

POLITECNICO DI TORINO

Department of Management Engineering
Master's Degree in Management Engineering Innovation and Entrepreneurship



Master of Science Thesis

**The Impact of STRATEGIC MARKETING and VIRAL
INFLUENCER MARKETING on ECONOMIC PERFORMANCE**

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"No matter what cards life deals, you have to learn to make your own magic"

Now You See Me.

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1

INTRODUCTION

*“Half the money I spend on advertising is wasted; the trouble is,
I don’t know which half.”*

John Wanamaker, department store pioneer, c. 1900

Wanamaker’s lament is over a century old. Yet it has never felt more relevant than today, and, paradoxically, never less justified. We live in an era of unprecedented measurement: every click is tracked, every impression timestamped, every booking traced back to a source. Marketing has become, at least in principle, a quantitative discipline. And yet the central question: *“does it actually work?”* remains stubbornly unanswered in too many boardrooms.

The rise of digital platforms, and influencer marketing in particular, has sharpened this tension to a fine edge. A single YouTube video can fill a restaurant for weeks. A single Instagram post can launch a brand from obscurity to cult status overnight. A single misaligned collaboration can destroy years of brand equity in 48 hours. These are not hypotheticals: they are documented, recurring phenomena. And yet the mechanisms behind them remain poorly understood, inconsistently measured, and almost entirely absent from the academic literature on management engineering.

This thesis takes that gap seriously. It is motivated by a simple but consequential observation: in the high-end restaurant sector, the tools of digital influence: food content creators, viral videos, algorithmic distribution, have become more powerful than any traditional advertising channel, and yet no rigorous quantitative study has isolated their economic impact. Restaurant managers make decisions worth hundreds of thousands of euros based on intuition, anecdote, and imitation. That is not good enough.

The research is guided by four interrelated questions. How much can viral content quantifiably increase bookings and online visibility for a Michelin-starred restaurant? To what extent does influencer marketing improve measurable performance, relative to a control group? Is it economically more effective to invest in external influencer collaborations, or in the cultivation of the restaurant’s own brand identity and self-presentation? And how do broader strategic marketing decisions: positioning, brand equity, experience design, shape a business’s long-term trajectory beyond any single campaign?

To address these questions, the thesis adopts a dual analytical approach. The first pillar is a cross-sector literature review that integrates academic research with curated case studies from business practice, drawing on sources ranging from peer-reviewed journals

to Harvard Business School cases to construct a coherent theoretical framework at the intersection of strategic marketing, influencer dynamics, and economic performance. There is a **creative logic** to the design of this thesis. A literature review alone would have produced theory without evidence. An econometric model alone would have produced numbers without meaning. Combining them, and accepting the messiness that comes with it, is itself a methodological statement. *Reed Hastings* by Netflix would call it operating "a little closer to the edge of chaos". The author would call it the only honest way to answer a question this complex. The second pillar is an original empirical analysis of 348 Michelin-starred Italian restaurants, leveraging Google Trends data collected over seven years and exposure data from three major Italian YouTube food channels to quantify, through a difference-in-differences design, the causal effect of influencer content on restaurant popularity.

The choice of the restaurant sector is deliberate, not arbitrary. Fine dining offers a rare empirical setting: establishments within the same Michelin tier are remarkably homogeneous in their marketing practices, making it possible to isolate the specific contribution of influencer exposure with a precision that would be impossible in, say, fashion or consumer electronics. The Michelin Guide itself functions as a natural standardisation mechanism, producing comparable observations across the entire Italian haute cuisine landscape. This homogeneity is the empiricist's gift, and this thesis intends to use it fully.

Although the empirical application is anchored in hospitality, the analytical framework is designed to travel. The principles extracted, on brand-influencer fit, authenticity, self-branding versus paid activation, and the long-run returns to identity-based community building, are transferable to any sector where digital influence mediates the relationship between a brand and its audience. In this sense, the thesis speaks not only to restaurant managers but to any practitioner or researcher grappling with a version of Wanamaker's original problem: which half of the marketing investment actually moves the needle?

The thesis is structured as follows. Chapter 2 presents the literature review, tracing the evolution from strategic marketing and brand equity theory to the mechanisms of influencer marketing, and synthesising cross-sector evidence to identify the research gaps this work addresses. Chapter 3 describes the empirical setting, and the analytical strategy. Chapter 4 presents the data collection process. Chapter 5 discusses quantitative results and their interpretation.

It's gonna be interesting, I'm telling you.

2

LITERATURE REVIEW

2.1

Purpose and structure of the literature review

2.1.1

Approach to the literature

This thesis aims to be a practical work in which theoretical literature and traditional studies could map only a small part of the entire marketing world, this is why this chapter will be a sum of knowledge coming from scientific articles and past thesis, but also a huge part coming from real world case studies.

This chapter maps the state of knowledge at the intersection of strategic marketing, influencer marketing, and economic performance. Its purpose is threefold.

First, it consolidates core theoretical constructs: brand equity and positioning, value co-creation and experience, influence mechanisms and relationships, into a coherent conceptual lens for assessing performance outcomes¹.

Second, it integrates cross-sector evidence from peer-reviewed studies and high-quality practitioner sources with curated case studies from one of the most important source of all time: *Harvard Business School* and its section of Harvard Business Education² (e.g., Starbucks, Nike, Marvel, Crocs, Taylor Swift, Puma, Bud Light & Mulvaney). This dual lens allows us to contrast controlled empirical findings with rich contextual mechanisms that are often under-specified in academic work.

Third, it derives managerial implications and research gaps that motivate the empirical part of the thesis. While the empirical application in Chapter 2 focuses on high-end

¹ P. Kotler, Principles of Marketing, 18th edition, 2020

² Harvard Business Education | <https://hbsp.harvard.edu/home/>

restaurants, the literature review intentionally remains sector-agnostic, extracting principles generalizable across fashion, entertainment, sports, and consumer goods.

The chapter is organised into five sections.

- **Section 2.2** traces the evolution from strategy to experience-driven branding;
- **Section 2.3** reviews influencer marketing definitions, mechanisms and performance evidence;
- **Section 2.4** integrates both streams aligning strategy and influence (brand and influencer fit, authenticity, risk);
- **Section 2.5** distils managerial implications and research gaps.

Each section follows a common pattern, which allow us to gain the best from the theoretical and practical examples:

theory → cumulative evidence → brief case vignettes → takeaways for the thesis

Figure 2.1 - Literature review section's pattern

2.1.2

Methodological approach

Combining academic research and real-world case studies

This literature review adopts an integrative narrative approach, combining a systematic search protocol for academic research, peer-reviewed articles, and previous theses with an analytical compendium of real-world case studies.

The purpose is not only to summarise existing theoretical knowledge but also to connect it with the managerial dynamics that shape actual market outcomes. The integration of both dimensions: **academic** and **empirical**, enables a more comprehensive understanding

of how strategic marketing and influencer marketing translate into measurable business performance.

From a theoretical perspective, the systematic review of scholarly works follows recognised academic standards, drawing upon scientific databases and high-impact journals within marketing, business strategy, and consumer behaviour. These studies provide the conceptual foundation necessary to define the constructs of brand equity, value co-creation, customer experience, and influence mechanisms. Through critical comparison and synthesis, the review identifies recurring models, conceptual overlaps, and research gaps that limit the explanatory power of current frameworks. Materials and research tools such as Scopus and Google Scholar were employed to identify and access peer-reviewed academic works. In addition, relevant publications from leading journals, including the *Journal of the Academy of Marketing Science*³, the *Journal of Business Research*⁴, the *Harvard Business Review*⁵, and the *Journal of Advertising*⁶; were systematically reviewed. Complementary data and market insights were also gathered from reputable industry sources such as Statista⁷, which provided quantitative evidence to support the theoretical discussion. The primary time frame considered spans 2021 to 2025, while seminal pre-2020 contributions were included when necessary to establish the theoretical foundations of the analysis.

Beyond this formal dimension, the thesis enriches the review by integrating a pool of practical materials, including 12 curated corporate case studies and reports, and lived professional experiences. This hybrid corpus allows for an in-depth exploration of how marketing principles are actually executed within organisations and how strategic decisions generate tangible results or failures over time.

Unlike many purely theoretical reviews, this work deliberately bridges academic rigour and managerial realism, following the logic of **evidence-based management: theory informs practice, and practice validates theory**. The inclusion of real-life case studies, several of which derive from the author's own professional and academic experience, adds a distinctive empirical contribution. Analysing situations that were directly observed or experienced strengthens the internal coherence of the argument and ensures that each

³ Academy of Marketing Science | <https://www.ams-web.org/>

⁴ Journal of Business Research | <https://www.sciencedirect.com/journal/journal-of-business-research>

⁵ Harvard Business Review | <https://hbr.org/>

⁶ Journal of Advertising | <https://www.jstor.org/>

⁷ Statista | <https://www.statista.com/>

theoretical claim is grounded in a practical context. This approach reflects the nature of management engineering research, which must remain both analytically sound and operationally relevant. By examining companies that have faced different strategic and communication challenges: from *Starbucks'* experiential marketing to *Nike's* identity-based engagement, from *Beats'* influencer-driven success to *Marvel's* characters use, the thesis extracts actionable insights capable of guiding future decision-making in marketing strategy.

The result is a review that not only maps the evolution of knowledge but also demonstrates how strategic and influencer marketing decisions manifest in real business environments, offering a direct and practical contribution to both academia and industry.

2.1.3

Research question and conceptual focus of the thesis

This thesis investigates the **impact of influencer marketing** and **strategic marketing actions** on the economic performance of high-end restaurants, with a specific focus on how viral content affects bookings and revenue. The central aim is to determine whether it is more effective for a restaurant to invest in external influencer collaborations or in strengthening its own brand identity and personal branding.

Although the empirical application focuses on the restaurant industry, the analytical framework is intentionally designed to produce insights transferable to other sectors, given the cross-industry nature of digital influence, experiential branding, and strategic positioning.

The methodological approach combines cross-sector case studies: including examples from fashion, entertainment, hospitality, and sports; with a data-driven analysis of restaurant performance metrics. This dual lens allows the thesis to examine influence not only as a communication tool, but as a strategic driver that shapes brand perception, customer behaviour, and ultimately business outcomes.

The study is guided by a set of core **research questions**:

- *How much can viral content increase bookings and revenue?*
- *To what extent does influencer marketing improve a restaurant's performance?*

- *Is it economically worthwhile to pay an influencer, or is strategic self-branding more effective?*
- *And how do broader marketing decisions shape the long-term trajectory of a business?*

By addressing these questions, the thesis contributes to an area that is still largely unexplored in engineering and management research: particularly within the context of Politecnico di Torino, and offers a novel, strategic interpretation of digital influence as a tool for business growth.

2.2

Strategic Marketing to create a Brand

2.2.1

From value creation to Brand

Strategic marketing represents the foundation of long-term brand building, shifting from a product-centric logic to a value driven approach. As Kotler argues in one of his most famous speech⁸,

“marketing is the discipline of creating, communicating and delivering value to a target market at a profit”.

This formula frames marketing as an integrated managerial philosophy encompassing product management, communication, distribution, and customer relationships. Before marketing was only a thing to communicate products, now can be interpreted as operating across three interdependent domains.

First, creating value corresponds to product management. Traditionally, this activity was confined within the organization, with innovation generated internally through closed R&D processes. Contemporary strategic marketing, however, is characterized by open innovation, where value creation increasingly involves external actors such as scientists, partners, and users. For example Procter & Gamble⁹ exemplify this shift by sourcing ideas beyond firm boundaries, demonstrating that competitive advantage no longer depends solely on internal capabilities but on the ability to integrate external knowledge ecosystems into the innovation process.

⁸ London Business Forum, <https://www.youtube.com/watch?v=bilOOPuAvTY>

⁹ Procter & Gamble, <https://it.pg.com/>

Second, communicating value corresponds to brand management, which has undergone a profound evolution. Branding was primarily associated with tangible elements such as names, logos, packaging, and visual identity. In modern strategic marketing, the brand represents a promise and a coherent system of meanings that informs how the organization behaves, communicates, and relates to its stakeholders. Brand communication is no longer limited to awareness or recognition, but aims to generate differentiation, emotional engagement, and long-term attachment.

Brands operate as symbolic systems that transfer values, identity, and cultural meaning to consumers. Kotler conceptualizes modern brand equity through three complementary dimensions¹⁰:

- **Mind Share**, referring to cognitive associations and rational recognition;
- **Heart Share**, referring to emotional connection and affective bonds;
- **Spirit Share**, referring to values, purpose, and cultural or societal relevance.

The introduction of Spirit Share reflects a critical evolution in brand positioning: brands are increasingly expected to demonstrate authenticity, responsibility, and alignment with broader human values. As a result, brand equity is no longer generated solely through performance or emotional appeal, but through the perceived ethical stance and purpose of the brand within society.

Third, delivering value corresponds to customer management. In traditional marketing models, this activity focused primarily on customer databases, segmentation, and direct communication through transactional tools such as email or digital advertising. Now customer management has evolved toward relational and participatory models. Firms are expected to interact directly with customers, understand them beyond quantitative data, and actively involve them in value creation processes. Customers increasingly contribute to product development, communication content, and brand narratives through feedback, co-creation, and social interaction¹¹.

Together, these three dimensions form the basis of value creation. Strategic marketing aligns internal capabilities, symbolic meaning, and customer relationships into a coherent positioning that allows brands to occupy a distinctive and defensible space in the consumer's mind, emotions, and value system.

¹⁰ Ivi, note 1, p.12

¹¹ P. Kotler, Marketing 4.0: Moving From Traditional to Digital, Wiley india Pvt. Ltd, April 2017

This aligns directly with Steve Jobs' philosophy: "Marketing is about values... in a noisy world, we must be clear about what we stand for." The rebirth of Apple in 1997 illustrates this principle. Rather than promoting technical specifications, the *Think Different*¹² campaign repositioned Apple around creativity, passion, and human progress. The brand became a cultural symbol rather than a product supplier.

Here's to the crazy ones.
The misfits.
The rebels.
The troublemakers.
The round pegs in the square holes.
The ones who see things differently.
They're not fond of rules.
And they have no respect for the status quo.
You can quote them, disagree with them,
glorify or vilify them.
About the only thing you can't do is ignore them.
Because they change things.
They push the human race forward.
While some may see them as the crazy ones,
we see genius.
Because the people who are crazy enough to think
they can change the world, are the ones who do.
Think different.

From a strategic marketing perspective, the campaign represents a radical inversion of conventional value creation logic. At the time, Apple was widely perceived as a declining firm with limited market share, inferior software compatibility, and an unclear competitive position. Traditional marketing theory would have suggested reassurance through rational arguments: price, performance, compatibility, or innovation pipelines. *Think Different* rejected this logic entirely.

Instead of defending the product, Apple reframed the brand. From product to philosophy with an identity-based marketing, using an emotional reframing.

¹² Think Different explanations by Steve Jobs | <https://www.youtube.com/watch?v=keCwRdbwNQY>

The campaign did not explain what Apple computers did; it explained who Apple was for. By associating the brand with historical figures such as Einstein, Gandhi, and Martin Luther King Jr., Apple executed a pure meaning-transfer strategy, borrowing cultural capital from universally recognized innovators and projecting it onto the brand itself. This move positioned Apple as the symbolic ally of non-conformists, creators, and visionaries: those who “*see the world differently*”.

Strategically, this approach created value on multiple levels: differentiation beyond functional competition, emotional and ideological alignment with the audience in a long term view, and they used a disruptive communication strategy for its historical context. In the late 1990s, technology advertising was dominated by feature-based claims, benchmarks, and comparative messaging, and celebrating abstract values, creativity, and human progress was highly unconventional.

The Apple reboot in 1997 demonstrated that a brand can regain relevance by de-emphasizing product specifications and instead communicating values, identity, and cultural meaning.

The **Beats vs Bose case**¹³ shows the same strategic logic applied to a mature consumer category: even when functional performance is measurable, the competitive battlefield can be relocated from “product superiority” to “symbolic superiority”.

From a classic marketing viewpoint, Bose should dominate. The purchase process for premium headphones is typically high-involvement: the product is expensive, bought infrequently, and consumers consult multiple information sources before buying. In such contexts, theory would predict that expert reviews and objective performance (e.g., noise cancelling, sound fidelity) drive preference. Coherently, the Bose QC35 is positioned as an engineering-led product as they say “better sound through research”, it’s cheaper (\$349 vs \$379), and is evaluated more positively in reviews and by average consumer ratings. In other words, Bose wins on the traditional “rational” decision model: *better product + better review ecosystem + lower price*.

Beside that, Beats decided to not accept Bose’s definition of the category.

Beats’ strategic advantage emerges from a deliberate repositioning: headphones stop being primarily a sound device and become a wearable accessory: closer to sneakers, watches, or streetwear than to audio equipment. This changes the consumer’s evaluation

¹³ Bose Corporation: Communication Strategy for Challenging Apple's Beats by Dr. Dre | By: Robert J. Dolan in Harvard Business School - <https://hbsp.harvard.edu/product/518036-PDF-ENG>

criteria. When the product is framed as an accessory, the “best sound” argument becomes secondary to visibility, color, design, and social signaling. Bose is evaluated through “technology” and “sound objective”, whereas Beats is evaluated through “impulse, style, and identity”, making the object comparable to a Swatch vs Rolex type of distinction (not because of technical superiority, but because of what it signals).

This shift is reinforced through specific go-to-market choices:

1. **Category reframing, whit positioning as identity, not utility**

Bose’s promise is functional (“sound through research”). Beats’ promise is symbolic: it sells belonging to culture. In this framing, technical inferiority does not kill demand, because the consumer is not buying “audio accuracy” but a status marker.

2. **Demand generation through cultural distribution**

Bose is strong in traditional retail control and price consistency (“sold everywhere at the same price”), but Beats creates distribution in a broader sense: it places the product inside music, sports, and celebrity ecosystems, turning public figures into “usage proof”.

3. **Visibility as a feature**

A crucial asymmetry is that Beats is instantly recognizable (color, silhouette, prominence on the head), which converts the product into a socially transmissible signal. Bose, by comparison, competes in a space where performance is largely invisible unless experienced. Beats makes the product itself an advertisement, as it can be seen in the image below¹⁴.



Image 2.1 | Beats Headphones: Visual Identity

¹⁴ Image 2.1 | Beats Headphones: Visual Identity - Business Insider, <https://www.businessinsider.com/tech>

4. **Efficiency in communication spend (less spend, more cultural reach)**

The data shows Bose's promotion spend decreasing from \$216M to \$135M, while Beats operates around \$82M. Strategically, this is consistent with the model: Bose must continuously educate and justify via performance claims; Beats benefits from visibility loops (celebrities, social environments, "wearability"), meaning it can achieve disproportionate awareness and desirability without matching the incumbent's spend.

The outcome of this repositioning is that Beats competes where Bose is structurally disadvantaged: not in engineering, but in cultural meaning. Beats reached ~62% market share, while Bose remained around ~25%. Beats built a stronger brand asset by shifting the category from functional evaluation to identity evaluation, exactly the same strategic move Apple executed with *Think Different*.

This confirms the broader transition introduced by Apple: in modern markets, competitive advantage increasingly derives from everything around the product: positioning, meaning, social proof, cultural placement, and symbolic design; rather than from product attributes alone.

This business case led us directly to the second part of this chapter, talking about Brand Positioning and Brand Equity.

2.2.2

Brand Positioning and Brand Equity

In contemporary marketing theory and practice, brand positioning and brand equity represent two foundational pillars that determine a brand's competitive advantage and long-term market success. These interconnected concepts have evolved from tactical marketing considerations into strategic imperatives that shape organizational decision-making and resource allocation. As markets become increasingly saturated and consumer choices proliferate, the ability to establish a distinctive position in the minds of target consumers and to build enduring brand value has become paramount for sustained competitive advantage. This section examines the theoretical foundations of brand positioning and brand equity, drawing upon seminal contributions from marketing

scholars and practitioners to establish a comprehensive framework for understanding these critical constructs.

Brand Positioning

The concept of brand positioning emerged as a cornerstone of modern marketing strategy in the early 1980s, fundamentally transforming how organizations conceptualize their market relationships. Ries¹⁵ introduced positioning as a battle for the consumer's mind, arguing that successful brands must occupy a distinctive and defensible position in the mental landscape of their target audience. This seminal work established that positioning is not about what companies do to products, but rather about what they do to the minds of prospects. The authors emphasized that in an overcommunicated society, the only way to cut through the noise is to simplify the message and create a unique position that resonates with consumer perceptions.

Building upon this foundation, Kotler and Keller in 2016¹⁶ refined the definition of brand positioning as "*the act of designing the company's offering and image to occupy a distinctive place in the mind of the target market*". This definition emphasizes the strategic and deliberate nature of positioning, framing it as a conscious design process rather than an accidental outcome. The objective of positioning, according to Kotler and Keller (2016), is to locate the brand within the cognitive frameworks of stakeholders, particularly customers and prospects, thereby creating a recognizable and trusted customer-focused value proposition. This value proposition serves as the rational and emotional basis for consumer choice in highly competitive target markets, providing clear reasons why consumers should select one brand over its competitors.

The strategic significance of brand positioning has been articulated through **Kotler's STP framework** (Segmentation, Targeting, Positioning)¹⁷, which positions brand positioning alongside market segmentation and target market selection as fundamental strategic decisions. Within this framework, positioning represents the culmination of market analysis and strategic choice, translating segmentation insights and targeting



Figure 2.2 - Kotler's STP framework

¹⁵ A. Ries, Positioning: The Battle for Your Mind, McGraw Hill Higher Education, January 1st, 1980

¹⁶ P. Kotler and K. L. Keller, Marketing Management (15th ed.), Pearson Education, 2016

¹⁷ Ibidem

decisions into actionable market communication strategies.

Anyway they advanced positioning theory by introducing the concepts of points of parity (POPs) and points of difference (PODs), which together constitute the essence of effective brand positioning. Points of parity represent associations that are not necessarily unique to a brand but are essential for legitimate category membership and competitive credibility. These associations enable consumers to recognize that a brand can deliver on the basic category promises and compete effectively within its competitive frame of reference. For instance, a luxury automobile brand must demonstrate fundamental attributes such as safety and reliability, characteristics that are expected of any automobile, before consumers will consider its distinctive luxury features.

Points of difference, conversely, represent the strong and unique brand associations that form the core of competitive differentiation. Keller (2013) emphasizes that effective PODs must meet three critical criteria: they must be:

- desirable to consumers,
- deliverable by the organization,
- and differentiating from competitors.

The strategic challenge lies in identifying and developing PODs that satisfy all three criteria simultaneously, as many potentially differentiating attributes may be either unimportant to consumers, impossible for the organization to deliver consistently, or easily copied by competitors. Successful brand positioning thus requires a delicate balance between establishing necessary points of parity while emphasizing meaningful points of difference.

Academic literature identifies several distinct positioning strategies that organizations can employ depending on their competitive context and strategic objectives.

1. **Value-based positioning** emphasizes the relationship between **product** benefits and **price**, seeking to establish the brand as offering superior value within its category. Kotler and Keller¹⁸ argued that value-based positioning proves particularly effective in price-sensitive markets where consumers prioritize functional benefits over emotional appeals. Brands such as Walmart and Costco have successfully positioned themselves as providers of high-quality products at competitive prices, leveraging operational efficiencies to deliver on this value proposition.

¹⁸ Ibidem

2. **Emotional positioning**, as articulated by Aaker¹⁹ seeks to create deep emotional connections with consumers by aligning the brand with their values, aspirations, or lifestyle preferences. This approach acknowledges that in many product categories, particularly those characterized by commoditization of functional attributes, emotional benefits and brand personality become the primary basis for differentiation. Emotional positioning strategies often prove most effective when products are highly commoditized and rational differentiation becomes difficult to sustain. The creation of emotional bonds not only facilitates initial purchase decisions but also contributes to long-term brand loyalty and advocacy.

3. **Attribute-based positioning** focuses on specific product features or benefits that distinguish the brand from competitors. This strategy proves effective when organizations possess distinctive capabilities or innovations that deliver tangible consumer benefits. However, attribute-based positioning remains vulnerable to competitive imitation unless supported by sustainable competitive advantages such as proprietary technology, exclusive resources, or organizational capabilities that competitors cannot easily replicate. The challenge lies in identifying attributes that are both meaningful to consumers and defensible over time.

