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Herding in Equity Crowdfunding Under Varying Behavioural Cues: Evidence from the Italian Market

Tutor
Prof.ssa Carmen Gallucci

Dottorando
Riccardo Tipaldi

Coordinatore del Dottorato
Prof. Roberto Tagliaferri

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Abstract

This thesis investigates how herding dynamics, defined as investors conditioning their decisions on the observed actions of others, unfold in the Italian equity crowdfunding market. Building on signalling theory and theoretical models of information cascades and herding, the analysis focuses on social signals generated by prior investment activity. Using high-frequency pledge-level data on approximately 26,000 investments across 226 equity crowdfunding campaigns hosted on a leading Italian platform between 2015 and 2025, the thesis examines how the strength and form of sequential dependence vary across informational settings that proxy distinct behavioural cues. Four results emerge. First, apparent herding in parsimonious specifications vanishes once campaign fixed effects and calendar-day shocks are controlled for. Second, unusually large pledges are typically followed by smaller ones, producing short-run oscillations rather than self-reinforcing escalation in pledge size. Third, after controlling for endogeneity in pledge timing, the elapsed time between contributions has no meaningful causal effect on subsequent pledge size, implying that temporal clustering primarily reflects synchronised attention rather than contagion. Fourth, campaign-stage progression, media coverage, and investor Q&A activity shift average pledge levels but do not generate persistent imitation in pledge magnitudes. Overall, the findings portray herding in equity crowdfunding as bounded and context-dependent, thereby refining the current understanding of social learning in fintech-mediated entrepreneurial finance.

Introduction

Motivation and Research Context

Equity crowdfunding has become an increasingly important channel for early-stage ventures to raise equity. By facilitating entrepreneurial finance through online platforms, it expands access to investment opportunities beyond traditional venture capital and business angel networks, enabling ventures with limited collateral and short operating histories to attract equity from a dispersed crowd. These institutional features give equity crowdfunding clear economic significance, but they also create a unique decision environment for investors: information is incomplete, uncertainty about venture quality is high, and credible fundamentals are often hard to verify at the time equity is committed.

In this context, the equity crowdfunding platform itself forms the primary informational infrastructure. Investors monitor fundraising progress in real time, alongside key indicators such as the order of previous investments, total funding relative to the target, and the presence of exceptionally large contributions. These cues offer a form of social information that can partly replace missing fundamentals. Consequently, equity crowdfunding is a market where valuation and participation are influenced by what others have already done and by what the platform makes visible. This structure makes crowdfunding a natural setting for examining herding behaviour and social learning in financial decision-making.

The importance of herding in such markets is not merely descriptive but also substantive. If investors infer project quality from observed contributions, social information can aid information gathering by enabling the aggregation of dispersed private signals through sequential actions. In favourable conditions, this process may resemble collective learning, in which early participation guides capital toward higher-quality ventures. In less favourable conditions, however, the same visibility can heighten noise, attention shocks, or early unique contributions, leading to path-dependent funding patterns that are only weakly connected to underlying fundamentals. Differentiating between these scenarios is therefore relevant for welfare and policy, as it affects how capital is distributed across ventures, how platforms should organise disclosure and interface design, and how regulators should evaluate investor protection in markets dominated by retail participation.

Equity crowdfunding is also theoretically informative because it is typically governed by institutional rules that differ from those prevailing in traditional securities markets. Many platforms operate under all-or-nothing funding mechanisms, in which a campaign is launched only if cumulative funding reaches a predetermined threshold. This feature alters the incentives underlying sequential decision-making. Early investors may face limited downside risk if the threshold is not met, while later

investors confront a different trade-off as implementation becomes more likely. As a result, herding in crowdfunding is plausibly shaped not only by informational inference but also by strategic coordination around the probability of success. Observable funding dynamics reflect a combination of learning about project quality and coordinating around the likelihood of implementation. These two mechanisms are analytically distinct but empirically difficult to disentangle without sufficiently granular data.

Against this conceptual and institutional backdrop, the empirical analysis of this thesis is situated in the Italian equity crowdfunding market. Italy provides a particularly relevant setting, as its crowdfunding sector is among the most developed in Europe. The Italian crowdfunding market, including other forms such as reward-based crowdfunding, is the fourth largest in Europe, with total capital raised of approximately €0.29 billion. Italy is also one of the largest crowdfunding providers in Europe, hosting some of the most active platforms (ESMA, 2025). More generally, Italy lags only behind Europe's largest equity crowdfunding markets, such as the United Kingdom and France (Crowdinform, 2025).

The data used in this thesis are drawn from Crowdfundme, one of Italy's leading equity crowdfunding platforms. As of 2024, Crowdfundme had raised approximately €127 million across more than 290 campaigns, several of which ranked among the most prominent equity crowdfunding campaigns in the Italian market over the previous year (Politecnico di Milano, 2025). Although larger platforms exist in Italy, most notably Mamacrowd, they did not display the high-frequency data required for the analyses conducted in this thesis, as discussed in the methodological section.

This thesis examines herding in equity crowdfunding as a micro-level behavioural process situated within a specific institutional environment. Instead of viewing sequential dependence as a general momentum phenomenon, it concentrates on how investors respond to observable prior actions, how these responses differ when presented with varying behavioural cues and across different campaign stages, and whether bursts of activity indicate imitation or synchronised attention. By doing so, the thesis seeks to clarify how herding unfolds in digitally mediated entrepreneurial finance and to provide evidence that informs both theories on social learning and information aggregation under threshold-based rules, as well as practical aspects such as platform design and investor protection.

Limitations of Existing Evidence

A growing empirical literature documents herding in equity crowdfunding and related digital investment markets. Across platforms and institutional settings, studies consistently show that prior funding activity predicts subsequent investment, that campaigns attracting early support tend to experience stronger later inflows, and that investment activity clusters in time. These regularities have

been widely interpreted as evidence that investors learn from and are influenced by others' actions. While this body of work has established the relevance of social information, it also leaves several conceptual and empirical issues unresolved.

A first limitation concerns the level of aggregation at which herding is typically measured. Much of the existing evidence relies on campaign-level, daily aggregates of investment activity. Without observing individual pledge sizes in sequence, it is difficult to determine whether herding reflects imitation in valuation, coordination in participation, or compositional changes in the investor pool. As a result, aggregate reinforcement is frequently interpreted as escalation, even though this interpretation is rarely tested directly.

A second limitation relates to the interpretation of temporal clustering. Investment bursts are a salient feature of crowdfunding data and are often taken as indicative of behavioural contagion. However, inter-arrival times are rarely treated as endogenous. Rapid sequences of investments may arise because multiple investors are simultaneously exposed to the same campaign through platform rankings, notifications, or external visibility shocks. In such cases, clustering reflects coordinated attention rather than imitation transmitted through time itself. Without empirical strategies that explicitly disentangle timing from valuation, it remains unclear whether the speed of investment has an independent behavioural effect or merely coincides with other influences.

A third limitation concerns the tendency to equate herding with monotonic reinforcement. Many empirical interpretations implicitly assume that if investors respond to social information, they must do so by matching or amplifying prior actions. Yet theoretical models of social learning do not require quantitative imitation. In environments characterised by heterogeneous resources, risk tolerance, and participation costs, investors may use observed actions as reference points while adjusting their own decisions in bounded ways. The absence of pledge-level evidence has made it difficult to assess whether herding in equity crowdfunding takes the form of escalation, anchoring, or partial adjustment.

A further issue involves the treatment of institutional design. Features such as all-or-nothing funding rules, visible funding thresholds, and campaign-stage progression are often included as controls or background characteristics, rather than analysed as mechanisms that actively shape behaviour. Yet threshold-based rules alter incentives over the course of a campaign, shifting the interpretation of observed contributions from informational signals about quality to coordination cues about the likelihood of implementation. Ignoring this evolution risks conflating learning with strategic coordination and obscuring how herding may change character as campaigns progress.

These limitations suggest that, although herding in equity crowdfunding is well documented, its underlying mechanisms remain imperfectly understood. Addressing these gaps requires data and

methods that follow individual decisions in sequence, separate timing from valuation, and embed behavioural responses within the institutional logic of crowdfunding. The next section outlines how this thesis responds to these challenges and positions its contribution.

Research Objectives and Contribution

The central objective of this thesis is to clarify how herding operates in equity crowdfunding by examining investor behaviour at the level at which decisions are made: the individual pledge, observed in sequence within a campaign. Rather than asking whether herding exists, a question for which the existing literature already provides substantial evidence, the thesis asks how investors condition their decisions on observable actions taken by others, through which channels this conditioning occurs, and how it is shaped by institutional design.

To this end, the analysis pursues three interrelated research objectives. First, it investigates how investors adjust the magnitude of their contributions in response to recent observable pledges within the same campaign. By modelling pledge sizes directly and incorporating short-horizon lags, the thesis examines whether social influence manifests as escalation, convergence, or bounded adjustment around recent reference points. This approach provides a more direct basis for distinguishing imitation in valuation from reinforcement in aggregate funding trajectories.

Second, the thesis seeks to disentangle coordination in participation from imitation in valuation. Investment activity in crowdfunding frequently clusters in time, but such clustering may reflect synchronised attention rather than behavioural contagion. By explicitly modelling inter-pledge timing and addressing its potential endogeneity, the analysis assesses whether the timing of investments exerts an independent influence on pledge behaviour, or whether timing operates primarily at the participation margin.

Third, the thesis examines how institutional features and campaign context shape herding dynamics. Particular attention is devoted to all-or-nothing funding rules, visible funding thresholds, campaign-stage progression, and periods of heightened activity. This perspective treats institutional design not as a background condition, but as a component of the behavioural environment in which social learning unfolds and in which the meaning of observed contributions can change over the campaign lifecycle.

The contribution of the thesis is therefore threefold. Empirically, it develops a pledge-level panel design that follows complete investment sequences across campaigns, enabling identification of within-campaign dynamics while controlling for both campaign-specific heterogeneity and common temporal shocks. Methodologically, it combines two-way fixed effects with an instrumental variables strategy to distinguish attention-driven clustering from valuation-driven responses. Conceptually, it

refines the interpretation of herding in equity crowdfunding by distinguishing bounded social learning and coordination from unbounded imitation and escalation.

By consolidating these elements, the thesis contributes to the behavioural finance literature on herding and social learning, as well as to the entrepreneurial finance literature on crowdfunding. It shows how social information can influence investor behaviour without necessarily producing destabilising cascades, and how institutional design can discipline herding. In doing so, it provides a micro-level foundation for understanding crowd behaviour in digitally mediated financial markets, complementing existing aggregate evidence with an account of individual decision-making under uncertainty.

Structure of the Thesis

The thesis is organised to move progressively from the structural foundations of early-stage finance to a granular behavioural analysis of investor decision-making, and finally to a synthesis of implications for theory, platform design, and regulation.

Chapter 2 develops the theoretical and empirical background. It reviews the literature on financing constraints faced by early-stage ventures, the emergence of fintech and equity crowdfunding as alternative funding mechanisms, and the persistence of information asymmetries in digital investment markets. It then treats equity crowdfunding explicitly as a behavioural environment, discussing signalling, information aggregation, and the conditions under which herding and social learning are expected to arise. The chapter establishes the conceptual framework that motivates the empirical analysis and clarifies the mechanisms that the thesis seeks to identify.

Chapter 3 describes the data, variable construction, and econometric strategy. It introduces the pledge-level dataset drawn from a leading Italian equity crowdfunding platform, , details the construction of sequential, timing, visibility, and herding measures, and explains the fixed-effects and instrumental-variables designs used to identify within-campaign behavioural dynamics. Particular attention is devoted to how the empirical approach separates campaign-specific heterogeneity, common time shocks, and potential endogeneity in inter-pledge timing.

Chapter 4 presents the empirical results. It begins with descriptive evidence on pledge behaviour and campaign dynamics, and then reports estimates from a sequence of increasingly restrictive models. The analysis progresses from one-way to two-way fixed-effects specifications, to instrumental-variables estimation addressing timing endogeneity, and finally to extended models that incorporate campaign stages, external visibility, and state-dependent herding. Throughout, the focus remains on how investors adjust pledge sizes in response to observable social information within campaigns.

Chapter 5 interprets the results in light of the theoretical and empirical literature on herding and social learning. It first reconciles the main empirical findings using pledge-level evidence, then synthesises them into a mechanism-based account of herding under all-or-nothing funding rules, and finally situates the Italian evidence within the broader crowdfunding literature. The chapter highlights how signalling, coordination, and bounded social learning interact over the campaign lifecycle, and clarifies how these dynamics refine existing interpretations of crowd behaviour.

Chapter 6 concludes the thesis. It consolidates the main insights, discusses their implications for theories of information aggregation, platform design, and investor protection, and outlines a focused set of extensions that are directly linked to the empirical design and findings. It also reflects on the scope and limitations of the analysis and identifies directions for future research on social learning in digitally mediated financial markets.

Chapter 1: Literature Review

1.1 Early-Stage Ventures and Access to Finance

Early-stage ventures operate in environments characterised by uncertainty, informational opacity, and scarce internal resources. Despite these constraints, they contribute meaningfully to economic dynamism and innovative activity. Empirical evidence shows that small firms often generate new products, foster technological advances, and contribute to competitive renewal, even in the absence of formal R&D departments or extensive financial resources (Acs and Audretsch, 1987). Because innovation and entrepreneurial activity are central to industry evolution, the ability of new firms to secure adequate financing is not merely a micro-level concern but a broader determinant of economic performance. Financing constraints faced by young ventures can therefore have economy-wide consequences, limiting innovation, firm entry, and productivity growth.

A central reason early-stage ventures struggle to obtain external finance is acute informational asymmetry between entrepreneurs and potential investors. Akerlof's (1970) "market for lemons" framework illustrates how quality uncertainty can undermine market functioning: when investors cannot distinguish high-quality from low-quality projects, average quality deteriorates as superior projects withdraw. In the context of entrepreneurial finance, this implies that even promising start-ups may be unable to credibly signal their quality to external investors, leading to underinvestment or market breakdown. Entrepreneurs typically possess superior information about project potential, effort, and downside risks, which creates adverse selection concerns for external financiers. As a result, the supply of finance to young firms is depressed, irrespective of their intrinsic value.

Theoretical contributions have explored how entrepreneurs may attempt to mitigate these information problems. One mechanism is signalling through insider ownership. Leland and Pyle (1977) show that

high-quality entrepreneurs can credibly signal confidence in their ventures by retaining substantial ownership stakes or committing personal wealth. Because low-quality entrepreneurs cannot mimic such behaviour without incurring disproportionate expected losses, insider equity functions as a separating signal of project quality. This mechanism helps explain why early-stage ventures rely heavily on personal savings, family resources, and insider finance, and why external equity markets rarely support firms at inception. Insider finance thus reflects both necessity under information asymmetry and optimal signalling behaviour predicted by theory.

Agency theory offers further insights into the financing constraints of young ventures. Jensen and Meckling (1976) demonstrate that separating ownership and control generates agency costs through incentive misalignment, monitoring expenditures, bonding activities, and residual losses. These costs are particularly acute for early-stage ventures, where entrepreneurs retain operational control and effort is difficult to observe or verify. External investors are therefore reluctant to provide capital without mechanisms to align incentives and monitor behaviour, both of which increase the cost of external finance. At the same time, entrepreneurs often prefer to retain high ownership stakes to preserve effort incentives, which further constrains the scope for external equity participation.

