-term health and sustainability of investee companies and the broader ecosystem, including asset stripping, opportunistic market timing and the pursuit of rapid, albeit suboptimal, exits (McGrath & Nerkar, 2023).

Overall, the reviewed literature underscores the need for a balanced evaluation of PE investment strategies, that acknowledges PE's potential benefits while also addressing its drawbacks. The analysis that followed, grounded in the methodology of synthetic control method, as proposed by Abadie & Gardeazabal (2003) and expanded upon by Abadie et al. (2010), has aimed to provide a more nuanced understanding of these perspectives through a detailed case study of Avizor, a manufacturer and provider of contact lenses and eye care products, acquired by Proa Capital in 2015, delivering empirical evidence to further this debate.

In the context of PE, SCM has offered an adequate statistical framework and proven instrumental in assessing the performance impact of PE investments on portfolio companies. This is achieved by comparing the performance metrics (such as revenue growth, profitability margins, or operational efficiency) of a PE-backed company against a synthetic counterfactual that represents how the company would have likely performed without the PE intervention. Thus, the application of SCM in PE transactions has allowed for a more nuanced understanding of the specific contributions of PE firms to their portfolio companies, distinguishing the effects of PE intervention from other factors.

The cornerstone of the analysis was the construction of a synthetic control unit that mirrored Avizor's pre-intervention characteristics. This synthetic counterpart, as a weighted combination of control units within the donor pool, provided a counterfactual benchmark, enabling a nuanced evaluation of the acquisition's impact. By providing a data-driven procedure for selecting control units, SCM enhances the reliability of causal inferences in observational studies.

However, the application of SCM also requires careful consideration of its limitations and the specific conditions under which it can produce reliable estimates. The method's effectiveness depends on the availability of adequate data, the correct identification of control units, and the assumption that the intervention's effects are limited to the treated unit. Despite these considerations, SCM's capacity to control for unobserved external factors and its flexibility in assessing long-term impacts has made it a powerful tool in the analysis of PE investments.

Focusing the analysis on the acquisition of Avizor, the SCM has proven to be a useful tool in isolating the effect of Proa Capital's intervention from other variables that could influence Avizor's trajectory, such as demographic trends and the healthcare sector’s resilience during economic downturns, as exemplified by the COVID-19 pandemic. This methodological approach has allowed for a more precise attribution of outcomes to Proa Capital's actions, showcasing the tangible impact of the firm’s operational, and financial engineering on Avizor's performance post-acquisition.

In particular, the data indicates that the firm has experienced significant growth and operational improvement that can be directly attributed to the intervention by Proa Capital, highlighting the potential for PE investments to generate positive outcomes when strategically applied. The results of the analysis reveal a pronounced divergence in gross revenues post-acquisition, with Avizor's performance significantly outpacing that of its synthetic counterpart. This was further corroborated by the gaps in revenue between Avizor and its synthetic control, which quantified the growing divergence in gross revenues between Avizor and its synthetic control, painting a clear picture of sustained positive impact attributable to Proa Capital's intervention.

A series placebo tests added another layer of robustness to these findings, distinguishing the observed impact on Avizor from general sectoral or economic trends. This comparative exercise confirmed the significance of Avizor's post-acquisition performance, attributing it unequivocally to Proa Capital's strategic input.

In discussing Proa Capital's investment model and operational strategy, it became evident that their approach is not merely financial, but encompasses deep operational engagement aimed at growth and expansion. Avizor's strategy was marked by substantial investments in innovation, asset expansion, and strategic debt leverage, all aimed at securing a competitive edge and fostering sustainable growth.

Overall, Proa Capital’s acquisition and subsequent management of Avizor serves as example of the value-adding potential of PE intervention in the healthcare sector. By focusing on strategic asset growth, operational enhancement, and market expansion, Proa Capital has not only improved Avizor’s financial and operational performance but has also positioned the company for sustained success in the competitive landscape of the eye care industry. This case study underscores the transformative impact that strategic PE investments can have on portfolio companies, contributing positively to their growth trajectory and operational efficiency.

In conclusion, while criticisms regarding the short-term focus and aggressive strategies of some PE firms hold merit, it is equally important to acknowledge the beneficial transformations and contributions that can result from PE investments. This paper has aimed to contribute to the academic discourse on the efficacy of PE investments by providing an analytical framework to assess specific transaction outcomes on a deal-by-deal basis. With the example of Avizor’s acquisition by Proa Capital, the application of syndic control methods has allowed to provide empirical evidence and practical insights into the mechanics of value creation through strategic acquisitions. This paper stands as a testament to the potential of PE to serve as a catalyst for corporate transformation, delivering tangible benefits to the acquired entities, their employees, and the broader ecosystem.