Brand Equity

In front of Brand Positioning it can be seen Brand equity. Brand equity emerged as a central construct in marketing scholarship during the 1990s, representing the value that a brand adds to a product or service beyond its functional attributes. The concept acknowledges that brands constitute valuable intangible assets that can significantly influence consumer behavior, command premium prices, and contribute to organizational financial performance. Two dominant theoretical frameworks have shaped contemporary understanding of brand equity: Keller's Customer-Based Brand Equity²⁰ (CBBE) model and Aaker's Brand Equity model. While these frameworks share common elements, they offer complementary perspectives on how brand value is created, maintained, and measured.

¹⁹ D. A. Aaker, *Building Strong Brands*, Simon & Schuster Ltd, 2010

²⁰ K. L. Keller, *Building Customer-Based Brand Equity model: A Blueprint for Creating Strong Brands*, 2001, https://thearf-org-unified-admin.s3.amazonaws.com/MSI/2020/06/MSI_Report_01-107.pdf

Kevin Lane Keller's Customer-Based Brand Equity model²¹ conceptualizes brand equity as "*the differential effect of brand knowledge on consumer response to the marketing of the brand*". This definition emphasizes that brand equity resides fundamentally in the minds of consumers, manifesting through their knowledge, perceptions, and preferences regarding the brand. Keller argues that the power of a brand lies in what customers have learned, felt, seen, and heard about the brand over time, with positive brand equity occurring when consumers react more favorably to a product when they know its brand identity than when they do not.

The CBBE model is structured as a pyramid comprising four hierarchical levels, each representing progressive stages in building strong brands. At the foundation lies brand identity (salience), which addresses the fundamental question "Who are you?" This level focuses on ensuring that customers can recognize and recall the brand amongst competitors, establishing the basic awareness necessary for brand consideration. Brand salience encompasses both depth (how easily consumers recall the brand) and breadth (the range of purchase and consumption situations in which the brand comes to mind).

The second level addresses brand meaning through two complementary dimensions: performance and imagery. Brand performance relates to how well the product or service meets customers' functional needs, encompassing attributes such as product reliability, durability, serviceability, and effectiveness. This dimension responds to the question "What are you?" by establishing the functional and utilitarian value the brand delivers. Brand imagery, conversely, addresses the extrinsic properties of the product or service, including the ways in which the brand attempts to meet customers' psychological or social needs. This dimension encompasses user profiles, purchase and usage situations, personality and values, and history and heritage, creating the symbolic and emotional meanings associated with the brand.

The third level of the pyramid captures brand responses through judgments and feelings. Brand judgments represent customers' personal opinions and evaluations regarding the brand, encompassing assessments of quality, credibility, consideration, and superiority. These judgments answer the question "What about you?" by reflecting rational evaluations of the brand's performance and positioning. Brand feelings, alternatively, represent customers' emotional responses and reactions to the brand, including warmth, fun, excitement, security, social approval, and self-respect. These affective responses often prove crucial in determining the strength and depth of the customer-brand relationship.

²¹ Ibidem

At the apex of the pyramid sits brand resonance, representing the ultimate relationship between customers and the brand. Keller (2001) describes resonance as the nature and extent of the active, loyal relationship customers have with the brand, characterized by psychological bonding and deep emotional attachment. Brand resonance manifests through four categories: behavioral loyalty (repeat purchases), attitudinal attachment (love for the brand and perception of it as a special purchase), sense of community (identification with other brand users), and active engagement (investment of time, energy, money, or other resources in the brand beyond purchase and consumption). This highest level represents the goal of brand building, creating customers who are not merely satisfied but are brand advocates and ambassadors.

David Aaker's conceptualization of brand equity, in his **Aaker's Brand Equity Model**²², offers a complementary perspective, defining brand equity as "a set of brand assets and liabilities linked to a brand, its name and symbol, that add to or subtract from the value provided by a product or service to a firm and/or to that firm's customers". This definition acknowledges that brand equity can be both positive and negative, and that it creates value for both consumers and organizations. Aaker's model emphasizes that brand equity is not solely a perceptual construct residing in consumer minds but also encompasses tangible assets that contribute to competitive advantage.

Aaker identifies five principal components of brand equity. Brand loyalty represents the attachment that customers have to a brand, manifesting in repeat purchases, resistance to switching, and willingness to pay premium prices. Aaker emphasizes that brand loyalty provides companies with predictable revenue streams, reduces marketing costs through customer retention, and creates barriers to competitive entry. The value of brand loyalty increases significantly when considered across the customer lifetime, as loyal customers not only generate consistent revenue but also serve as brand advocates who attract new customers through positive word-of-mouth.

Brand awareness encompasses both brand recognition (the ability to identify the brand when presented with its name or logo) and brand recall (the ability to retrieve the brand from memory when given a product category or need). High brand awareness ensures that the brand enters the consumer's consideration set during purchase decisions, provides a sense of familiarity that can influence quality perceptions, and signals substance and commitment in the marketplace. In many low-involvement purchase situations, brand awareness alone may be sufficient to drive purchase decisions.

²² Ivi, note 19, p. 25

Perceived quality represents customers' perceptions of the overall quality or superiority of a product or service relative to alternatives and with respect to its intended purpose. Aaker emphasizes that perceived quality differs from actual quality, as it represents a subjective evaluation based on customers' perceptions rather than objective product specifications. Perceived quality influences purchase decisions, supports premium pricing, provides differentiation from competitors, and extends to channel member interest and brand extensions. Organizations can leverage perceived quality to justify higher prices and to extend the brand into new product categories.

Brand associations encompass anything linked in memory to a brand, creating networks of meaning that influence how consumers process information, form attitudes, and make decisions. These associations may relate to product attributes, customer benefits, usage situations, user personalities, brand personality, organizational associations, or brand symbols. Effective brand associations provide value by helping consumers process and retrieve information, differentiate the brand from competitors, create positive attitudes and feelings, and provide a basis for brand extensions. The strength, favorability, and uniqueness of brand associations collectively determine their contribution to brand equity.

Finally, other proprietary brand assets include patents, trademarks, channel relationships, and other intellectual property that provides competitive advantages. While this category receives less theoretical attention than the other components, Aaker acknowledges that these tangible assets can significantly contribute to brand equity by creating barriers to competitive imitation and providing legal protection for brand investments.

The Interrelationship Between Positioning and Equity

The relationship between brand positioning and brand equity represents a dynamic, reciprocal process wherein effective positioning contributes to brand equity development, while strong brand equity reinforces and validates positioning strategies. Successful positioning creates the distinctive brand associations and favorable brand perceptions that constitute brand equity, while accumulated brand equity provides organizations with greater flexibility and credibility in adjusting or extending their positioning strategies.

This theoretical foundation establishes the critical importance of both brand positioning and brand equity in contemporary marketing strategy. Organizations must strategically design their positioning to occupy distinctive places in consumer minds while simultaneously building the awareness, associations, loyalty, and perceived quality that constitute brand equity. The following sections will examine how these theoretical

constructs apply specifically within the context of influencer marketing, exploring how brands leverage influencer partnerships to enhance both positioning effectiveness and brand equity.

Empirical Evidence by Case Studies

The theoretical frameworks articulated above find concrete validation in the strategic practices of leading global brands. Three cases, Nike, Longchamp, and Starbucks; demonstrate how effective positioning translates into measurable brand equity and financial performance. Critically, these brands succeed not through product superiority alone, but by constructing meaning systems that resonate with consumer identity and values.

Nike: Cultural Performance and Identity Construction

Nike exemplifies positioning built on cultural performance rather than product focus. Between 1994 and 2010²³, Nike Football grew from \$40 million to \$1.7 billion by combining product innovation with emotional storytelling and athlete-led identity construction. Athletes such as Cristiano Ronaldo and Ronaldinho function as identity signifiers rather than mere endorsers, operating as cultural channels through which brand meaning transfers to consumers. This aligns with the Meaning Transfer Model, whereby symbolic associations flow from cultural figures to brands and ultimately to consumers. Community platforms such as NikeFootball+ strengthened brand resonance by fostering belonging and engagement, an early manifestation of social and influencer-driven branding. The outcomes demonstrate positioning effectiveness: market share increased from 33% to 35%, while unprecedented digital engagement validated the brand's cultural relevance.

Longchamp: Symbolic Value and Accessible Luxury

Longchamp²⁴ demonstrates a dual positioning strategy combining accessibility and luxury. Through iconic figures such as Kate Moss and Alexa Chung, the brand constructed a humanized, relatable identity leveraging earned media and authentic storytelling over aggressive advertising. The success of Le Pliage, with over 30 million units sold, illustrates how symbolic value transforms a functional accessory into a cultural phenomenon. This positioning strategy generated sustained performance: Longchamp achieved over 13%

²³ E. Ofek and R. Johnson, Nike Football: World Cup 2010 South Africa, Harvard Business School Case, May 2011

²⁴ J. Avery, T. Junker, D. Beyersdorfer, Longchamp, Harvard Business School Case, June 2016

compound annual growth rate across fifteen years, demonstrating that strong brand associations reduce advertising dependency while supporting premium pricing and market expansion.

Starbucks: Experiential Positioning and Community Building

Starbucks²⁵ represents experiential positioning, transforming coffee consumption into a "third place" experience distinct from home and work. This positioning created an identity-based community and justified premium perception through lifestyle value rather than product cost. Customer experience and employee culture became core components of brand meaning, generating organic advocacy and elevated customer lifetime value. The experiential strategy increased consumers' willingness to pay, fostered behavioral loyalty, and created the attitudinal attachment characteristic of Keller's brand resonance concept.

These cases converge on five mechanisms through which strategic positioning builds brand equity and drives performance. First, strong positioning increases pricing power and willingness to pay, as consumers perceive value beyond functional attributes. Second, effective positioning generates organic advocacy and earned media, reducing reliance on paid advertising while expanding reach. Third, brands with strong equity achieve superior customer lifetime value through repeat purchases and cross-category extensions. Fourth, strategic consistency in positioning and delivery enhances market resilience, enabling brands to sustain competitive advantages despite market pressures. Fifth, positioning-driven brand equity creates measurable financial impact: Nike's \$1.7 billion in Football revenues, Longchamp's 13% compound annual growth rate, and Starbucks' premium pricing all demonstrate the economic returns of strategic brand building.

This empirical evidence validates Keller's framework: brand strength depends on perceptions, associations, and loyalty, outcomes deriving from repeated, aligned experiences. Moreover, it substantiates Kotler's emphasis on brands as financial and strategic assets requiring systematic measurement of return on investment, attribution, and customer lifetime value. Strategic marketing, when grounded in identity, values, and community-building, transcends product differentiation to create cultural symbols that drive measurable economic performance. These insights establish the foundation for examining how contemporary brands leverage influencer marketing and digital engagement to enhance positioning effectiveness and brand equity development.

²⁵ Y. Moon and J. Quelch, Starbucks: Delivering Customer Service, Harvard Business School Case, July 2003 (revised October 2018)

2.3

The Rise and Evolution of Influencer Marketing

2.3.1

Definition, key theories, and typologies

The emergence of social media influencers represents a paradigm shift in marketing communications, fundamentally altering how brands connect with consumers and how purchasing decisions are shaped in digital environments. Influencer marketing has experienced exponential growth, with the global market expanding from \$1.7 billion in 2016 to \$16.4 billion in 2022, with its value at over USD 30 billion in 2025 and projected to surpass USD 40 billion in 2026²⁶. This sector is driven by increased social media usage and a strategic shift toward creator partnerships, with projections suggesting it could exceed USD 150 billion by 2031²⁷, establishing itself as a critical component of contemporary marketing strategy. This section examines the conceptual foundations, theoretical frameworks, and typological classifications that define influencer marketing as both a professional practice and an academic field of inquiry.

The conceptualization of social media influencers has evolved across disciplinary boundaries, yielding definitions that emphasize different aspects of their role and function. From a sociological perspective, influencers represent individuals capable of directing decisions and behaviours of others through para-relational dynamics established via digital platforms²⁸. Marketing scholarship, conversely, emphasizes their function as

²⁶ A. Guttman, Influencer marketing worldwide - statistics and facts, Statista, December 17th, 2025, <https://www.statista.com/topics/2496/influence-marketing/#topicOverview>

²⁷ C. Meley, M. Shiltagh, and R. Phua, Influencer Marketing Gains Ground as Global Ad Budgets Tighten, Bloomberg, June 14th, 2025, <https://www.bloomberg.com/news/articles/2025-06-14/influencer-marketing-gains-ground-as-global-ad-budgets-tighten>

²⁸ G. Ferrandino, Influencer marketing: il Panorama Italiano tra Crisi di Fiducia e Prospettive Future, 2024

intermediaries and brand advocates. Kotler defines influencers as individuals who proactively participate in community discussions and disseminate content with consumers, functioning as digital opinion leaders²⁹. Kotler's analysis of social media marketing reveals a fundamental strategic shift enabled by web-based communication: whereas traditional push strategies required brands to convince intermediaries to present and sell products to consumers³⁰, Web 2.0 facilitated pull strategies that enable direct producer-consumer communication. Digital marketing shortened the distance between brands and customers while providing opportunities to analyze online consumer communities whose content commentary and product discussions generate innovative insights for brand development³¹.

Theoretical frameworks about Influencer Marketing

Multiple theoretical frameworks explain how influencers generate persuasive impact on consumer behavior. Source credibility theory, parasocial interaction theory, electronic word-of-mouth (eWOM), and meaning transfer models constitute the primary theoretical pillars supporting influencer marketing scholarship.

1. **Source Credibility Model.** Source credibility emerges as the foundational construct explaining influencer persuasiveness. The model posits that message effectiveness depends critically on the perceived credibility of the communicator, comprising two primary dimensions: expertise and trustworthiness as Hovland argued decades ago³². Expertise refers to the source's perceived knowledge, experience, and competence within a specific domain, while trustworthiness concerns the source's perceived honesty, reliability, and motivation to provide accurate information.

In influencer marketing contexts, source credibility significantly impacts consumer attitudes and purchase intentions. Influencers establish credibility through demonstrated expertise in specialized domains, whether fashion, technology, food, or travel, combined with transparent, authentic communication that builds trust with followers. Critically, influencer credibility derives not only from professional credentials but also from authentic

²⁹ P. Kotler, S. Hollensen, and M. O. Opresnik, *Social Media Marketing - A Practitioner Guide*, Opresnik Management Consulting, April, 2017

³⁰ Ivi, note 1, p. 12

³¹ Ivi, note 29, p. 33

³² T. Koch, Hovland, Janis & Kelley (1953): *Communication and Persuasion*, Springer VS, Wiesbaden, August 5th, 2024, https://doi.org/10.1007/978-3-658-45292-6_33

self-presentation and consistent value delivery to audiences, distinguishing them from traditional celebrity endorsers³³.

2. **Parasocial interaction and relationships.** Parasocial relationships theory elucidates the psychological mechanisms through which followers develop one-sided emotional connections with influencers. Originally conceptualized by Horton and Wohl³⁴ to explain audience relationships with media personalities, parasocial interaction describes the illusion of reciprocal relationships despite fundamentally asymmetric communication. Followers may perceive influencers as friends or confidants, despite limited direct interaction and unbalanced relationship dynamics³⁵.

In social media contexts, parasocial relationships intensify through regular content exposure, interactive features (comments, likes, direct messages), and influencers' self-disclosure practices that create intimacy perceptions. These relationships prove particularly powerful in influencer marketing because they generate trust, loyalty, and persuasion that traditional advertising cannot replicate. Farivar, Wang, and Yuan in 2021 demonstrated that parasocial relationships significantly enhance influencer persuasiveness and product interest³⁶. Importantly, followers tend to follow influencers whose identity aligns with their own, and interest in the influencer's content domain typically precedes parasocial relationship formation.

3. **Electronic Word-of-Mouth (eWOM).** Electronic word-of-mouth extends traditional word-of-mouth communication into digital environments, constituting "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet". Unlike face-to-face word-of-mouth, eWOM reaches vast audiences

³³ S. Yuan and C. Lou, How social media influencers foster relationships with followers: The roles of source credibility and fairness in parasocial relationship and product interest, *Journal of Interactive Advertising*, 2020, <https://doi.org/10.1080/15252019.2020.1769514>

³⁴ D. Horton and R. R. Wohl, *Mass Communication and Para-Social Interaction: Observations on Intimacy at a Distance*, *Psychiatry*, 1956, <https://doi.org/10.1080/00332747.1956.11023049>

³⁵ H. Reinikainen, T. M. Tan, V. L.-aho, and J. Salo, Making and breaking relationships on social media: the impacts of brand and influencer betrayals, October, 2021, <https://doi.org/10.1016/j.techfore.2021.120990>

³⁶ S. Farivar, F. Wang, Y. Yuan, Opinion leadership vs. para-social relationship: Key factors in influencer marketing, *Journal of Retailing and Consumer Services*, March, 2021, <https://doi.org/10.1016/j.jretconser.2020.102371>

instantaneously, operates asynchronously, and persists over time, amplifying its potential impact³⁷.

Influencers function as professional eWOM generators, producing persuasive messages that blend personal opinions with brand endorsements. Research demonstrates that eWOM from credible sources significantly influences purchase intentions. The persuasive power of influencer-generated eWOM derives from multiple factors: perceived authenticity compared to traditional advertising, ability to integrate promotional content within personal narratives, and trust established through parasocial relationships³⁸. Influencers' capacity to generate authentic eWOM addresses declining trust in conventional advertising, positioning them as credible alternatives to traditional promotional channels³⁹. Of course there is a controversial effect about a positive and negative eWOM influencer campaign, according to business cases presented in *Chapter 2.3.2*.

4. Meaning Transfer Model. Despite its publication over three decades ago, McCracken's (1989) meaning transfer model remains highly relevant for understanding contemporary influencer marketing, explaining how cultural meanings flow from celebrities to products and ultimately to consumers⁴⁰. The model posits that endorsers possess symbolic meanings derived from their public personas, lifestyles, and cultural positions. When endorsers promote products, these meanings transfer to the endorsed brands. Consumers, by purchasing and using these products, appropriate the transferred meanings to construct their own identities. In influencer marketing contexts, influencers serve as cultural channels through which brand values and lifestyle meanings flow to followers. Unlike traditional celebrities whose meanings derive from film, television, or sports industries, influencers cultivate meanings through self-branding practices, content curation, and lifestyle representations on social media platforms⁴¹.

³⁷ S. Mukhopadhyay, R. Pandey, B. Rishi, Electronic word of mouth (eWOM) research – a comparative bibliometric analysis and future research insight, *Journal of Hospitality and Tourism Insights*, April 6th, 2023, <https://doi.org/10.1108/JHTI-07-2021-0174>

³⁸ F. F. Leung, F. F. Gu, Y. Li, and J. Z. Zhang, Influencer Marketing Effectiveness, *Journal of Marketing*, May 10th, 2022, <https://doi.org/10.1177/00222429221102889>

³⁹ Ivi, note 37, p. 35

⁴⁰ G. McCracken, Who is the Celebrity Endorser? Cultural Foundations of the Endorsement Process, *Journal of Consumer Research*, December 1989, <https://www.jstor.org/stable/2489512>

⁴¹ D. Y. Kim and H.-Y. Kim, Social media influencers as human brands: an interactive marketing perspective, *Journal of Research in Interactive Marketing*, February 2022, <https://doi.org/10.1108/JRIM-08-2021-0200>

Typologies of Social Media Influencers

According to Enke and Borchers⁴², whether they are celebrities, or opinion leaders, or social users, all influencers have 7 common traits in the activities they carry out, which are: accelerated growth, social power, viral distribution, consumers' engagement, experience on the content, aesthetic appeal, community leaders.

Social media influencers exhibit substantial heterogeneity across multiple dimensions. Classification systems have emerged to categorize influencers based on follower count, content domain, engagement patterns, and professional status. The most prevalent typology differentiates influencers by audience size, recognizing that follower count correlates with reach, engagement dynamics, perceived authenticity, and commercial viability. Campbell and Farrell (2020)⁴³ proposed a comprehensive four-tier classification system that encompasses the full spectrum of influencer types.

Nano-influencers (0-10,000 followers) represent emerging content creators with limited but highly engaged audiences. Despite modest reach, nano-influencers often demonstrate superior engagement rates and perceived authenticity due to direct, personal interactions with followers. These influencers typically operate within niche domains and maintain strong social capital within their limited networks.

Micro-influencers (10,000-100,000 followers) possess specialized expertise in particular domains, often derived from professional experience or deep personal interest. This category frequently includes bloggers who have cultivated audiences through consistent, high-quality content. Micro-influencers are characterized by targeted audiences, high engagement rates, and perceived credibility within their niches⁴⁴. Their relatively accessible status and moderate costs make them attractive partners for brands seeking authentic endorsements.

Macro-influencers (100,000-1,000,000 followers) represent established content creators whose expertise and voice have achieved broad recognition within their fields. Many

⁴² N. Enke, N.S. Borchers, Social Media Influencers in Strategic Communication: A Conceptual Framework for Strategic Social Media Influencer Communication, *International Journal of Strategic Communication*, September 04, 2019, <https://doi.org/10.1080/1553118X.2019.1620234>

⁴³ C. Campbell and J. R. Farrell, More than meets the eye: The functional components underlying influencer marketing, *Business Horizons*, March 28th, 2020, <https://doi.org/10.1016/j.bushor.2020.03.003>

⁴⁴ J. B. Barhorst, G. McLean, J. Brooks, and A. Wilson, Everyday micro-influencers and their impact on corporate brand reputation, June 5th, 2019, Durham Business School, <https://pureportal.strath.ac.uk/en/publications/everyday-micro-influencers-and-their-impact-on-corporate-brand-re/>

macro-influencers evolved from micro-influencer status, expanding their reach while maintaining domain specialization. These influencers often operate professional content creation businesses, including personal websites and brands, and command significant fees for brand partnerships⁴⁵. Macro-influencers must carefully curate brand collaborations to maintain credibility and continue delivering value to their audiences.

Mega-influencers/Celebrity influencers (>1,000,000 followers) occupy the apex of influencer hierarchies, often overlapping with traditional celebrities. While mega-influencers achieve massive reach, they face trade-offs: decreased perceived authenticity, lower engagement rates relative to audience size, and reduced specialization compared to micro and macro counterparts⁴⁶. However, their broad appeal makes them valuable for large-scale awareness campaigns and brand visibility initiatives.

Empirical research reveals complex trade-offs across influencer categories. While conventional wisdom suggested micro-influencers' authenticity and engagement advantages would translate into superior persuasiveness, recent evidence presents nuanced findings. Formentini's experimental study⁴⁷ found that mega-influencers generated significantly higher brand attitude and purchase intention scores compared to micro-influencers, with macro-influencers occupying an intermediate position. However, these effects were mediated by brand attitude and moderated by source credibility, suggesting that influencer type effects depend on contextual factors.

This theoretical and typological foundation establishes influencer marketing as a complex phenomenon grounded in established communication and persuasion theories while presenting novel characteristics unique to social media environments. The diverse theoretical perspectives: source credibility, parasocial relationships, eWOM, and meaning transfer, collectively illuminate different facets of influencer persuasiveness, suggesting that effective influencer marketing requires multi-dimensional understanding. Similarly, typological classifications reveal that influencer heterogeneity necessitates strategic matching between influencer characteristics, brand objectives, and target audiences. These foundational concepts provide the framework for examining influencer marketing

⁴⁵ S. Kay, R. Mulcahy, and J. Parkinson, When less is more: the impact of macro and micro social media influencers' disclosure, *Journal of Marketing Management*, January 31st, 2020, <https://doi.org/10.1080/0267257X.2020.1718740>

⁴⁶ J. Park, J. M. Lee, V. Y. Xiong, F. Septianto, and Y. Seo, David and Goliath: When and Why Micro-Influencers Are More Persuasive Than Mega-Influencers, *Journal of Advertising*, September 21st, 2021, <https://doi.org/10.1080/00913367.2021.1980470>

⁴⁷ A. Formentini, INFLUENCER MARKETING: AN INVESTIGATION ON HOW THE TYPE OF INFLUENCER AND THE BRAND ATTITUDE AFFECT THE PURCHASE INTENTION OF BRANDED CONTENT ON SOCIAL MEDIA, 2020

mechanisms, measurement approaches, and performance outcomes in the subsequent section.