Closely related to these agency concerns is the moral hazard problem formalised by Holmström (1979). When entrepreneurial effort is unobservable, contracts cannot be conditioned directly on actions, precluding first-best risk-sharing. Financiers must instead design second-best contracts that distort risk-sharing to induce effort, often requiring entrepreneurs to bear greater risk or to accept compensation tied to noisy performance signals. These distortions contribute to the high cost of external finance for start-ups.

Information and incentive frictions also affect access to debt finance. Stiglitz and Weiss (1981) show that in the presence of adverse selection and moral hazard, raising interest rates may reduce lender returns by attracting riskier borrowers and encouraging excessive risk-taking. Credit markets may therefore clear through rationing rather than prices. For early-stage ventures, typically lacking collateral, audited financial statements, or stable cash flows, credit exclusion emerges as a structural equilibrium outcome rather than a consequence of insufficient willingness to pay.

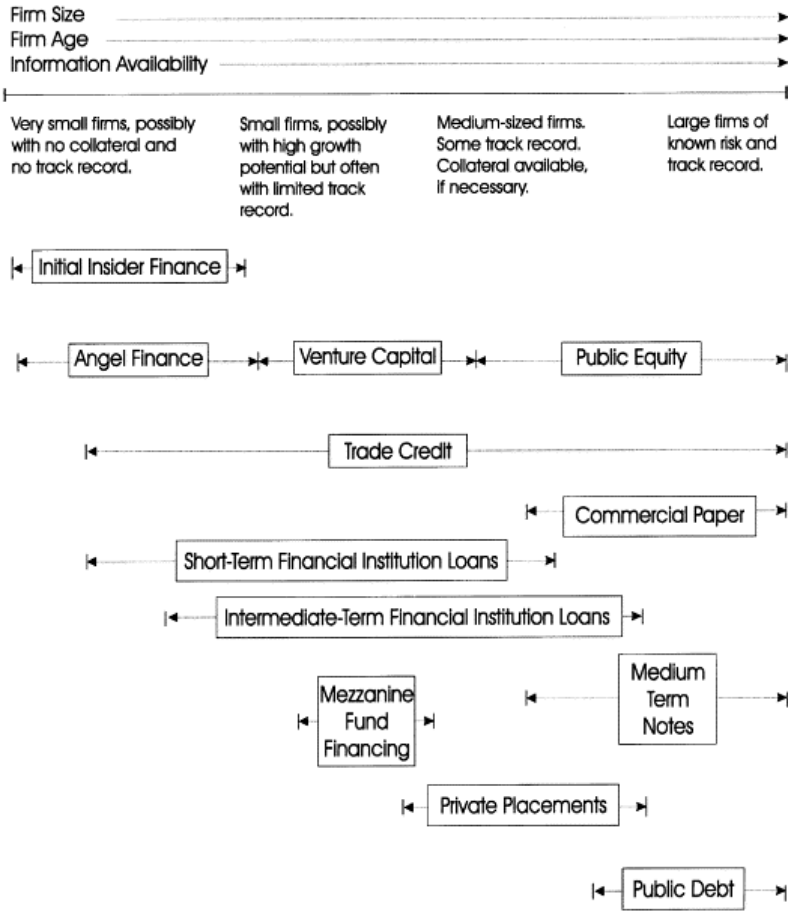
The role of financial intermediaries in reducing these frictions is better understood through Diamond's (1984) theory of delegated monitoring. Monitoring borrowers is costly and subject to free-rider problems when many small lenders are involved. Financial intermediaries such as banks can overcome these problems by specialising in monitoring and diversifying across borrowers. However, Diamond's (1984) framework also highlights that intermediated lending becomes viable only when projects generate sufficiently verifiable information. Early-stage ventures, with limited track records

and opaque operations, are therefore poorly suited to bank lending. Moreover, loans to start-ups tend to be illiquid because monitoring information is private and non-transferable.

Empirical evidence confirms that these theoretical frictions translate into binding financing constraints. Evans and Jovanovic (1989) show that liquidity constraints strongly influence entrepreneurial entry: individuals with greater personal wealth are significantly more likely to start businesses, and those who do enter often invest at levels below the social optimum. This pattern indicates that financing frictions deter firm creation and constrain growth among surviving ventures, consistent with the predictions of asymmetric information and agency models.

These insights are synthesised in the financial growth cycle framework articulated by Berger and Udell (1998) (Figure 1). Firms progress through a sequence of financing sources as they accumulate information and reduce opacity. Start-ups rely predominantly on insider funds and informal finance in the earliest stages, when information problems are most severe. As ventures mature and develop observable performance indicators, external equity from angel investors and venture capitalists becomes accessible. Only after establishing a verifiable track record do firms typically gain access to bank loans and other forms of intermediated debt. The financial growth cycle thus highlights the co-evolution of firm maturity and financing opportunities in response to underlying information frictions.

Figure 1: Firm continuum and sources of finance.



Source: Berger, A. N., & Udell, G. F. (1998). The economics of small business finance: The roles of private equity and debt markets in the financial growth cycle. Journal of Banking & Finance, 22(6–8), 613–673. https://doi.org/10.1016/S0378-4266(98)00038-7

Taken together, these theoretical and empirical contributions provide a coherent explanation for the persistent financing difficulties faced by early-stage ventures. Young firms confront a dense web of informational and incentive frictions, including adverse selection (Akerlof, 1970), signalling constraints (Leland and Pyle, 1977), agency conflicts (Jensen and Meckling, 1976), moral hazard (Holmström, 1979), credit rationing (Stiglitz and Weiss, 1981), and costly monitoring (Diamond, 1984). Empirical evidence corroborates the real-world consequences of these frictions, including liquidity constraints, underinvestment, and reduced entrepreneurial entry (Evans and Jovanovic, 1989). At the same time, the innovative capacity of small firms (Acs and Audretsch, 1987) underscores the broader economic relevance of alleviating such barriers. This structural financing gap provides the foundation for understanding the emergence of alternative financing mechanisms, including fintech platforms and equity crowdfunding, which seek to reduce information asymmetries, broaden investor participation, and expand access to early-stage capital.

1.2 Fintech and the Democratisation of Finance

The structural financing challenges faced by early-stage ventures have contributed to the rise of financial technologies designed to reduce informational frictions, widen participation, and expand access to capital. Fintech innovations leverage digital infrastructures, data availability, and platform-based intermediation to address limitations of traditional financial institutions, particularly in environments where opacity, geographic dispersion, and scale inefficiencies constrain financial inclusion. As technological change reshapes bank-based intermediation, new entrants have emerged that provide financial services through low-cost, digitally enabled channels, challenging long-standing barriers to entry and altering how entrepreneurs and investors interact with financial markets (Boot et al., 2021; Gomber et al., 2018).

A central aspect of this transformation is the expansion of access to finance for firms that have historically been underserved. Fintech platforms such as equity crowdfunding, peer-to-peer lending, and token-based fundraising create alternative pathways for entrepreneurs who lack collateral, operating history, or proximity to established financial centres. These models reduce distribution costs, automate components of screening and matching, and enable participation independently of local banking infrastructures (Bollaert et al., 2021; Farag and Johan, 2022). As a result, younger, smaller, and more opaque ventures, those most constrained by information asymmetries in traditional markets, can raise capital at earlier stages and from a broader pool of investors.

Cross-country evidence supports this access-expansion interpretation. Haddad and Hornuf (2019) show that fintech activity grows most rapidly in environments where traditional financial institutions are less effective at allocating credit, including countries with weaker banking sectors, lower trust in financial intermediaries, or limited access to finance for small and medium-sized enterprises. These findings suggest that fintech adoption reflects a structural response to unmet financial needs rather than a purely technological trend.

On the demand side, fintech has also broadened access to investment opportunities. Digital investment platforms enable individuals to participate in asset classes that were previously accessible primarily to institutional or accredited investors (Bollaert et al., 2021). Low minimum investment thresholds, simplified interfaces, and real-time information reduce participation costs and lower barriers to entry for retail investors. Farag and Johan (2022) note that as technology has reduced complexity and transaction costs, regulatory frameworks in many jurisdictions have progressively permitted broader participation in alternative investments, thereby expanding the investor base.

The platformisation of finance plays a key role in this process. Many fintech business models operate as two-sided digital platforms that connect firms directly with large and geographically dispersed pools of investors. These platforms reduce search and matching frictions, decentralise information

flows, and enhance visibility for ventures located outside established financial hubs or operating in niche markets (Gomber et al., 2018). Platform dynamics also generate network effects: as participation increases, information becomes richer and markets more liquid, reinforcing engagement on both sides of the platform.

In sum, the literature indicates that fintech broadens financial inclusion by reducing entry barriers, expanding participation, and creating alternative pathways for funding and investment. Through digital channels, platform-based intermediation, and new organisational forms, fintech reshapes who can supply and access capital. At the same time, this expansion introduces new challenges. By lowering participation thresholds and reducing reliance on traditional gatekeepers, fintech markets often operate under conditions of heterogeneous disclosure quality, limited verification, and persistent information asymmetry. These features create environments in which investors struggle to assess underlying project quality and issuers face incentives that may not fully align with those of funders. As a result, the democratisation of finance is accompanied by risks that closely resemble the dynamics described in classic models of adverse selection.

Therefore, to shed light on some of the inherent limitations of this new, democratised form of access to finance, the next section examines how structural frictions in fintech markets can lead to lemons-type problems and why information asymmetry, screening limitations, and moral hazard, just as in traditional financial markets, remain central for a comprehensive, grounded understanding of their functioning.

1.3 Fintech Markets, Information Frictions, and the "Market for Lemons" Problem

Digitalisation has transformed the mechanisms through which early-stage ventures obtain external financing, but it has not eliminated the fundamental frictions that shape financial markets. At the core of these frictions lies the problem of quality uncertainty formalised by Akerlof (1970), who showed that when buyers cannot distinguish between high- and low-quality offerings, markets may degenerate into a "market for lemons". In such environments, inferior products and less-deserving firms survive disproportionately, while higher-quality sellers and more deserving firms withdraw because prices fail to reflect actual value. Fintech funding markets exhibit many of the conditions that give rise to this dynamic. These platforms enable large numbers of retail investors to allocate capital in the absence of the intensive screening, verification, and monitoring traditionally performed by financial intermediaries. As a result, information asymmetry is structural rather than incidental, weakening the link between observable signals and underlying quality.

A defining characteristic of fintech markets is their reliance on digital disclosures, soft information, and behavioural cues rather than on standardised, verifiable indicators of project or borrower quality.

As emphasised by Bollaert et al. (2021), the scarcity of reliable and comparable information about early-stage ventures constitutes a central challenge for unsophisticated investors. In many fintech segments, platforms conduct only limited due diligence, and in some cases, screening and verification are delegated almost entirely to investors. This informational environment closely mirrors the conditions highlighted by Akerlof (1970), in which market participants must rely on aggregate or socially generated signals rather than objective measures of quality.

These informational constraints create fertile ground for adverse selection. Ventures that struggle to access traditional finance, such as those lacking internal funds and reaching their debt capacity (Walthoff-Borm et al., 2018), may more often turn to fintech alternatives, not only because of lower transaction costs but also because platform-based models generally require less disclosure, governance, and financial reporting. Empirical evidence reviewed by Bollaert et al. (2021) indicates that firms with high leverage, limited collateral, or weak financial histories are overrepresented in certain segments of crowdfunding and peer-to-peer lending. This selection effect skews the pool of available projects toward lower average quality, precisely the setting in which opportunistic issuers benefit from investors' limited ability to distinguish between high- and low-quality ventures. As in the lemons framework, the presence of weaker or opportunistic projects can depress overall market quality and reduce investor confidence, ultimately constraining market depth.

Adverse selection is further compounded by moral hazard once capital has been committed. Fintech platforms frequently facilitate investments in settings where investors possess limited control rights, weak monitoring capacity, and few contractual protections. In equity crowdfunding, retail investors often hold minority stakes and have minimal governance power, and formal mechanisms that align managerial incentives with investor interests are frequently absent. The anonymity and limited scope for repeated interactions in digital markets weaken reputational discipline, thereby increasing the likelihood of opportunistic behaviour. In Akerlofian terms, the costs of misrepresentation and underperformance are not borne solely by individual investors; they also spill over to the market as a whole, eroding trust and discouraging participation by higher-quality issuers.

The implications of these frictions extend beyond individual losses. Akerlof's (1970) insight that quality uncertainty can undermine entire markets is particularly salient in fintech funding ecosystems. If investors become sceptical about the average quality of offerings, participation may decline, liquidity may dry up, and platforms may struggle to fulfil their matching function. Fintech markets, therefore, face an inherent tension: by lowering entry barriers and broadening access, they expand participation, yet these same features increase exposure to adverse selection and moral hazard, potentially triggering the downward spiral characteristic of a lemons market.

At the same time, fintech environments introduce behavioural mechanisms, such as social proof, herding, and attention dynamics, that can partially substitute for missing quality information, but also distort inference. Early contributions, trending indicators, and platform-generated statistics can create self-reinforcing patterns of visibility that obscure underlying fundamentals. In such settings, investment outcomes may depend as much on momentum and salience as on economic quality. These behavioural cues do not resolve the lemons problem; rather, they reshape it by allowing social information to stand in for fundamentals, sometimes amplifying noise and path dependence when signals are weak or manipulable.

Overall, the existing literature indicates that fintech funding markets are not immune to the traditional issues of quality uncertainty, adverse selection, and moral hazard. Digital intermediation often amplifies these frictions by expanding participation while reducing standardised verification, creating environments in which investors struggle to assess project quality with precision. Platforms respond to these challenges through various design and disclosure mechanisms, but the baseline informational environment remains structurally opaque. This observation provides a natural entry point into the study of equity crowdfunding, arguably the most institutionalised and regulated form of fintech funding, where these informational challenges are especially pronounced. Understanding how equity crowdfunding navigates this tension between access and information frictions is essential before examining how signalling, behavioural responses, and herding dynamics shape the efficiency of capital allocation in such markets.

The following section focuses on equity crowdfunding, as it provides a key example of how traditional issues of information asymmetry, adverse selection, and moral hazard arise in a modern financial market and how these mechanisms interact with behavioural dynamics.

1.4 Equity Crowdfunding: Successes and Structural Challenges

Equity crowdfunding has emerged as one of the most distinctive and institutionally developed forms of fintech-based entrepreneurial finance. Through digital platforms, early-stage ventures raise equity capital directly from a dispersed crowd of predominantly retail investors, bypassing traditional intermediaries such as venture capitalists. This structure enables entrepreneurs to mobilise financial resources from a broad, geographically diverse investor base, functioning as a platform-mediated mechanism to expand access to early-stage equity investment (Vulkan et al., 2016). Equity crowdfunding thus extends the broader fintech logic introduced in earlier sections: it lowers participation barriers for both entrepreneurs and investors, broadens the pool of capital available to young firms, and provides an entry point into equity markets for individuals historically excluded from private investment opportunities (Geiger & Oranburg, 2018). At the same time, existing

evidence indicates that these democratising benefits are uneven and depend critically on platform design, regulatory frameworks, and investor capabilities (Schwienbacher, 2019).

The model's appeal lies in its ability to pool small investments at scale, reduce reliance on network-based deal sourcing, as seen in angel and venture capital club deals, and utilise digital infrastructure to connect early-stage ventures with large audiences. Platforms standardise key aspects of the fundraising process, lowering transaction and coordination costs and enabling founders to present campaigns simultaneously to thousands of potential investors (Vulkan et al., 2016). These features enhance the visibility of young firms and allow entrepreneurs to convey market interest through real-time funding dynamics. In this respect, equity crowdfunding offers an alternative financing route for ventures that fall below the threshold for institutional investors, particularly in contexts where traditional mechanisms, based on collateral, networks, or intensive due diligence, exclude them.