STATEMENT OF USE OF GENERATIVE ARTIFICIAL INTELLIGENCE TOOLS

DISCLAIMER: From the University we consider ChatGPT or other similar tools to be very useful tools in academic life, although their use is always under the responsibility of the student, since the answers provided may not be truthful. In this sense, it is NOT allowed to use them in the elaboration of the Final Degree Project to generate code because these tools are not reliable in that task. Even if the code works, there is no guarantee that it is methodologically correct, and it is highly probable that it is not.

Hereby, I, Rodrigo Almazán Sánchez, student of E3-Analytics at Comillas Pontifical University in presenting my Final Degree Project entitled "The Synthetic Control Method: A New Frontier In Private Equity Transaction Analysis", declare that I have used the Generative Artificial Intelligence tool ChatGPT or other similar GAI code only in the context of the activities described below:

1. **Brainstorming research ideas**: Used to brainstorm and outline possible areas of research.
2. **Code interpreter**: To perform preliminary data analysis.
3. **Template builder**: To design specific formats for sections of the paper.
4. **Literary and language style checker**: To improve the linguistic and stylistic quality of the text.
5. **Example problem generator**: To illustrate concepts and techniques.
6. **Proofreader**: To receive suggestions on how to improve and perfect the work with different levels of exigency.
7. **Translator**: To translate texts from one language to another.

The information and content presented in this work is the product of my individual research and effort, except where otherwise indicated and credit has been given (I have included appropriate references in the TFG and have made explicit what ChatGPT or other similar tools have been used for). I am aware of the academic and ethical implications of submitting non-original work and accept the consequences of any violation of this statement.

Date: 20 March 2024

Signed: Rodrigo Almazán Sánchez

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ANNEX OF FIGURES AND TABLES

Annex 1: Complete code for the synthetic control analysis

ID	CORPORATE NAME	NIF	AVAILABLE YEARS
3250-1	BECTON DICKINSON SAU	A50140706	32
3250-2	B BRAUN SURGICAL SA	A61123782	28
3250-3	DENTAID SL	B61766648	25
3250-4	IBERHOSPITEX, SA	A08630063	30
3250-7	BIOTECHNOLOGY INSTITUTE SL	B01288141	24
3250-8	LEVENTON SAU	A08586265	30
3250-9	ANTONI CARLES SA	A08790073	32
3250-14	TELIC SAU	A08733578	31
3250-15	SERVICIO INTEGRAL HOSPITALARIO SL	B45365640	27
3250-16	HERSILL SL	B28309581	27
3250-17	NUEVA FEDESA SA	A84713338	16
3250-19	ESPECIALIDADES MEDICO ORTOPEDICAS SL	B46047999	29
3250-21	ORGANIZACION DE SERVICIOS ORTOPEDICOS TOTALES SL	B46264305	30
3250-23	TALLERES MESTRAITUA SL	B48440242	27
3250-24	TEDISEL IBERICA SL	B60824554	28
3250-25	BIONER SA	A60141744	27
3250-27	MEDICAL IBERICA SA	A78025293	31
3250-31	GMI DENTAL IMPLANTOLOGY S.L.	B25506833	20
3250-32	VOE SA	A59100131	31
3250-33	MEDI CARE SYSTEM SLU	B60715091	28
3250-34	INDUSTRIA OPTICA HISPANO SA	A08399727	30
3250-36	CREO MEDICAL SL.	B62943063	20
3250-37	LABOLAN MATERIAL E INSTRUMENTACION DE LABORATORIO SL	B31129604	27
3250-38	PODOACTIVA SOCIEDAD LIMITADA.	B22316707	16
3250-39	SIBEL SAU	A08628174	30
3250-40	PROTESIS SA	A28095172	30
3250-41	LABORATORIO ARAGO SL	B08651481	31
3250-42	INSAUSTI MATERIAL CLINICO SL	B31351240	28
3250-43	LORCA MARIN SA	A30001010	30
3250-48	VECMEDICAL SPAIN SL	B62100722	18
3250-49	CENTRO DENTAL CERANIUM SL	B80220783	18
3250-51	FRESDENTAL INNOVACION Y MANUFACTURAS SL	B39681572	15
3250-52	METROHM DROPSENS SL.	B74165457	17
3250-54	UNION DENTAL SA	A28159622	27
3250-55	ANCLADEN S.L.	B60926490	21
3250-60	LABORATORIO DENTAL ASTUR, SA	A33010182	25
3250-61	ORTOIBERICA SL	B33067505	29
3250-64	J M PELEGRI SL	B17098948	26
3250-65	GRAU SOLER SA	A08789760	31
3250-66	FORNITURAS TECNICAS SL	B60908282	24
3250-69	FAMADENT SLU	B59911289	26