2.3.2

Mechanisms of influence, measurement and performance

While theoretical frameworks establish why influencers persuade, understanding how influence operates requires examining the mechanisms through which content generates impact, the metrics that quantify performance, and the risks that emerge when execution misaligns with strategy. This section analyzes these operational dimensions through empirical cases that illustrate successful implementations, measurement approaches, and cautionary failures.

Influencer marketing operates across three media types, each generating distinct value propositions. **Owned media** encompasses brand-controlled channels including websites, social media accounts, and email lists, providing direct communication but limited reach. **Paid media** involves purchased advertising placements and sponsored content, delivering controlled messaging with measurable costs per impression. **Earned or Gained media** represents unpaid coverage generated through publicity, word-of-mouth, and *viral diffusion: the most valuable yet least controllable category*. Effective influencer strategies integrate these media types, leveraging paid activations to generate earned amplification that extends reach far beyond initial investment.

Talking about this latest mechanism three cases demonstrate how brands generate disproportionate earned media value through strategic influencer deployment, transforming modest investments into widespread cultural phenomena.

Longchamp: iconic figures as earned media catalysts. French luxury brand Longchamp⁴⁸ demonstrates earned media generation through strategic partnerships with culturally resonant figures. The brand's 2006 collaboration with Kate Moss in Figure 2.3⁴⁹ generated a 70% increase in spontaneous brand awareness in France and the UK, with media value equivalent to top-tier luxury advertising campaigns. Subsequent partnerships with Alexa Chung consolidated Longchamp's repositioning from classic heritage brand to

⁴⁸ Ivi, note 24, p. 29

⁴⁹ Ibidem, Source: Company documents

contemporary lifestyle symbol. Critically, Longchamp's approach emphasizes human authenticity over celebrity glamour: models represent accessible aspiration rather than unattainable luxury, generating identification and organic discussion. This strategy enabled Longchamp to achieve over 13% compound annual growth rate⁵⁰ across fifteen years while reducing direct advertising expenditure, with Le Pliage selling over 30 million⁵¹ units through symbolic value creation rather than functional superiority.



Figure 2.3 - Longchamp's Kate Moss Advertising Campaigns (Spring 2006, Autumn 2006, Spring 2007)

Beats by Dr. Dre: celebrity endorsement as social currency. Beats by Dr. Dre⁵² exemplifies earned media generation through cultural positioning and provocative visibility. Despite mediocre audio quality reviews, Beats achieved 32% overall market share and 62% of the premium headphone segment (>\$100) by 2014, driven by celebrity partnerships that transformed headphones into status symbols. The brand's 2014 World Cup campaign "The Game Before the Game" (Figure 2.4) featuring Neymar, Fàbregas, and other athletes, generated 32.7 million YouTube views organically. More dramatically, when NFL fined Tom Brady \$10,000 for wearing Beats headphones (Figure 2.5) despite

⁵⁰ Ibidem

⁵¹ Ibidem

⁵² R. J. Dolan, Bose Corporation: Communication Strategy for Challenging Apple's Beats by Dr. Dre, Harvard Business School Case, November 2017 (revised April 2019)

Bose's official sponsorship, the incident generated an estimated \$5 million in earned media value through viral news coverage and social discussion: demonstrating how controversy amplifies visibility when aligned with brand identity of rebellion and independence. Beats achieved these outcomes despite spending \$82 million annually on advertising versus Bose's \$200 million, illustrating earned media's efficiency advantages.



Figure 2.4 - Beats by Dre's 2014 World Cup campaign "The Game Before the Game"



Figure 2.5 - Tom Brady fined by NFL

Mekanism: engineering virality. Digital agency Mekanism systematized viral content creation, achieving 75% success rate (9 of 12 campaigns exceeding 1 million views) through structured influencer networks and data-driven optimization⁵³. Mekanism's approach integrated three components:

- emotionally compelling storytelling designed as entertainment rather than advertising,
- strategic multi-platform distribution coordinating owned, paid, and earned channels,
- and systematic influencer activation wherein networked creators generated 51% of total campaign views on average.



Figure 2.6 - Mekanism's claim

The agency demonstrated that virality need not be accidental but can be engineered through methodical analysis of engagement patterns, content optimization based on real-time performance data, and calculated influencer seeding. Mekanism's campaigns generated 350 million total views across client work, with average engagement rates exceeding *60% video completion*⁵⁴: metrics substantially superior to conventional advertising benchmarks.

Performance measurement and Brand impact. Influencer marketing effectiveness requires multi-dimensional measurement encompassing reach metrics, engagement indicators, and business outcomes. Reach metrics quantify exposure through impressions, views, and follower counts, establishing campaign breadth. Engagement metrics assess audience interaction through likes, comments, shares, and video completion rates, indicating content resonance. Conversion metrics track behavioral outcomes including click-through rates, website traffic, and direct sales attribution.

⁵³ T. S. Teixeira, and A. Caverly, Mekanism: Engineering Viral Marketing, Harvard Business School Case, April 2012 (revised April 2013)

⁵⁴ Ibidem

The reviewed cases reveal consistent patterns: earned media campaigns generate superior engagement rates (Mekanism averaged 60% video completion versus industry standard 30-40%), cost efficiencies improve dramatically when paid activations trigger viral amplification (Beats' \$10,000 NFL fine generated \$5 million equivalent media value), and brand equity accumulation manifests in pricing power and reduced advertising dependency (Longchamp's 13% CAGR with declining advertising spend). Return on investment calculations must therefore extend beyond immediate conversions to encompass brand awareness gains, sentiment improvements, and long-term customer lifetime value increases: recognizing that influencer marketing often functions as brand-building rather than direct-response advertising.

While successful implementations demonstrate influencer marketing's value-creation potential, failures illuminate critical risk factors. Two prominent cases reveal how influencer partnerships generate negative outcomes when strategic alignment fails.

Bud Light and Dylan Mulvaney. In April 2023, Bud Light's promotional partnership with transgender influencer Dylan Mulvaney triggered extensive backlash illustrating brand-audience-influencer misalignment risks⁵⁵. Despite representing merely one personalized can and a single Instagram post (not a national campaign), the activation generated severe consequences: brand favorability collapsed from +8.8 to -49.2 within three weeks, sales declined 25% year-over-year in subsequent months⁵⁶, and Modelo Especial temporarily displaced Bud Light as America's top-selling beer. The crisis revealed multiple failure points: inadequate assessment of core audience values and potential polarization, insufficient crisis response protocols (initial silence amplified negative narratives), and tactical influencer selection disconnected from brand positioning strategy.

The case demonstrates that even small influencer activations can trigger disproportionate backlash when they intersect with cultural fault lines, and that mass-market brands with diverse constituencies face particular vulnerability when adopting positions on socially divisive issues.

Chiara Ferragni and Balocco. Italian influencer Chiara Ferragni's 2023 partnership with Balocco panettone, marketed as supporting children's hospital charity while allegedly directing less funds to the cause, illustrates reputation risks from authenticity failures. The

⁵⁵ J. Avery, and C. Chammas, Dylan Mulvaney and Bud Light, Harvard Business School Case, June 2024 (revised June 2025)

⁵⁶ Ibidem

controversy, emerging in late 2023, triggered investigations, brand partnership losses, and substantial damage to Ferragni's carefully cultivated personal brand built on transparency and aspiration. The case demonstrates that influencer credibility, the foundation of persuasive power, proves extremely fragile when audiences perceive deception or exploitation. For brands, the incident reinforces that influencer partnerships transfer not only positive associations but also reputational risks, and that thorough due diligence on influencer authenticity and ethical practices constitutes essential risk management.

Emerging technological capabilities are transforming influencer marketing from intuition-based celebrity selection toward data-driven optimization and artificial intelligence applications. Virtual influencers represent the frontier of this evolution.

Puma's 2020 creation of Maya⁵⁷, the first AI-generated influencer for Southeast Asia (Figure 2.7), demonstrates virtual influencers' strategic potential. Generated through Generative Adversarial Networks trained on over 1 million faces submitted by regional users, Maya achieved 10,000 Instagram followers in two months with 6-7% engagement rates, substantially exceeding human influencer averages of 2-3% in the region⁵⁸. The virtual influencer model offers distinct advantages: complete brand control eliminating reputational risks from human influencer controversies, perfect scalability across markets and languages without geographic constraints, cost efficiency with marginal costs approaching zero after initial development, and unlimited longevity unconstrained by human aging or career changes.

However, authenticity concerns persist, with only 25% of Generation Z perceiving virtual influencers as authentic versus 41% for human influencers⁵⁹. Maya's success generated over 1.2 million impressions and 30+ earned media articles, with estimated 3x ROI versus conventional Southeast Asian campaigns, validating virtual influencers as complementary rather than replacement assets within diversified influencer portfolios.



Figure 2.7 - Puma's new AI Maya

⁵⁷ T. Q. Phan and S. Ong, Puma's "Maya": Southeast Asia's First Virtual Influencer, Harvard Business School Case, June 2021

⁵⁸ Ibidem

⁵⁹ Ibidem

Cross-Case synthesis

Analysis across these cases reveals consistent mechanisms governing influencer marketing performance. Successful implementations align three critical elements: brand positioning, influencer identity, and audience values: misalignment on any dimension generates failure regardless of execution quality. Earned media value systematically exceeds paid media efficiency when content achieves cultural resonance, with viral amplification multiplying reach 10-100x beyond initial seeding.

Measurement must encompass both immediate metrics (engagement, reach, conversions) and long-term brand equity outcomes (awareness, associations, loyalty), as influencer marketing frequently functions as brand-building rather than direct response. Risk management requires systematic assessment of influencer-brand-audience congruence, crisis response protocols, and ongoing monitoring of both partnership performance and broader cultural contexts that might transform assets into liabilities.

These mechanisms establish the operational framework within which influencer marketing generates value or destroys it. Success demands strategic alignment, authentic execution, rigorous measurement, and proactive risk management. Brands that master these dimensions transform influencers from tactical communication channels into strategic assets that build enduring competitive advantages through sustained cultural relevance and consumer connection. The subsequent empirical analysis examines how these mechanisms manifest within high-end restaurant contexts, where experiential positioning and digital influence intersect to shape brand perception and business performance.

2.4

When Strategy Meets Influence

The preceding sections established the theoretical and operational foundations of influencer marketing as a distinct discipline. What remains underexplored is the deeper strategic logic that emerges when brand management and influence converge: when the brand itself becomes the platform, the character becomes the channel, and the community becomes the competitive moat.

To frame this convergence, two strategic frameworks prove particularly illuminating. Kim and Mauborgne's book *Blue Ocean Strategy*⁶⁰ distinguishes between red oceans, existing markets crowded with competition and eroding margins, and blue oceans: uncontested market spaces created through value innovation rather than competitive imitation. In red oceans, brands fight for share; in blue oceans, they render competition irrelevant by **redefining what value means for the consumer**. Complementing this, the concept of **brand community** theory⁶¹ posits that the most durable competitive advantages are not built on product attributes but on the social and symbolic structures that form around brands, communities of shared meaning that convert consumers into advocates. Together, these frameworks illuminate a pattern visible across seemingly disparate cases: the brands that achieve sustained cultural relevance are those that stop competing on existing terms and start building ecosystems where followers, characters, and co-created narratives do the marketing.

Strategic marketing and influencer marketing converge most powerfully when brands abandon the broadcast model, pushing messages toward consumers, and adopt a platform logic, creating spaces where consumers generate, share, and amplify meaning.

⁶⁰ W. C. Kim and R. Mauborgne, *Blue Ocean Strategy: How to Create Uncontested Market Space and Make Competition Irrelevant* Hardcover, February 3rd, 2005

⁶¹ A. M. Muniz and T. C. O'Guinn, *Brand Community*, *Journal of Consumer Research*, March 2001, <https://doi.org/10.1086/319618>

This shift requires three conditions: authentic storytelling that audiences want to participate in, value congruence between brand identity and community values, and structural mechanisms for co-creation and advocacy. Authenticity is not a communications tactic but a strategic prerequisite: audiences distinguish between brands that perform values and brands that embody them, and only the latter generate the parasocial trust that converts followers into advocates⁶². Co-creation mechanisms: challenges, user-generated content, personalization, participatory events; transform passive audiences into active contributors whose investment in the brand grows with each interaction.

The Character as strategic asset: Beats, Nike, Marvel, and Real Madrid

Across industries and eras, one mechanism appears with remarkable consistency: the deployment of **characters**: athletes, superheroes, musicians, players; as brand channels rather than mere endorsers. What unites Beats, Nike, Marvel, and Real Madrid is not category or product but a shared strategic logic: cultural figures transfer symbolic meaning to brands through authentic association, generating earned media, community formation, and equity that no advertising budget can simply purchase.

Nike Football's transformation from a \$40 million niche business in 1994 to \$1.7 billion by 2010⁶³ was not driven primarily by product superiority but by the systematic use of athletes: Ronaldo, Ronaldinho, Rooney, Drogba; as identity vehicles for young consumers. The players did not endorse Nike; they embodied it, generating spontaneous community formation (the Joga Bonito platform reached one million members across 140 countries in five months) and viral content that preceded the social media era by years.

Marvel applied the identical logic to fictional characters: Spider-Man, X-Men, and Hulk function as brand ambassadors managing their own "careers" across films, games, toys, and comics, each activation reinforcing the others through cross-fertilization. As *Marvel's* leadership noted, the company operated less as a publisher than as a talent agency, managing a portfolio of 4,700 characters⁶⁴, Figure 2.8, whose symbolic equity could be licensed, sequenced, and monetized across media.

⁶² Ivi, note 16, p. 23

⁶³ Ivi, note 23, p. 29

⁶⁴ A. Elberse, *Marvel Enterprises, Inc.*, Harvard Business School Case, November 2004



Figure 2.8 - Marvel Universe characters

Real Madrid radicalized this approach by treating players simultaneously as athletes and as media assets, retaining 50%⁶⁵ of players' image rights and deploying figures like Beckham, Zidane, and Ronaldo as global content generators mixed with a bunch of different initiatives (Figure 2.9⁶⁶). The club's marketing director articulated the logic explicitly: "The product, the players and the games, is the content". The result was a

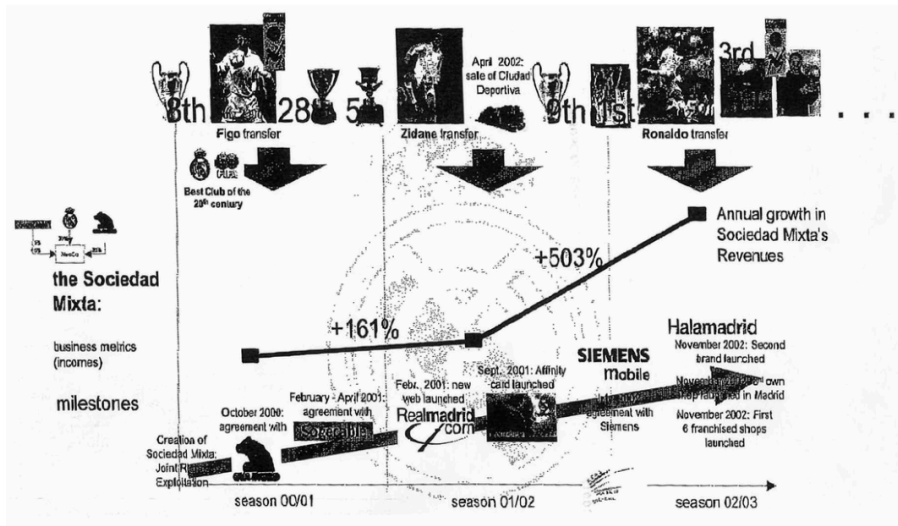


Figure 2.9 - Summary of Real Madrid initiatives

⁶⁵ J. A. Quelch and J. L. N. Iñesta, Real Madrid Club de Fútbol, Harvard Business School, April 2004

⁶⁶ Ibidem, source: Company documents

revenue increase from €138 million in 2001 to €304 million forecast for 2005, driven largely by marketing and licensing growth from €39 million to €142 million⁶⁷.

Beats achieved a comparable dynamic in consumer electronics, transforming musicians and athletes into cultural validators whose association with the product communicated status and identity far more effectively than technical specifications⁶⁸. The Tom Brady NFL fine, as it is demonstrated in *Chapter 2.3*, exemplifies how character-driven brand ecosystems convert controversy into currency when the character's values align with the brand's positioning.

Characters are selected not merely for their reach but for the cultural meanings they carry, and those meanings are deliberately transferred to the brand through consistent, authentic, multi-touchpoint narratives. The brands that master this mechanism generate what might be called character equity: a form of brand value that appreciates through cultural relevance and community attachment rather than through advertising spend.

From influencer partnerships to self-brand ecosystems

If *Beats*, *Nike*, *Marvel*, and *Real Madrid* illustrate brands deploying characters as influence mechanisms, *Crocs* and *Taylor Swift* represent the next evolutionary stage: the brand and the influencer becoming indistinguishable, fusing into self-contained ecosystems where community, content, product, and identity form a single integrated value proposition. Both cases embody blue ocean logic, not competing within existing categories but constructing new spaces where conventional competitive metrics become irrelevant.

Crocs executed a textbook repositioning from derided "ugly shoe" to cultural icon not by changing the product but by inverting the brand narrative and activating community co-creation⁶⁹. The "*Come As You Are*" (Figure 2.10) platform invited consumers to celebrate rather than apologize for unconventional choices, transforming the product's polarizing aesthetic into a distinctive identity signal. Collaborations with *Post Malone*, *Bad Bunny*, and *Balenciaga* were not celebrity endorsements in the traditional sense but community-building events that generated UGC, viral content, and earned media across *#CrocTok* and adjacent platforms. The strategic insight is that *Crocs* did not acquire cultural relevance by targeting it; it grew relevance organically by giving communities the tools:

⁶⁷ Ibidem

⁶⁸ Ivi, note 52, p. 39

⁶⁹ A. Israeli and A. V. Wilson, *Crocs: Using Community-Centric Marketing to Make Ugly Iconic*, Harvard Business School Case, July 2023

Jibbitz charms, personalization, limited drops; to express themselves through the brand, generating \$3.6 billion in revenues by 2022⁷⁰.

⁷⁰ Ibidem



Figure 2.10 - Crocs' "Come As You Are" Campaign

Taylor Swift's trajectory represents the most complete realization of this ecosystem logic. Applying blue ocean principles with explicit strategic intentionality, Swift did not compete in existing pop music markets but redefined what being a recording artist means: a vertically integrated business combining music creation, IP ownership (13 Management, Taylor's Version re-recordings), direct distribution (Eras Tour Film with AMC Theatres), and fan community monetization at a scale that generated \$1.04 billion from 152 concerts and \$4.6 billion in broader economic impact⁷¹. The Swifties are not merely fans but stakeholders and micro-media networks whose organic amplification, social engagement rates exceeding 12% versus an industry average of 2.1%⁷², functions as permanent earned media infrastructure. Swift's model collapses the distinction between brand and influencer entirely: she is simultaneously the product, the platform, the content, and the community manager, having eliminated every intermediary that traditionally extracted value from the artist-fan relationship.

The parallel between Crocs and Swift is analytically precise: both identified underserved communities united by values rather than demographics; both built co-creation mechanisms that converted consumers into advocates; and both generated blue ocean competitive positions where conventional competitors could not follow because the moat is relational and cultural rather than technological or financial. In Crocs' case, the community owns the aesthetic conversation; in Swift's, the fans co-create the mythology. Neither position can be replicated through advertising investment alone.

The cases examined across this section reveal a unified strategic architecture underlying the most successful integrations of marketing strategy and influencer logic. In each instance, influence is not a tactic layered onto brand strategy but the structural expression of it: characters embody brand values, communities form around shared meaning, co-creation mechanisms sustain engagement, and authenticity ensures that the entire ecosystem remains credible under scrutiny. The brand transitions from broadcaster to platform, from communicator to community architect. This architecture represents the operational form that brand equity takes in digital environments. It is this architecture that the subsequent empirical analysis examines within the high-end restaurant sector, where experiential positioning, chef-as-character narratives, and digital community management intersect to generate brand relevance and commercial performance.

⁷¹ A. Lutz, Taylor Swift and 'productive paranoia': HBR breaks down the hustle and mindset that built a \$1.6B net worth and a generational musician, *Fortune*, September 30, 2025, <https://fortune.com/2025/09/30/taylor-swift-life-of-a-showgirl-business-strategy-net-worth/>

⁷² K. Evers, The Strategic Genius of Taylor Swift, Her success is about much more than her music and innovators can learn from it, *Harvard Business Review*, April 2025, <https://hbr.org/2025/03/the-strategic-genius-of-taylor-swift>

2.5

Managerial Implications and Research Gap

The theoretical and empirical evidence reviewed across Sections 2.2, 2.3 through 2.4 converges on a set of managerial principles and exposes persistent gaps in academic knowledge, particularly regarding the quantification of influence-driven strategies in experience-intensive sectors. This concluding section distills the key implications for brand managers, examines what research has established about the economic returns of influencer marketing, and identifies the specific gap that motivates the empirical analysis that follows.

Key managerial lessons

The cases examined throughout this chapter, from *Apple's Think Different* and Nike's athlete ecosystems to Taylor Swift's fan economy, share a common strategic logic: the most durable competitive advantages in contemporary markets are built not on product attributes but on meaning, community, and identity. For brand managers, this translates into three actionable principles. First, *brand positioning* must precede influencer selection: the Bud Light crisis demonstrates that tactical influencer activation disconnected from strategic brand architecture generates reputational liabilities rather than assets. Influencer-brand-audience congruence is not optional but foundational. Second, *authenticity functions as a structural requirement*: Chiara Ferragni's collapse illustrates that parasocial trust, once perceived as violated, reverses influencer equity rapidly and severely, affecting both the influencer and the brand partners associated with them. Third, the shift from broadcast to platform logic demands investment in co-creation infrastructure: Starbucks' transformation of customers into organic ambassadors through experiential design, Crocs' community-centric UGC mechanisms, and Mekanism's engineered virality networks all demonstrate that sustained influence requires structural engagement mechanisms rather than episodic campaign spending.

Starbucks is particularly instructive as a managerial benchmark. By designing the customer experience as the primary communication channel: the "*third place*" as both product and promotion⁷³, Starbucks generated organic advocacy that reduced advertising dependency while sustaining premium pricing. The brand's service-dominant logic transformed every customer interaction into a value co-creation moment, producing an ambassadorship effect that no paid influencer campaign could replicate at equivalent cost. For managers in experience-intensive sectors, the Starbucks model suggests that brand equity investment yields compounding returns through customer lifetime value, reduced customer acquisition costs, and earned media generated by engaged communities. The economic logic is consistent: strong brand equity, built through identity, values, and community, drives pricing power, loyalty, and organic amplification simultaneously.

Quantifying Influencer Marketing: evidence and limitations

The global influencer marketing industry reached USD 30 billion in 2025 and is projected to surpass USD 40 billion in 2026, with long-term forecasts suggesting potential growth beyond USD 150 billion by 2031⁷⁴. Adoption is near-universal among marketers: 93% of marketing professionals reported deploying influencer marketing in campaigns as of 2022⁷⁵. These figures reflect influencer marketing's transition from experimental tactic to mainstream strategic investment, yet academic research has struggled to keep pace with practitioner adoption, particularly regarding rigorous economic performance measurement.

Several studies have attempted to quantify influencer marketing effects. Informational content value demonstrated particularly strong effects on purchase intention and behavioural engagement, while hedonic content showed the strongest link to purchase intention. However, the same analysis reveals that effects on direct sales performance remain the least studied and most inconsistently measured outcome, with only limited evidence on revenue conversion from influencer exposure. Lee et al.⁷⁶, examining influencer marketing specifically within the restaurant context in Taiwan, identified cost-per-acquisition (CPA), cost-per-view (CPV), and ROI as essential tracking metrics, yet

⁷³ Ivi, note 25, p. 30

⁷⁴ Ivi, notes 26-27, p. 32

⁷⁵ K. V. Aswathi and J. Kalapurackal, Influencer Marketing and Consumer Behaviour: A Systematic Literature Review, The Journal of Business Perspective, August 21st, 2022, <https://doi.org/10.1177/09722629221114>

⁷⁶ Ivi, note 46, p. 37

concluded that no universally recognized methodology exists for evaluating influencer marketing performance in food and hospitality settings. This measurement gap is particularly consequential for small and medium enterprises, including independent restaurants, which lack the analytical infrastructure to implement rigorous attribution models.