At the same time, the conditions under which equity crowdfunding operates embed significant structural vulnerabilities. Campaigns typically involve early-stage ventures characterised by high uncertainty and limited verifiable information, creating pronounced information asymmetries between entrepreneurs and retail investors (Kukk, 2022). Most crowd participants lack the time, expertise, or incentives to perform detailed due diligence. As Kukk (2022) notes, retail investors generally do not conduct independent screening and instead rely on issuer-provided disclosures and platform-level filters. Disclosure quality varies widely, and much of the available information consists of soft signals, narratives, pitch videos, and forward-looking projections that are only imperfectly related to underlying venture quality. These challenges are compounded by investor heterogeneity: financial illiteracy, limited technical expertise, and difficulty processing complex disclosures reduce the effectiveness of mandated information regimes. Moreover, because equity crowdfunding markets lack continuous price discovery mechanisms, unsophisticated investors cannot rely on prices to aggregate information or correct misperceptions, further heightening exposure to adverse selection (Ibrahim, 2015).

Given these constraints, platforms play a central gatekeeping role. When investors cannot efficiently screen opportunities themselves, platform-level due diligence becomes critical in determining which ventures reach the market and under what conditions (Kukk, 2022). However, the intensity and quality of screening vary substantially across platforms (Kleinert et al., 2021). Some implement relatively rigorous checks, employ professionalised screening processes, or co-invest alongside sophisticated investors, thereby acting as reputational intermediaries. Others perform minimal screening beyond basic compliance. Evidence from Schwienbacher (2019) indicates that these differences are associated with variation in post-campaign failure rates. In the United States, funding portals authorised under Title III are legally constrained to act mainly as intermediaries, "limited to putting

buyers and sellers together", with little scope for substantive prescreening (Ibrahim, 2015). In the absence of effective reputational intermediation, platforms may struggle to filter out low-quality issuers or protect unsophisticated investors, increasing vulnerability to "market for lemons" dynamics.

Differences in platform design and regulation further reinforce structural heterogeneity. Platforms vary in disclosure formats, screening intensity, securities offered, minimum investment thresholds, pooling mechanisms, and investor base composition. Dushnitsky and Fitza (2018) show that empirical findings from one platform often do not generalise to others precisely because platforms differentiate themselves along dimensions that shape both issuer selection and investor behaviour. Schwienbacher (2019) similarly highlights variation in security structures and participation rules, each of which influences risk exposure and decision-making. In this context, regulatory fragmentation further restricts platform growth, standardisation, and cross-border integration, reinforcing institutional heterogeneity and hindering the development of standard market norms. These factors complicate investors' interpretation of available information and contribute to persistent system-level frictions.

Investor behaviour further amplifies these challenges. Under conditions of limited information and bounded attention, investors frequently rely on heuristics when evaluating opportunities. Evidence from early-stage investment contexts indicates that superficial traits, such as textual readability or persuasiveness, can have a disproportionate impact on investor assessments, sometimes outweighing substantive financial details (Chan et al., 2020; Johan & Zhang, 2020). Such patterns indicate that presentation and salience may distort judgment in environments with high information asymmetry and limited formal due diligence. The ambiguous role of "the crowd" adds another layer of complexity: while collective decision-making can aggregate information under certain conditions, it may fail when participants are inexperienced, behaviourally biased, or lack domain-specific knowledge (Ibrahim, 2015). In these settings, investment behaviour may respond to social proof and visibility rather than to fundamentals.

Market dynamics also reflect strategic behaviour by issuing firms. Cerpentier et al. (2022) document the existence of "hot" and "cold" market phases in equity crowdfunding, during which firms strategically time campaign launches, set higher funding targets, and raise larger amounts under favourable conditions. In markets with limited verification and weaker information infrastructures, such timing behaviour can further decouple funding outcomes from underlying quality. These dynamics underscore the fragility of information environments in equity crowdfunding, where investor beliefs may fluctuate with sentiment and visibility rather than with fundamentals.

What emerges from combining this evidence is that, while equity crowdfunding broadens financing opportunities and increases participation, it remains highly vulnerable to information asymmetry, varied platform governance, heuristic-based investor behaviour, and strategic timing by issuers. The model's success, therefore, coexists with persistent informational challenges that shape capital allocation.

Considering these factors, it is difficult to determine whether equity crowdfunding can produce efficient market outcomes. This largely depends on how effectively signalling mechanisms and investor inference processes mitigate the aforementioned frictions. Therefore, the next section examines how signals within campaign dynamics and investor behaviour patterns, including herding, can partially mitigate these challenges and influence the efficiency of capital allocation in equity crowdfunding markets.

1.5 Efficient Allocation of Capital in Equity Crowdfunding Markets

In principle, equity crowdfunding can enhance capital allocation efficiency by enabling investors to infer venture quality from observable signals transmitted by entrepreneurs. Classical signalling theory (Spence, 1973) shows that, under specific conditions, costly, observable, and quality-correlated signals allow decision-makers to distinguish between high- and low-ability agents. In the context of entrepreneurial finance, this framework implies that founders may credibly communicate venture prospects through signals such as human capital, intellectual property, equity retention, or structured disclosure (Ahlers et al., 2015). When such signals are informative and correctly interpreted, capital should flow toward higher-quality ventures, mitigating informational frictions that would otherwise impede financing.

However, this theoretical benchmark relies on conditions that are rarely fully satisfied in early-stage crowdfunding markets. Effective signalling presumes that high-quality entrepreneurs can bear the costs of credible signals, that these signals are sufficiently correlated with underlying quality, and that investors possess the cognitive capacity and incentives to interpret them accurately.

A growing literature questions whether these assumptions hold in practice. Conceptual work on entrepreneurial signalling suggests that many signals commonly observed in crowdfunding are ambiguous, inexpensive, and easy to mimic, thereby limiting their ability to reliably discriminate between venture types (Svetek, 2022). Moreover, the proliferation of heterogeneous signal categories, including team characteristics, textual features, social media presence, and updates, has generated definitional ambiguity and made it difficult to identify which elements function as genuine signals and which operate primarily as presentational cues (Bafera & Kleinert, 2023). As a result, the

correspondence between observable signals and venture fundamentals is often imprecise, weakening their capacity to support efficient capital allocation.

Empirical evidence reinforces this cautious view. Even conceptually robust signals, such as disclosure quality, tend to influence only subsets of investors, particularly those with greater sophistication or experience (Bafera & Kleinert, 2023). Other forms of communication, including campaign updates or promotional content, frequently affect investment behaviour through channels unrelated to uncertainty reduction, such as affective responses, narrative engagement, or salience (Steigenberger et al., 2025). In these cases, communication shapes investor decisions without necessarily improving their assessment of venture fundamentals. This divergence between theoretical and empirical signalling mechanisms illustrates a limitation already recognised in signalling theory itself: markets may converge to equilibria in which signals are weakly informative, excessively noisy, or loosely connected to quality, leading to behaviour that departs from efficient sorting (Spence, 1973).

Certification signals, most notably affiliations with venture capitalists, business angels, or publicly funded programmes, represent a partial exception. Such signals entail reputational and screening costs for certifying agents and therefore tend to correlate more closely with underlying venture quality. Empirical evidence indicates that prior financing or external validation can reduce information asymmetry and support more informed investment decisions, particularly for seed-stage ventures operating under high uncertainty (Kleinert et al., 2020). Nonetheless, certification signals are unevenly distributed across the venture population, vary in salience across investor types, and do not uniformly predict post-campaign performance. As a result, while certification provides a valuable benchmark for evaluating other signals, it remains too scarce to ensure allocative efficiency at the market level.

The fragility of signalling as a mechanism for efficient allocation is further underscored by evidence linking investor responses to signals with subsequent firm outcomes. Several studies document that investors may reward signals that are weakly or even negatively correlated with ex post performance. For example, large early investments are associated in some settings with higher failure risk, suggesting that investors may initiate cascades that do not reflect underlying venture quality (Reichenbach & Walther, 2021). Similarly, specific categories of campaign updates, particularly those emphasising external promotion or general activity, are correlated with weaker post-offering survival, indicating that investors may overweight attention-grabbing cues rather than informative ones. These patterns suggest that capital can be drawn toward ventures with strong superficial signals rather than robust fundamentals.

In this environment, social information becomes a key element in investor decision-making. In equity crowdfunding, investors observe the actions and sometimes the identities of earlier backers, and these

observable choices serve as belief-based signals when formal indicators are lacking or difficult to interpret. Prior research conceptualises these dynamics as information cascades: under sequential decision-making and uncertainty, individuals rationally infer quality from predecessors' actions, particularly when early contributors appear informed or sophisticated (Vismara, 2018). Such cascades may arise from Bayesian updating, but they are often reinforced by behavioural factors such as conformity, limited attention, and platform-driven visibility.

These insights suggest that efficient capital allocation in equity crowdfunding cannot rely solely on signalling mechanisms. The theoretical prerequisites for effective signalling, costliness, observability, correlation with quality, and interpretability are inconsistently satisfied. Many signals influence behaviour without conveying reliable information, and social cues, including early investor actions, play a prominent role in shaping investment flows. The interaction of incomplete signals, bounded cognition, and socially transmitted information implies that crowdfunding markets operate under hybrid informational regimes, in which allocative efficiency depends not only on venture characteristics but also on the behavioural and structural properties of the crowd.

This environment provides fertile ground for the development of herding dynamics. Consequently, the next chapter will explore the theoretical foundations of herding behaviour to offer an overview of how early peer actions influence subsequent behavioural responses, both generally and more specifically within financial markets, including traditional and fintech-based ones.

Chapter 2: Theoretical Background

2.1 What Is Herding Behaviour and How It Occurs

Herding behaviour refers to the tendency of individuals to align their actions or judgements with those of others, resulting in the convergence of behaviour within a group. A defining feature of herding is that such convergence does not arise from explicit central coordination, but rather from decentralised interactions among agents (Raafat et al., 2009; Kameda et al., 2014). What appears ex post as coordinated collective behaviour is therefore an emergent outcome of local decision-making: individuals react to social cues in their immediate environment, and the aggregation of these reactions generates large-scale patterns. This logic of emergent alignment underpins herding phenomena across domains, from animal flocking to human social and financial systems.

Building on this intuition, interdisciplinary research has proposed a helpful distinction between pattern-based and transmission-based approaches to herding (Raafat et al., 2009). Pattern-based explanations focus on how interaction structures and network topology generate aggregate outcomes. Individuals are typically modelled as following simple behavioural rules, such as imitating neighbours, switching actions once a threshold is crossed, or responding to local majorities, while analytical attention is directed toward the resulting collective patterns. In such models, cascades, clusters, and waves of behaviour arise not from complex individual cognition but from the network configuration and the strength of local dependencies. From this perspective, herding is primarily a structural phenomenon: altering network connectivity or visibility can substantially alter aggregate outcomes even when individual decision rules remain unchanged.

Transmission-based approaches, by contrast, focus on the mechanisms through which behaviour, beliefs, or affect are conveyed from one individual to another (Raafat et al., 2009; Kameda et al., 2014). Rather than abstracting from individual cognition, this perspective emphasises the psychological and informational processes underlying social influence. A central distinction within this strand separates informational from non-informational transmission. Informational transmission occurs when individuals interpret others' actions as informative signals about the state of the world or the expected payoff of choices. Non-informational transmission encompasses processes such as emotional contagion, mimicry, and normative conformity, in which individuals align with others' behaviour without inferring anything about underlying fundamentals.

Informational herding is typically grounded in inference under uncertainty. Individuals observe the actions of others and reason that these actions reflect private information, superior judgment, or expertise. When uncertainty is high and private signals are noisy, it may be rational to place substantial weight on observed behaviour, particularly if earlier actors are perceived as better

informed. Formal models of informational cascades demonstrate that, under sequential decision-making, individuals may optimally disregard their own private signals once public evidence becomes sufficiently strong, leading to widespread imitation even when the underlying informational base is thin or biased (Kameda et al., 2014). In this sense, herding need not be irrational; it can emerge as a belief-based response to asymmetric information.

Non-informational mechanisms capture a distinct set of processes. Emotional contagion refers to the automatic spread of affective states through unconscious mimicry of expressions, posture, or tone (Raafat et al., 2009; Kameda et al., 2014). Individuals may internalise others' emotions and adjust their behaviour accordingly, thereby generating synchronised responses within groups. Normative conformity represents another key channel: individuals align their expressed opinions or actions with those of a group to avoid social sanctions, gain approval, or maintain social identity. Classic evidence from social psychology shows that individuals may adopt clearly incorrect judgments when confronted with unanimous group pressure, In these cases, herding reflects sensitivity to social rewards and penalties rather than to informational content.

Both pattern-based and transmission-based perspectives highlight the role of network structure in shaping how herding unfolds. Who observes whom, with what frequency, and under what institutional constraints determines which behaviours are visible, how rapidly they spread, and where clusters of alignment emerge (Raafat et al., 2009). Dense networks and highly connected hubs can accelerate diffusion, while sparse structures or weak ties may dampen or fragment it. In human settings, these network properties are rarely exogenous: they are shaped by institutional arrangements, media architectures, and digital platforms that govern visibility and information flow. Herding is therefore not solely a property of individual psychology, but also of the social and technological environments in which decisions are embedded.

Importantly, herding is not intrinsically maladaptive. Under certain conditions, such as when individual errors are independent and social influence is moderate, aggregating dispersed information through social interaction can yield accurate collective judgements and efficient coordination, often described as “wisdom of crowds” effects (Kameda et al., 2014). Problems arise when dependence becomes excessive, either because individuals overweight others’ actions or because network structures disproportionately amplify particular signals. In such cases, collective outcomes may deviate systematically from underlying fundamentals. Thus, understanding herding demands a nuanced explanation of how informational and non-informational transmission mechanisms interact with network structure and institutional design. This conceptual foundation provides the basis for examining how financial economics has traditionally conceptualised market efficiency, and how herding challenges the assumptions underlying the efficient market hypothesis.

2.2 From the Efficient Market Hypothesis to Behavioural Finance

The Efficient Market Hypothesis (EMH) occupies a central position in modern financial economics by formalising the claim that competitive markets aggregate information efficiently into prices. In its canonical formulation, a market is efficient if security prices fully reflect all available information, implying that no investor can systematically earn excess risk-adjusted returns by trading on that information (Fama, 1970). Prices thus serve as sufficient statistics for underlying fundamentals, coordinating resource allocation by summarising dispersed knowledge across market participants. This framework relies on strong assumptions: information must be widely available, investors must process it rationally, and arbitrage must be sufficiently robust to eliminate any mispricing.

However, the internal logic of the EMH reveals important tensions. If information were costless and instantaneously incorporated into prices, agents who expend resources to acquire private information would be unable to earn compensating returns. Grossman and Stiglitz (1980) formalise this paradox by showing that perfectly informationally efficient markets cannot exist in equilibrium when information acquisition is costly. Prices must remain at least partially noisy to preserve incentives for information production. Inefficiency, in this sense, is not a failure of markets but a necessary condition for their functioning. This impossibility result exposes a fundamental limitation of the EMH: its strongest form cannot simultaneously sustain incentives for informed trading and full informational efficiency.

Further challenges arise from empirical evidence on price dynamics. Even when information is publicly available, asset prices often exhibit movements that cannot be reconciled with changes in fundamentals alone. Morck, Shleifer, and Vishny (1990) document that stock returns contain a substantial component attributable to investor sentiment rather than to rational responses to economic information. Correlated non-informational trading can therefore generate price fluctuations unrelated to underlying value. These effects persist despite the presence of rational traders, suggesting that prices aggregate psychological and social influences alongside fundamentals. Such findings complicate the EMH's depiction of prices as unbiased summaries of economic information.