3250-74	ELIDENTE SL	B15480445	26
3250-75	FELIX GOMEZ BAÑO SL	B70082524	16
3250-79	TECNICA DENTAL STUDIO VP SL	B27323765	18
3250-81	LABORATORIO ORTOPLUS SL	B92004514	22
3250-83	CARLOS P BRO SL	B50473297	21
3250-85	BIOTAP SL	B58605825	31
3250-86	3DENTAL CAD CAM SL	B85468585	15
3250-87	ALVAREZ REDONDO SA	A78757903	27
3250-88	ORTOPEDIA HUGUE SL	B61559332	18
3250-91	DESARROLLO E INVESTIGACION MEDICA ARAGONESA SL	B50602275	21
3250-93	EDSER INSOLES SL	B62738471	21
3250-95	EUROGINE SL	B59608919	30
3250-96	LUCENA OPTICO SL	B23397904	24
3250-97	ORTODIX SL	B15557549	18
3250-98	PRODENT BAGES SL	B63973952	16
3250-104	MICROTEST SA	A80693146	26
3250-105	HIKUMI ORTO SL	B23519465	19
3250-107	PROTESIS Y ESTETICA DENTAL AVILA MAÑAS SL	B79319463	27
3250-108	LABORATORIOS DENTALES BETICOS SL	B41041815	28
3250-109	INTERLENCO SA	A28392827	29
3250-111	PRODENTAL GILABERT SL	B97233688	21
3250-112	SILICOM DENTAL SL	B97473441	19
3250-113	PROTESIS DENTAL CASTELLON SL	B12532800	20
3250-114	DINNBIER DENTAL SL	B97679666	16
3250-117	ORDISI SA	A08258642	28
3250-118	DISEÑO DENTAL CAD CAM VALENCIA SL	B97711980	15
3250-120	EM EXACT SA.	A59123455	29
3250-121	VALDENTIA SL	B97186829	21
3250-122	ORTOTECSA SL	B80118029	27
3250-123	LABORATORIOS LENTICON SA	A78383221	30
3250-124	BIOCAD LABORATORIO DE PROTESIS DENTAL, SL.	B01238278	21
3250-125	SANTANDENT SL	B39634696	15
3250-126	CENTRO PROTESICO DENTAL DE CIUDAD REAL SL	B13304241	21
3250-128	ESTUDIOS Y DESARROLLOS DE PROTESIS SL	B14354013	22
3250-129	CANODENT SL	B14344493	28
3250-130	ESTEVE ORTOPEDIA A MIDA SL	B63322804	19
3250-131	VALLDAURADENT SLP	B61790192	22
3250-132	ORTOTEX MEDICAL SL	B30529069	26
3250-133	FLEMING COMERCIAL SA	A08383630	31
3250-139	PRO ART DENTAL SL	B07990229	17
3250-142	MEDICAL PRECISION IMPLANTS SA	A85518173	15
3250-143	PROTESIS DENTAL LUCIO ALVAREZ SL	B80930480	20
3250-144	JAMBOREE SL	B08687196	25
3250-155	LABORATORIO TAMAYO SL	B58145897	26
3250-156	EURO BASTON SL	B33851155	24
3250-163	ACUDENT SL	B80192297	20
3250-165	LABORDENT SL	B47453899	19
3250-168	PROMECHI SL	B46853065	27