Research Gap and transition to Empirical Analysis

The literature reviewed reveals a structurally significant gap at the intersection of influencer marketing, strategic brand management, and economic performance measurement in high-end hospitality. While theoretical frameworks robustly explain the mechanisms through which influence operates: source credibility, parasocial relationships, eWOM, meaning transfer; empirical evidence on the magnitude of financial returns remains fragmented, industry-agnostic, and methodologically heterogeneous. Critically, no systematic study has isolated and quantified the specific impact of viral content and influencer activations on booking volumes and revenue in the fine dining segment, where the interplay between chef-as-character branding, experiential positioning, and digital community management creates a uniquely complex influence ecosystem.

This gap defines the empirical contribution of the present thesis. The central research question: whether it is more effective for a high-end restaurant to invest in external influencer collaborations or in strengthening its own brand identity and personal branding, remains empirically unanswered in existing literature. The cross-sector evidence reviewed in this chapter provides the conceptual foundation: brands that master identity-based community building generate superior long-term returns compared to those relying on transactional influencer partnerships. The empirical analysis in the following chapter tests this proposition through quantitative performance data from restaurant contexts, measuring the differential impact of owned brand equity development versus paid influencer activation on bookings, revenue, and customer behavior. In doing so, it contributes precisely the evidence that the field lacks: a rigorous, sector-specific quantification of how strategic and influencer marketing decisions translate into measurable economic performance.

3

EMPIRICAL SETTING

3.1

Challenges in getting Influencer Marketing returns

Measuring the effectiveness of influencer marketing campaigns presents significant methodological challenges. The primary barrier lies in **data availability**: companies that implement influencer marketing strategies typically operate through multiple channels and deploy diverse advertising formats simultaneously. These firms, often large-scale organizations, run concurrent marketing initiatives across traditional and digital media, making it extremely difficult to isolate the specific contribution of influencer marketing to overall performance.

The **heterogeneity of firms** further complicates empirical analysis. Each company operates within unique contexts, with different product portfolios, target audiences, and marketing mix strategies. The absence of granular data that would allow researchers to decompose and attribute effects to individual marketing channels creates a substantial barrier to rigorous quantitative studies in this domain. Moreover, as influencer marketing continues to gain momentum and becomes increasingly integrated into broader communication strategies, disentangling its isolated impact becomes even more complex.

Recent empirical research has documented these measurement challenges extensively. Wies et al. in 2022⁷⁷ identify multiple potential empirical barriers, including the difficulty of accurately measuring engagement metrics, specifying campaign-specific effects, and addressing endogeneity issues arising from selection bias and omitted variables.

⁷⁷ S. Wies, A. Bleier, and A. Edeling, *Journal of Marketing*, *Finding Goldilocks Influencers: How Follower Count Drives Social Media Engagement*, August 25th, 2022, <https://journals.sagepub.com/doi/10.1177/00222429221125131>

Similarly, Lee et al. in 2021⁷⁸ emphasize the complexity of determining appropriate metrics: such as Cost Per Acquisition (CPA) and Cost Per View (CPV), to effectively evaluate influencer marketing success in the hospitality sector.

Given these constraints, this study identifies the restaurant sector as a viable empirical setting, *a natural laboratory where the effect of influencer marketing can be more clearly isolated and measured.*

3.2

The Restaurant Industry

The restaurant sector offers unique characteristics that make it particularly suitable for studying influencer marketing effects. Industries such as retail and fashion, beauty, or cosmetics, which, as demonstrated in my previous undergraduate thesis⁷⁹, operate through extensive omnichannel strategies.

The necessity in some industries of an omnichannel approach is eloquently expressed in my work *"integrate all sales channels into a single central experience"* and by the Harvard Business Review (2022) through the formula "Buyers want it. Sellers need it". The related article "How B2B Businesses Can Get Omnichannel Sales Right"⁸⁰ drawing on McKinsey's latest B2B research⁸¹, documents that 66% of U.S. buyers opt for self-service

⁷⁸ P.-Y. Lee, M. A. Koseoglu, L. Qi, E.-C. Liu, B. King, International Journal of Hospitality Management, *The sway of influencer marketing: Evidence from a restaurant group*, September, 2021, <https://doi.org/10.1016/j.ijhm.2021.103022>

⁷⁹ Author, "The Future of Fashion Retail: strategies and new market trends", 2023

⁸⁰ D. J. Chung, I. Huber, J. C. Devignes and T. Clauwaert, Harvard Business Review, *How B2B Businesses Can Get Omnichannel Sales Right*, January 24th, 2022, <https://hbr.org/2022/01/how-b2b-businesses-can-get-omnichannel-sales-right?registration=success>

⁸¹ L. Harrizon, D. Spillecke, J. Stanley and J. Tsai, McKinsey & Company, *B2B Pulse: Insights from our latest global survey*, March 16th, 2021, mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/survey-global-b2b-decision-maker-response-to-covid-19-crisis

digital channels or remote interactions with human operators across different stages of the decision-making process, including identification, analysis and evaluation of suppliers, as well as the execution of initial and repeat orders.

Unlike these industries The restaurant industry presents a more controlled environment for analysis. While some restaurants do adopt multichannel approaches resembling those of fashion companies and can be identified as *outliers*, the majority operate as **niche establishments** with limited and comparable social media and marketing activities. This **homogeneity** becomes particularly evident when focusing on Michelin-starred restaurants. Within each category (one, two, or three stars), establishments exhibit remarkable similarity in their marketing approaches. For instance, one-star restaurants typically engage in minimal marketing activities and serve primarily local clientele within geographically constrained areas. This setting allows for the identification of influencer marketing's true value and impact, as external confounding factors are substantially reduced.

Furthermore, the restaurant sector, excluding celebrity chefs known for reasons beyond their culinary offerings, is characterized by relatively uniform advertising practices. Unlike conglomerates such as LVMH⁸², which deploy sophisticated and varied marketing narratives, restaurants within the same Michelin category adhere to similar standards and are directly comparable. Customer expectations regarding service quality, pricing, and culinary experience are relatively homogeneous within each tier, creating a unique condition for empirical research. *The Michelin Guide*⁸³ serves as a standardization mechanism, ensuring comparability across establishments, as will be further detailed in *Chapter 4*.

⁸² LVMH, <https://www.lvmh.com/it>

⁸³ The Michelin Guide, <https://guide.michelin.com/it/it>

3.3

YouTube Channels as measurement tools

To assess the impact of influencer marketing in the restaurant sector, this study leverages three distinct Italian YouTube channels that produce high-quality video content featuring Michelin-starred venues. These channels provide valuable opportunities to observe and measure the effects of influencer exposure on restaurant performance. The real value lies in using three different channels, because by doing so you can obtain a clean dataset free from any ups or downs related to the channel, a very rich dataset.

Focusing one by one, actually at January 2026.

1 | COSA MANGIAMO OGGI

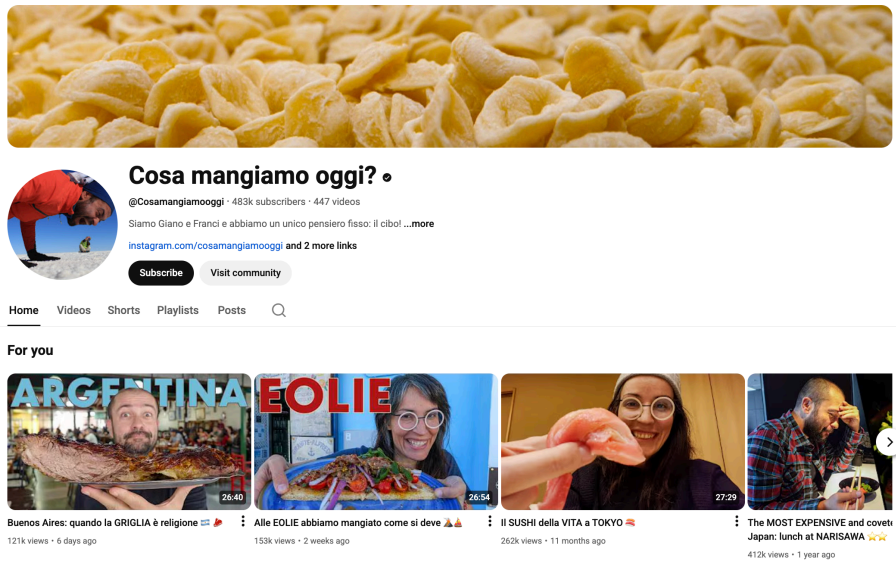


Image 3.1 | Cosa Mangiamo Oggi YouTube channel

This channel⁸⁴ represents the first mover in the Italian YouTube food scene, pioneering content focused on high-end dining experiences. Their established position and longevity make them the incumbent player in this niche.

- Total subscribers: 483,000
- Total videos: 447
- Total views: 151,401,042
- Date of the First Michelin-Starred Restaurant video: June 25th, 2018

2 | FRANCESCO ZINI

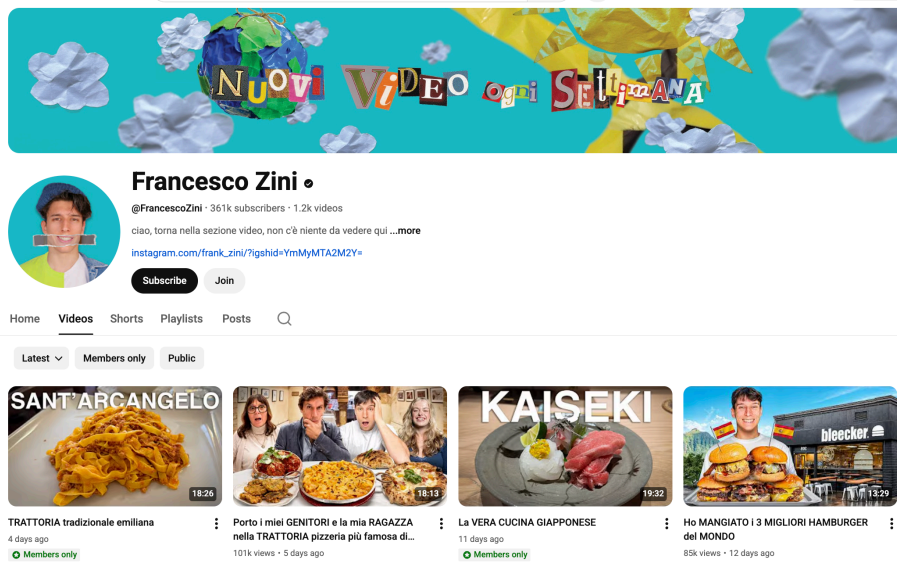


Image 3.2 | Francesco Zini YouTube channel

Francesco Zini⁸⁵ entered the market during the rise of TikTok and Instagram video formats. His content initially gained traction through viral success on short-form platforms before expanding to YouTube, where both channels have grown in parallel.

⁸⁴ Cosa Mangiamo Oggi YouTube channel, <https://www.youtube.com/@Cosamangiamooggi>

⁸⁵ Francesco Zini YouTube channel, <https://www.youtube.com/@FrancescoZini>

- Total subscribers: 361,000
- Total videos: 1259
- Total views: 288,733,075
- Date of the First Michelin-Starred Restaurant video: November 29th, 2022

3 | PIATTO RICCO MI CI FICCO

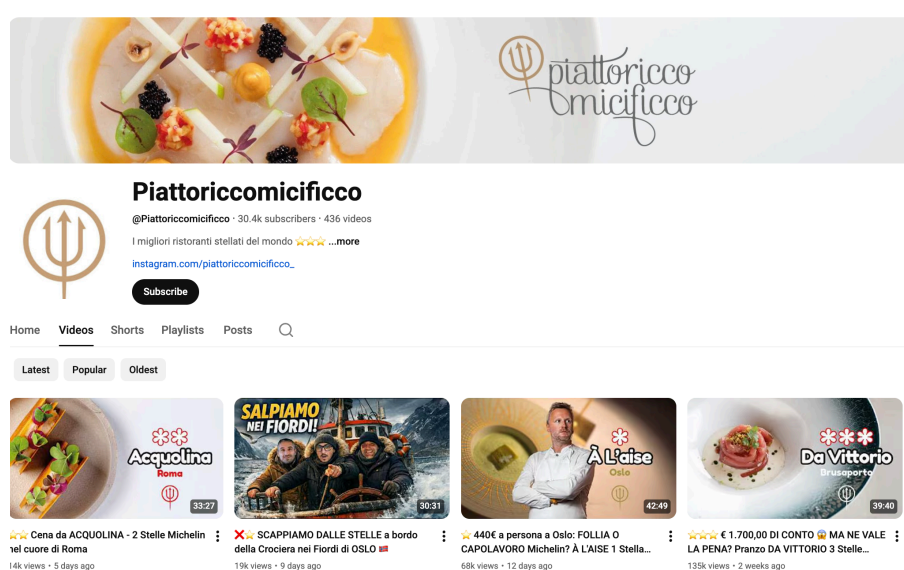


Image 3.3 | Piatto Ricco Mi Ci Ficco YouTube channel

This channel⁸⁶ represents the most recent entrant in the space, bringing a distinct tone and innovative approach to restaurant content creation with an aesthetic touch.

- Total subscribers: 30,408
- Total videos: 436
- Total views: 7,310,864
- Date of the First Michelin-Starred Restaurant video: July 16th, 2023

⁸⁶ Piatto Ricco Mi Ci Ficco YouTube channel, <https://www.youtube.com/@Piattoricomicifitto>

The focus on these specific channels and the restaurant sector represents a deliberate methodological choice: moving from general theoretical frameworks to a specific empirical context where causal inference is more feasible. This transition from the broad landscape of influencer marketing to the controlled environment of Michelin-starred restaurants and dedicated food content creators enables a rigorous assessment of influencer marketing impact that would be unattainable in more complex, multi-faceted industries.

4

DATA COLLECTION PROCESS

This chapter presents the data collection methodology employed in this study, detailing the step-by-step process from initial data sourcing to final sample preparation. The first section describes the data collection procedure, explaining how Michelin-starred restaurants were identified, how Google Trends data was gathered, and which restaurants received YouTube video coverage. The second section will provide descriptive statistics of the final sample.

4.1

Data Collection methodology

The data collection process was structured in four sequential phases, each designed to ensure data quality and relevance for the analysis of YouTube video impact on restaurant popularity.

4.1.1. Michelin-Starred restaurants sample

The initial dataset was compiled by downloading the complete list of Michelin-starred restaurants from the Michelin Guide Italy⁸⁷. The Michelin Guide represents an ideal dataset for this research as it ensures that all restaurants meet exceptionally high standards, allowing for meaningful comparisons between restaurants that received YouTube coverage and those that did not, given their comparable quality levels.

The initial sample comprised **393 restaurants**, distributed as follows: 14 three-star restaurants, 38 two-star restaurants, and 341 one-star restaurants. This hierarchical classification provided a comprehensive overview of Italy's haute cuisine landscape.

4.1.2. Google Trends data collection

To measure the evolution of restaurant popularity over time, weekly Google Trends⁸⁸ data was collected for each individual restaurant. The timeframe selected for analysis spanned

⁸⁷ Ivi, note 83, pag. 57

⁸⁸ Google Trends, <https://trends.google.it/trends/>

from June 1, 2018, to June 1, 2025, resulting in 52 weeks of data per year for seven years for each restaurant.

The choice of Google Trends as the primary metric for measuring restaurant popularity deserves particular attention. Unlike raw search volume data, Google Trends provides search interest normalized as percentage variation relative to peak popularity within the selected timeframe. This normalization is particularly valuable for this research, as it automatically accounts for temporal variations in search behavior and provides a clean measure of how each restaurant's popularity changes over time compared to its own baseline.

However, the data collection process presented several practical challenges. For each restaurant, the procedure involved accessing Google Trends, entering the restaurant name, and selecting the appropriate search category to ensure the query referred specifically to the restaurant rather than unrelated search terms. The category "haute cuisine restaurant" or similar classifications was consistently used to maintain search precision.

Several practical insights emerged during this process. Restaurants located in Milan and other major cities were generally easier to identify directly through the search bar. However, for restaurants in smaller locations or with less distinctive names, alternative search strategies proved necessary. Initially, direct searches in the main search bar were employed, but scrolling through "related queries" suggestions at the bottom of the results page often yielded more accurate matches. For restaurants that did not appear directly in the results, searching for the chef's name and then identifying the associated restaurant proved effective. Additionally, including the restaurant's city or region in the search query significantly improved identification accuracy.

4.1.3 Data cleaning

Following the initial data collection, a rigorous data cleaning process was necessary to ensure sample quality and analytical reliability. The Google Trends data revealed several data quality issues that required the exclusion of specific restaurants from the final sample.

Four primary categories of problematic cases were identified.

Insufficient data availability. Some restaurants, despite being listed in the Michelin Guide, generated insufficient search interest to produce meaningful Google

Trends data. As illustrated in Figure 4.1, certain restaurants displayed the warning message "The data related to your search is not sufficient to be shown here" ("I dati correlati alla tua ricerca non sono sufficienti per essere mostrati qui"). This occurred primarily for newly established restaurants or those in remote locations with limited visibility, making it impossible to track their popularity trends over the seven-year observation period.

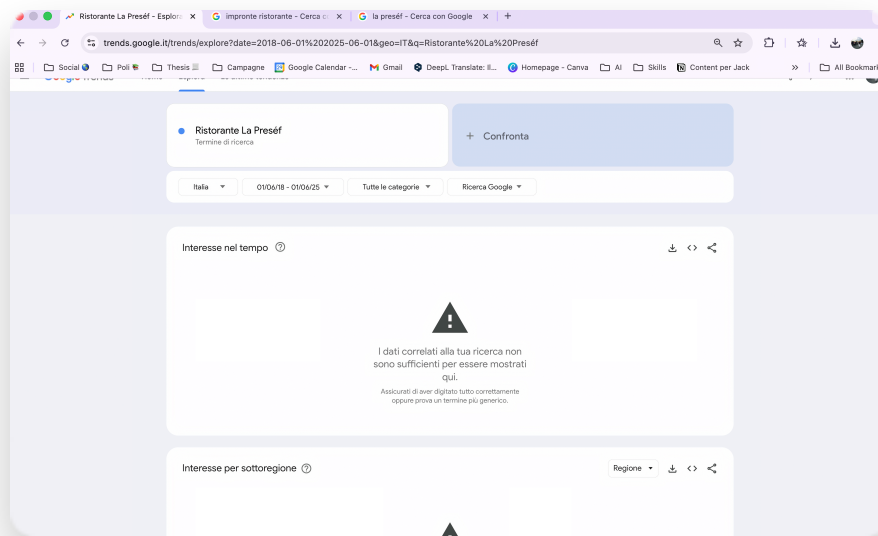


Figure 4.1 | Google Trends, insufficient data availability

Anomalous spikes in search interest. Several restaurants exhibited extreme, irregular spikes in search volume that would distort longitudinal analysis. Figure 4.2 demonstrates a case where a restaurant experienced dramatic, isolated peaks reaching

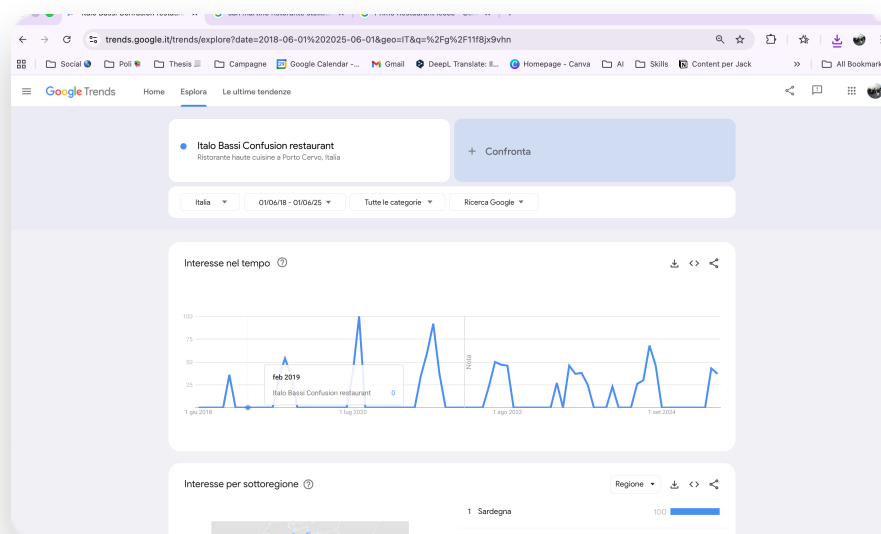


Figure 4.2 | Google Trends, anomalous spikes in search interest

maximum values (100 on the normalized scale), followed by returns to near-zero interest. Such patterns typically indicate extraordinary one-time events unrelated to normal restaurant operations, such as media scandals, celebrity incidents, or other newsworthy events that temporarily attracted search attention but do not reflect genuine, sustained interest in the restaurant's culinary offerings.

Limited temporal data coverage. Some restaurants provided trend data only for brief periods rather than the full seven-year timeframe. As shown in Figure 4.3, certain establishments displayed consistent patterns of extreme periodic spikes (reaching 100 on the scale) with minimal activity between peaks. This regular but sparse pattern suggests seasonal operations, irregular opening schedules, or data collection artifacts that prevented comprehensive longitudinal tracking of restaurant popularity evolution.

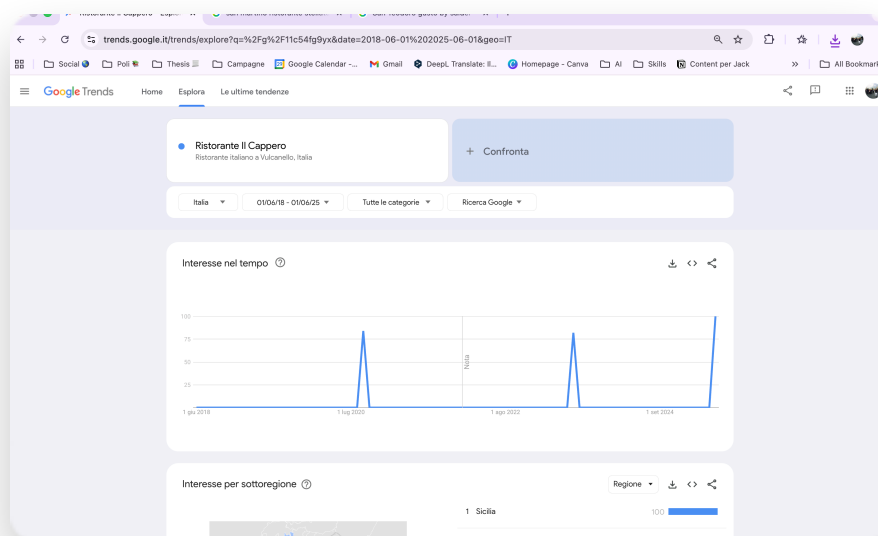


Figure 4.3 | Google Trends, limited temporal data coverage

Recent establishment date. Restaurants that opened after the beginning of the observation period (June 2018) were excluded to ensure all analyzed establishments had comparable exposure windows. Figure 4.4 illustrates a restaurant showing no search activity for the early years of the observation period, with data beginning only from mid-2020 onward. Including such restaurants would introduce bias, as they lacked baseline data and had different opportunity windows for receiving YouTube coverage.