The assumption that arbitrage enforces efficiency also proves fragile. De Long, Shleifer, Summers, and Waldmann (1990) demonstrate that rational arbitrageurs face an additional source of risk when correcting mispricing: noise traders may become more optimistic or pessimistic before prices converge to fundamentals, generating interim losses. Because arbitrageurs are typically risk-averse, capital-constrained, and subject to finite investment horizons, they may rationally limit their exposure. As a result, mispricing can persist even in the absence of fundamental uncertainty. This framework establishes that arbitrage is neither frictionless nor unlimited, undermining the EMH's core corrective mechanism.

A further tension concerns the assumption of homogeneous beliefs. Tirole (1982) shows that in markets populated by rational agents with common priors, speculative trade cannot arise. Once information is incorporated into prices, there is no motive to trade on differing expectations. Yet real markets exhibit substantial trading volume, recurrent speculative episodes, and waves of optimism and pessimism. Explaining these phenomena requires relaxing the EMH's assumptions by introducing heterogeneous beliefs, limits to rationality, or deviations from Bayesian updating. These departures are conceptually incompatible with the classical EMH, yet essential for explaining observed market behaviour.

Empirical evidence reinforces these theoretical critiques. Shiller's (1981) excess volatility result shows that stock prices fluctuate far more than can be justified by subsequent movements in dividends under the present-value model implied by the EMH. By constructing an ex post rational benchmark using realised dividends, Shiller demonstrates that observed price volatility exceeds the maximum variability permitted by the theory. These patterns cannot be plausibly attributed to time-varying discount rates or measurement error. Instead, they point to the influence of sentiment, feedback trading, and socially transmitted expectations. Excess volatility thus provides early and compelling evidence that the EMH fails to hold descriptively, even under generous assumptions.

Together, these arguments reveal that the EMH rests on assumptions about information, beliefs, and arbitrage that are difficult to sustain empirically. Information is costly; prices reflect sentiment as well as fundamentals; arbitrage is risky and constrained; and speculation requires heterogeneity that the EMH suppresses. This body of evidence highlighting the limitations of EHM paved the way for behavioural finance, which relaxes the assumptions of complete rationality and homogeneous beliefs to examine how cognitive biases, social interaction, and informational frictions influence market outcomes. The following section builds on this foundation by examining formal models of herding and informational cascades, which show how individually rational behaviour under uncertainty can generate collective dynamics that systematically depart from the efficient aggregation of information.

2.3 Classical Theoretical Foundations of Herding

The limitations of the EMH discussed in the preceding section imply that investors often operate in environments in which prices do not fully or transparently reflect underlying fundamentals. When uncertainty is high, and prices fail to summarise dispersed information effectively, individuals must rely on alternative inference mechanisms. In such settings, observing others' actions becomes a natural and potentially rational strategy for belief formation. Early contributions in information economics formalise this intuition by showing that, when private signals are noisy and information is dispersed, individuals optimally condition their behaviour on the observed decisions of predecessors.

This shift from price-based inference to socially mediated inference marks a conceptual turning point in the analysis of financial behaviour. Rather than assuming that markets aggregate information frictionlessly through prices, these models recognise that information is transmitted through sequences of individual decisions. Each agent observes both a private signal and the publicly observable actions of others, and updates beliefs accordingly. The aggregation of these local inferences can generate conformity, cascades, and herding even when all agents are rational and unbiased. Importantly, these outcomes do not rely on psychological anomalies or behavioural errors; they arise from the structural properties of information flow in environments characterised by opacity, uncertainty, and sequential observability.

The foundational model of rational herding is provided by Banerjee (1992). In his framework, individuals make decisions sequentially, observe the actions of earlier decision-makers, and receive private signals about the underlying state of the world. Because earlier actions embed private information, later individuals rationally treat observed behaviour as an additional signal. When a sufficiently strong pattern emerges, the informational content of predecessors' actions dominates an individual's own signal, leading to imitation even when private information points in the opposite direction. Herding thus emerges as the outcome of Bayesian updating in a sequential environment with imperfect information, rather than from any intrinsic preference for conformity or coordination.

Bikhchandani, Hirshleifer, and Welch (1992) formalise this intuition through the concept of informational cascades. In their model, once enough individuals act in the same direction, subsequent decisions no longer depend on private signals. At that point, actions no longer reveal new information to observers, and learning effectively stops, even though private information continues to arrive. Informational cascades, therefore, represent a breakdown in information aggregation: public belief formation becomes detached from underlying signals, and outcomes become highly path dependent. This insight has profound implications for financial markets, where the visibility of early decisions, such as large trades, analyst recommendations, or initial subscription patterns, can disproportionately shape the beliefs and behaviour of later participants.

Welch (1992) extends the cascade theory to a concrete financial setting by analysing the sequential sale of shares in initial public offerings. In his model, potential investors infer information from the participation decisions of earlier subscribers. Strong early demand signals favourable private information and induces later investors to participate regardless of their own assessments, while weak early demand discourages participation. These dynamics generate path dependence in offering outcomes: success depends not only on fundamentals but also on the order in which investors are approached. Welch's analysis illustrates how rational cascades can form rapidly and helps explain

empirical phenomena such as IPO underpricing, which can be interpreted as a mechanism to secure favourable early participation and avoid negative cascades.

A distinct but complementary mechanism of herding arises from reputational rather than informational considerations. Scharfstein and Stein (1990) develop a model in which managers care about how external observers evaluate their actions. Because observers cannot perfectly distinguish between poor outcomes caused by poor ability and those caused by adverse shocks, deviating from peers' actions exposes managers to reputational risk. Mimicking others, therefore, becomes a rational strategy for career preservation, even when private information suggests an alternative course of action. This form of herding suppresses information aggregation, not because agents learn from others, but because they strategically conceal their private information by conforming to the majority.

While early cascade models suggest that herding arises readily in sequential environments, later work shows that its emergence depends critically on informational structure. Avery and Zemsky (1998) demonstrate that in markets with a single dimension of uncertainty and fully revealing prices, informational cascades cannot occur: prices adjust in ways that incorporate private information, preventing agents from ignoring their signals. Herding becomes possible only in richer informational environments characterised by multidimensional uncertainty, for example, uncertainty about whether an informational event has occurred or about the fraction of informed traders. In such settings, prices may fail to fully aggregate information, allowing sequences of trades to lose informational content and generating rational herding, bubbles, or abrupt reversals. This contribution refines the theoretical foundations of herding by highlighting that limits to information aggregation are essential.

These classical models establish that herding is not an anomaly or a manifestation of irrationality, but a natural outcome of rational decision-making under uncertainty, asymmetric information, and sequential observation. Whether driven by informational inference or reputational incentives, herding can generate correlated behaviour, suppress private information, and produce path-dependent outcomes that are only weakly related to fundamentals. These insights provide a baseline for understanding herding in contemporary financial environments. The following section reviews empirical evidence on herding in traditional financial markets, setting the stage for analysing how these mechanisms operate in platform-mediated contexts such as equity crowdfunding.

2.4 Herding in Traditional Financial Markets

Empirical research on herding in traditional financial markets shows that investor imitation is neither universal nor homogeneous. Instead, herding varies systematically across investor types, market structures, and informational environments. Evidence from developed equity markets, characterised

by deep liquidity, extensive disclosure, and professional intermediation, suggests that correlated behaviour is generally limited and conditional rather than pervasive.

Early evidence from U.S. equity markets illustrates this point. Lakonishok, Shleifer, and Vishny (1992) provide one of the first systematic measures of institutional herding and find that, on average, professional investors display only modest correlated trading. Where herding is observed, it is concentrated in smaller, less transparent stocks, suggesting that alignment often reflects shared information constraints rather than blind imitation. Institutional investors appear to react to similar signals, analytical frameworks, or investment mandates, producing correlated outcomes without necessarily abandoning independent judgment.

Subsequent work highlights the dynamic dimension of institutional herding. Sias (2004) shows that correlations in institutional demand persist across adjacent quarters, consistent with investors conditioning on others' recent trades. This persistence supports interpretations based on informational and herding, whereby investors infer insights from the actions of peers perceived as informed. Importantly, this behaviour differs from non-informational imitation: institutional herding tends to be structured, gradual, and embedded in professional information-processing systems rather than driven by sentiment or conformity per se. Taken together, these findings indicate that institutional herding is of limited magnitude and largely grounded in information extraction rather than behavioural contagion.

Retail investors exhibit markedly different patterns. Unlike institutions, individual investors typically lack access to proprietary research, face higher information-processing costs, and are more exposed to attention constraints and behavioural biases. Barber, Odean, and Zhu (2009) document that retail investors systematically concentrate their trades in the same stocks over short horizons and respond strongly to attention-grabbing cues such as abnormal trading volume or large price movements. Their evidence shows pronounced temporal and cross-sectional clustering in retail demand, generating short-lived price pressure and reversals. In contrast to institutional herding, which often reflects inference from others' information, retail clustering appears to arise primarily from bounded rationality, limited attention, and reliance on salient but noisy signals.

Cross-market evidence further underscores the role of informational environments in shaping herding. Chang, Cheng, and Khorana (2000) examine return dispersion during periods of large market movements and find little evidence of herding in developed markets such as the United States, Japan, and Hong Kong. In contrast, they document significant herding in South Korea and Taiwan. In these markets, firm-level information is relatively scarce, and investors rely more heavily on common macroeconomic signals, especially during periods of stress. These findings indicate that herding intensifies when private information is weak and common signals dominate decision-making,

reinforcing the view that imitation is conditioned by information availability rather than being an inherent investor trait.

Evidence from China's equity markets provides a particularly clear illustration of retail-driven herding. Tan, Chiang, Mason, and Nelling (2008) document strong, statistically robust herding in the Shanghai and Shenzhen A-share markets, which are dominated by domestic retail investors. Herding intensifies during rising markets, high-volume periods, and episodes of elevated volatility, suggesting that uncertainty and heightened attention amplify behavioural convergence. Although herding is also present in B-shares, which attract more institutional participation, its effects are substantially weaker and do not exhibit the pronounced asymmetries observed in A-shares. These results align with broader evidence from emerging markets, where limited disclosure, thin information infrastructures, and speculative participation increase susceptibility to behavioural clustering.

Underlying these market-level patterns are systematic differences in investor cognition and behaviour. İpek and Mandacı (2025) show that susceptibility to herding varies with experience, financial literacy, and cultural context. Their meta-analytic evidence indicates that investors in developing and more collectivist societies are more prone to herding, reflecting greater reliance on social cues in ambiguous contexts. These micro-level differences help explain why retail-dominated and emerging markets exhibit stronger herding than markets populated by sophisticated institutional investors with access to robust information-processing and monitoring mechanisms.

Comprehensive reviews by Spyrou (2013) and Komalasari et al. (2022) synthesise this heterogeneous evidence. They emphasise that herding is a multifaceted phenomenon encompassing information-based inference, correlated reactions to shared signals, reputational incentives, and behavioural convergence. Empirical results differ across contexts partly because herding itself takes different forms, and partly because measurement strategies capture distinct dimensions of collective behaviour. In markets with strong disclosure regimes and effective arbitrage, herding tends to be modest and primarily informational. In markets characterised by opacity, retail dominance, and elevated uncertainty, herding becomes more pronounced and more behavioural in nature.

Overall, evidence from traditional financial markets demonstrates that informational frictions, investor composition, and market microstructure shape herding. Institutional investors tend to herd selectively and informationally, while retail investors exhibit stronger, attention-driven clustering. These distinctions are essential for understanding crowdfunding markets. Equity crowdfunding amplifies many of the conditions associated with pronounced herding: participation is dominated by retail investors, uncertainty is high, disclosure is soft and heterogeneous, and digital platforms make others' actions highly visible in real time. As a result, the mechanisms that generate herding in conventional markets are likely to operate with equal or greater intensity in crowdfunding settings.

The next section, therefore, turns to herding in crowdfunding markets, examining how these theoretical and empirical insights translate to platform-mediated environments in which prices are absent and social information plays a central role.

2.5 Theoretical Perspectives on Herding in Crowdfunding Markets

The informational environment of crowdfunding markets is particularly conducive to herding behaviour. Unlike traditional financial markets, crowdfunding platforms are populated predominantly by retail investors operating under high uncertainty, performing limited due diligence, and aggregating sparse, unverifiable information. In this setting, observable actions by other investors become central inputs into decision-making. The sequential and highly transparent structure of crowdfunding campaigns amplifies the salience of these social cues, making crowdfunding a natural laboratory for studying herding and social learning.

A key theoretical advance in understanding these dynamics is provided by Cong and Xiao's (2024) model of sequential contribution under all-or-nothing implementation thresholds. Their framework departs fundamentally from classical informational cascade models by showing how threshold-based payoffs reshape both information revelation and strategic incentives. In crowdfunding, a project is only if the total contributions reach a predetermined target (all-or-nothing mechanism). This institutional feature alters the meaning of early actions, the persistence of information in sequences, and the conditions under which cascades form.

In Cong and Xiao's (2024) model, each potential contributor observes a private signal about project quality as well as the full history of past contributions. In this context, contributors only incur costs if the threshold is ultimately reached. This payoff contingency creates strategic complementarity: the value of contributing increases with the expected likelihood that others will contribute as well. Early contributors with positive private signals have incentives to support the project even when early momentum is weak, because doing so preserves the option of implementation if later contributors, who may be better informed or closer to the threshold, also support. Rejecting early, by contrast, eliminates this option value.

This structure eliminates sustained downward cascades. In classical cascade models, early negative actions can suppress later private information and lock the sequence into persistent rejection. Under an all-or-nothing rule, however, any positively informed contributor has an incentive to interrupt a negative trend, since non-participation forecloses the possibility of later success. As a result, downward cascades collapse before they can form. Upward cascades, by contrast, remain feasible. Once sufficient early support accumulates, the information inferred from observed contributions dominates private signals, inducing later contributors to follow regardless of their own information.

This asymmetry generates informational dynamics that differ sharply from those in standard financial markets. Because contributors with positive signals continue to reveal information through their actions, the sequence remains informative over a longer horizon. Cong and Xiao (2024) show that as the crowd grows large, this process yields asymptotically efficient information aggregation: high-quality projects are implemented with high probability, while low-quality projects rarely reach the threshold. From this perspective, herding in crowdfunding can reflect an efficient "wisdom of crowds" mechanism rather than a breakdown of information aggregation.

At the same time, the same mechanism produces behaviour that resembles momentum or fear of missing out. As campaigns approach their funding targets, the expected payoff to contributing rises sharply: the probability of implementation increases, while the cost of contributing remains conditional. Late contributors, observing strong cumulative support, rationally rush to participate, producing a rapid acceleration in contributions. What appears behaviourally as FOMO is, in this framework, a rational response to threshold-dependent incentives rather than irrational imitation.

Platform design further amplifies these dynamics. As Vismara (2018) emphasises, crowdfunding platforms prominently display the number, timing, and, often, the identities of prior contributors, thereby transforming each investment into a visible public signal. Early contributions, particularly those perceived as originating from credible or sophisticated investors, serve as focal reference points for subsequent decision-makers. In environments where retail investors face high information-processing costs, these early actions substitute for a detailed fundamental analysis. Accumulated capital itself becomes a salient signal: Agrawal et al. (2014) describe cumulative funding as an informative but noisy proxy for project quality, allowing later investors to update beliefs based on the observed trajectory of support.