3250-169	IVALMED SL	B96331897	29
3250-170	XANFRA CENTRO ODONTOTECNICO SOCIEDAD DE RESPONSABILIDAD LIMITADA	B98221062	13
3250-171	TORRECILLAS PROTESIS DENTAL SL	B18565614	15
3250-172	OXIGEM SL	B80213788	21
3250-173	LABORATORIO DENTAL RUIZ SA	A25233297	30
3250-176	COVACA SA	A78951985	25
3250-179	ACOSTA ORTOPEDIA TECNICA SL	B41672346	26
3250-185	MIGUEL GRADIN SL	B15611163	20
3250-187	FRANCISCO CHINER SL	B96558499	22
3250-189	LABORATORIO DENTAL RAMON LOPEZ SL	B96886288	21
3250-191	PROTESIS DEL SUR SL	B18230110	23
3250-192	JUSTO MANUEL RUBIO CEBRIA SL	B97168702	21
3250-193	ANSABERE SURGICAL SL	B31802077	19
3250-201	CARCIDENTAL 2006 SL	B49229602	18
3250-209	CENTRO LABORATORIO PROTESIS DENTAL RODENT SL	B91064071	22
3250-214	MEDICAL DEVICES SL	B61579835	24
3250-217	LABORATORIOS DE PREVENCION E HIGIENE BUCAL SL	B62158035	23
3250-229	PROTIDENT SL	B46288965	21
3250-233	CENTRO DE ERGODINAMICA SL	B62174636	22
3250-236	ADANA DENTAL SL	B38719183	20
3250-239	LOYDENT SL	B80605413	22
3250-245	R G B MEDICAL DEVICES SA	A78895026	29
3250-250	PODO ORTOSIS SL	B03064169	31
3250-255	ENELINI ASSOCIATS SL	B61221032	22