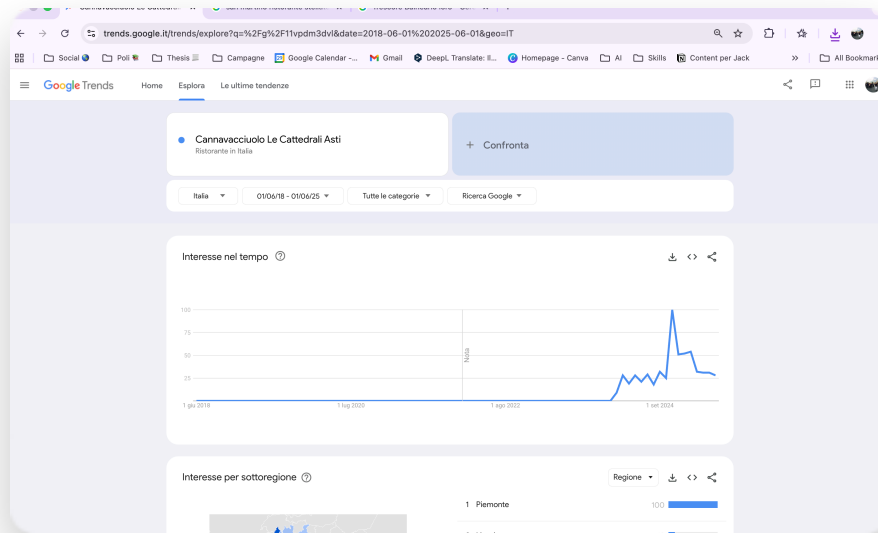


Figure 4.4 | Google Trends, recent establishment date

After systematically identifying and removing restaurants falling into these four categories, the analytical sample was reduced from the initial 393 Michelin-starred restaurants to a final sample of 348 restaurants with complete, reliable data suitable for rigorous quantitative analysis.

4.1.4 YouTube video coverage identification

The final step involved identifying which restaurants had been featured in YouTube videos, referred to as "*treated*" restaurants in this study. For each treated restaurant, data was collected for each video built, on the number of videos received, the publication dates of these videos, and which YouTube channels produced them, how many views, likes, and comments they got.

The analysis revealed that 70 restaurants received YouTube video coverage, representing approximately 20% of the final sample. This substantial proportion of treated restaurants provides sufficient statistical power for meaningful comparative analysis as will be shown in *Chapter 5*.

4.2

Descriptive Statistics

For the descriptive analysis and statistical computations, the software Stata was employed. Prior to conducting any analysis, comprehensive data preparation was performed to ensure analytical clarity and efficiency. This preparation involved renaming all variables with standardized, intuitive labels and creating additional variables essential for subsequent analysis.

The dataset transformation included renaming the original Italian variable names to English equivalents with clear, descriptive labels. For instance, the restaurant name variable was renamed from "NOMERISTORANTE" to "rest_name" and labeled as "Name of the restaurant," while the Google Trends data was renamed from "interesseGoogle" to "google_interest" and labeled as "Google search query intensity at the corresponding month". Similarly, geographical variables (city and region), the Michelin star classification, and treatment indicators for each YouTube channel were systematically renamed and labeled.

Beyond simple renaming, several derived variables were created to facilitate analysis. A unique restaurant identifier (id_restaurant) was generated through alphabetical grouping of restaurant names, and a unique time identifier (id_time) was created for each observation date. Most importantly, a consolidated treatment variable (tr_ALL) was constructed by combining the individual channel treatment indicators (tr_CMO, tr_FZ, tr_PRMCF), coded as 1 if the restaurant received treatment from any channel and 0 otherwise. Additionally, a composite unique identifier (id_unique) was created by combining restaurant and time identifiers, ensuring each observation could be uniquely identified in the panel dataset structure.

Following this data preparation, descriptive statistics were computed to characterize the sample composition and treatment distribution.

Sample characteristics and treatment distribution

The final analytical sample of 348 restaurants demonstrates a distribution heavily concentrated in one-star establishments, reflecting the hierarchical structure of the Michelin Guide system. Table 1 presents the distribution of restaurants across the three Michelin star categories.

Table 1. Restaurants Michelin Star distribution

Number of Michelin Stars	Freq.	Percent
1	297	85,34%
2	37	10,63%
3	14	4,02%
Total	348	100,00%

The distribution reveals a pronounced pyramidal structure characteristic of the Michelin Guide rating system. One-star restaurants constitute the overwhelming majority of the sample (85.34%), representing establishments that the Michelin Guide describes as offering "high quality cooking, worth a stop." Two-star restaurants account for 10.63% of the sample, representing "excellent cooking, worth a detour," while three-star establishments comprise only 4.02% of the sample, representing the pinnacle of "exceptional cuisine, worth a special journey."

This distribution pattern is consistent with the Michelin Guide's evaluation philosophy, which maintains increasingly stringent criteria at higher star levels, resulting in progressively fewer restaurants achieving two- and three-star status.

Table 2 presents the geographic distribution of Michelin-starred restaurants across Italian regions, cross-tabulated with star classifications. The distribution reveals significant regional concentration patterns.

The geographic analysis reveals pronounced concentration in specific regions. Lombardia emerges as the leading region with 56 restaurants (16.09% of the total sample), including 3 three-star establishments. Toscana follows with 37 restaurants (10.63%), while Campania, Piemonte, and Veneto each contribute 32-35 restaurants. These five regions collectively account for more than half of all Michelin-starred restaurants in the sample.

The distribution of higher-tier establishments (two- and three-star) also shows regional concentration. Lombardia and Campania lead in two-star restaurants (7 each), while Lombardia hosts the highest number of three-star establishments (3), followed by Piemonte and Veneto (2 each). Notably, several regions such as Liguria, Puglia, Calabria, and Umbria contain only one-star restaurants, reflecting regional differences in haute cuisine development and culinary tradition recognition by the Michelin Guide.

This geographic heterogeneity provides an important contextual dimension for the subsequent analysis, as regional location may influence both restaurant visibility and the likelihood of receiving YouTube coverage.

Table 2. Distribution of Restaurants by Region and Michelin Stars

Region	Number of Michelin Stars			Total
	1	2	3	
Abruzzo	4	0	1	5
Basilicata	1	0	0	1
Calabria	4	0	0	4
Campania	27	7	1	35
Emilia Romagna	20	2	1	23
Friuli Venezia Giulia	5	2	0	7
Lazio	25	3	1	29
Liguria	11	0	0	11
Lombardia	46	7	3	56
Marche	6	1	1	8
Molise	1	0	0	1
Piemonte	27	3	2	32
Puglia	10	0	0	10
Sardegna	3	0	0	3
Sicilia	20	3	0	23
Toscana	31	5	1	37
Trentino Alto Adige	20	1	1	22
Umbria	6	0	0	6
Valle d'Aosta	3	0	0	3
Veneto	27	3	2	32
Total	297	37	14	348

A critical component of this study involves identifying which restaurants received YouTube video coverage (the "**treatment**" group) versus those that did not. Table 3 presents the overall treatment distribution across Michelin star categories.

Table 3. Treatment Distribution by Michelin Stars

Unique variable treatment	Number of Michelin Stars			Total
	1	2	3	
0 (= not treated)	245	30	3	278
1 (= treated)	52	7	11	70
Total	297	37	14	348

Out of the 348 restaurants in the final sample, 70 restaurants (20.11%) received YouTube video coverage from at least one of the three analyzed channels, while 278 restaurants (79.89%) received no coverage during the observation period. This substantial treatment rate of approximately one-fifth of the sample provides sufficient statistical power for comparative analysis. The treatment distribution across star categories reveals notable patterns. Among one-star restaurants, 52 out of 297 (17.51%) received coverage. For two-star establishments, 7 out of 37 (18.92%) were treated. Most strikingly, three-star restaurants show the highest treatment rate, with 11 out of 14 (78.57%) receiving YouTube coverage. This pronounced difference suggests that higher Michelin star ratings may be associated with greater YouTube channel interest, though this pattern will require formal statistical testing in subsequent analyses.

The three YouTube channels analyzed in this study, Cosa Mangiamo Oggi (CMO), Francesco Zini (FZ), and Piatto Ricco Mi Ci Ficco (PRMCF), demonstrate distinct coverage patterns. Table 4 presents the detailed breakdown of treatments by channel and Michelin star category.

Table 4. Treatment Distribution by YouTube Channel

YouTube Channel	Number of Michelin Stars			Total
	1	2	3	
CMO	10	5	17	32
FZ	4	2	11	17
PRMCF	3	1	31	35
Total Treatments	17	8	59	84
Total Treated Restaurants	11	7	52	70
<i>% Treated over Total</i>	<i>78,6%</i>	<i>18,9%</i>	<i>17,5%</i>	<i>20,1%</i>
Total Restaurants Analyzed	14	37	297	348

Notes: a) CMO = Cosa Mangiamo Oggi, b) FZ = Francesco Zini, c) PRMCF = Piatto Ricco Mi Ci Ficco, d) Total Treatments means that there are restaurants which have received video by more than one only channel.

Several important observations emerge from this analysis. First, the total number of treatments (84) exceeds the total number of treated restaurants (70), indicating that some restaurants received coverage from multiple channels. This overlap suggests that certain establishments attracted attention from more than one YouTube creator.

Second, channel coverage patterns differ substantially. PRMCF produced the most treatments (35), followed by CMO (32) and FZ (17). However, the distribution across star categories varies considerably by channel. PRMCF shows an extreme concentration in three-star restaurants (31 out of 35 treatments, or 88.57%), while CMO demonstrates a more balanced distribution across all star categories, and FZ focuses primarily on three-star establishments (11 out of 17 treatments, or 64.71%). Third, the aggregate treatment percentages reveal stark differences by star category. Again, while 78.6% of three-star restaurants received coverage, only 18.9% of two-star and 17.5% of one-star restaurants were treated. This pattern suggests that YouTube channels in this domain exhibit strong preference for featuring the highest-rated establishments, potentially reflecting audience interest in experiencing Italy's most elite culinary destinations through video content. Beside that, Figure 4.5 illustrates the temporal distribution of treatments across the observation period. The cumulative treatment curve reveals a relatively steady accumulation of video coverage over time, with a notable acceleration beginning around period 60 (corresponding to mid-2022) and continuing through the end of the observation window. The progression from zero treatments in the early observation period to 84 total treatments by period 85 demonstrates sustained content production activity, with the steepest growth occurring in the final 25 periods, suggesting increasing channel activity and audience interest in haute cuisine content in recent years.

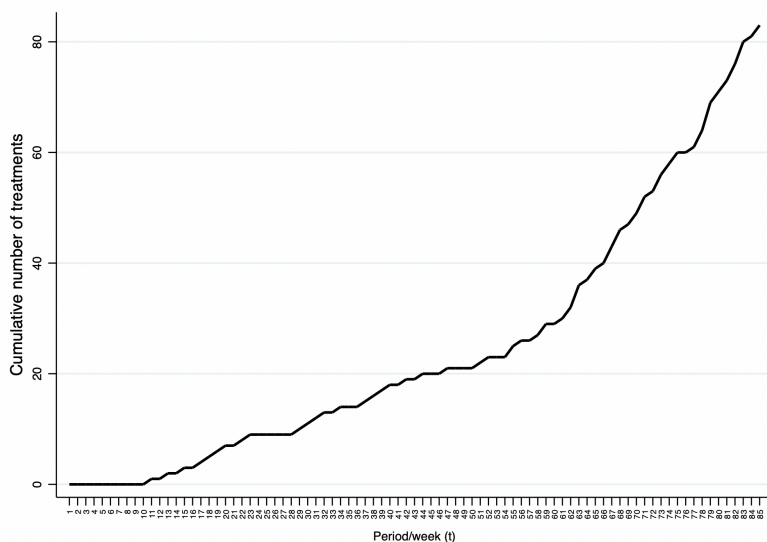


Figure 4.5. Temporal distribution of treatments

5

METHODS AND RESULTS

5.1

Search interest analysis and treatment comparison

Having established the sample composition and treatment distribution patterns, this section examines the evolution of restaurant popularity as measured by Google Trends data. The analysis begins with overall temporal patterns of search interest, followed by comparisons between treated and non-treated restaurants, and concludes with formal statistical tests of mean differences.

Figure 4.6 presents the average Google search interest over the entire observation period (June 2018 - June 2025), disaggregated by Michelin star category. The graph reveals several notable patterns in how search interest evolved across the seven-year timeframe for restaurants of different quality tiers.

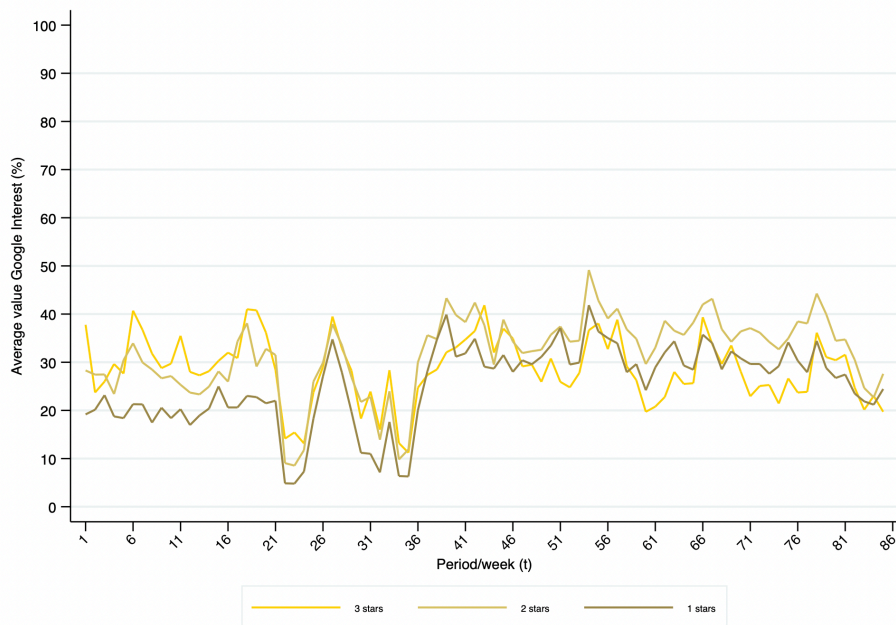


Figure 4.6. Average Google Interest over time by Michelin Stars

The temporal patterns reveal distinct differences across star categories. Three-star restaurants (yellow line) consistently maintain higher average search interest throughout most of the observation period, with values typically ranging between 25-40% on the normalized scale. The volatility in this category is particularly pronounced, with several dramatic fluctuations including a sharp drop around period 26 (corresponding to early 2020, likely reflecting the COVID-19 pandemic's initial impact on fine dining) and subsequent recovery phases.

Two-star restaurants (light tan line) demonstrate intermediate search interest levels, generally ranging between 25-35% with moderate volatility. This category shows relative stability in the earlier periods before experiencing increased variation from period 35 onward, suggesting growing differentiation in popularity among two-star establishments over time.

One-star restaurants (dark brown line) exhibit the lowest and most stable average search interest, predominantly ranging between 18-22% throughout the observation period. This category shows less dramatic fluctuations compared to higher-tier establishments, suggesting that one-star restaurants may attract more consistent, though lower-intensity, search attention that is less susceptible to temporal shocks or trending effects.

A notable feature across all categories is the pronounced dip around periods 26-31 (early to mid-2020), coinciding with the COVID-19 pandemic lockdowns that severely restricted restaurant operations. The subsequent recovery patterns differ by star category, with three-star establishments showing more pronounced rebounds, potentially reflecting pent-up demand for premium dining experiences as restrictions eased.

Complete Sample Analysis

To assess the potential impact of YouTube video coverage on restaurant popularity, the average Google search interest was calculated separately for pre-treatment periods ($tr_post = 0$) and post-treatment periods ($tr_post = 1$) for the 70 treated restaurants. This comparison provides initial evidence regarding whether receiving YouTube coverage is associated with changes in search interest levels.

Table 5 presents the comprehensive comparison of mean Google interest before and after treatment for all treated restaurants, including detailed restaurant-level data.

The aggregate results reveal a meaningful increase in average Google search interest following YouTube video coverage. Across all treated restaurants, the mean Google

interest increased from 25.50% in the pre-treatment period to 30.49% in the post-treatment period, representing an improvement of **4.98 percentage points** (a relative increase of approximately 19.5%). This substantial shift suggests that YouTube coverage is associated with heightened search interest in featured restaurants.

Table 5. Pre-Treatment vs Post-Treatment Google Interest in Complete Sample

value = google_interest				
Restaurant ID	Restaurant Name	Mean Pre-Treatment	Mean Post-Treatment	Difference
4	Abocar DueCucine	30,72152	25,83333	-4,888186
17	All'Enoteca	0	22,61905	22,61905
23	Andrea Larossa	24,44706	.	.
24	Andreina	15,93902	14	-1,939024
29	Antica Corte Pallavicina	54,95082	58,79167	3,840847
34	Arnaldo	9,316667	40,12	30,80333
38	Atelier Moessmer Norbert Niederkofer	0	34,4	34,4
44	Borgo San Jacopo	15,14815	8,258064	-6,890084
45	Borgo Sant'Anna	35,89189	36,27273	0,3808365
47	Bros'	14,39535	10,30952	-4,085825
52	Cannavaciuolo Bistrot	69,91666	39,12329	-30,79338
54	Cannavaciuolo Le Cattedrali Asti	3,961539	39,85714	35,8956
62	Casa Perbellini 12 Apostoli	27,125	33,61905	6,494049
65	Casamatta	20,51282	7,142857	-13,36996
71	Contrada Bricconi	11,74242	42,94737	31,20494
72	Contraste	51,0625	48,31884	-2,74366
75	Cracco in Galleria	36,25862	25,62963	-10,62899
78	D'O	21,11765	20,39706	-0,7205887
81	Da Vittorio	25,59016	26,91667	1,326502
83	Dalla Gioconda	28,925	49	20,075
95	Enoteca La Torre	29,08537	21	-8,085365
97	Enrico Bartolini al Mudec	5,4	11,88	6,48
101	FRE	4,033333	47,05455	43,02121
102	Famiglia Rana	16,39506	28	11,60494
104	Gabbiano 3.0	18,75	0	-18,75
115	Harry's Piccolo	29,34546	37,73333	8,387878
116	Horto	15,81429	58,8	42,98571
139	Il Papavero	23,74359	14,85714	-8,886447
150	Il Tino	13,91935	10,3913	-3,52805
155	Inkiostro	5,277778	7,61194	2,334163
158	Iyo	63,46429	62,07018	-1,394112
160	Johannesstube	1,960784	1,676471	-0,2843137
163	Krösios	24,24561	42,75	18,50439
187	La Rucola 2.0	46,94203	32,5625	-14,37953
190	La Stùade Michil	30,04167	29,15385	-0,8878193
191	La Tana Gourmet	33,71642	21,94444	-11,77197
194	La Trota	54,54839	38,34783	-16,20056
199	Le Calandre	59,25926	42,29032	-16,96894
200	Le Trabe	33,8	30,6	-3,199999
202	Lido 84	21,95238	27,23438	5,281994
206	Locanda Don Serafino	38,63889	28,46154	-10,17735
208	Locanda Margon	48,60606	46,61538	-1,990677
217	Madonna del Pescatore	28,42105	30,42553	2,004478
224	Marotta	46,5375	40,4	-6,137497
226	Materlapr1ma	13,57353	23,23529	9,661765
227	Materia	12,06897	11,42857	-0,6403942
241	Orma Roma	8,351352	38,36364	30,01228
248	Osteria Franciscana	18,90322	13,38889	-5,514336
249	Osteria del Viantante	20,31884	29,375	9,05616
257	Pashà	32,62195	38	5,378048
260	Piano35	49,75325	51,75	1,996754
261	Piazza Duomo	19	16,38028	-2,619719
263	Pipero Roma	39,46914	38,75	-0,7191353
269	Pulejo	9,776119	28,66667	18,89055
270	Quadri	1,717949	55,17391	53,45596
271	Quattro Passi	2,628205	20,42857	17,80037
274	Reale	47,90625	36,95238	-10,95387
281	San Domenico	56,66667	42	-14,66667
284	SanBrite	11,76087	22,30769	10,54682
293	Seta by Antonio Guida	41,30556	49,77551	8,469952
298	Sintesi	8,268657	19,72222	11,45356
316	Trattoria da Amerigo	34,72581	69,43478	34,70898
317	Tre Olivi	9	2,833333	-6,166667
318	Uliassi	10,4878	12,40909	1,921287
320	Unforgettable	24,69136	45,25	20,55864
321	Vecchia Malcesine	25,17143	12,93333	-12,2381
323	Venissa	15,78378	28,8125	13,02872
329	Villa Crespi	40,47368	33,68182	-6,791862
335	Vintage1997	13,66667	35,46154	23,43376
344	Zia	27,46479	32	4,535212
MEAN (without outliers)		25,49769	30,49177	4,97885
N. Restaurants analyzed		70		

Outlier-Adjusted Analysis

To ensure the robustness of these findings, the analysis was repeated after excluding outliers: specifically, restaurants whose exceptional popularity might be attributable to factors other than YouTube coverage alone, such as celebrity chef status, participation in television programs like MasterChef, or other extraordinary media events. Table 6 presents the outlier-adjusted results.

Table 6. Pre-Treatment vs Post-Treatment Google Interest - Outlier-Adjusted Sample

value = google_interest				
Restaurant ID	Restaurant Name	Mean Pre-Treatment	Mean Post-Treatment	Difference
4	Abocar Due Cucine	30,72152	25,83333	-4,888186
24	Andreina	15,93902	14	-1,939024
29	Antica Corte Pallavicina	54,95082	58,79167	3,840847
34	Arnaldo	9,316667	40,12	30,80333
44	Borgo San Jacopo	15,14815	8,258064	-6,890084
45	Borgo Sant'Anna	35,89189	36,27273	0,3808365
47	Bros'	14,39535	10,30952	-4,085825
62	Casa Perbellini 12 Apostoli	27,125	33,61905	6,494049
65	Casamatta	20,51282	7,142857	-13,36996
71	Contrada Bricconi	11,74242	42,94737	31,20494
72	Contraste	51,0625	48,31884	-2,74366
78	D'O	21,11765	20,39706	-0,7205887
83	Dalla Gioconda	28,925	49	20,075
95	Enoteca La Torre	29,08537	21	-8,085365
97	Enrico Bartolini al Mudec	5,4	11,88	6,48
101	FRE	4,033333	47,05455	43,02121
102	Famiglia Rana	16,39506	28	11,60494
115	Harry's Piccolo	29,34546	37,73333	8,387878
116	Horto	15,81429	58,8	42,98571
139	Il Papavero	23,74359	14,85714	-8,886447
150	IlTino	13,91935	10,3913	-3,52805
155	Inkiostro	5,277778	7,61194	2,334163
158	Iyo	63,46429	62,07018	-1,394112
160	Johannesstube	1,960784	1,676471	-0,2843137
163	Krèslòs	24,24561	42,75	18,50439
187	La Rucola 2.0	46,94203	32,5625	-14,37953
190	La Stúa de Michil	30,04167	29,15385	-0,8878193
191	La Tana Gourmet	33,71642	21,94444	-11,77197
194	La Trota	54,54839	38,34783	-16,20056
199	Le Calandre	59,25926	42,29032	-16,96894
200	Le Trabe	33,8	30,6	-3,199999
202	Lido 84	21,95238	27,23438	5,281994
206	Locanda Don Serafino	38,63889	28,46154	-10,17735
208	Locanda Margon	48,60606	46,61538	-1,990677
217	Madonnina del Pescatore	28,42105	30,42553	2,004478
224	Marotta	46,5375	40,4	-6,137497
226	MateriaPrima	13,57353	23,23529	9,661765
227	Materia	12,06897	11,42857	-0,6403942
241	Orma Roma	8,351352	38,36364	30,01228
249	Osteria del Viandante	20,31884	29,375	9,05616
257	Pashà	32,62195	38	5,378048
260	Piano35	49,75325	51,75	1,996754
263	Pipero Roma	39,46914	38,75	-0,7191353
269	Pulejo	9,776119	28,66667	18,89055
270	Quadri	1,717949	55,17391	53,45596
271	Quattro Passi	2,628205	20,42857	17,80037
274	Reale	47,90625	36,95238	-10,95387
281	San Domenico	56,66667	42	-14,66667
284	SanBrite	11,76087	22,30769	10,54682
293	Seta by Antonio Guida	41,30556	49,77551	8,469952
298	Sintesi	8,268657	19,72222	11,45356
316	Trattoria da Amerigo	34,72581	69,43478	34,70898
317	Tre Olivi	9	2,833333	-6,166667
318	Ulassi	10,4878	12,40909	1,921287
320	Unforgettable	24,69136	45,25	20,55864
321	Vecchia Malcesine	25,17143	12,93333	-12,2381
323	Venissa	15,78378	28,8125	13,02872
335	Vintage 1997	12,02778	35,46154	23,43376
344	Zia	27,46479	32	4,535212
MEAN (without outliers)		25,89046	31,38873	5,498268
N. RESTAURANTS ANALYZED		59		

After excluding outliers, the pattern remains consistent and even strengthens slightly. The mean Google interest for the 59 remaining treated restaurants increased from 25.89% pre-treatment to 31.39% post-treatment, yielding an improvement of **5.50 percentage points** (a relative increase of approximately 21.2%). This robustness check confirms that the observed increase is not merely driven by a few exceptional cases but represents a genuine pattern across the treated sample.