However, the informational content of early contributions is not guaranteed. Tzur and Segev (2025) show that early inflows may arise from heterogeneous motives unrelated to quality, including emotional attachment, social ties, or promotional activity. When such factors drive early support, accumulated capital ceases to function as a reliable signal, and later contributors may initiate cascades based on distorted information. This insight highlights a central vulnerability of crowdfunding markets: the efficiency of herding depends critically on the credibility and informational grounding of early contributions.

The absence of formally identifiable experts does not preclude cascades. Rodríguez-Garnica et al. (2025) argue that expertise is endogenously revealed through timing. Early backers tend to be individuals with greater familiarity with the creator or with superior domain knowledge, while later contributors are more likely to rely on social inference. As a result, an informal informational hierarchy emerges through self-selection: informed investors move early, and less informed investors

follow. This sequencing creates the conditions necessary for informational cascades even in markets dominated by retail participants. When early contributors act on genuine quality signals, cascades enhance information aggregation; when they act on sentiment or noise, imitation propagates error.

Finally, informational dynamics extend beyond the platform itself. Hervé et al. (2019) show that investors acquire information through personal networks and informal social interactions, which supplement platform-based signals. Socially connected investors tend to be better informed and more willing to invest, reinforcing the role of socially mediated inference in crowdfunding. These off-platform channels further blur the distinction between private and public information, strengthening the social foundations of herding.

These theoretical perspectives portray herding in crowdfunding as a hybrid phenomenon shaped by institutional design, sequential observability, distributed expertise, and social learning. All-or-nothing thresholds eliminate early negative cascades, prolong information revelation, and generate strong upward momentum near funding targets. Platform visibility amplifies early signals, accumulated capital acts as a public proxy for quality, timing reveals informational heterogeneity among investors, and external social networks enrich the informational environment. Herding in crowdfunding, therefore, spans a spectrum: under favourable conditions, it supports efficient information aggregation; under unfavourable conditions, it propagates sentiment, noise, or manipulation.

This theoretical framework provides the foundation for evaluating empirical evidence on herding in equity crowdfunding. The next section reviews that evidence, assessing whether observed funding dynamics align more closely with efficient social learning or with momentum-driven imitation.

2.6 Herding in Equity Crowdfunding

Equity crowdfunding combines the structural conditions identified in the previous sections as conducive to herding: severe information asymmetry, sequential contribution decisions, real-time visibility into others' actions, and participation by predominantly retail investors. Campaign pages continuously display funding progress, the number of backers, and, often, the identities or types of prominent investors. In this environment, investors can economise on costly information acquisition by conditioning their decisions on the behaviour of prior contributors, using cumulative investments, large pledges, or dynamic updates as indirect signals of venture quality. At the same time, platform design, cognitive constraints, and social identity biases create scope for imitation that is only weakly related to fundamentals. The emerging literature on equity crowdfunding therefore treats herding not as a marginal anomaly, but as a central mechanism through which information is aggregated, attention is allocated, and capital is distributed across campaigns.

A central theoretical and empirical reference point is the model by Åstebro et al. (2024), which formalises sequential investment behaviour under the all-or-nothing funding rule that characterises many equity crowdfunding platforms, including the Italian one analysed in the following chapters. In their framework, investors arrive over time, observe the campaign's funding history and a private signal about project quality, and decide whether to invest. Because the project is implemented only if the funding target is reached, early investors bear no cost if later investors do not follow, thereby fundamentally altering the classic cascade logic developed for environments with unconditional payoffs. Positively informed early investors have an incentive to invest even when previous contributions are limited, effectively delegating the ultimate implementation decision to later, better-informed investors. This structure prevents sustained downward cascades before the funding threshold is approached and instead permits strong upward cascades once sufficient support has accumulated. In this setting, pledge autocorrelation and accelerating contribution dynamics near the target do not necessarily signal irrational fads; rather, they are consistent with rational Bayesian updating in which cumulative investment acts as a sufficient statistic for dispersed private information (Åstebro et al., 2024).

Empirical work broadly aligns with this view that investors condition on prior funding decisions when forming their own. Several studies show that both the likelihood and the size of new investments respond to recent activity, even after controlling for campaign characteristics. Walther and Bade (2020) analyse investment-level data and document that investors commit larger amounts when there have been many large prior investments in the same campaign, consistent with investors interpreting conspicuous past contributions as informative signals about venture quality. Similarly, Hornuf and Neuenkirch (2017) exploit a multi-unit second-price auction design and find that the premium investors are willing to pay above the minimum ticket increases with the volume of earlier bids during the same day. Because the auction format is designed to elicit true valuations, the systematic responsiveness of willingness to pay to prior investment provides particularly clear evidence that investors update valuations in response to observed funding momentum. These findings indicate that herding in equity crowdfunding operates not only at the participation margin, but also at the level of investment intensity.

A second strand of research emphasises the role of dynamic and entrepreneur-controlled signals that are especially salient in the crowdfunding environment. Block et al. (2018) treat campaign updates as a flexible communication channel and show that updates on campaign development, new external funding, and business progress significantly increase subsequent investment activity, with effects unfolding over several days rather than instantaneously. Notably, static characteristics of the team or business model play a limited role once the campaign is live; investors appear to respond more

strongly to dynamic, socially visible cues than to underlying fundamentals. Walther and Bade (2020) similarly show that "hot" campaigns, those accumulating substantial funding over short intervals, receive larger incremental contributions, suggesting that investors condition not only on the level but also on the trajectory of funding. Wang et al. (2019) examine "jump" pledges, large, discrete investments that generate visible steps in the funding curve, and find that such jumps significantly increase the amounts pledged by subsequent investors. When the jump is made by a business angel rather than an ordinary crowd investor, the effect is even stronger, indicating that investors treat large, identity-linked contributions as particularly informative. These studies complement previous evidence by emphasising how salient funding events shape investment trajectories through observational learning.

While much of this literature focuses on how herding affects funding dynamics, Li et al. (2022) extend the analysis to its allocative consequences by examining overfunding. They conceptualise early herding as an "initial herd" characterised by its timing, intensity, and persistence. Using detailed transaction-level data, they adapt herding measures from the asset management literature and show that earlier, stronger, and more persistent herds are associated with greater overfunding, defined as funding levels exceeding the initial target. Their interpretation frames overfunding as a potential inefficiency: once the target has been reached, additional capital does not necessarily improve project outcomes and may instead reflect continued crowd following without reassessment of fundamentals (Li et al., 2022). This analysis links the temporal structure of herding to a concrete distortion in capital allocation, suggesting that the same dynamics that facilitate campaign success may, under certain conditions, generate overshooting.

The distinction between rational, information-driven herding and more behavioural, heuristic-based imitation becomes central in interpreting these findings. Yi et al. (2024) address this distinction directly by combining platform data from a Chinese equity crowdfunding portal with controlled experiments. Drawing on social learning theory, they define rational herding as behaviour in which investors incorporate publicly observable decisions as an additional signal while still processing their own private information. In their data, cumulative investment positively predicts current investment, particularly when project ratings are weaker or more ambiguous, indicating heavier reliance on social information when private signals are noisy. Their experimental results replicate this pattern: participants observing early informed investors are more likely to align with those decisions when project information is limited. Yi et al. (2024) thus provide cross-method evidence that at least part of herding in equity crowdfunding reflects rational inference rather than mechanical imitation.

By contrast, Ferretti et al. (2021) provide evidence of more behavioural herding mechanisms. They argue that equity crowdfunding platforms often confront investors with multiple simultaneous

campaigns, increasing the complexity of the decision environment. Using Italian data, they show that as the number of competing campaigns rises, investors reduce the amount invested per pledge and rely more heavily on accumulated funding as a heuristic. In their framework, "irrational herding" emerges when investors substitute coarse social cues for substantive evaluation under cognitive overload. The positive interaction between platform crowdedness and prior funding is difficult to reconcile with a purely informational learning story, as the informational content of accumulated funding does not increase mechanically with the number of alternatives. Instead, complexity appears to push investors toward simplified decision rules such as following the most funded campaign (Ferretti et al., 2021).

Other studies show that the identity and composition of prior investors systematically shape herding. Mohammadi and Shafi (2018) examine gender-specific herding and find that female investors are more likely to invest when a higher proportion of prior investors are male, while a higher share of female prior investors reduces female participation. This pattern contradicts simple homophily and suggests that female investors, on average, perceive male investors as more competent or better informed. Importantly, this effect does not attenuate when observable firm characteristics improve, indicating that gender-directed herding is not merely a proxy for quality inference but reflects socially structured perceptions of expertise.

Investor heterogeneity extends beyond gender to differences in information, attention, and experience. Bade and Walther (2021) show that investors with informational advantage, such as geographic proximity, allocate more attention to local campaigns and respond more strongly to social cues within those campaigns. On a German platform, they find that local investors are particularly sensitive to recent investments and updates, consistent with the idea that those who already possess superior information treat others' behaviour as especially informative within familiar domains. Hornuf et al. (2022) document related local bias at the portfolio level, showing that geographically proximate investments are more common and, for certain investor types, more likely to fail. Their specifications explicitly control for prior investments, implicitly recognising that local bias and herding interact rather than operate independently.

Differences in investor sophistication and status further condition the impact of social information. Wang et al. (2019) show that large pledges by business angels serve as compelling signals, eliciting larger subsequent investments than comparable pledges by non-angel investors. This effect is strongest in larger campaigns, where uncertainty is greater, and information asymmetry is more severe. Walther and Bade (2020) add nuance by showing that while large prior investments increase subsequent contributions, a very high number of prior investors can reduce willingness to pay, consistent with a congestion or crowding-out mechanism. When participation becomes too dense,

additional investments may convey less incremental information, dampening further escalation. These results highlight that herding depends not only on the amount invested but also on who invested and on how saturated the campaign appears.

A further complication is that not all correlated investment patterns originate from on-platform social learning. Cai and Polzin (2025) study repeated coinvestment patterns and show that investors who have previously funded the same campaigns are more likely to invest together again and to do so quickly. Their evidence suggests that these correlations are driven primarily by offline social networks and pre-existing relationships rather than by platform-based observation. From the perspective of platform data, such patterns resemble herding, but the causal mechanism is distinct: coordination occurs through private communication rather than public signals. This distinction is important for empirical work, as it implies that not all temporal dependence in crowdfunding investments reflects observational learning from visible funding trajectories.

In sum, the literature portrays equity crowdfunding herding as a layered and multifaceted phenomenon. At its core lies a rational component: investors face high information acquisition costs and treat prior funding decisions as noisy signals of venture quality, producing sequential dependence consistent with informational herding (Åstebro et al., 2024; Walther & Bade, 2020; Yi et al., 2024; Wang et al., 2019). Surrounding this core are behavioural and contextual forces that shape the strength and direction of herding. Platform complexity encourages heuristic reliance on accumulated funding (Ferretti et al., 2021); social identity and perceived expertise determine whose actions carry disproportionate weight (Mohammadi & Shafi, 2018; Wang et al., 2019); local connections and attention allocation intensify herding in specific domains (Bade & Walther, 2021; Hornuf et al., 2022); and offline networks generate correlated behaviour that may be misattributed to on-platform dynamics (Cai & Polzin, 2025). The welfare implications of these dynamics are ambivalent: herding can facilitate information aggregation and campaign success, but it can also contribute to overfunding and misallocation when cascades become detached from fundamentals (Li et al., 2022).

Despite the breadth of this evidence, the literature remains fragmented along methodological, theoretical, and contextual lines. Studies differ in their interpretation of sequential dependence as rational learning, heuristic imitation, or the outcome of deeper social and structural forces, and these mechanisms are infrequently integrated within a single empirical framework. Furthermore, most analyses report herding behaviour without fully addressing its welfare implications, especially in differentiating between information discovery and self-reinforcing misallocation. The next section builds on these unresolved issues by identifying the main conceptual and empirical gaps in the literature and outlining how subsequent chapters address them.

2.7 Gaps in the Existing Literature and Contribution of This Thesis

Research on herding in equity crowdfunding has expanded rapidly, yet important conceptual, empirical, and contextual gaps remain. Existing work has generated insights into how investors interpret social information, respond to visible funding dynamics, and update beliefs in environments characterised by high uncertainty and asymmetric information (e.g., Åstebro et al., 2024; Walther & Bade, 2020; Wang et al., 2019; Yi et al., 2024). However, the literature also exhibits several limitations that restrict the generalisability of its conclusions and leave open questions about the mechanisms driving sequential dependence in crowdfunding markets. This study addresses these shortcomings by providing new evidence from the Italian equity crowdfunding market and by jointly modelling behavioural channels that prior studies have typically examined in isolation.

A first gap concerns the geographical and institutional concentration of existing evidence. Most empirical studies of herding in equity crowdfunding focus on the United Kingdom, Germany, China, and a small number of Northern and Central European platforms (e.g., Mohammadi & Shafi, 2018; Walther & Bade, 2020; Hornuf & Neuenkirch, 2017; Wang et al., 2019; Yi et al., 2024; Bade & Walther, 2021; Hornuf et al., 2022). These markets operate under specific regulatory frameworks, platform architectures, and investor compositions, all of which may shape both the visibility of social information and the behavioural responses it elicits. As a result, it remains uncertain whether the mechanisms documented in these settings generalise to other institutional contexts. The Italian market, despite being one of the earliest regulated equity crowdfunding environments in Europe, has received comparatively little attention in the behavioural finance literature, with only a small number of studies examining platform complexity and herding (Ferretti et al., 2021). The Italian equity crowdfunding market combines three features that make it a particularly informative test case (Politecnico di Milano, 2025). First, it is one of the earliest fully regulated ECF ecosystems in Europe, offering a long horizon over which platform design, regulatory adaptations, and investor learning have unfolded. Second, despite this institutional maturity, the market remains small, concentrated, and structurally fragile, with limited scale and liquidity, conditions under which information frictions and behavioural responses are likely to be especially salient. Third, the Italian context simultaneously embodies the promises and limits of "democratised" entrepreneurial finance: regulation has broadened access for retail investors, yet unresolved issues surrounding secondary markets, post-campaign performance, and investor protection persist. Studying herding in Italy, therefore, does more than fill a geographic gap; it tests whether mechanisms identified in larger and more mature ecosystems remain operative when formal investor protections coexist with limited market depth and persistent opacity. By analysing over 25,000 pledges across 226 Italian campaigns hosted on one of Italy's leading equity crowdfunding platforms, Crowdfundme, from 2015 to 2025, this study provides

new evidence from a previously underexplored setting and offers a test of the external validity of previous findings.

A second gap relates to the fragmentation of behavioural mechanisms across separate empirical studies. Prior research has identified multiple channels through which sequential patterns may arise, such as Bayesian observational learning (Åstebro et al., 2024; Yi et al., 2024), platform-induced visibility and momentum cues (Walther & Bade, 2020; Block et al., 2018), large-pledge "jumps" and identity-specific signals (Wang et al., 2019), gender-based spillovers (Mohammadi & Shafi, 2018), geographic proximity and local attention (Bade & Walther, 2021; Hornuf et al., 2022), and offline coordination via repeated coinvestments (Cai & Polzin, 2025). These mechanisms are typically analysed in isolation, creating a conceptual limitation: observed herding patterns may reflect the interaction of several behavioural cues rather than a single dominant channel. Without modelling these cues jointly, empirical results risk attributing sequential dependence to a single mechanism when another may instead generate it. This study addresses this limitation by incorporating multiple behavioural inputs, including campaign-stage visibility, cumulative news coverage, Q&A activity, and an LSV-based measure of time-varying herding intensity, within a unified sequential framework. Simultaneously estimating their effects allows the analysis to distinguish cues that genuinely shape pledge behaviour from those that merely correlate with broader activity cycles.