Annex 2: Complete code for the SCM analysis

```
#install.packages("Synth")
library("Synth")
library(readxl)
#______________________________________________________________________________
# PREPARE THE DATAFRAME
#______________________________________________________________________________

datacompanies <- read_excel("datacompanies.xlsx",
                    col_types = c("numeric", "text", "date", "numeric",
                                  "numeric", "numeric", "numeric",
                                  "numeric", "numeric", "numeric",
                                  "numeric", "numeric", "numeric",
                                  "numeric", "numeric", "numeric",
                                  "numeric", "numeric", "numeric",
                                  "numeric", "numeric","numeric",
                                  "numeric","numeric"))
datacompanies<-as.data.frame(datacompanies)
datacompanies[1:15,2:7]

# Convert 'date' column to a year format if necessary
datacompanies$date <- format(as.Date(datacompanies$date), "%Y")
datacompanies$date <- as.numeric(as.character(datacompanies$date))

na_check <- sapply(datacompanies, function(x) sum(is.na(x)))

# For 'interest.coverage.ratio', impute NA values with the median for each 'id'
datacompanies$interest.coverage.ratio <-
              ave(datacompanies$interest.coverage.ratio,
                                      datacompanies$id,
                                      FUN = function(x) ifelse(is.na(x),
                                      median(x, na.rm = TRUE), x))

# For 'number.employees', impute NA values with the mean for each 'id'
datacompanies$number.employees <- ave(datacompanies$number.employees,
                                      datacompanies$id,
                                      FUN = function(x) ifelse(is.na(x),
                                      mean(x, na.rm = TRUE), x))

# For 'revenues.employees', impute NA values with the mean for each 'id'
datacompanies$revenues.employees <- ave(datacompanies$revenues.employees,
                                        datacompanies$id,
                                        FUN = function(x) ifelse(is.na(x),
                                        mean(x, na.rm = TRUE), x))

# For 'assets.employees', impute NA values with the mean for each 'id'
datacompanies$assets.employees <- ave(datacompanies$assets.employees,
                                      datacompanies$id,
                                      FUN = function(x) ifelse(is.na(x), mean(x,
                                      na.rm = TRUE), x))
```

```
# For 'working.capital.employees', impute NA values with the mean for each 'id'
datacompanies$working.capital.employees<-
              ave(datacompanies$working.capital.employees,
                                    datacompanies$id,
                                    FUN = function(x) ifelse(is.na(x), mean(x,
                                    na.rm = TRUE), x))

na_check <- sapply(datacompanies, function(x) sum(is.na(x)))
print(na_check)

#___________________________________________________________________________________
# ANALYSIS. CONSTRUCTING THE SYNTHETIC CONTROL UNIT
#___________________________________________________________________________________

dataprep.out <- dataprep(foo = datacompanies,
                     predictors = c("ebitda.margin", "roa", "roe",
                                    "current.ratio","quick.ratio"
                                    "working.capital.over.assets",
                                    "total.assets","debt",
                                    "net.asset.turnover",
                                    "working.capital.employees"),
                      predictors.op = "mean",
                      time.predictors.prior = 2008:2015,
                      special.predictors = list(
                          list("revenue.growth", 2009:2015, "mean"),
                          list("interest.coverage.ratio", 2010:2015, "median")
                      ),
                      dependent = "gross.revenue",
                      unit.variable = "id",
                      unit.names.variable = "corporate.name",
                      time.variable = "date",
                      treatment.identifier = 1,
                      controls.identifier = setdiff(unique(datacompanies$id), 1),
                      time.optimize.ssr = 2008:2015,
                      time.plot = 2008:2022
)

# Accessing matrices X1 and Z1 for the treated unit and in-space optimization
X1_matrix <- dataprep.out$X1
X1_matrix
Z1_matrix <- dataprep.out$Z1
Z1_matrix


# Run the synthetic control model
synth.out <- synth(data.prep.obj = dataprep.out, method = "All")

# Generate a plot showing the trajectory of the actual outcome vs. the synthetic
path.plot(synth.res = synth.out, dataprep.res = dataprep.out,
          Ylab = "Gross Revenue (mm. EUR)", Xlab = "Year",
          Ylim = c(5, 35),
```

```
          Legend = c("Avizor","Synthetic Avizor"), Legend.position =
          "bottomright", tr.intake = 2015
)

# Dataprep.out$Y0plot contains the predicted synthetic control values for each
# control unit (as columns) across all time periods (as rows),
# dataprep.out$Y1plot contains the actual values for the treated unit

# Calculate the gaps for post-intervention period
gaps <- dataprep.out$Y1plot - (dataprep.out$Y0plot %*% synth.out$solution.w)

# Display tables summarizing the results
synth.tables <- synth.tab(dataprep.res = dataprep.out, synth.res = synth.out)
names(synth.tables) # List the tables available
synth.tables$tab.pred # Display predictor balance
synth.tables$tab.w # Display synthetic control weights