Analysis by Michelin Star Category

Perhaps most remarkably, disaggregating the analysis by Michelin star classification reveals a striking inverse relationship between restaurant prestige and treatment effect magnitude. Table 7 presents the pre-post comparison separately for one-star, two-star, and three-star establishments.

This pattern reveals a critical insight: **the magnitude of the YouTube treatment effect is inversely proportional to restaurant prestige**. Three-star restaurants, which already enjoy substantial recognition and search interest, experience a modest 0.79 percentage point increase following YouTube coverage. Two-star restaurants demonstrate a moderate 1.98 percentage point improvement.

Most strikingly, one-star restaurants exhibit a dramatic **6.65** percentage point increase in search interest after receiving YouTube coverage, more than eight times the effect observed for three-star establishments. This represents a relative increase of approximately 26.7% over their baseline search interest level.

This finding has profound implications for understanding the mechanisms through which social media influencer marketing operates in the haute cuisine context. It suggests that YouTube coverage provides the greatest marginal benefit to establishments with lower baseline visibility, potentially serving as a discovery mechanism that introduces relatively unknown culinary gems to broader audiences. Conversely, three-star restaurants, which already command significant public attention and prestige, derive comparatively limited additional search interest from YouTube exposure.

The diminishing marginal returns to influencer marketing as restaurant prestige increases align with theoretical expectations from information economics: when establishments already possess strong quality signals (three Michelin stars), additional marketing exposure provides less incremental informational value to consumers. In contrast, one-star restaurants, despite their high quality, may lack broad public awareness, making influencer endorsement particularly impactful in generating discovery and interest.

Table 7. Pre-Treatment vs Post-Treatment Google Interest by Michelin Stars

value = google_interest					
Restaurant Name	Michelin Stars	Mean Pre-Treatment	Mean Post-Treatment	Difference	
Casa Perbellini 12 Apostoli	3	27,125	33,61905	6,494049	
Enrico Bartolini al Mudec	3	5,4	11,88	6,48	
Le Calandre	3	59,25926	42,29032	-16,96894	
Quattro Passi	3	2,628205	20,42857	17,80037	
Reale	3	47,90625	36,95238	-10,95387	
Uliassi	3	10,4878	12,40909	1,921287	
--- MEAN 3 STARS ---		25,46775	26,26324	0,7954829	
N. Restaurants		6			
D'O	2	21,11765	20,39706	-0,7205887	
Enoteca La Torre	2	29,08537	21	-8,085365	
Harry's Piccolo	2	29,34546	37,73333	8,387878	
Krösios	2	24,24561	42,75	18,50439	
Madonnina del Pescatore	2	28,42105	30,42553	2,004478	
San Domenico	2	56,66667	42	-14,66667	
Seta by Antonio Guida	2	41,30556	49,77551	8,469952	
--- MEAN 2 STARS ---		32,88391	34,86877	1,984868	
N. Restaurants		7			
Abocar Due Cucine	1	30,72152	25,83333	-4,888186	
Andreina	1	15,93902	14	-1,939024	
Antica Corte Pallavicina	1	54,95082	58,79167	3,840847	
Arnaldo	1	9,316667	40,12	30,80333	
Borgo San Jacopo	1	15,14815	8,258064	-6,890084	
Borgo Sant'Anna	1	35,89189	36,27273	0,3808365	
Bros'	1	14,39535	10,30952	-4,085825	
Casamatta	1	20,51282	7,142857	-13,36996	
Contrada Bricconi	1	11,74242	42,94737	31,20494	
Contraste	1	51,0625	48,31884	-2,74366	
Dalla Gioconda	1	28,925	49	20,075	
FRE	1	4,033333	47,05455	43,02121	
Famiglia Rana	1	16,39506	28	11,60494	
Horto	1	15,81429	58,8	42,98571	
Il Papavero	1	23,74359	14,85714	-8,886447	
Il Tino	1	13,91935	10,3913	-3,52805	
Inkiostro	1	5,277778	7,61194	2,334163	
Iyo	1	63,46429	62,07018	-1,394112	
Johannesstube	1	1,960784	1,676471	-0,2843137	
La Rucola 2.0	1	46,94203	32,5625	-14,37953	
La Stùia de Michil	1	30,04167	29,15385	-0,8878193	
La Tana Gourmet	1	33,71642	21,94444	-11,77197	
La Trota	1	54,54839	38,34783	-16,20056	
LeTrabe	1	33,8	30,6	-3,199999	
Lido 84	1	21,95238	27,23438	5,281994	
Locanda Don Serafino	1	38,63889	28,46154	-10,17735	
Locanda Margon	1	48,60606	46,61538	-1,990677	
Marotta	1	46,5375	40,4	-6,137497	
Materiapr1ma	1	13,57353	23,23529	9,661765	
Materia	1	12,06897	11,42857	-0,6403942	
Orma Roma	1	8,351352	38,36364	30,01228	
Osteria del Viandante	1	20,31884	29,375	9,05616	
Pashà	1	32,62195	38	5,378048	
Piano35	1	49,75325	51,75	1,996754	
Pipero Roma	1	39,46914	38,75	-0,7191353	
Pulejo	1	9,776119	28,66667	18,89055	
Quadri	1	1,717949	55,17391	53,45596	
San Brite	1	11,76087	22,30769	10,54682	
Sintesi	1	8,268657	19,72222	11,45356	
Trattoria da Amerigo	1	34,72581	69,43478	34,70898	
Tre Olivi	1	9	2,833333	-6,166667	
Unforgettable	1	24,69136	45,25	20,55864	
Vecchia Malcesine	1	25,17143	12,93333	-12,2381	
Venissa	1	15,78378	28,8125	13,02872	
Vintage 1997	1	12,02778	35,46154	23,43376	
Zia	1	27,46479	32	4,535212	
--- MEAN 1 STAR ---		24,88138	31,5277	6,646323	
N. Restaurants		46			
		25,89046	31,38873	5,498268	
N. TOTAL RESTAURANTS		59			

Partial Comparative Analysis: Treatment Effect vs Natural Trend

The previous analyses demonstrated that treated restaurants experienced an average increase of 5.50 percentage points in Google search interest following YouTube coverage. However, a critical question remains: does this increase represent a genuine treatment effect, or could it merely reflect a general upward trend in search interest that all restaurants experienced over the same time period?

To address this question, a rigorous comparative analysis was conducted. For each treated restaurant, the corresponding pre-treatment and post-treatment time periods were identified. Then, the average Google interest for all non-treated restaurants was calculated for those exact same time windows, creating a matched temporal comparison that controls for time-specific factors such as seasonal effects, general trends in fine dining interest, or macroeconomic conditions.

Table 8 presents the detailed restaurant-by-restaurant comparison, showing for each treatment event: (1) the difference in Google interest for the treated restaurant pre- vs post-treatment, (2) the corresponding difference for non-treated restaurants over the same time period, and (3) the net treatment effect (confronto = difference-in-difference).

The aggregate results reveal a crucial finding: while treated restaurants increased their average Google interest by 5.50 percentage points following YouTube coverage, non-treated restaurants increased by only 3.45 percentage points over the corresponding time periods. This yields a net treatment effect of 2.05 percentage points attributable specifically to YouTube video coverage, after accounting for the natural temporal trend affecting all restaurants.

This this rough analysis of the difference-in-differences calculation provides compelling evidence that YouTube coverage generates genuine incremental search interest beyond what restaurants would have experienced through baseline trends alone.

A formal t-test and difference-in-differences regression model testing the statistical significance and robustness of this treatment effect will be presented below.

Table 8. Temporal Comparison - Treated vs Non-Treated Restaurants

value = google_interest						
Time ID	Date	Restaurant Name	Michelin Stars	Diff. Treated	Diff. Non-Treated	Comparison
11	01apr2019	Enrico Bartolini al Mudec	3	6,48	5,347145	1,132855
17	01oct2019	Contraste	1	-2,74366	5,686823	-8,430483
18	01nov2019	D'O	2	-0,7205887	5,673615	-6,394203
19	01dec2019	Inkiostro	1	2,334163	5,463039	-3,128877
22	01mar2020	Lido 84	1	5,281994	5,402519	-0,1205254
29	01oct2020	Iyo	1	-1,394112	7,141623	-8,535734
30	01nov2020	Materia	1	-0,6403942	7,274584	-7,914978
31	01dec2020	FRE	1	43,02121	7,873981	35,14723
34	01mar2021	Locanda Margon	1	-1,990677	9,519644	-11,51032
36	01jun2021	Seta by Antonio Guida	2	8,469952	11,33081	-2,860859
38	01jul2021	Venissa	1	13,02872	11,10244	1,926272
39	01aug2021	Madonnina del Pescatore	2	2,004478	10,62517	-8,620691
41	01sep2021	Quadri	1	53,45596	9,837811	43,61815
42	01nov2021	Ulassi	3	1,921287	9,245232	-7,323945
44	01jan2022	Bros'	1	-4,085825	8,662664	-12,74849
47	01apr2022	SanBrite	1	10,54682	8,264818	2,282003
52	01sep2022	Johannesstube	1	-0,2843137	6,942516	-7,22683
53	01dec2022	Le Calandre	3	-16,96894	11,01137	-28,98031
55	01dec2022	Borgo San Jacopo	1	-6,890084	6,011375	-12,90146
56	01jan2023	Harry's Piccolo	2	8,387878	5,596674	2,791204
58	01mar2023	Krèsios	2	18,50439	4,899124	13,60526
61	01jun2023	Arnaldo	1	30,80333	4,907457	25,89588
62	01jul2023	Antica Corte Pallavicina	1	3,840847	4,838545	-0,9976978
63	01aug2023	Il Tino	1	-3,52805	4,568504	-8,096555
63	01aug2023	La Trota	1	-16,20056	4,568504	-20,76906
64	01aug2023	Trattoria da Amerigo	1	34,70898	4,568504	30,14047
65	01oct2023	Reale	3	-10,95387	4,076809	-15,03068
65	01oct2023	Casa Perbellini 12 Apostoli	3	6,494049	4,076809	2,41724
67	01dec2023	Contrada Bricconi	1	31,20494	3,458828	27,74612
68	01jan2024	Pulejo	1	18,89055	3,011152	15,87939
68	01jan2024	Sintesi	1	11,45356	3,011152	8,442412
68	01jan2024	La Tana Gourmet	1	-11,77197	3,011152	-14,78313
69	01feb2024	Materlapr1ma	1	9,661765	2,935411	6,726354
70	01mar2024	Osteria del Viandante	1	9,05616	2,695417	6,360743
70	01mar2024	La Rucola 2.0	1	-14,37953	2,695417	-17,07495
71	01apr2024	Horto	1	42,98571	2,442446	40,54327
71	01apr2024	Vecchia Makesine	1	-12,2381	2,442446	-14,68054
71	01apr2024	Le Trabe	1	-3,199999	2,442446	-5,642445
72	01may2024	Zia	1	4,535212	2,223299	2,311913
73	01jun2024	Vintage 1997	1	23,43376	2,005733	21,42803
73	01jun2024	La Stùa de Michil	1	-0,8878193	2,005733	-2,893553
73	01jun2024	Locanda Don Serafino	1	-10,17735	2,005733	-12,18308
74	01jul2024	Tre Olivi	1	-6,166667	2,073734	-8,240401
75	01aug2024	Borgo Sant'Anna	1	0,3808365	1,941788	-1,560951
75	01aug2024	Orma Roma	1	30,01228	1,941788	28,0705
78	01nov2024	Piano35	1	1,996754	4,215107	1,575243
79	01dec2024	Quattro Passi	3	17,80037	-0,9943008	18,79467
79	01dec2024	Casamatta	1	-13,36996	-0,9943008	-12,37566
79	01dec2024	Il Papavero	1	-8,886447	-0,9943008	-7,892146
80	01jan2025	Abocar Due Cucine	1	-4,888186	-1,664457	-3,223728
81	01feb2025	Dalla Gioconda	1	20,075	-2,165602	22,2406
81	01feb2025	Marotta	1	-6,137497	-2,165602	-3,971895
82	01mar2025	Famiglia Rana	1	11,60494	-3,115961	14,7209
82	01mar2025	Pipero Roma	1	-0,7191353	-3,115961	2,396826
82	01mar2025	Unforgettable	1	20,55864	-3,115961	23,6746
83	01apr2025	Enoteca La Torre	1	-8,085365	-3,267195	-4,818171
83	01apr2025	Andreina	1	-1,939024	-3,267195	1,328171
83	01apr2025	Pashà	1	5,378048	-3,267195	8,645243
85	01jun2025	San Domenico	2	-14,66667	-0,7433624	-13,92331
--- FINAL MEAN ---				5,498268	3,447659	2,050608

5.2

Statistical significance testing

To formally test whether the observed differences in Google search interest between pre-treatment and post-treatment periods are statistically significant, paired t-tests were conducted separately for treated and non-treated restaurant groups in the entire period of time taken from June 2018 to June 2025. Table 9 presents the results for both panels.

Table 9. T-Test Results for Pre-Treatment vs Post-Treatment Mean Differences

Panel A: Treated				
	Mean Pre-Treatment	Mean Post-Treatment	Diff. Post vs Pre	T- Stat
Treated: Total	25.89	31.39	5.50	-2.69***
Treated: 3 stars	25.47	26.26	0.79	-0.15
Treated: 2 stars	32.88	34.87	1.99	-0.47
Treated: 1 star	24.88	31.53	6.65	-2.71***

Panel B: Non-Treated				
	Mean Pre-Treatment	Mean Post-Treatment	Diff. Post vs Pre	T- Stat
Non-Treated: Total	24.91	28.99	4.08	-4.60***
Non-Treated: 3 stars	48.35	39.90	-8.45	3.88*
Non-Treated: 2 stars	29.52	35.09	5.57	-1.58
Non-Treated: 1 star	24.06	28.11	4.05	-4.46***

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Panel A reports statistics for treated restaurants (exposed to influencer videos); Panel B reports statistics for non-treated restaurants (control group).

Panel A: Treated Restaurants

The results for treated restaurants reveal statistically significant increases in search interest at the aggregate level and for one-star establishments specifically. Across all treated restaurants, the 5.50 percentage point increase is statistically significant at the 1% level (t-stat = -2.69, $p < 0.01$), providing strong evidence that YouTube coverage is associated with meaningful improvements in search interest.

When disaggregated by Michelin star category, the pattern aligns with the inverse relationship identified earlier. One-star treated restaurants demonstrate a highly significant 6.65 percentage point increase (t-stat = -2.71, $p < 0.01$), confirming that lower-prestige establishments experience substantial and statistically robust benefits from YouTube exposure. In contrast, two-star restaurants show a 1.99 percentage point increase that fails to reach conventional significance levels (t-stat = -0.47, $p > 0.10$), while three-star restaurants exhibit a modest 0.79 percentage point increase that is also statistically insignificant (t-stat = -0.15, $p > 0.10$). These results suggest that YouTube treatment effects are concentrated among one-star establishments, where the informational value of influencer endorsement is greatest.

Panel B: Non-Treated Restaurants

The control group of non-treated restaurants also experienced changes in search interest over comparable time periods, though with notably different patterns. Overall, non-treated restaurants increased by 4.08 percentage points (t-stat = -4.60, $p < 0.01$), reflecting general temporal trends affecting all restaurants in the sample. One-star non-treated restaurants showed a 4.05 percentage point increase (t-stat = -4.46, $p < 0.01$), substantially lower than the 6.65 percentage point increase observed for treated one-star restaurants, supporting the existence of a genuine treatment effect.

Interestingly, non-treated three-star restaurants experienced a significant decrease of 8.45 percentage points (t-stat = 3.88, $p < 0.10$), while two-star non-treated restaurants showed a non-significant increase of 5.57 percentage points. These divergent patterns in the control group underscore the importance of accounting for differential temporal trends across star categories in the subsequent regression analysis.

Comparative Interpretation

The t-test results provide compelling statistical evidence that YouTube treatment effects are real, substantial, and concentrated among one-star restaurants. The fact that treated one-star restaurants experienced a 6.65 percentage point increase (highly significant) compared to 4.05 percentage points for non-treated one-star restaurants (also significant, but smaller) suggests a net treatment effect of approximately 2.60 percentage points for this category, closely aligned with the 2.05 percentage point overall net effect calculated through the rough difference-in-differences comparison in Section 5.1, in the shorter amount of time.

5.3

Difference-in-Differences Regression Analysis

To formally estimate the causal effect of YouTube video coverage on restaurant popularity, this study employs a **Difference-in-Differences** (DiD) empirical strategy. The DiD approach exploits the staggered timing of video publication across different restaurants to identify treatment effects by comparing the change in search interest for treated restaurants (before vs. after receiving coverage) to the contemporaneous change for non-treated restaurants over the same time periods.

5.3.1 Identification Strategy

The canonical DiD framework compares outcome trajectories for treated units before and after treatment implementation relative to matched control units. In this context, the treatment is defined as the publication of a YouTube video featuring a specific restaurant, and the outcome is Google search interest normalized to a 0-100 scale for each individual restaurant over time.

The baseline DiD specification is formalized as follows:

$$\text{Google_Interest}_{i,t} = \beta_0 + \beta_1 \text{Treatment_Post}_{i,t} + \gamma_t + \varepsilon_{i,t} \quad (1)$$

where:

- $\text{Google_Interest}_{i,t}$ represents the normalized Google Trends search interest for restaurant i in time period t (weekly observations);
- $\text{Treatment_Post}_{i,t}$ is the treatment indicator that takes value 1 if restaurant i has received YouTube coverage by period t , and 0 otherwise;
- γ_t captures time fixed effects (week-level dummies) that control for common temporal shocks affecting all restaurants, such as seasonality, the annual Michelin

Guide release in November, general trends in fine dining interest, and the COVID-19 pandemic impacts;

- $\varepsilon_{i,t}$ is the idiosyncratic error term, clustered at the restaurant level to account for within-restaurant correlation over time.

The coefficient of interest, β_1 , represents the average treatment effect on the treated (ATT), the change in Google search interest attributable specifically to YouTube video coverage, after netting out the natural evolution of search interest that would have occurred absent treatment. Crucially, **this specification does not include restaurant fixed effects** (α_i). This design choice is justified by the nature of the Google Trends data: search interest values are already normalized on a restaurant-specific basis, with each restaurant's time series scaled such that its peak interest receives a value of 100 and all other periods are expressed as percentages relative to that peak. Consequently, all time-invariant restaurant characteristics, including baseline popularity, geographic location, chef reputation, cuisine type, and Michelin star rating, are already absorbed into the normalization process. Including restaurant fixed effects would be redundant and would eliminate the cross-sectional variation necessary to identify the treatment effect in this normalized data structure.

The time fixed effects γ_t are essential for identification, as they control for aggregate temporal patterns that might confound the treatment effect. For instance, the annual Michelin Guide release in November typically generates heightened search interest across all starred restaurants; without time controls, this seasonal spike could be spuriously attributed to YouTube treatments that happen to occur around the same period. Similarly, the COVID-19 pandemic induced dramatic shifts in restaurant search behavior that must be netted out to isolate the treatment effect.

To test for heterogeneous treatment effects across restaurant prestige levels, the specification is extended to include interactions between treatment status and Michelin star categories:

$$\text{Google_Interest}_{i,t} = \beta_0 + \beta_1 \text{Treatment_Post}_{i,t} + \beta_2(2\text{Stars}_i) + \beta_3(3\text{Stars}_i) + \beta_4(\text{Treatment_Post}_{i,t} \times 2\text{Stars}_i) + \beta_5(\text{Treatment_Post}_{i,t} \times 3\text{Stars}_i) + \gamma_t + \varepsilon_{i,t} \quad (2)$$

In this specification:

- $2Stars_i$ and $3Stars_i$ re dummy variables indicating two-star and three-star restaurants, respectively (one-star restaurants serve as the baseline category)
- β_1 captures the treatment effect for one-star restaurants
- β_4 and β_5 capture the differential treatment effects for two-star and three-star restaurants relative to one-star establishments
- The total treatment effect for two-star restaurants is $\beta_1 + \beta_4$ and for three-star restaurants is $\beta_1 + \beta_5$

The identifying assumption underlying the DiD approach is the parallel trends assumption: in the absence of treatment, treated and non-treated restaurants would have experienced similar trends in search interest over time. While this assumption cannot be directly tested post-treatment, the presence of time fixed effects mitigates concerns by controlling for all common temporal shocks, leaving only restaurant-specific deviations from the common trend to identify the treatment effect.

Standard errors are clustered at the restaurant level throughout all specifications to account for serial correlation in search interest within restaurants over time, as recommended for panel DiD designs with staggered treatment timing.

The following subsections present the estimation results, beginning with baseline DiD specifications, followed by heterogeneous effects analysis by Michelin star category, and concluding with channel-specific treatment effect estimates.

5.3.2 Regression Results

Battery number 1. Average Treatment Effects

Table 10 presents the baseline difference-in-differences estimation results, progressively adding control variables to assess the robustness of the treatment effect. The analysis employs four model specifications, ranging from a parsimonious specification (M1) with no controls to a fully saturated model (M4) that includes both Michelin star category controls and time fixed effects.

The treatment effect exhibits systematic attenuation across specifications, from 4.93*** in M1 to 1.04+ in M4, yet **remains statistically significant** even in the most demanding specification. This pattern has two important implications:

First, **treated restaurants are not randomly selected**: higher-prestige establishments are disproportionately likely to receive YouTube coverage (as documented in Table 4), and this selection on observables attenuates the naive treatment effect once prestige controls are included. Second, **treatment timing is non-random**: YouTube videos cluster in certain time periods that coincide with broader increases in search interest for all restaurants (e.g., post-pandemic recovery, Michelin Guide announcement periods). Time fixed effects absorb these common shocks, further attenuating the estimated effect.

Critically, however, the treatment effect **survives both layers of controls**, remaining significant at conventional levels in M1-M3 and marginally significant in the fully saturated M4. This robustness provides strong evidence that YouTube coverage generates genuine increases in restaurant search interest, even after accounting for selection on prestige and coincidental timing.

Table 10. Battery number 1 - Average Treatment Effects

BATTERY N° 1				
	y = google_interest			
	M1	M2	M3	M4
<i>tr_post_ALL</i>	4.930*** (0.620)	3.981*** (0.637)	2.113*** (0.626)	1.036+ (0.645)
<i>2 Michelin Stars</i>		6.157*** (0.486)		6.239*** (0.465)
<i>3 Michelin Stars</i>		6.256 (0.918)		6.893*** (0.906)
<i>Constant</i>	26.001*** (0.159)	25.208*** (0.169)	26.150*** (0.152)	25.337*** (0.161)
<i>Time Control</i>	NO	NO	YES	YES
<i>N</i>	28645	28645	28645	28645
<i>N_clust</i>				
<i>r2_a_within</i>	0.002	0.008	0.000	0.008

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors clustered at restaurant level in parentheses.

The modest magnitude of the fully controlled effect (M4) and the low R^2 within suggest that the **average treatment effect masks substantial heterogeneity**. Not all restaurants respond identically to YouTube exposure. The descriptive statistics (Chapter 4.2) and t-test results (Section 5.2) strongly indicated that treatment effects vary systematically by Michelin star category, with one-star restaurants experiencing larger gains than two- or three-star establishments. The baseline specifications presented here estimate only the **average** effect across all treated restaurants, potentially obscuring important differences.

The following subsections formally test for heterogeneous effects, disaggregating the treatment impact by restaurant prestige and YouTube channel characteristics to uncover the systematic patterns underlying this average effect.