A third gap concerns the temporal resolution at which herding is typically inferred. Many influential studies rely on daily, campaign-level, or event-level aggregates that cannot capture fine-grained behavioural adjustments. Such coarse measures may obscure short-run dynamics or overstate persistence in sequential dependence. For example, if large pledges are systematically followed by smaller ones, a pattern invisible at the daily level, aggregate models may incorrectly suggest reinforcement when underlying behaviour is oscillatory. The present study addresses this identification issue by exploiting pledge-level data and high-dimensional fixed-effects models that isolate within-campaign, within-day variation. This approach enables a clean separation between sequential responses to recent pledges and simultaneous reactions to platform-wide daily shocks, complementing existing investment-level evidence on momentum and jump effects (Hornuf & Neuenkirch, 2017; Walther & Bade, 2020; Wang et al., 2019).

A fourth gap concerns the endogeneity of temporal clustering, which is rarely addressed explicitly. Many studies implicitly interpret short inter-pledge intervals or bursts in funding activity as evidence of contagion or imitation (e.g., Block et al., 2018; Walther & Bade, 2020; Wang et al., 2019; Li et al., 2022; Yi et al., 2024). Yet such clustering may instead arise from predictable platform rhythms, attention shocks, or campaign-specific dynamics unrelated to herding. To address this issue, the study

implements an instrumental-variables strategy that uses the weekend occurrence of the prior pledge to generate exogenous variation in the spacing between contributions (Åstebro et al., 2024).

A fifth gap concerns the integration of campaign-stage effects and external visibility dynamics. Prior research shows that funding visibility, salient dynamic signals, and the composition of prior investors influence investment behaviour (Block et al., 2018; Walther & Bade, 2020; Wang et al., 2019; Ferretti et al., 2021; Mohammadi & Shafi, 2018; Bade & Walther, 2021; Hornuf et al., 2022; Cai & Polzin, 2025), yet little is known about how stage progression interacts with sequential dependence or whether external information flows, such as media coverage or Q&A activity, amplify or dampen responses to recent pledges. The present study incorporates campaign-stage indicators and cumulative external signals directly into the sequential structure.

Finally, the literature has not fully examined how time-varying herding intensity interacts with sequential dynamics within campaigns. Building on the Lakonishok, Shleifer, and Vishny (1992) framework, this study adapts an LSV-type measure to equity crowdfunding by benchmarking observed daily investment patterns against a Poisson process in which investors act independently. The resulting LSV index captures excess clustering in pledge arrivals beyond what would be expected under a no-herding benchmark, in line with approaches introduced in the crowdfunding context by Li et al. (2022).

Taken together, these contributions situate the Italian equity crowdfunding market within the broader behavioural finance literature while refining existing interpretations of herding (Åstebro et al., 2024; Walther & Bade, 2020; Li et al., 2022; Yi et al., 2024). By focusing on Italy, the analysis examines herding in a market that is institutionally mature yet structurally constrained, where regulatory intervention has not eliminated underlying opacity or fully stabilised market dynamics (Politecnico di Milano, 2025). This makes Italy a stringent setting for assessing whether herding reflects efficient information aggregation, behavioural contagion, or both. By combining high-frequency pledge-level data, fixed-effects structures, instrumental variables, and multiple behavioural channels, the study shows that patterns often labelled as herding are better understood as the interaction of attention synchronisation, oscillatory adjustment, stage-based visibility, and heterogeneous information processing.

The following empirical chapter introduces the Italian dataset, outlines the modelling approach, and demonstrates how high-frequency pledge-level evidence can clarify whether observed funding patterns result from imitation, strategic information use, or synchronised attention.

Chapter 3: Materials and Methods

3.1 Data and Variables

The empirical analysis relies on public transaction-level data from Crowdfundme, Italy's second-largest authorised equity crowdfunding platform. Crowdfundme operates under Italy's dedicated regulatory framework for online equity offerings and hosts campaigns by small and medium-sized enterprises and innovative start-ups. It was selected as the empirical setting for two main reasons. First, together with Mamacrowd, it accounts for the majority of Italian equity crowdfunding activity (Politecnico di Milano, 2025). Second, unlike Mamacrowd, Crowdfundme discloses detailed, pledge-level investment records and rich campaign-page information to registered users. This disclosure structure enables the reconstruction of high-frequency investment sequences and the construction of visibility and social-information metrics that are well suited to modelling within-campaign behavioural dynamics.

The final dataset consists of 226 completed equity campaigns and 25,768 individual investments recorded between 2015 and 2025. The sample includes all campaigns listed in the platform's public project archive as of October 2025. From this universe, only equity-based offerings were retained, regardless of share class, whereas all non-equity instruments, such as minibonds, were excluded. Each row in the pledge-level panel corresponds to a single investor commitment on a specific calendar day within a given campaign. The raw transaction data include the pledged amount, the investment date (day, month, and year), and the campaign's funding target. Additional information extracted from campaign pages includes the cumulative number of news items released by the issuer and the number of questions and answers posted by investors. All other variables used in the empirical analysis were constructed mechanically from these primitives or derived from campaign-page metadata.

This data structure yields a high-frequency panel that follows each campaign throughout its funding period and preserves the complete temporal ordering of individual funding decisions. Both successful and unsuccessful campaigns are included, allowing behavioural responses to be estimated without conditioning on ex post funding outcomes.

Two variables required integration of external data sources. Daily closing values of the FTSE MIB index were obtained from Yahoo Finance and merged with pledge dates to capture broad market conditions and investor sentiment. Public interest in crowdfunding was proxied using Google Trends. Because Google Trends reports daily indices only over limited time horizons, the Italian daily series for the keyword "crowdfunding" was downloaded in multiple overlapping windows, extracted manually, and subsequently normalised and concatenated into a single continuous daily series covering the whole 2015–2025 period.

3.2 Data Collection Through Web Scraping

All pledge-level and campaign-page data were obtained by extracting publicly visible information on Crowdfunder using Octoparse, a point-and-click web scraping environment designed to interact with dynamically rendered webpages. Data collection proceeded in two stages.

The first stage involved identifying the full population of completed campaigns hosted on the platform. Crowdfundme's project archive is organised as a vertically scrolling grid in which additional campaigns load progressively as the user scrolls down the page. Octoparse's infinite-scrolling functionality was configured to load the entire archive automatically, after which the scraper extracted the direct URL associated with each campaign tile. All extracted URLs were then manually inspected to verify that they corresponded to equity crowdfunding offerings. This filtering process yielded the final list of 226 campaign pages used for subsequent data extraction.

The second stage consisted of collecting the complete sequence of pledge-level records and campaign-page metadata for each campaign. Because detailed investment histories and interactive sections are visible only to logged-in users, a user account was created on the platform and authenticated within the Octoparse browser session. For each campaign page, the scraper navigated to the section displaying individual investments and iteratively expanded the list whenever additional records were revealed through "load more" controls. For each pledge, Octoparse captured the amount invested and the transaction date. In parallel, the scraper extracted the campaign's funding target from the campaign header section.

Within the same authenticated session, Octoparse also collected the information required to construct visibility and interaction variables. From the campaign overview and updates sections, the scraper retrieved the complete list of news items and announcements, which were subsequently counted at the daily level to produce news-intensity measures. From the Q&A section, it extracted all questions and answers associated with each campaign and computed cumulative counts of Q&A interactions up to each pledge date. These elements were scraped directly from the same HTML pages as the investment records, using additional navigation steps and extraction rules within Octoparse, without relying on private, undocumented, or platform-specific APIs.

To protect platform stability and comply with basic web-scraping ethics, all automated actions, including navigation, page loading, scrolling, clicking, and data extraction, were executed with a fixed delay of approximately five seconds between actions. After data extraction was completed, several data-quality checks were performed. Pledge counts and cumulative funding values were verified against the summary figures reported by the platform; duplicate observations arising from repeated page loads were removed; and all pledge timestamps were checked to ensure that they fell within each campaign's official funding window. News and Q&A counts were cross-checked against

the visible entries on a subset of campaigns to confirm that Octoparse had captured all items displayed in the platform interface. These checks ensured that the final dataset accurately reproduced campaign-level investment histories and associated visibility metrics as observed by investors on the platform.

3.3 Variable Definitions

The empirical analysis relies on pledge-level observations, where each row corresponds to a single investment made in a specific campaign to a particular point in time. All monetary variables are recorded in euros. Log-transformations are applied using the natural logarithm in the form $\ln(x + 1)$, both to accommodate zero-valued quantities and to reduce the influence of extremely large pledges. The overall variable design follows recent work on sequential investment behaviour in equity crowdfunding, which models within-campaign dynamics using pledge-level logs, short-horizon lags, and measures of platform activity (Åstebro et al., 2024).

The dependent variable is the logarithm of the pledge amount made at time t. This transformation stabilises the distribution of pledge sizes across heterogeneous campaigns and mitigates the leverage exerted by unusually large contributions. To capture within-campaign sequential dependence, I construct lagged versions of the dependent variable corresponding to the five most recent pledges. For each pledge, these lags are defined as the logarithm of the amounts pledged one to five positions earlier within the same campaign.

I include the five lags of the dependent variable rather than only the first lag because this methodological choice allows me to account for short-term autocorrelation in pledge behaviour while identifying the extent to which investors base their decisions on immediately preceding actions. This is not limited solely to the first lag because, when investors decide to invest in a campaign, and that's the case for the CrowdfundMe platform examined here, they have access not only to the immediately preceding pledge, but also to all previous pledges. Consequently, the real-world heuristic to which backers revert is more complex than one considering only the first lag. The structure of herding as a multi-stage heuristic, as employed here, has also been used in previous analyses of the sequential contribution behaviour of investors in ECF (Åstebro et al., 2024).

Timing dynamics are measured through the log-transformed number of days since the previous pledge in the same campaign. The underlying spacing is computed as the difference between pledge timestamps, divided by the number of seconds in a day, and transformed as $\ln(\Delta\text{days} + 1)$, where Δdays denotes the elapsed time between consecutive pledges. This variable captures whether pledge sizes systematically respond to shorter or longer inter-arrival intervals.

To differentiate investors by their relative prominence within a campaign, I define a binary indicator for sophisticated investors. This variable equals 1 for pledges made by contributors whose pledge size

falls within the top 10% of the campaign-specific distribution. Because the classification is campaign-specific rather than platform-wide, it captures relative investor prominence within each fundraising environment rather than absolute wealth or experience.

Several variables reflect the contemporaneous environment in which pledges occur. Platform-wide activity is measured using two standardised indicators. The first, denoted *Hotness*, captures the total number of pledges recorded across all campaigns on the day of the focal pledge and is standardised as a z-score. The second, *Hotness (Rest)*, measures daily platform activity excluding the focal campaign and is also standardised. These indicators proxy for market-wide fluctuations in attention and overall investor engagement, independent of a specific campaign's momentum. In addition to these daily measures, an intraday momentum indicator is included. This variable equals one whenever the cumulative funds raised by the campaign at the time of the pledge exceed the cumulative amount recorded at the previous pledge within the same day, indicating whether the campaign is experiencing a visible positive shift in funding progress at that moment. The joint use of platform-wide and campaign-specific activity measures is consistent with the modelling of all-or-nothing thresholds and participation intensity in the equity crowdfunding literature (Åstebro et al., 2024).

External conditions and informational visibility are captured through additional controls. The closing value of the FTSE MIB index on the pledge date proxies for overall market sentiment. Public attention to crowdfunding is measured using Google Trends data for the keyword "crowdfunding". Media visibility at the campaign level is captured through a standardised count of campaign-related news items recorded on the pledge day. Engagement in the platform's Q&A section is measured using a z-score of the cumulative number of questions or interactions posted by prospective investors up to the pledge date. Both variables capture external or platform-internal visibility shocks that may influence investor behaviour independently of recent contribution history.

To account for nonlinear changes in investor perception and campaign visibility over the funding lifecycle, I construct indicator variables that indicate the campaign's funding stage at the time of each pledge. Progress is divided into six mutually exclusive intervals: 0–25 per cent (the reference category), 25–50 per cent, 50–75 per cent, 75–100 per cent, 100–125 per cent, and above 125 per cent of the funding target. These stages capture increasing urgency, visibility, and platform prominence as campaigns approach or exceed their targets, and mirror the threshold-oriented treatment of campaign progress adopted in recent models of sequential crowdfunding decisions (Rodríguez-Garnica et al., 2025).

A key variable for capturing herding intensity is the LSV index, adapted to equity crowdfunding following the Poisson-based formulation proposed by Li et al. (2022). For each campaign, the daily number of pledges is compared with a counterfactual scenario in which pledges arrive as independent

Poisson events with a campaign-specific mean arrival rate. Deviations from the expected Poisson distribution are adjusted by subtracting the analytically derived deviation expected under the null hypothesis of no herding. The resulting measure isolates excess clustering in pledge arrivals and provides a daily indicator of the degree to which pledge activity exhibits herd-like concentration.

To address potential endogeneity in sequential dynamics, I employ an instrumental variable that exploits the discontinuity induced by weekends and equals one when the previous pledge occurred on a Saturday or Sunday (Åstebro et al., 2024). Because platform activity patterns differ sharply between weekdays and weekends, this instrument generates exogenous variation in inter-arrival times that affects pledge spacing but is plausibly unrelated to unobserved determinants of pledge size within a given campaign.

Campaign fixed effects are included to absorb all time-invariant heterogeneity across campaigns. Depending on the specification, either calendar-day or campaign-day fixed effects are added to control for unobserved shocks that are common to all campaigns or specific to each campaign-day cell. Data quality checks confirmed that all pledge amounts and timestamps are valid; consequently, no winsorisation, trimming, or additional cleaning rules were required.

3.4 Econometric approach

The empirical analysis exploits a high-frequency, pledge-level panel to estimate within-campaign behavioural dynamics while progressively controlling for unobserved heterogeneity and potential endogeneity in pledge timing. Let y_{itk} denote the natural logarithm of the amount pledged in campaign i at pledge order t on calendar day k. The core set of regressors includes up to five lags of the log pledge amount within the same campaign, the log of the elapsed time since the previous pledge, investor-type indicators (e.g. Sophisticated), and platform- and campaign-level controls capturing contemporaneous conditions (Hotness, Intraday Increase, Hotness (Rest), cumulative funding progress, and external information proxies such as FTSE, Google Trends, news, and Q&A activity).

The analysis proceeds in four steps. First, I estimate a baseline one-way fixed-effects model with campaign dummies and cluster-robust standard errors. This specification absorbs all time-invariant campaign characteristics, such as sector, business model, initial target, and valuation, while leaving common temporal variation across campaigns unrestricted. Formally, the baseline equation can be written as:

$$y_{itk} = \alpha_i + \sum_{j=1}^{5} \beta_j y_{i,t-j,k} + \gamma \, ln(DaysSincePrev_{itk}) + \delta' X_{itk} + u_{itk}$$

where α_i denotes campaign fixed effects, X_{itk} is the vector of investor-type, campaign-stage, platform-activity, and external-information controls, and u_{itk} is an idiosyncratic error term. This model serves

as a benchmark for the appearance of sequential patterns when only project-specific heterogeneity is controlled for.