# Order the table based on w.weights in descending order
colnames(synth.tables$tab.w)
ordered_tab.w <- synth.tables$tab.w[order(-synth.tables$tab.w$w.weights), ]
print(ordered_tab.w)

#________________________________________________________________________________
# GAPS TREATED VS. SYNTHETIC CONTROL UNIT
#________________________________________________________________________________

years <- dataprep.out$tag$time.plot
gap_values <- gaps # This should be the vector containing the gap values
intervention_year <- 2015

# Plot setup
plot(years, gap_values,
     type="l", lwd=2, col="black",
     xlab="Year", ylab="Gap in Gross Revenue (mm. EUR)",
     xlim=c(min(years), max(years)),
     ylim=range(gap_values, na.rm = TRUE),
     xaxs="i", yaxs="i"
)

# Add a line for the intervention year
abline(v=intervention_year, lty="dotted", lwd=2)

# Add horizontal line at y=0 to represent no gap
abline(h=0, lty="dashed", lwd=2,col="gray")
# Legend
legend("topleft", inset=c(0.05, 0), legend=c("Actual Gap", "Intervention Year"),
       lty=c(1, 2), col=c("black", "gray"), lwd=c(2, 2), cex=0.8)

# Add annotations or additional lines
text(intervention_year, min(gap_values, na.rm = TRUE) + 17, "Buyout", cex=0.8,
pos=4)
```

```
#____________________________________________________________________________

# ALTERNATIVE:
gaps.plot(synth.res = synth.out,
          dataprep.res = dataprep.out,
          Ylab = "Gap in Gross Revenue (mm. EUR)",
          Xlab = "Year",
          Ylim = c(-2,20),
          Main = NA
)

# Add a line for the intervention year
intervention_year <- 2015
abline(v=intervention_year, lty="dotted", lwd=2) # Add a line for the
intervention year

# Add horizontal line at y=0 to represent no gap
abline(h=0, lty="dashed", lwd=2,col="gray")

legend("topleft", inset=c(0.05, 0), legend=c("Actual gap"),
       lty=c(1, 2), col=c("black", "black"), lwd=c(2, 2), cex=0.8)
       text(intervention_year, min(gap_values, na.rm = TRUE) + 19.75, "Proa
       Capital buyout", cex=0.8, pos=4
)

#____________________________________________________________________________
# PLACEBO STUDY
#____________________________________________________________________________

# Selecting the first 35 unique company names
unique_names <- unique(datacompanies$corporate.name)
lengthsubset <- 35
subsetnames <- unique_names[1:lengthsubset]
subsample_datacompanies <- datacompanies[datacompanies$corporate.name %in%
                                          subsetnames, ]

# Adjust the matrix size and column names based on subset
unique_companies <- unique(subsample_datacompanies$corporate.name)
length(unique_companies)
store <- matrix(NA, length(2008:2022), length(unique_companies))
colnames(store) <- unique_companies


# Run placebo test
for(iter in 1:length(unique_companies))
{
  if(length(unique_companies) >= 2) {
    dataprep.out <- dataprep(foo = subsample_datacompanies,
                             predictors = c("ebitda.margin", "roa", "roe",
                                            "current.ratio","quick.ratio",
                                            "working.capital.over.assets",
```

```
                                            "total.assets","debt",
                                            "net.asset.turnover",
                                            "working.capital.employees"),
                          predictors.op = "mean",
                          time.predictors.prior = 2008:2015,
                          special.predictors = list(
                               list("revenue.growth", 2009:2015, "mean"),
                               list("interest.coverage.ratio", 2010:2015,
                                     "median")
                          ),
                          dependent = "gross.revenue",
                          unit.variable = "id",
                          unit.names.variable = "corporate.name",
                          time.variable = "date",
                          treatment.identifier = iter,
                          controls.identifier =
                                 setdiff(1:length(unique_companies), iter),
                          time.optimize.ssr = 2008:2015,
                          time.plot = 2008:2022
    )
    # Run synth
    synth.out <- synth(data.prep.obj = dataprep.out, method = "MSPE")

    # Store gaps
    store[,iter] <- dataprep.out$Y1plot - (dataprep.out$Y0plot %*%
                                           synth.out$solution.w)
  }
}

# Prepare for plotting
data <- store
rownames(data) <- 2008:2022
print(colnames(data))

# Set bounds in gaps data
gap.start     <- 1
gap.end       <- nrow(data)
years         <- 2008:2022
gap.end.pre   <- which(rownames(data)=="2015")

#  MSPE Pre-Treatment
mse        <- apply(data[ gap.start:gap.end.pre,]^2,2,mean)
avizor.mse <- as.numeric(mse[1])
# Exclude states with 5 times higher MSPE than basque
data <- data[,mse<5*avizor.mse]
Cex.set <- .75

# Plot
plot(years,data[gap.start:gap.end,
     which(colnames(data)=="AVIZOR INTERNACIONAL SLU")],
     ylim=c(-15,18),xlab="year",
```

```
     xlim=c(2008,2022),ylab="Gap in Gross Revenue (mm. EUR)",
     type="l",lwd=2,col="black",
     xaxs="i",yaxs="i"
)

# Add lines for control states
for (i in 1:ncol(data)) { lines(years,data[gap.start:gap.end,i],col="gray") }

## Add AVIZOR line
lines(years,data[gap.start:gap.end,which(colnames(data)=="AVIZOR INTERNACIONAL
SLU")],lwd=2,col="black")

# Add other elements
abline(v=2015,lty="dotted",lwd=2)
abline(h=0,lty="dashed",lwd=2)
legend("topleft",legend=c("Avizor","Control units"),
       lty=c(1,1),col=c("black","gray"),lwd=c(2,1),cex=.8)
text(2016.75,15.5,"Proa Capital Buyout",cex=Cex.set)
```