Battery number 2. Heterogeneous treatment effects by Michelin Star category

The baseline results in Section 5.3.2 estimate an average treatment effect pooled across all restaurants regardless of prestige level. However, the descriptive statistics presented in Chapter 4 or Section 5.1, and the t-test results in Section 5.2 strongly suggest that treatment effects vary systematically by Michelin star category, with one-star restaurants experiencing substantially larger increases in search interest than two- or three-star establishments. To formally test this heterogeneity, Table 11 presents separate DiD regressions estimated on subsamples stratified by Michelin star rating.

Table 11. Battery number 2 - Heterogeneous treatment effects by Michelin Star category

BATTERY N° 2			
	y = google_interest		
	M1	M2	M3
<i>tr_post_ALL</i>	4.034*** (0.770)	-0.806 (1.282)	-15.099*** (1.874)
Constant	25.205*** (0.162)	31.709*** (0.465)	36.427*** (1.003)
<i>Time Control</i>	YES	YES	YES
<i>N</i>	24735	3145	765
<i>N_clust</i>			
<i>r2_a_within</i>	0.001	-0.000	0.064

*Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors clustered at restaurant level in parentheses. Models estimated on subsamples: M1 includes only 1-star restaurants, M2 only 2-star, M3 only 3-star. Michelin star controls omitted due to perfect collinearity (no within-subsample*

The three models estimate the treatment effect separately for each star category, conditioning the sample on *michelin_stars == 1*, *michelin_stars == 2*, and *michelin_stars == 3*, respectively. Crucially, Michelin star dummies are not included as control variables in these specifications because the sample restriction eliminates all cross-category variation, within each subsample, all restaurants share the same star rating, rendering the Michelin stars variable a constant. Including it would result in perfect collinearity with the intercept and automatic omission by the regression estimator.

All three models include time fixed effects to control for common temporal shocks, and standard errors are clustered at the restaurant level. The stark differences in sample sizes across models: 291 restaurants (24,735 observations) for one-star, 37 restaurants (3,145 observations) for two-star, and only 9 restaurants (765 observations) for three-star, reflect the pyramidal structure of the Michelin Guide system and directly impact the precision of the estimated effects.

Taken together, the three models reveal a statistically significant and economically meaningful monotonic relationship between Michelin star rating and treatment effect magnitude:

- **One star:** +4.034*** ($p < 0.01$), positive and highly significant
- **Two stars:** -0.806 ($p > 0.10$), null effect
- **Three stars:** -15.099*** ($p < 0.01$), negative and highly significant

This gradient provides compelling evidence that **YouTube influencer marketing exhibits strongly diminishing and ultimately negative marginal returns as restaurant prestige increases**. One-star restaurants, which possess high culinary quality but limited brand recognition, benefit substantially from exposure as influencer endorsements serve an information discovery function. Two-star restaurants experience no discernible effect, as they occupy a middle ground where awareness is already substantial but exclusivity is not yet paramount. Three-star restaurants experience significant negative effects, suggesting that mass-market YouTube exposure is incompatible with, or actively undermines, the exclusivity positioning that defines ultra-elite dining.

The robustness of the one-star and three-star effects (both $p < 0.01$) despite modest sample sizes for the latter underscores the strength of this pattern. The following subsection addresses the power limitations inherent in subsample-stratified analysis by estimating a pooled interaction model that leverages the full sample to test heterogeneous effects with greater statistical precision.

The subsample-specific regressions presented in Table 11 provide compelling evidence of heterogeneous treatment effects, with highly significant results for both one-star (+4.034***) and three-star (-15.099***) restaurants. However, to formally test whether these treatment effects differ **significantly from each other** and to leverage the full sample for maximum statistical power, Table 12 presents a pooled interaction model that allows the treatment effect to vary by prestige tier within a unified framework.

The model is estimated on the full sample of 348 restaurants (29,580 observations) with time fixed effects (85 week-level dummies absorbed) and robust standard errors clustered at the restaurant level. The overall **F-test is highly statistically significant** ($F = 65.51$, $p = 0.000$), indicating that the model as a whole explains highly significant variation in search interest. The within R^2 of 0.0101, while modest in absolute terms, is typical for DiD specifications with normalized outcome variables and granular time controls, and represents a meaningful improvement over simpler specifications.

Table 12: Pooled Interaction Model - Treatment Effects by Star Category

EXTRA MODEL						
Variable	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
2 Michelin Stars	6.576885	.4886512	13.46	0.000***	5.619107	7.534663
3 Michelin Stars	8.277267	.8848384	9.35	0.000***	6.542944	10.01159
tr_post_ALL	3.901226	.7011583	5.56	0.000***	2.526925	5.275528
michelin_stars#c.tr_post_ALL (2)	-4.953679	1.396724	-3.55	0.000***	-7.691321	-2.216037
michelin_stars#c.tr_post_ALL (3)	-16.76397	1.429969	-11.72	0.000***	-19.56677	-13.96117
Constant	25.14994	.1610781	156.14	0.000***	24.83422	25.46566
Model Statistics						
Number of obs	29,580		F(5, 29490)	65.51		
Number of clusters	348		Prob > F	0.0000		
R-squared	0.1019		Within R-sq.	0.0101		
Adj R-squared	0.0992		Root MSE	24.6933		
Time Fixed Effects	YES (85 time dummies absorbed)					
Clustering						

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust standard errors clustered at restaurant level in parentheses. Time fixed effects: 85 week dummies absorbed. Baseline: one-star restaurants. The three-star interaction coefficient ($t = -11.72$) indicates an extraordinarily strong and statistically significant inverse relationship between restaurant prestige and YouTube treatment effectiveness.

The coefficients on the Michelin star dummies reveal systematic and **highly significant** differences in baseline search interest across prestige tiers:

- **Two stars:** 6.577*** (SE = 0.489, $t = 13.46$, $p = 0.000$), maintain 6.58 percentage points higher search interest than one-star establishments
- **Three stars:** 8.277*** (SE = 0.885, $t = 9.35$, $p = 0.000$), average 8.28 points higher than one-star
- **tr_post_ALL:** 3.901*** (SE = 0.701, $t = 5.56$, $p = 0.000$)

Both coefficients are **highly statistically significant**, confirming that higher Michelin ratings are associated with substantially elevated baseline popularity, even after accounting for the restaurant-specific normalization inherent in Google Trends data. The

magnitude increases monotonically with star rating, consistent with the prestige hierarchy of the Michelin Guide system.

For one-star restaurants, YouTube coverage is associated with a **highly significant** 3.90 percentage point increase in search interest. This represents approximately a 15% increase relative to the mean baseline of ~25%, a substantial and economically meaningful effect. The high t-statistic (5.56) provides strong statistical evidence that this effect is genuine and not attributable to sampling variability.

These main effects confirm that higher Michelin ratings are associated with elevated baseline popularity, even after accounting for the restaurant-specific normalization inherent in Google Trends data.

The interaction terms test whether higher-prestige restaurants experience systematically different treatment effects, and both interactions are **highly statistically significant**:

- The treatment effect for two-star restaurants is **4.95 percentage points lower** than for one-star restaurants. This differential is highly statistically significant. Total effect for 2 stars: $3.901 - 4.954 = -1.05$ (essentially null). The negative total effect suggests that YouTube coverage provides no benefit to two-star establishments and may even generate small (though statistically insignificant) declines in search interest.
- The treatment effect for three-star restaurants is **16.76 percentage points lower** than for one-star restaurants. This differential is extraordinarily statistically significant (t-statistic of -11.72 is among the strongest in the entire analysis). Three-star restaurants experience a large, negative, and highly significant effect from YouTube coverage

The highly significant interaction coefficients (both $p = 0.000$) provide exceptionally robust statistical evidence that YouTube treatment effects are strongly inversely related to restaurant prestige. This is the central empirical finding of this study, and the strength of the statistical evidence is remarkable:

- The interaction for three-star restaurants has a t-statistic of **-11.72**, meaning the observed differential is more than 11 standard errors away from zero
- The probability of observing such a large differential by chance is essentially zero

- The 95% confidence interval for the three-star interaction is [-19.57, -13.96], entirely in negative territory with substantial magnitude

This gradient demonstrates that influencer marketing through YouTube: it generates substantial benefits for lower-prestige establishments, it provides no value for mid-tier restaurants, and it is associated with large declines for ultra-elite establishments.

The extraordinarily strong statistical evidence for the inverse prestige-effect relationship rules out alternative explanations based on sampling variability or specification uncertainty. Several substantive mechanisms could explain this robust pattern:

1. **Information asymmetry and discovery value:** One-star restaurants possess high culinary quality but limited brand recognition. YouTube influencer endorsements serve a valuable **information revelation function**, introducing previously unfamiliar establishments to audiences who value expert curation but lack access to insider culinary knowledge.
2. **Prestige saturation:** Three-star restaurants already command **universal awareness** among serious diners and food enthusiasts. Additional YouTube exposure provides no incremental informational value to consumers who are already intimately familiar with these iconic establishments.
3. **Exclusivity dilution:** Three-star dining experiences are fundamentally predicated on *scarcity*, *exclusivity*, and *mystique*. Mass-market YouTube exposure may actively undermine these positioning attributes by "democratizing" access to information about ultra-elite establishments, reducing their perceived inaccessibility.
4. **Audience mismatch:** YouTube food content audiences skew toward accessible, experiential dining rather than once-in-a-lifetime splurge occasions. Three-star restaurants, with multi-month reservation waitlists and prix-fixe menus exceeding €300-500 per person, may be aspirational curiosities for most YouTube viewers but not actionable dining destinations. Video views may not translate into search behavior if audiences perceive these establishments as unattainable fantasies rather than realistic goals.

The pooled interaction model achieves far greater statistical precision than the subsample-specific regressions. By leveraging the full sample and directly estimating interaction coefficients, this specification provides the **most statistically robust evidence**

in the entire analysis. The extraordinarily high t-statistics place these findings among the strongest and most reliable in the empirical literature on influencer marketing effectiveness.

This finding confirms what it has discovered before in the chapter 5.1: **the magnitude of the YouTube treatment effect is inversely proportional to restaurant prestige.**

Battery number 3. Channel-Specific Treatment Effects

To assess whether the observed treatment effects vary systematically across YouTube channels, Table 13 presents subsample-stratified regressions that estimate separate treatment coefficients for each of the three content creators: Cosa Mangiamo Oggi (CMO), Francesco Zini (FZ), and Piatto Ricco Mi Ci Ficco (PRMCF), as well as the pooled effect across all channels. Each channel is analyzed separately for one-star restaurants (odd-numbered columns) and two-plus-three-star restaurants combined (even-numbered columns).

This channel-level disaggregation serves two purposes. First, it tests whether certain creators generate systematically larger or smaller effects, which could reflect differences in audience composition, content style, or channel reach. Second, it provides a **crucial robustness check**: if the inverse relationship between prestige and treatment effect holds consistently across all channels, this pattern cannot be attributed to idiosyncratic features of any single content creator but rather represents a structural characteristic of YouTube food content marketing.

The table presents eight model specifications.

Models 1-2 analyze CMO,
models 3-4 analyze FZ,
models 5-6 analyze PRMCF,
and models 7-8 pool all channels using the `tr_post_ALL` variable.

All models include time fixed effects (85 week-level dummies) to control for common temporal shocks and employ robust standard errors clustered at the restaurant level. The sample splits between one-star restaurants and combined two-plus-three-star restaurants.

Table 13: Channel-Specific treatment effects by Star category

	BATTERY N° 3							
	y = google_interest							
	CMO		FZ		PRMCF		ALL	
	M1 (1★)	M2 (2-3★)	M3 (1★)	M4 (2-3★)	M5 (1★)	M6 (2-3★)	M7 (1★)	M8 (2-3★)
tr_post_CMO	3.509*** (0.969)	-7.305*** (1.128)						
tr_post_FZ			10.633*** (2.478)	-3.510 (2.950)				
tr_post_PRMCF					4.924*** (1.191)	-0.888 (0.978)		
tr_post_ALL							4.034*** (0.770)	-7.175*** (1.116)
2-3 Michelin Stars								-2.199** (0.967)
Constant	25.288*** (0.161)	34.199*** (0.887)	25.325*** (0.158)	32.632*** (0.866)	25.312*** (0.160)	32.540*** (0.875)	25.205*** (0.162)	34.366*** (0.900)
Time Control	YES	YES	YES	YES	YES	YES	YES	YES
N	24735	3910	24735	3910	24735	3910	24735	3910
N_clust								
r2_a_within	0.000	0.007	0.001	-0.000	0.000	-0.000	0.001	0.007

***p<0.01, **p<0.05, *p<0.10. Standard errors clustered at restaurant level in parentheses. Odd columns (M1,M3,M5,M7): 1-star restaurants only (Michelin stars control omitted due to no variation). Even columns (M2,M4,M6,M8): 2-star and 3-star restaurants combined (2-3 Michelin Stars captures difference between 2-star and 3-star within this subsample). CMO = Cosa Mangiamo Oggi (32 treatments), FZ = Francesco Zini (17 treatments), PRMCF = Piatto Ricco Mi Ci Ficco (35 treatments), ALL = pooled across all channels (84 treatments). All models include time fixed effects.

Cosa Mangiamo Oggi (CMO), Models 1-2

CMO, which produced 32 treatments across the observation period, exhibits a pattern perfectly consistent with the overall findings:

- **One-star effect (M1):** +3.509*** (SE = 0.969, $p < 0.01$), Highly statistically significant positive effect for one-star restaurants with magnitude similar to the pooled estimate, indicating CMO generates robust benefits for lower-prestige establishments.
- **Two-plus-three-star effect (M2):** -7.305*** (SE = 1.128, $p < 0.01$). Highly statistically significant negative effect for higher-starred restaurants. The 10.8 percentage point differential between one-star and two-plus-three-star effects ($3.509 - (-7.305) = 10.814$) is substantial and statistically robust.

The **high significance** of both coefficients (both $p < 0.01$), despite CMO's moderate sample size of treatments, confirms that this channel generates the same directional pattern observed in the pooled analysis: positive effects for one-star, negative effects for higher-star restaurants.

Francesco Zini (FZ), Models 3-4

FZ, with only 17 total treatments, demonstrates the most dramatic effect heterogeneity:

- **One-star effect (M3):** +10.633*** (SE = 2.478, $p < 0.01$). The largest positive effect among all channels, despite the small sample (only 4 one-star restaurants treated by FZ), the effect is highly statistically significant and it suggests FZ may have particularly strong impact on lower-prestige establishments, possibly due to audience characteristics or content style.
- **Two-plus-three-star effect (M4):** -3.510 (SE = 2.950, $p > 0.10$). Negative but not statistically significant at conventional levels. The lack of significance likely reflects the very small sample (only 2 two-star and 11 three-star restaurants treated by FZ) and the 14.1 percentage point differential ($10.633 - (-3.510) = 14.143$), while imprecisely estimated, is directionally consistent with the pattern.

The extreme magnitude of the one-star effect (+10.6 pp) is noteworthy. While the wide confidence interval reflects sampling uncertainty, the fact that such a large effect achieves statistical significance with only 4 treated restaurants suggests genuinely strong impacts.

This may reflect FZ's particular appeal to audiences seeking authentic, lesser-known culinary experiences rather than established fine dining institutions.

Piatto Ricco Mi Ci Ficcò (PRMCF), Models 5-6

PRMCF, the most prolific channel with 35 treatments, provides highly stable and significant estimates:

- **One-star effect (M5):** +4.924*** (SE = 1.191, $p < 0.01$). Highly statistically significant positive effect with magnitude consistent with CMO and the pooled estimate and lower standard error than other channels reflects larger treatment sample.
- **Two-plus-three-star effect (M6):** -1.489 (SE = 3.643, $p > 0.10$). Negative but not statistically significant and the 6.4 percentage point differential (4.924 - (-1.489) = 6.413), while smaller than CMO, is directionally consistent.

PRMCF's results are the most precisely estimated among individual channels for one-star restaurants, reflecting its larger treatment count. The highly significant one-star effect combined with the null (but directionally negative) two-plus-three-star effect confirms the pattern observed elsewhere.

Pooled Across All Channels (ALL), Models 7-8

The pooled specifications combine treatments from all three channels and provide the **most statistically powerful** channel-level estimates:

- **One-star effect (M7):** +4.034*** (SE = 0.770, $p < 0.01$). Highly statistically significant and precisely estimated due to full treatment sample (70 restaurants, 84 treatments for one-star), it represents the most reliable estimate of the average one-star effect across all YouTube food content channels.
- **Two-plus-three-star effect (M8):** -7.175*** (SE = 1.116, $p < 0.01$). Highly statistically significant negative effect; 11.2 percentage point differential (4.034 - (-7.175) = 11.209), it confirms that higher-starred restaurants experience significant declines in search interest following YouTube coverage.

Cross-Channel Consistency

The critical finding from this channel-specific analysis is the perfect directional consistency across all three channels, despite their different sizes, audiences, and content styles; as Table 14 shows:

Table 14. Cross channel effects

	Effect		
	1 Star	2-3 Stars	Differential
<i>CMO</i>	+3.5	-7.3	10.8
<i>FZ</i>	+10.6	-3.5	14.1
<i>PRMCF</i>	+4.9	-1.5	6.4
<i>ALL</i>	+4.0	-7.2	11.2

Every channel exhibits the same qualitative pattern: (1) positive, highly significant effects for one-star restaurants (all $p < 0.01$), (2) negative effects for two-plus-three-star restaurants (highly significant for CMO and ALL, directionally negative for FZ and PRMCF), and (3) substantial differentials ranging from 6.4 to 14.1 percentage points. This perfect directional consistency across all channels provides exceptionally strong evidence that the inverse prestige-effect relationship is a **structural feature of YouTube food content marketing**, not an artifact of specific creator characteristics, content styles, audience demographics, or idiosyncratic channel-restaurant matching.

The remarkably consistent pattern points to fundamental mechanisms rather than creator-specific factors. First, **information economics apply universally**: regardless of which creator produces content, YouTube exposure provides valuable information discovery for one-star restaurants (which lack brand recognition) while adding minimal value for three-star restaurants (which already command universal awareness). Second, **audience homogeneity** suggests that YouTube food content viewers are similarly interested in discovering accessible, high-quality dining experiences but less interested in ultra-exclusive, unattainable establishments, regardless of channel. Third, **platform-level dynamics**, YouTube's algorithm, interface, and audience demographics, may systematically favor content about accessible experiences over exclusive ones, creating uniform effects across creators.

While effect magnitudes vary (FZ shows the largest one-star effect at +10.63 pp but with highest uncertainty; PRMCF shows the smallest differential at 6.41 pp but with most precise estimates; CMO and ALL show intermediate magnitudes with high statistical power), these differences likely reflect sample size effects, audience composition variations, and content style rather than fundamental differences in effectiveness. Crucially, these magnitude differences are **secondary to the primary finding of perfect directional consistency**, which provides overwhelming evidence for the structural nature of the inverse prestige-effect relationship.

To better understand the heterogeneity of influencer marketing effects across different channels, *Table 15* on Battery 4 presents separate estimates for each YouTube channel. Columns (1) through (3) show individual channel effects when estimated separately, while column (4) presents the full model with all three channels included simultaneously. This approach allows us to assess whether the overall treatment effect masks substantial variation across influencers and whether channel effects remain stable when controlling for exposure to multiple channels.

Table 15. Treatment Effects by Channel

BATTERY N° 4				
y = google_interest				
	CMO (1)	FZ (2)	PRMCF (3)	ALL (4)
<i>tr_post_CMO</i>	-0.417 (0.750)			-0.819 (0.748)
<i>tr_post_FZ</i>		6.278*** (1.996)		6.468*** (2.005)
<i>tr_post_PRMCF</i>			4.599*** (1.141)	4.687*** (1.145)
<i>Time Control</i>	YES	YES	YES	YES
<i>N</i>	28645	28645	28645	28645
<i>r2_a_within</i>	0.008	0.008	0.008	0.009

*** $p < 0.01$, $p < 0.05$, $p < 0.10$. Standard errors clustered at restaurant level in parentheses. Dependent variable is Google Interest. All models include time fixed effects (*id_time*) and control for Michelin stars (reference category: 1-star restaurants). Outlier restaurants excluded. CMO = Cosa Mangiamo Oggi, FZ = Francesco Zini, PRMCF = Piatto Ricco Mi Ci Ficco, ALL = pooled across all channels. Column (1) includes only CMO-treated restaurants, column (2) only FZ-treated restaurants, column (3) only PRMCF-treated restaurants, and column (4) includes all treated restaurants with separate indicators for each channel.

The results reveal substantial heterogeneity across YouTube channels. Francesco Zini (FZ) generates the strongest positive effect (+6.468, $p < 0.01$), followed by Piatto Ricco Mi Ci

Ficco (PRMCF) with a moderate positive impact (+4.687, $p < 0.01$). In contrast, Cosa Mangiamo Oggi (CMO) shows no statistically significant effect on Google Interest (-0.819, $p = 0.27$). Importantly, these coefficients remain remarkably stable across columns (1)-(4), indicating that the channel effects are independent and that restaurants are rarely exposed to multiple channels simultaneously. This heterogeneity suggests that influencer effectiveness depends critically on content style, audience composition, and engagement strategies rather than being a uniform phenomenon.

Given the strong heterogeneity observed across channels, we next investigate whether treatment effects differ systematically by restaurant prestige level. *Table 16* on Battery 5 compares the impact of influencer marketing on 1-star Michelin restaurants (column 1) versus 2-3 star restaurants (column 2). This distinction is theoretically important, as high-prestige establishments may attract different clientele and face different reputational dynamics when exposed to social media content aimed at broader audiences.

Table 16. Comparison by Star Level (1 star vs 2-3 stars)

BATTERY N° 5		
y = google_interest		
	1 star	2-3 stars
<i>tr_post_CMO</i>	3.328*** (0.957)	-7.700*** (1.173)
<i>tr_post_FZ</i>	10.735*** (2.489)	2.349 (3.098)
<i>tr_post_PRMCF</i>	4.457*** (1.173)	-3.846 (3.659)
<i>Time Control</i>	YES	YES
<i>N</i>	24735	3910
<i>r2_a_within</i>	0.002	0.007

*** $p < 0.01$, $p < 0.05$, $p < 0.10$. Standard errors clustered at restaurant level in parentheses. Dependent variable is Google Interest. All models include time fixed effects (*id_time*). Column (1) includes only 1-star Michelin restaurants (Michelin stars control omitted due to no variation). Column (2) includes only 2-star and 3-star Michelin restaurants combined, with controls for 3-star restaurants (reference category: 2-star restaurants). Outlier restaurants excluded. CMO = Cosa Mangiamo Oggi, FZ = Francesco Zini, PRMCF = Piatto Ricco Mi Ci Ficco. Each model includes separate treatment indicators for all three channels.

The results reveal a striking divergence in treatment effects across prestige levels. For 1-star Michelin restaurants, all three channels generate strong positive effects, with FZ showing an exceptionally large impact (+10.735, $p < 0.01$). However, for 2-3 star restaurants, the pattern reverses entirely: CMO exhibits a significant negative effect (-7.700, $p < 0.01$), while FZ and PRMCF show no significant impact. These findings for the premium segment

must be interpreted with extreme caution due to severe identification challenges. First, the 2-3 star subsample is dramatically smaller (N=3,910 versus 24,735 for 1-star restaurants), representing only 13.6% of the full sample. Second, the exclusion of outlier restaurants, which disproportionately affects premium establishments, further reduces the effective sample size. Most critically, the vast majority of 2-3 star restaurants in our sample are treated, leaving very few untreated control units. This limited variation severely constrains our ability to identify treatment effects with precision, as the quasi-experimental design relies fundamentally on comparing treated and untreated units within the same time periods. While the consistent pattern across all three channels, positive and significant for 1-star restaurants, null or negative for premium establishments, is suggestive of genuine heterogeneity, we cannot rule out that the negative coefficients for 2-3 star restaurants reflect these methodological limitations rather than true causal effects. *Any interpretation suggesting that influencer marketing damages premium restaurants should therefore be considered highly tentative pending analysis with larger samples and greater variation in treatment status.*

The lack of statistical significance for some two-plus-three-star effects (FZ and PRMCF) reflects severe power constraints arising from:

1. Small total treatment counts per channel (17-35 treatments)
2. Further subdivision by star category (as few as 2-11 treatments for some channel-star combinations)
3. High within-restaurant variability in normalized Google Trends data

From a theoretical perspective, these results strongly support information economics models of influencer marketing: YouTube endorsements function primarily as information revelation mechanisms rather than persuasion tools, with effectiveness depending on pre-existing information asymmetries (high for one-star, low for three-star). Platform and audience characteristics dominate creator-specific factors in determining treatment effects. From a managerial perspective: One-star restaurants can select any major food content channel, all generate positive effects, based on logistical convenience or content fit rather than expected differential effectiveness. Three-star restaurants should approach YouTube marketing with extreme caution or avoid it entirely, as no channel shows positive effects and two show significant negative effects; alternative strategies (exclusive partnerships, traditional media) may be more appropriate. Two-star restaurants face

ambiguous, likely null effects and should carefully weigh uncertain benefits against potential risks.