Second, I adopt a two-way fixed-effects design, which is the preferred specification for interpreting within-campaign dynamics. In this framework, I introduce a complete set of calendar-day dummies λ_k, indexed at the year–month–day level, in addition to campaign fixed effects. The central estimating equation becomes:

$$y_{itk} = \alpha_i + \lambda_k + \sum_{j=1}^{5} \beta_j y_{i,t-j,k} + \gamma\, ln(DaysSincePrev_{itk}) + \delta' X_{itk} + u_{itk}$$

Campaign fixed effects remove all time-invariant differences across projects. In contrast, day fixed effects absorb shocks common to all campaigns on a given date, including market-wide sentiment, platform-wide activity cycles, coordinated marketing events, and macroeconomic news. Identification of β_j and γ, therefore, relies on variation in pledge sequences within campaigns and within days, net of both project-level and day-level unobservables. This two-way fixed-effects specification is treated as the econometric workhorse. Estimation relies on the within estimator with campaign- and day-demeaned variables and cluster-robust standard errors at the campaign level, allowing for arbitrary serial correlation and heteroskedasticity within campaigns.

Third, I address potential endogeneity in pledge spacing through an instrumental-variables specification that preserves the two-way fixed-effects structure. The concern is that $\ln(\text{DaysSincePrev}_{itk})$ may be correlated with unobserved attention cycles, campaign-specific news, or latent demand shocks that also affect pledge size. To mitigate this concern, I exploit exogenous variation induced by weekends. The instrument $\text{Weekend}_{i,\,t-1,\,k}$ equals one if the previous pledge in the same campaign occurred on a Saturday or Sunday and zero otherwise. Because platform activity and investor availability exhibit predictable weekend slowdowns, this indicator generates variation in inter-pledge spacing that is plausibly exogenous to unobserved determinants of pledge size, conditional on campaign and day fixed effects.

In the first stage, $\ln(\text{DaysSincePrev}_{itk})$ is regressed on $\text{Weekend}_{i,\,t-1,\,k}$, the lag structure of pledge amounts, and the complete set of fixed effects and controls. In the second stage, $\ln(\text{DaysSincePrev}_{itk})$ in the outcome equation is replaced with its fitted values from the first stage, yielding an IV–FE estimator of the effect of inter-pledge spacing on pledge size.

Fourth, I embed the two-way fixed-effects structure in a series of extended models that incorporate additional behavioural mechanisms and information environments. Campaign-stage indicators partition progress toward the funding target into mutually exclusive intervals (0–25%, 25–50%, 50–75%, 75–100%, 100–125%, and above 125%) and are specified as level shifts in the conditional mean of pledge size. News and Q&A variables are introduced both as standalone covariates and interacted

with lagged pledge amounts to test whether external media coverage and investor engagement reweight the influence of recent pledge history. Finally, I incorporate the daily LSV-based herding index as a measure of time-varying behavioural clustering and interact it with the most recent lag of the log pledge amount to examine whether investors in high-LSV periods respond differently to sequential signals.

All extensions are estimated on top of the core fixed-effects structure. For models with stage effects, news interactions, and LSV interactions without timing instrumentation, campaign and day fixed effects are included to preserve within-campaign, within-day identification of sequential coefficients. For timing-robust variants, the same specifications are re-estimated using IV with the weekend instrument for $\ln(\text{DaysSincePrev}_{itk})$. Estimation relies on linear panel FE and FE–2SLS procedures with standard errors clustered at the campaign level. This layered strategy, moving from one-way FE to two-way FE, and then to IV–FE and interaction models, allows the analysis to disentangle apparent herding driven by shared temporal shocks from genuine within-campaign behavioural dynamics, and to test whether these dynamics vary systematically with campaign stage, external visibility, investor engagement, and LSV-based herding intensity.

Having established the data structure, variable construction, and identification strategy, the next chapter applies these models to the full pledge-level panel. The analysis begins by documenting descriptive patterns in investor behaviour and campaign activity. Then it estimates the sequence of fixed-effects, two-way fixed-effects, and instrumental-variables specifications outlined above. This progression enables the distinction between apparent persistence arising from unobserved temporal shocks and genuine within-campaign behavioural dynamics, and the assessment of how these dynamics evolve across campaign stages and informational environments. The following section presents these results.

Chapter 4: Results

4.1 Descriptive Statistics

Table 1 reports descriptive statistics for all variables employed in the pledge-level analysis. The sample consists of approximately 26,000 individual investments across 226 equity crowdfunding campaigns. Minor differences in the number of observations across variables reflect the construction of lagged measures and campaign-level indicators.

Table 1: Descriptive Statistics.

Variable	N	M	SD	Min	Max
Amount	25,768	4,040.16	33,035.80	30.00	3,396,831.00
Days since previous pledge	25,770	0.61	2.40	0.00	277.00
Sophisticated investor	25,770	0.13	0.33	0.00	1.00
Cumulative amount	25,768	1.64	1.46	0.00	14.21
Hotness (campaign)	25,768	30.88	18.11	0.06	98.21
Intraday investment	25,768	0.61	0.49	0.00	1.00
Hotness (platform)	25,768	31.31	15.34	0.00	100.00
FTSE closing value	25,768	24,041.33	4,437.27	14,894.44	39,712.66
Trend in crowdfunding	25,768	53.64	9.53	32.00	94.00
News	25,770	3.46	11.40	0	138
Q&As	25,770	0.84	1.67	0	14
LSV	25,727	2.10	6.41	-16.84	59.47

Note: Amount is the individual pledge value in EUR. Days since previous pledge is the elapsed time in days between pledge t and pledge t−1 within the same campaign (based on pledge timestamps). Sophisticated investor is a dummy equal to 1 if the pledge amount falls in the top decile of the campaign-specific pledge-size distribution, and zero otherwise. Cumulative amount is cumulative capital raised up to (and including) pledge t divided by the campaign funding target. Hotness (campaign) is the platform-provided hotness score (0–100), computed as a weighted average of components measured over the last three days (amount invested, number of investors, investment traction, and days since campaign start). Intraday investment is a dummy equal to 1 if at least one other pledge occurs on the same calendar day within the campaign (0 otherwise). Hotness (platform) is the daily platform-wide activity index (0–100), computed from aggregate investment activity across all campaigns on the pledge date (scaled to the 0–100 range for comparability over time). The FTSE closing value is the FTSE MIB close price on the pledge date. The trend in crowdfunding is the Google Trends index (0–100) for the query "crowdfunding" on the pledge date. News is the number of campaign-related media items recorded on the pledge date. Q&As is the cumulative number of investor questions/answers recorded on the campaign page up to the pledge date. LSV is an index of excess clustering in daily pledge arrivals relative to a Poisson benchmark; higher values indicate stronger temporal clustering.

Pledge amounts display substantial heterogeneity. The average investment equals EUR 4,040.16, with a minimum contribution of EUR 30 and a maximum exceeding EUR 3.39 million. This wide dispersion highlights the coexistence of small and substantial investments within the same platform environment. The elapsed time since the previous pledge averages 0.61 days, indicating that contributions tend to arrive in rapid succession, although longer gaps are occasionally observed.

Thirteen per cent of pledges are classified as being made by sophisticated investors. Sophistication is defined based on pledge size, with investors classified as sophisticated when their contribution falls

within the top decile of the campaign-specific pledge distribution. This definition captures relative investment intensity within campaigns rather than absolute wealth differences across investors.

The variable Cumulative amount measures the total funds raised relative to the campaign's funding target as of the pledge date. Its mean value is 1.64, with observations ranging from 0.00 to 14.21. This distribution reflects substantial variation in campaign progress.

Campaign-level visibility and contemporaneous platform activity are captured through several indicators. The hotness index, which reflects recent investment activity within the focal campaign, has a mean value of 30.88. The intraday investment dummy equals one for 61 per cent of pledges, indicating that multiple investments frequently occur on the same calendar day. The broader Hotness measure, which captures total daily investment activity across the platform, has a mean of 31.31, suggesting meaningful variation in platform-wide attention over time.

External market conditions and public interest are proxied by the FTSE MIB closing value and a Google Trends–based index for the search term "crowdfunding". The average FTSE closing value over the sample period is 24,041.33, whereas the crowdfunding trend index averages 53.64 on a 0–100 scale, indicating moderate, time-varying public attention to the sector.

Informational visibility at the campaign level is measured using the News and Q&A variables. News captures the number of campaign-related media items recorded on the pledge date and ranges from 0 to 138, reflecting highly uneven media exposure across campaigns and over time. Q&A measures cumulative investor interactions in the campaign's question-and-answer section up to the pledge date and ranges from 0 to 14, indicating that some campaigns generate sustained investor engagement while others attract little interaction.

Finally, the LSV index has a mean value of 2.10 and ranges from –16.84 to 59.47, suggesting substantial variation in the degree of temporal concentration of investments across campaigns and days.

4.2 One-Way Fixed-Effects Results

Table 2 reports estimates from a one-way fixed-effects (within) regression that controls for all time-invariant campaign-specific heterogeneity. The dependent variable is the natural logarithm of the individual pledge amount. The specification includes five lags of the log pledge amount within each campaign, the log of the elapsed time since the previous pledge, an indicator for sophisticated investors, measures of campaign- and platform-level activity, and controls for external market conditions and public attention. Standard errors are clustered at the campaign level.

Table 2: One-Way Fixed Effects (Within) Regression.

Predictor	B	SE	t	p	95% CI
ln Amount (t – 1)	0.02 **	0.01	2.77	.006	[0.00, 0.03]
ln Amount (t – 2)	0.02 **	0.01	3.01	.003	[0.01, 0.03]
ln Amount (t – 3)	0.01	0.01	1.34	.183	[–0.00, 0.02]
ln Amount (t – 4)	0.01	0.01	0.96	.337	[–0.01, 0.02]
ln Amount (t – 5)	0.02 ***	0.01	4.17	< .001	[0.01, 0.03]
ln Days Since Prev	0.01	0.01	0.81	.419	[–0.01, 0.03]
Sophisticated	2.40 ***	0.03	70.24	< .001	[2.34, 2.47]
Hotness (Std.)	0.00 ***	0.00	8.69	< .001	[0.00, 0.00]
Intraday Increase	0.03 **	0.01	2.84	.005	[0.01, 0.05]
Hotness (Rest Std.)	0.00 **	0.00	2.99	.003	[0.00, 0.00]
FTSE Close	–0.00	0.00	–1.27	.206	[–0.00, 0.00]
Trend Crowdfunding	0.00	0.00	1.58	.115	[–0.00, 0.00]
Constant	6.26 ***	0.24	26.14	< .001	[5.79, 6.73]
Observations	24,633				
Campaigns	226				
Within R^2	0.54				
F (12, 225)	460.87 ***				

Note. Cluster-robust standard errors (by campaign) in parentheses.
*p < .10, **p < .05, ***p < .001.

The model is estimated on 24,633 pledge observations from 226 campaigns and achieves a within R^2 of 0.54, indicating substantial explanatory power for within-campaign variation in pledge size. Several lagged pledge variables enter positively and are statistically significant. In particular, the first, second, and fifth lags of the log pledge amount exhibit positive coefficients that are statistically significant at conventional levels. In contrast, the third and fourth lags are positive but not statistically distinguishable from zero. These results indicate a positive serial association in pledge sizes across campaigns, after controlling for time-invariant campaign characteristics.

The coefficient on the log of days since the previous pledge is small in magnitude and not statistically significant, suggesting that variation in inter-pledge timing is not systematically associated with pledge size in this specification. By contrast, the sophisticated-investor indicator exhibits a large, precisely estimated coefficient.

Measures of campaign- and platform-level activity are also statistically significant. The standardised hotness measure for the focal campaign enters with a positive and highly significant coefficient, as does the residual hotness measure capturing contemporaneous activity in other campaigns. The intraday increase indicator is likewise positive and statistically significant, indicating that pledge sizes tend to be larger on days with multiple investments. In contrast, external conditions proxied by the FTSE MIB closing value and the crowdfunding trend index do not yield statistically significant coefficients in this specification.

The joint significance of the regressors is confirmed by an F-statistic of 460.87 (12, 225), which is statistically significant at conventional levels.

4.3 Two-Way Fixed-Effects Results

Table 3 reports estimates from the two-way fixed-effects regression that includes both campaign and calendar-day fixed effects. Relative to the one-way specification, this model additionally absorbs all time-specific shocks common to campaigns on the same day, such as platform-wide attention fluctuations or aggregate market conditions. The dependent variable is the natural logarithm of the individual pledge amount. The specification retains five lags of the log pledge amount, the log of the elapsed time since the previous pledge, an indicator for sophisticated investors, and measures of campaign- and platform-level activity. Standard errors are clustered at the campaign level.

Table 3: Two-Way Fixed Effects (Within) Regression.

Predictor	B	SE	t	p	95% CI
ln Amount (t – 1)	–0.02 ***	0.01	–4.56	< .001	[–0.03, –0.01]
ln Amount (t – 2)	–0.01 **	0.01	–2.13	.034	[–0.02, –0.00]
ln Amount (t – 3)	–0.01 *	0.01	–1.92	.056	[–0.02, 0.00]
ln Amount (t – 4)	–0.01 *	0.01	–1.96	.051	[–0.02, 0.00]
ln Amount (t – 5)	0.01 **	0.01	1.98	.049	[0.00, 0.02]
ln Days Since Prev	0.02	0.01	1.22	.223	[–0.01, 0.04]
Sophisticated	2.37 ***	0.03	68.97	< .001	[2.30, 2.44]
Hotness (Std.)	0.01 ***	0.00	5.24	< .001	[0.00, 0.01]
Intraday Increase	–0.00	0.02	–0.20	.838	[–0.03, 0.03]
Hotness (Rest Std.)	–0.00	0.00	–0.55	.582	[–0.01, 0.00]
Constant	6.88 ***	0.14	47.50	< .001	[6.60, 7.17]
Observations	24,394				
Campaigns	226				
Within R^2	0.54				
F (10, 225)	569.71 ***				

Note. Cluster-robust standard errors (by campaign) in parentheses.
*p < .10, **p < .05, ***p < .001.

The model is estimated using 24,394 pledges from 226 campaigns and achieves a within R^2 of 0.54, comparable to that of the one-way fixed-effects specification. The estimated lag structure of pledge amounts differs markedly from the one-way results. The first four lags of the log pledge amount enter with negative coefficients that are statistically significant at conventional or marginal levels. In contrast, the fifth lag is positive and statistically significant. This pattern indicates that, once common daily shocks are absorbed, larger recent pledges within a campaign are, on average, followed by smaller subsequent pledges over short horizons, with a positive association re-emerging at longer lags.

The coefficient on the log of days since the previous pledge remains small in magnitude and statistically indistinguishable from zero, suggesting that inter-pledge timing is not systematically associated with pledge size even after controlling for both campaign-specific heterogeneity and common daily shocks.

The sophisticated-investor indicator continues to exhibit a large, precisely estimated coefficient. The standardised hotness measure for the focal campaign remains positive and statistically significant, indicating a positive association between contemporaneous campaign visibility and pledge size. In contrast, the intraday increase indicator and the residual hotness measure capturing activity in other campaigns are no longer statistically distinguishable from zero after including calendar-day fixed effects. This change suggests that the positive associations observed in the one-way specification largely reflect common time-specific factors rather than independent effects of platform-wide activity. The constant term is positive and highly significant. The joint significance of the regressors is supported by an F-statistic of 569.71 (10, 225), which is statistically significant at conventional levels. To assess whether the null association between inter-pledge timing and pledge size may be affected by endogeneity in the elapsed-time measure, the following section implements an instrumental-variables two-way fixed-effects specification that instruments inter-pledge duration using predetermined weekend timing of the previous pledge (Åstebro et al., 2024).