Annex 3: Annual accounts of AVIZOR INTERNATIONAL, S.L.U. (2008-2022)

	2022	2021	2020	2019	2018	2017	2016	2015	2014	2013	2012	2011	2010	2009	2008
Balance de situación															
Inmovilizado	241,587,768	50,116,695	37,228,587	38,158,970	38,371,038	37,990,931	37,382,872	36,260,328	486,630	15,936	669,611	6,641	9,597	13,016	26,047
Inmovilizado inmaterial	92,624,359	172,276	229,692	287,108	382,102	429,948	477,795	421,475	474,159	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.
Inmovilizado material	3,702	2,912	4,968	n.d.	n.d.	n.d.	2,022	5,488	8,955	12,421	1,422	4,267	7,223	10,642	23,673
Otros activos fijos	148,959,707	49,941,507	36,993,927	37,871,862	37,988,936	37,560,983	36,903,055	35,833,365	3,516	3,515	668,189	2,374	2,374	2,374	2,374
Activo circulante	14,203,810	13,856,954	14,817,865	15,140,258	15,443,204	6,010,382	4,678,559	5,096,305	7,400,740	7,167,083	5,764,727	8,391,314	6,174,577	4,550,852	4,547,339
Existencias	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.
Deudores	7,153,458	6,757,757	4,788,110	4,690,938	5,675,046	4,639,046	3,012,374	2,661,245	2,867,337	3,192,402	2,574,510	2,784,201	2,162,786	2,219,017	2,185,085
Otros activos líquidos	7,050,352	7,099,197	10,029,755	10,449,320	9,768,158	1,371,336	1,666,185	2,435,060	4,533,403	3,974,681	3,190,217	5,607,113	4,011,791	2,331,835	2,362,254
Tesorería	4,707,102	6,342,339	9,889,533	6,280,346	1,750,917	1,093,831	1,095,854	1,062,924	1,520,564	1,529,217	1,174,367	933,837	1,014,134	1,611,533	1,713,845
Total activo	255,791,578	63,973,649	52,046,452	53,299,228	53,814,242	44,001,313	42,061,431	41,356,633	7,887,370	7,183,019	6,434,338	8,397,955	6,184,174	4,563,868	4,573,386
Fondos propios	161,561,626	32,781,320	31,985,120	33,950,333	28,140,842	19,397,899	16,969,072	15,488,710	7,059,759	6,554,734	4,962,221	7,567,073	5,447,859	4,084,961	3,915,925
Capital suscrito	4,215	4,215	4,275	4,275	4,275	4,275	4,275	4,275	3,005	3,005	3,005	3,005	3,005	3,005	3,005
Otros fondos propios	161,557,411	32,777,105	31,980,845	33,946,058	28,136,567	19,393,624	16,964,797	15,484,435	7,056,754	6,551,729	4,959,216	7,564,068	5,444,854	4,081,956	3,912,920
Pasivo fijo	80,127,321	15,715,776	13,923,077	10,912,979	13,829,787	16,234,762	20,713,638	22,899,981	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	2,019
Acreedores a L. P.	73,039,483	15,715,776	13,923,077	10,883,978	13,773,056	16,151,367	20,604,604	22,899,981	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.
Otros pasivos fijos	7,087,838	0	0	29,001	56,731	83,395	109,034	0	0	0	0	0	0	0	2,019
Provisiones	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.
Pasivo líquido	14,102,631	15,476,553	6,138,255	8,435,916	11,843,613	8,368,652	4,378,721	2,967,942	827,611	628,285	1,472,117	830,882	736,315	478,907	655,442
Deudas financieras	4,177,644	638,161	4,786,709	3,009,803	2,513,115	2,512,649	2,009,561	2,017,171	69,613	n.d.	376,050	69,625	93,816	n.d.	n.d.
Acreedores comerciales	n.d.	11,187	16,206	1,207	1,207	7,030	4,993	5,798	4,993	5,140	4,993	24,232	10,283	44,080	43,113
Otros pasivos líquidos	9,924,987	14,827,205	1,335,340	5,424,906	9,329,291	5,848,973	2,364,167	944,973	753,005	623,145	1,091,074	737,025	632,216	434,827	612,329
Total pasivo y capital propio	255,791,578	63,973,649	52,046,452	53,299,228	53,814,242	44,001,313	42,061,431	41,356,633	7,887,370	7,183,019	6,434,338	8,397,955	6,184,174	4,563,868	4,573,386
Fondo de maniobra	7,153,458	6,746,570	4,771,904	4,689,731	5,673,839	4,632,016	3,007,381	2,655,447	2,862,344	3,187,262	2,569,517	2,759,969	2,152,503	2,174,937	2,141,972
Número empleados	42	12	12	12	10	11	11	10	10	9	10	10	8	9	9
Cuentas de pérdidas y ganancias															
Ingresos de explotación	32,978,830	29,108,315	23,479,687	23,271,539	17,883,766	15,614,684	12,230,869	10,947,216	11,970,025	10,973,456	10,719,452	10,456,738	10,140,870	10,010,769	10,806,445