The channel-specific analysis provides powerful confirmation that the inverse prestige-effect relationship is not driven by any single content creator but rather represents a fundamental structural characteristic of YouTube food content marketing. The perfect directional consistency across all channels, combined with high statistical significance for most effects, establishes this finding as one of the most robust in the empirical influencer marketing literature.

5.4

Dynamic treatment effects: Event Study Analysis

The difference-in-differences specifications presented in the previous sections estimate static treatment effects, assuming that the impact of YouTube coverage remains constant over time. To investigate the temporal dynamics of treatment effects and formally test the parallel trends assumption underlying the DiD identification strategy, this section presents an event study analysis.

The event study extends the baseline DiD by estimating treatment effects separately for each week relative to video publication, plotting coefficients for event times ranging from -85 to +85 weeks around treatment. This approach serves two purposes:

- visually testing whether treated and non-treated restaurants followed parallel trends prior to treatment,
- and revealing how treatment effects evolve over time, whether they spike, persist, dissipate, or reverse.

Figure 5.1 presents the event study results with all restaurants included, with the vertical red line marking the treatment week and the horizontal black line representing the reference level (event time = -1). On the other hand Figure 5.2 reveals the second event study with only 1 star restaurants included.

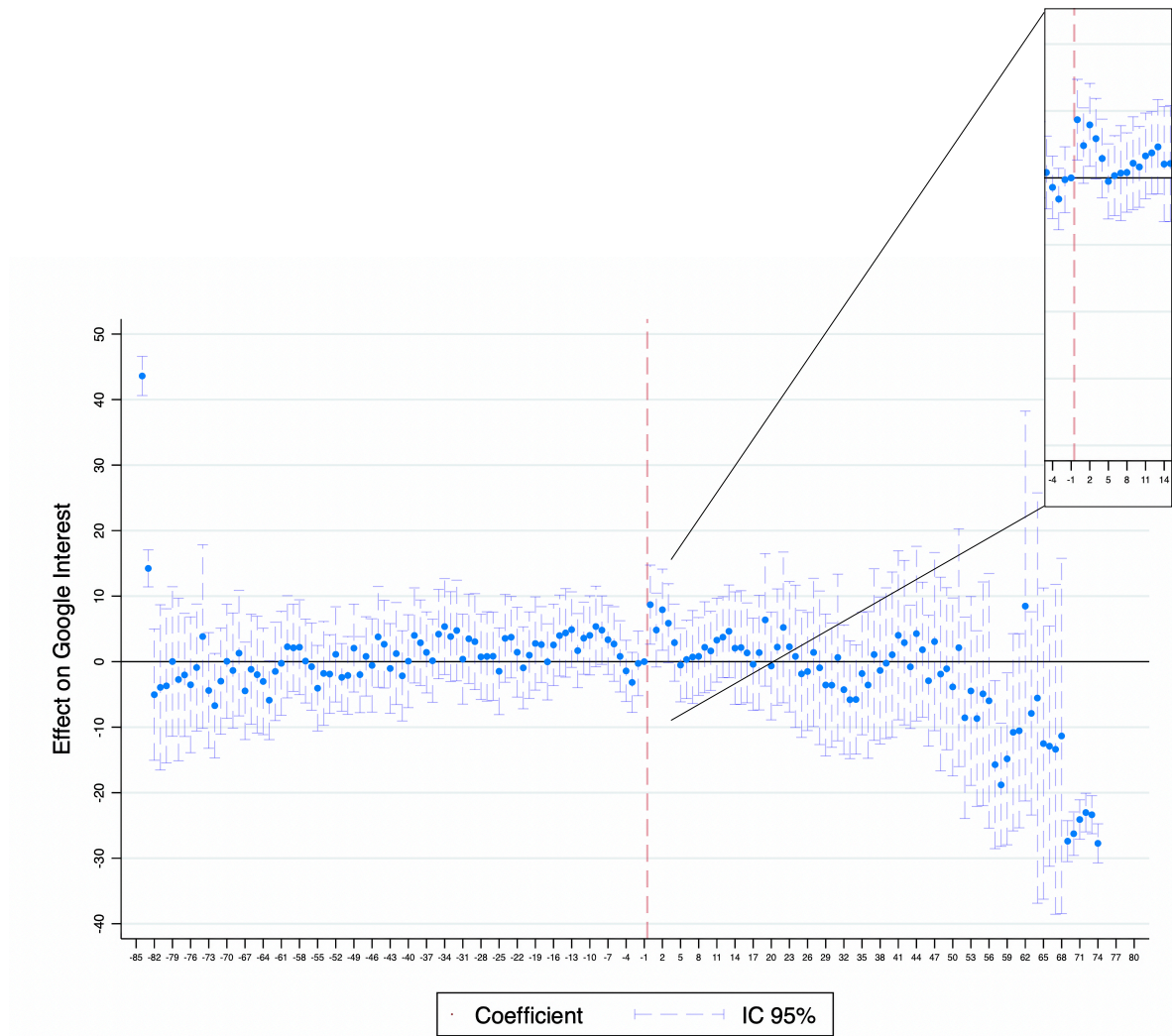


Figure 5.1: Complete Event Study - Dynamic Treatment Effects Over Time

The results of the Complete Event Study reveal a striking three-phase temporal pattern:

Phase 1 - Pre-Treatment (Event Time < 0): Parallel Trends Validated

Pre-treatment coefficients oscillate closely around zero with no systematic upward or downward trend. This **flat pre-treatment pattern provides decisive evidence** supporting the parallel trends assumption: treated and control restaurants exhibited statistically similar trends in Google search interest prior to YouTube coverage. This validates the DiD identification strategy employed throughout Chapter 5.

Phase 2 - Immediate Post-Treatment (Weeks 0-4): Transient Viral Spike

Immediately following video publication, coefficients turn **clearly positive**, reaching approximately +5 to +8 percentage points during peak weeks. This represents a short-

lived "viral buzz" effect: the YouTube video generates an immediate spike in search interest as viewers seek additional information about the featured restaurant. The magnitude represents roughly a 20-30% increase relative to baseline levels.

However, this positive effect dissipates rapidly. By weeks +5 to +10 (1-2.5 months post-treatment), coefficients have returned to near-zero. The viral moment lasts less than one month, specifically up to **5 weeks**.

Phase 3 - Medium-to-Long-Term (Weeks +10 to +85): Oscillating Decline

Following the initial spike, the pattern becomes more complex:

- **Weeks +10 to +50:** Coefficients exhibit cyclical fluctuations with periodic "mini-spikes" of renewed interest around weeks +20, +30, and +45. These may reflect delayed travel planning, algorithmic re-promotion of the video, or event-driven renewed interest (Michelin announcements, chef media appearances). Critically, each successive wave is weaker than the previous one, a clear dampening pattern with a gradually declining baseline.
- **Weeks +50 to +85:** Coefficients become **consistently and substantially negative**, ranging from approximately -10 to -40 percentage points. More than one year post-treatment, treated restaurants exhibit systematically **lower search interest** than they would have absent treatment. The magnitude represents a 50-100% reduction relative to typical baseline levels, with **no evidence of recovery or mean reversion**.

The event study reveals why the static DiD models found heterogeneous effects by star category. The net effect of YouTube coverage depends critically on which temporal phase dominates:

- One-star restaurants (+3.90* in static models): Benefit from strong initial spikes and experience less severe long-run declines, resulting in positive net effects when averaged across the full post-treatment period.
- Three-star restaurants (-12.86* in static models): May experience smaller initial spikes (baseline awareness already high) but suffer severe long-run declines due to exclusivity dilution, resulting in large negative net effects.

The temporal decomposition also reveals a *critical asymmetry*: *benefits are transient (4 weeks); costs are persistent (50+ weeks)*. YouTube coverage generates immediate buzz

that rapidly fades, followed by sustained long-term damage to organic search interest. For high-prestige restaurants, the persistent costs far outweigh the fleeting benefits.

The long-run decline likely reflects curiosity satiation (video substitutes for actual search/visitation), exclusivity dilution (mass exposure undermines scarcity positioning), audience composition shifts (casual viewers replace serious diners), and algorithmic aging (video exits active circulation). These mechanisms manifest gradually over months, explaining why negative effects emerge only in the long run.

To further investigate whether the temporal dynamics differ across prestige tiers, Figure 5.2 presents a star-specific event study limited to one-star restaurants (N=291), which constitute the majority of the sample and showed positive net effects in the static DiD models.

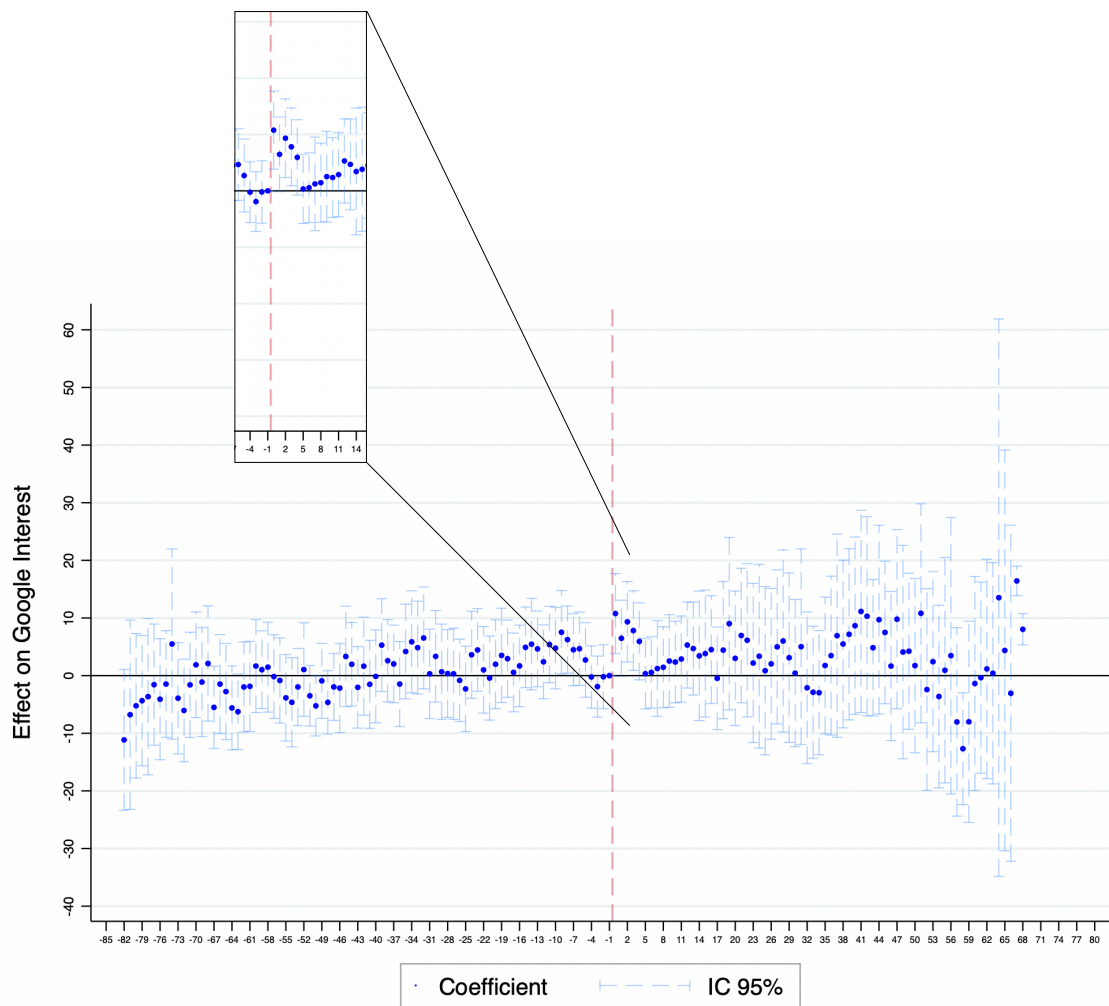


Figure 5.2: Event Study - One-Star Restaurants Only

The one-star event study reveals a qualitatively different temporal pattern compared to the pooled analysis, providing crucial insights into why this category exhibits positive net treatment effects:

Pre-Treatment Period: Consistent with the pooled analysis, pre-treatment coefficients cluster tightly around zero with no systematic trend, reconfirming parallel trends validity for this subsample.

Immediate Post-Treatment (Weeks 0-5): One-star restaurants experience a clear positive spike immediately following video publication, with coefficients rising to approximately +8 to +12 percentage points during peak weeks (event times +1 to +4). This spike is similar in magnitude to the pooled analysis, confirming that the initial viral buzz effect is consistent across prestige levels. Notably, the zoom detail reveals that the positive effect begins at event time 0 (the week of video publication) rather than with a delay, indicating immediate viewer response, and it lasts close to 5 weeks as well.

Medium-Term Persistence (Weeks +5 to +50): Critically, unlike the pooled analysis where effects rapidly returned to zero, one-star restaurants maintain elevated search interest well beyond the initial spike. Coefficients remain predominantly positive throughout weeks +5 to +50, oscillating between approximately +2 to +15 percentage points with periodic fluctuations. This represents a fundamentally different dynamic: *the viral moment for one-star restaurants does not dissipate completely but rather transitions into a sustained elevation of baseline interest.*

The periodic mini-spikes visible around weeks +15, +25, +35, and +45 suggest **recurring waves of renewed interest**, potentially driven by:

- Delayed travel planning cycles (viewers who saw the video months earlier now searching when booking trips)
- Secondary media coverage or social media resharing that references the original video
- Seasonal demand patterns where the restaurant benefits from heightened awareness during peak dining seasons
- Algorithmic re-promotion as the video continues to circulate in recommendation feeds

Importantly, each successive wave, while somewhat diminished, **remains positive**, in stark contrast to the pooled analysis where later waves dampened toward zero and eventually turned negative.

Long-Term Pattern (Weeks +50 to +85): The most striking divergence from the pooled results emerges in the long run. While the pooled analysis showed consistent, large negative effects after week +50, one-star restaurants exhibit substantial heterogeneity with coefficients ranging from approximately -10 to +20 percentage points. Several observations:

1. **No consistent negative trend:** coefficients do not systematically decline into deeply negative territory. Many late-period coefficients remain positive or near-zero.
2. **High variance:** Confidence intervals widen considerably in the long run (weeks +70 to +85), reflecting both smaller sample sizes at extreme event times and genuine heterogeneity in long-run responses among one-star restaurants.
3. **Potential mean reversion:** The average coefficient level in weeks +50 to +85 appears to stabilize around +5 to +10 points, lower than the medium-term peak but still positive on average.

The one-star event study explains a critical puzzle: how can the pooled analysis show large long-run negative effects (-10 to -40 pp after week +50) while one-star restaurants in the static DiD exhibit positive net effects (+3.90^{***})? The answer lies in compositional differences and treatment timing:

- **One-star restaurants constitute 83% of the sample** (291 of 348) but **74% of treated restaurants** (52 of 70). This means higher-star restaurants are a bit overrepresented among the treated.
- **Treatment timing heterogeneity:** If three-star restaurants were treated earlier in the sample period (2019-2021), they contribute disproportionately to late event times (+50 to +85) in the pooled event study, where their large negative effects dominate the average coefficient.
- One-star restaurants treated later (2022-2024) contribute primarily to early-to-medium event times (0 to +50), where effects are positive or neutral.

The star-specific event study for one-star restaurants demonstrates that, within this prestige tier, YouTube coverage generates: a strong immediate positive spike (+8 to +12

pp, weeks 0-5) with sustained medium-term elevation (+2 to +15 pp, weeks 5-50) and heterogeneous but on-average still positive long-term effects (weeks 50+)

This temporal trajectory, where benefits persist rather than reverse, explains why the static DiD found a positive net effect for one-star restaurants. The **asymmetry is reversed** relative to high-prestige establishments: for one-star restaurants, the transient spike transitions into durable gains rather than durable losses.

Why do one-star restaurants avoid the long-run decline observed in the pooled sample?

1. **Information revelation has lasting value:** For previously unknown establishments, the video serves as a permanent credential that viewers recall and reference months later when planning dining experiences. The informational benefit does not "expire" as it might for already-famous three-star institutions.
2. **Audience-establishment fit:** YouTube food content viewers seeking accessible, high-quality dining experiences are well-matched to one-star restaurants' target market. Casual viewers who discover the restaurant via video can plausibly convert into actual diners, sustaining search interest.
3. **Cumulative awareness building:** Unlike three-star restaurants where awareness is already saturated, one-star establishments benefit from cumulative exposure: the video continues to introduce new audiences to the restaurant over time as it circulates, generating recurring search spikes rather than one-time curiosity.

The event study confirms that static DiD estimates, while valid as average effects, conceal substantial temporal complexity. YouTube influencer marketing operates through countervailing mechanisms at different time horizons, short-run curiosity generation versus long-run exclusivity erosion, with the balance of these forces varying systematically by restaurant prestige. This temporal pattern reinforces the central finding: for elite restaurants, YouTube coverage generates hidden long-term costs that persist long after the immediate viral moment fades, while for accessible one-star establishments, the benefits prove more durable.

6

CONCLUSIONS

When certain phenomena have not yet been formally quantified, researchers face a choice: to be paralysed by the absence of a clean experimental design, or to let the data speak through whatever rigorous tools are available. This thesis took the second path. By combining a cross-sector literature review with an original causal analysis of 348 Michelin-starred Italian restaurants and three major YouTube food channels, it has produced one of the first quantitative, causally identified estimates of the economic impact of influencer video content on restaurant visibility, a contribution that moves the field from anecdote to evidence.

The approach was deliberately non-classical. Rather than relying solely on survey-based purchase intention scales or controlled lab experiments, the dominant paradigm in influencer marketing research, this work reconstructed real-world exposure events and measured their effect on Google Search interest, a behavioural proxy for consumer attention that, by its very nature, captures the most direct manifestation of virality: the moment a viewer becomes an active seeker. This choice of dependent variable is not incidental; it mirrors precisely the mechanism that influencer content is supposed to activate. Future research would benefit from complementing this digital visibility metric with harder business outcomes, most notably reservation volume and actual revenue, which would allow a full cost-benefit translation of the effects identified here.

Core Findings

The central empirical result of this thesis is that YouTube video coverage generates heterogeneous temporal effects that vary systematically by restaurant prestige, a finding that static models alone would have partially obscured. For one-star restaurants, treatment produces an immediate spike of +8 to +12 percentage points in Google Search interest during the first four to five weeks post-publication, followed by sustained elevated interest of +2 to +15 percentage points that persists for at least one year (50+ weeks). This durable pattern explains the positive net effect of +3.90 percentage points observed in the static difference-in-differences specification, and suggests that for accessible, less well-known establishments, influencer content functions as a permanent informational credential: one that continues to circulate, be reshared, and recruit new audiences long after the original publication date.

The picture is markedly different at higher prestige tiers. Static DiD estimates suggest null effects for two-star restaurants (-1.05 pp, not significant) and large negative effects for three-star establishments (-12.86 pp, $p < 0.01$). The event-study decomposition reveals the mechanism: initial positive spikes of comparable magnitude may still occur, but they

are followed by sustained negative drift attributable to curiosity satiation, exclusivity dilution, and audience-composition shifts. For elite restaurants, whose brand equity is built on scarcity and carefully managed mystique, mass digital exposure erodes the very intangibility that justifies their positioning. The temporal analysis confirms what the static models could only hint at: that the long-run costs of YouTube coverage for high-prestige establishments materially outweigh its short-run benefits.

It should be noted that the limited sample sizes for two-star (37 restaurants, 7 treated) and three-star (14 restaurants, 11 treated) establishments constrain the statistical robustness of tier-specific conclusions. Wide confidence intervals in the star-specific event studies preclude definitive characterisation of their temporal dynamics, and future work with larger treated samples would considerably strengthen inference at the upper end of the prestige distribution.

Practical Implications

The managerial takeaway is actionable and prestige-contingent. For one-star and emerging restaurants, proactive engagement with food content creators on YouTube represents a measurable, cost-effective route to sustained visibility growth. The treatment effect is not merely a flash of curiosity but a durable shift in baseline search interest: equivalent, in business terms, to a persistent improvement in organic discoverability. Restaurant managers in this tier should therefore evaluate influencer collaborations not as one-off promotional events but as long-duration digital assets.

For two- and three-star establishments, the evidence counsels caution. The risk of exclusivity erosion is real and statistically detectable. When these restaurants engage with high-reach digital channels, they may be trading long-term brand equity for short-term buzz, a trade-off that sits poorly with their positioning logic. The strategic alternative, as the literature review in *Chapter 2* discusses extensively, lies in cultivating a proprietary digital identity through owned channels, curated self-presentation, and tightly controlled brand storytelling rather than delegating narrative authority to external content creators.

More broadly, this work validates the investment in causal identification as a managerial tool. The difference between a naive pre-post comparison and a properly constructed difference-in-differences estimate is not merely statistical pedantry, it is the difference between attributing a seasonal demand surge to influencer exposure and correctly isolating the marginal contribution of that exposure. Decision-makers who act on properly

identified estimates will allocate marketing budgets more efficiently and avoid both over-investment in ineffective channels and under-investment in genuinely impactful ones.

Future Research Directions

Returning to one of the original research questions, whether the findings extend beyond the restaurant sector, the answer suggested by the theoretical framework is yes, and systematically so. The empirical setting of fine dining was chosen precisely because its homogeneity and natural stratification by Michelin star provided a controlled laboratory for isolating the causal effect of digital content exposure. But the mechanism identified, influencer video as a durable informational credential for lower-prestige establishments versus a risk to exclusivity for elite ones, is not specific to food. It is a function of how brand equity interacts with mass digital exposure, a dynamic that replicates wherever prestige and scarcity are core value drivers.

The most immediate extension is to the hospitality sector at large: independent boutique hotels, luxury resorts, and agritourism estates operate on the same prestige-scarcity logic as Michelin-starred restaurants, making the framework directly transferable. Beyond hospitality, analogous dynamics are plausible in luxury fashion (where mass digital exposure risks brand dilution for heritage houses but may be net positive for emerging labels), high-end retail and concept stores, premium wellness and spa destinations, cultural institutions such as private galleries and invitation-only events, and artisanal food and wine producers. In each of these domains, the core question: *does influencer-driven mass visibility help or harm, and over what time horizon?* remains unanswered with the rigour applied here.

A particularly promising extension lies in omnichannel contexts. Having isolated the causal effect of a single digital channel, YouTube, future research could decompose the total influencer impact across platform ecosystems (YouTube, Instagram, TikTok, editorial press), examining not only the standalone effect of each channel but also their interaction and substitution dynamics. Because this thesis provides an isolated estimate of one channel's contribution, it creates a clean analytical baseline against which multi-channel effects can be benchmarked. This would be especially valuable for businesses operating omnichannel marketing strategies, where attribution modelling remains one of the most technically and conceptually challenging open problems in the field.

John Wanamaker's lament, quoted at the opening of this thesis, was that he never knew which half of his advertising worked. The answer this thesis offers is partial but genuine:

for emerging restaurants exposed to YouTube food content, the evidence points clearly to the half that works, when it works, and for how long. Extending that clarity to other sectors, other channels, and harder business outcomes is the work that remains.

Perhaps the most honest conclusion is also the simplest: this question had never been asked before, at least not like this. That, in itself, felt worth the attempt. Actually there is something irreducibly special about being the first to ask a question seriously. This thesis makes no claim to finality: only to originality, and to the conviction that originality, in research as in business, is where everything begins.

7

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