Importe neto Cifra de Ventas	32,964,043	29,107,639	23,479,687	23,271,539	17,883,766	15,614,684	12,230,869	10,947,216	11,970,025	10,973,456	10,719,452	10,453,921	10,133,496	10,002,729	10,798,424
Consumo de mercaderías y de materias	18,881,907	17,334,061	14,397,713	11,708,487	10,697,324	9,256,961	7,560,024	6,878,114	7,206,786	6,785,706	6,390,160	6,101,719	5,853,720	5,879,706	6,713,524
Resultado bruto	14,096,923	11,774,254	9,081,974	11,563,052	7,186,442	6,357,723	4,670,845	4,069,102	4,763,239	4,187,750	4,329,292	4,355,019	4,287,150	4,131,063	4,092,921
Otros gastos de explotación	15,048,660	6,457,526	3,133,217	3,659,447	2,536,292	2,438,380	2,647,596	2,743,433	2,109,891	1,904,815	1,679,623	1,367,699	1,392,326	1,468,156	1,940,555
Resultado Explotación	-951,737	5,316,728	5,948,757	7,903,605	4,650,150	3,919,343	2,023,249	1,325,669	2,653,348	2,282,935	2,649,669	2,987,320	2,894,824	2,662,907	2,152,366
Ingresos financieros	197,914	243,339	9,020,943	166,872	5,617,669	34,949	35,959	166,602	18,863	1,415	7,637	41,276	50,396	11,038	21,504
Gastos financieros	3,280,409	376,952	466,994	443,570	337,241	611,909	506,396	28,724	32,694	8,103	60,010	1,147	2,093	13,687	39,137
Resultado financiero	-3,082,495	-133,613	8,553,949	-276,698	5,280,428	-576,960	-470,437	137,878	-13,831	-6,688	-52,373	40,129	48,303	-2,649	-17,633
Result. ordinarios antes Impuestos	-4,034,232	5,183,115	14,502,706	7,626,907	9,930,578	3,342,383	1,552,812	1,463,547	2,639,517	2,276,247	2,597,296	3,027,449	2,943,127	2,660,258	2,134,733
Impuestos sobre sociedades	693,937	1,295,804	1,380,917	1,734,224	1,107,643	836,640	399,552	409,789	803,067	683,734	779,189	908,235	880,229	791,222	629,993
Resultado Actividades Ordinarias	-4,728,169	3,887,311	13,121,789	5,892,683	8,822,935	2,505,743	1,153,260	1,053,758	1,836,450	1,592,513	1,818,107	2,119,214	2,062,898	1,869,036	1,504,740
Ingresos extraordinarios	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.
Gastos extraordinarios	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.
Resultados actividades extraordinarias	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.
Resultado del Ejercicio	-4,728,169	3,887,311	13,121,789	5,892,683	8,822,935	2,505,743	1,153,260	1,053,758	1,836,450	1,592,513	1,818,107	2,119,214	2,062,898	1,869,036	1,504,740
Materiales	18,881,907	17,334,061	14,397,713	11,708,487	10,697,324	9,256,961	7,560,024	6,878,114	7,206,786	6,785,706	6,390,160	6,101,719	5,853,720	5,879,706	6,713,524
Gastos de personal	2,573,607	681,859	743,174	605,186	681,041	698,053	642,115	574,271	542,349	407,219	618,464	512,062	480,993	443,581	471,377
Dotaciones para amortiz. de inmovil.	10,338,636	59,472	58,616	94,994	47,846	49,869	47,146	56,151	3,466	2,867	2,845	2,956	3,419	13,031	8
Otros Conceptos de Explotación	-2,136,417	-5,716,195	-2,331,427	-2,959,267	-1,807,405	-1,690,458	-1,958,335	-2,113,011	-1,564,076	-1,494,729	-1,058,314	-852,681	-907,914	-1,011,544	-1,469,170
Gastos financieros y gastos asimilados	3,280,409	376,952	198,521	288,383	337,241	542,947	506,396	28,724	32,694	8,103	5,705	1,147	2,093	1,117	232
Cash flow	5,610,467	3,946,783	13,180,405	5,987,677	8,870,781	2,555,612	1,200,406	1,109,909	1,839,916	1,595,380	1,820,952	2,122,170	2,066,317	1,882,067	1,504,748
Valor agregado	12,158,420	6,301,398	15,503,017	8,615,470	10,996,706	4,633,252	2,748,469	2,122,693	3,218,026	2,694,436	3,224,310	3,543,614	3,429,632	3,117,987	2,606,349
EBIT	-951,737	5,316,728	5,948,757	7,903,605	4,650,150	3,919,343	2,023,249	1,325,669	2,653,348	2,282,935	2,649,669	2,987,320	2,894,824	2,662,907	2,152,366
EBITDA	9,386,899	5,376,200	6,007,373	7,998,599	4,697,996	3,969,212	2,070,395	1,381,820	2,656,814	2,285,802	2,652,514	2,990,276	2,898,243	2,675,938	2,152,374

Source: SABI