4.4 First-Stage Results for the IV–FE Specification

Inter-pledge duration may be endogenous to unobserved demand conditions or campaign-specific shocks that simultaneously influence both the timing and the size of investments. To address this concern, an instrumental-variables two-way fixed-effects approach is estimated, with the elapsed time since the previous pledge instrumented by an indicator for whether the preceding pledge occurred on a weekend (Åstebro et al., 2024).

Table 4 reports the first-stage regression for the instrumental-variables two-way fixed-effects model. The dependent variable is the natural logarithm of the elapsed time between consecutive pledges. The instrument, Weekend (t – 1), equals one if the immediately preceding pledge within the same campaign occurred on a Saturday or Sunday. The specification includes the same set of covariates as the second-stage equation, lagged pledge amounts, investor-type indicators, campaign visibility measures, and platform-wide activity controls, and absorbs both campaign and calendar-day fixed effects. Standard errors are clustered at the campaign level.

Table 4: First-Stage Regression for Instrumental Variable (IV–FE Model).

Predictor	B	SE	t	p	95% CI
Weekend (t – 1)	0.06 ***	0.01	5.19	< .001	[0.04, 0.09]
ln Amount (t – 1)	0.03 ***	0.00	9.88	< .001	[0.02, 0.03]
ln Amount (t – 2)	–0.00	0.00	–0.51	.608	[–0.01, 0.00]
ln Amount (t – 3)	–0.00	0.00	–0.59	.555	[–0.01, 0.00]
ln Amount (t – 4)	–0.00	0.00	–1.36	.175	[–0.01, 0.00]
ln Amount (t – 5)	0.00	0.00	0.50	.618	[–0.00, 0.01]
Sophisticated	0.03 ***	0.01	3.46	.001	[0.01, 0.05]
Cumulative Amount / Target	–0.05 ***	0.01	–5.88	< .001	[–0.07, –0.03]
Hotness (Std.)	–0.01 ***	0.00	–13.92	< .001	[–0.01, –0.01]
Intraday Increase	0.03 **	0.01	3.04	.003	[0.01, 0.04]
Hotness (Rest Std.)	–0.00	0.00	–1.01	.311	[–0.00, 0.00]
Constant	0.63 ***	0.09	7.10	< .001	[0.46, 0.81]
Observations	24,394				
Campaigns	226				
Within R^2	0.09				
F (11, 225)	82.49 ***				

Note. Cluster-robust standard errors (by campaign) in parentheses.
*p < .10, **p < .05, ***p < .001.

The model is estimated on 24,394 observations from 226 campaigns and achieves a within R^2 of 0.09, which is typical for first-stage regressions in high-frequency panel settings. The instrument is strongly associated with inter-pledge duration: the coefficient on Weekend (t – 1) is positive, precisely estimated, and statistically significant at the 1% level. This indicates that pledges following weekend contributions are, on average, separated by longer intervals, consistent with institutional and behavioural differences between weekend and weekday investment activity.

Among the lagged pledge variables, only the first lag of the log pledge amount is positively and statistically significantly associated with inter-pledge duration. In contrast, the remaining lags are small and not statistically distinguishable from zero. Several control variables also enter significantly. The sophisticated-investor indicator is positively associated with the elapsed time between pledges, suggesting that longer pauses follow larger or more informed contributions. By contrast, the cumulative amount raised relative to the funding target enters with a negative and statistically significant coefficient, indicating that pledges arrive more rapidly as campaigns progress toward or beyond their funding goals.

Campaign visibility and platform activity measures also display systematic associations with inter-pledge timing. The standardised hotness measure for the focal campaign is negative and precisely estimated, implying shorter inter-pledge intervals during periods of heightened campaign visibility. Conversely, the intraday increase indicator is positive and statistically significant, reflecting longer measured gaps when multiple pledges occur on the same day. The residual hotness measure capturing activity in other campaigns is not statistically significant in this specification.

The joint significance of the regressors is confirmed by an F-statistic of 82.49 (11, 225), which exceeds conventional thresholds for weak-instrument concerns and supports the instrument's relevance in the first stage.

4.5 Second-Stage IV–FE Results

Table 5 reports the second-stage estimates from the instrumental-variables fixed-effects regression. The dependent variable is the natural logarithm of the individual pledge amount. The potentially endogenous regressor, the log of days since the previous pledge, is instrumented with the indicator Weekend (t – 1), which equals 1 if the immediately preceding pledge in the same campaign occurred on a Saturday or Sunday. The specification includes five lags of the log-pledge amount, an indicator of sophisticated investors, measures of campaign- and platform-level activity, and the cumulative amount raised relative to the funding target. Both campaign and calendar-day fixed effects are included, and standard errors are clustered at the campaign level.

Table 5: IV (2SLS) Fixed-Effects Regression.

Predictor	B	SE	t	p	95% CI
ln Days Since Previous Pledge (instrumented)	–0.28	0.33	–0.84	.400	[–0.92, 0.37]
ln Amount (t – 1)	–0.02	0.01	–1.53	.127	[–0.03, 0.00]
ln Amount (t – 2)	–0.01 **	0.01	–2.22	.027	[–0.02, –0.00]
ln Amount (t – 3)	–0.01 *	0.01	–1.97	.050	[–0.02, 0.00]
ln Amount (t – 4)	–0.01 **	0.01	–2.09	.038	[–0.02, –0.00]
ln Amount (t – 5)	0.01 **	0.01	1.98	.048	[0.00, 0.02]
Sophisticated	2.38 ***	0.04	61.47	< .001	[2.30, 2.46]
Cumulative Amount / Target	0.01	0.02	0.49	.628	[–0.03, 0.05]
Hotness (Std.)	0.00	0.00	0.74	.458	[–0.01, 0.01]
Intraday Increase	0.01	0.02	0.39	.698	[–0.03, 0.04]
Hotness (Rest Std.)	–0.00	0.00	–0.67	.503	[–0.01, 0.00]
Observations	24,394				
Campaigns	226				
Centered R^2	0.53				
F (11, 225)	518.93 ***				

Note. Cluster-robust standard errors (by campaign) are reported in parentheses.
*p < .10, **p < .05, ***p < .001.

The model is estimated using 24,394 pledges from 226 campaigns and achieves a centred R^2 of 0.53, comparable to the corresponding two-way fixed-effects specification. The coefficient on the instrumented log of days since the previous pledge is negative but not statistically distinguishable from zero, with a relatively wide confidence interval. This result indicates that, once endogeneity in inter-pledge timing is addressed and common daily shocks are absorbed, there is no detectable association between the length of the inter-pledge interval and the size of subsequent pledges within campaigns.

The estimated lag structure of pledge amounts closely mirrors that observed in the two-way fixed-effects model. The second, third, and fourth lags of the log pledge amount enter with negative and statistically significant coefficients, while the fifth lag is positive and statistically significant. The first lag is negative but not statistically significant in this specification. This pattern suggests that the mean-

reverting structure of pledge sizes identified in the two-way fixed-effects results is robust to the instrumentation of inter-pledge timing.

The sophisticated-investor indicator remains large in magnitude and precisely estimated. The coefficient on the cumulative amount raised relative to the funding target is small and statistically insignificant, indicating that, conditional on fixed effects and other controls, funding progress has no independent effect on pledge size in this specification.

Platform-activity measures, including the standardised hotness index for the focal campaign, the intraday increase indicator, and the residual hotness measure capturing activity in other campaigns, do not yield statistically significant coefficients in the IV specification. This finding suggests that the associations between pledge size and contemporaneous platform activity observed in simpler specifications are primarily attributable to common time-specific factors or to endogenous variation correlated with inter-pledge timing.

The joint significance of the regressors is supported by an F-statistic of 518.93 (11, 225), which is statistically significant at conventional levels.

4.6 Extended Two-Way Fixed-Effects Model with Campaign-Stage Indicators

Table 6 reports estimates from a two-way fixed-effects regression that augments the baseline specification with campaign-stage indicators. The dependent variable is the natural logarithm of the individual pledge amount. The model includes campaign and calendar-day fixed effects, five lags of the log pledge amount, the log of the elapsed time since the previous pledge, an indicator for sophisticated investors, measures of campaign- and platform-level activity, and a series of mutually exclusive dummy variables capturing the campaign's funding stage relative to its target. Standard errors are clustered at the campaign level.

Table 6: Two-Way Fixed Effects (Within) Regression with Campaign-Stage Indicators.

Predictor	B	SE	t	p	95% CI
ln Amount (t – 1)	–0.02 ***	0.01	–4.74	< .001	[–0.03, –0.01]
ln Amount (t – 2)	–0.01 **	0.01	–2.29	.023	[–0.02, –0.00]
ln Amount (t – 3)	–0.01 **	0.01	–2.08	.039	[–0.02, –0.00]
ln Amount (t – 4)	–0.01 **	0.01	–2.15	.033	[–0.02, –0.00]
ln Amount (t – 5)	0.01 *	0.01	1.82	.071	[–0.00, 0.02]
ln Days Since Prev	0.02	0.01	1.28	.204	[–0.01, 0.04]
Sophisticated	2.37 ***	0.03	69.02	< .001	[2.30, 2.44]
Hotness (Std.)	0.01 ***	0.00	5.23	< .001	[0.00, 0.01]
Intraday Increase	–0.00	0.02	–0.26	.797	[–0.03, 0.03]
Hotness (Rest Std.)	–0.00	0.00	–0.60	.550	[–0.01, 0.00]
Stage 25–50 %	0.08 **	0.04	2.03	.043	[0.00, 0.16]
Stage 50–75 %	0.13 ***	0.04	3.44	.001	[0.06, 0.21]
Stage 75–100 %	0.12 ***	0.04	2.77	.006	[0.04, 0.21]
Stage 100–125 %	0.08 *	0.04	1.76	.079	[–0.01, 0.16]
Stage >125 %	0.09 **	0.04	2.01	.046	[0.00, 0.18]
Constant	6.83 ***	0.15	44.35	< .001	[6.53, 7.13]
Observations	24,394				
Campaigns	226				
Within R^2	0.54				
F (15, 225)	393.27 ***				

Note. Cluster-robust standard errors (by campaign) in parentheses.
*p < .10, **p < .05, ***p < .001.

The model is estimated on 24,394 pledges from 226 campaigns and attains a within R^2 of 0.54, consistent with earlier two-way fixed-effects specifications. The estimated lag structure of pledge amounts remains stable relative to the baseline model. The first four lags of the log pledge amount enter with negative, statistically significant coefficients, whereas the fifth lag is positive and weakly significant. The coefficient on the log of days since the previous pledge remains small in magnitude and statistically insignificant, indicating that inter-pledge timing is not systematically associated with pledge size after controlling for campaign and calendar-day fixed effects.

The sophisticated-investor indicator continues to exhibit a large, precisely estimated coefficient. The standardised hotness measure associated with the focal campaign remains positive and statistically

significant. In contrast, the intraday increase indicator and the residual hotness measure capturing activity in other campaigns are not statistically distinguishable from zero in this specification.

The campaign-stage indicators reveal systematic differences in average pledge size across funding milestones. Relative to the reference category for campaigns funded at less than 25 per cent of their target, all subsequent funding stages have positive coefficients. The indicators for the 25–50 per cent, 50–75 per cent, and 75–100 per cent funding intervals are positive and statistically significant, as are the indicators for stages exceeding the funding target. The largest coefficient is observed for the 50–75 per cent funding stage. These results indicate that, holding constant campaign-specific characteristics and common daily shocks, pledge sizes tend to be higher at more advanced stages of the fundraising process.

The joint significance of the regressors is confirmed by an F-statistic of 393.27 (15, 225), which is statistically significant at conventional levels.

4.7 Two-Way Fixed-Effects Model with News Coverage Interaction Effects

Table 7 reports estimates from a two-way fixed-effects regression that allows the association between lagged pledge amounts and current pledge size to vary with cumulative news coverage. The dependent variable is the natural logarithm of the individual pledge amount. The specification includes campaign and calendar-day fixed effects; five lags of the log pledge amount; interactions between each lag and standardised cumulative news coverage; the log of the elapsed time since the previous pledge; an indicator for sophisticated investors; and measures of campaign- and platform-level activity. Standard errors are clustered at the campaign level.

Table 7: Two-Way Fixed-Effects Regression of Within-Campaign Pledge Amounts With Interactions Between Lagged Pledges and Cumulative News Coverage

Predictor	B	SE	t	p	95% CI
ln Amount (t – 1)	–0.02 ***	0.01	–4.54	< .001	[–0.03, –0.01]
ln Amount (t – 1) × News (Std.)	–0.00	0.01	–0.22	.825	[–0.01, 0.01]
ln Amount (t – 2)	–0.01 **	0.00	–2.16	.032	[–0.02, –0.00]
ln Amount (t – 2) × News (Std.)	–0.01 *	0.00	–1.97	.051	[–0.02, 0.00]
ln Amount (t – 3)	–0.01 *	0.01	–1.90	.058	[–0.02, 0.00]
ln Amount (t – 3) × News (Std.)	0.01 **	0.00	2.73	.007	[0.00, 0.02]
ln Amount (t – 4)	–0.01 *	0.01	–1.96	.051	[–0.02, 0.00]
ln Amount (t – 4) × News (Std.)	–0.00	0.00	–0.11	.910	[–0.01, 0.01]
ln Amount (t – 5)	0.01 **	0.01	2.01	.045	[0.00, 0.02]
ln Amount (t – 5) × News (Std.)	–0.00	0.01	–0.83	.407	[–0.02, 0.01]
ln Days Since Prev	0.02	0.01	1.22	.226	[–0.01, 0.04]
Sophisticated	2.37 ***	0.03	69.10	< .001	[2.30, 2.44]
Hotness (Std.)	0.01 ***	0.00	5.23	< .001	[0.00, 0.01]
Intraday Increase	–0.00	0.02	–0.20	.839	[–0.03, 0.03]
Hotness (Rest Std.)	–0.00	0.00	–0.55	.586	[–0.01, 0.00]
Constant	6.88 ***	0.15	47.44	< .001	[6.59, 7.16]
Observations	24,394				
Campaigns	226				
Within R^2	0.54				
F (16, 225)	405.23 ***				

Note. Cluster-robust standard errors (by campaign) in parentheses.
*p < .10, **p < .05, ***p < .001.

The model is estimated on 24,394 pledges from 226 campaigns and attains a within R^2 of 0.54, comparable to the baseline two-way fixed-effects specification. The coefficients on the lagged pledge amounts closely follow the same sign pattern observed previously. The first four lags enter with negative coefficients, with statistical significance ranging from conventional to marginal, whereas the fifth lag is positive and statistically significant. This confirms that the mean-reverting structure of pledge sizes persists when allowing for interaction effects with external information.

The interaction terms between lagged pledge amounts and cumulative news coverage display limited and heterogeneous effects. The interaction with the first lag is small in magnitude and statistically

insignificant. The interaction with the second lag is negative and weakly significant, while the interaction with the third lag is positive and statistically significant. Interactions involving the fourth and fifth lags are close to zero and not statistically distinguishable from zero. Taken together, these results do not reveal a stable or monotonic pattern in how news coverage moderates the association between recent pledge sizes and current contributions.

The coefficient on the log of the number of days since the previous pledge remains statistically insignificant, consistent with earlier specifications. The sophisticated-investor indicator continues to exhibit a large, precisely estimated coefficient. The standardised hotness measure associated with the focal campaign remains positive and statistically significant. In contrast, the intraday increase indicator and the residual hotness measure capturing activity in other campaigns are not statistically significant after including calendar-day fixed effects.

Overall, the interaction results suggest that cumulative news coverage does not systematically amplify or dampen within-campaign sequential dependence in pledge sizes. Although isolated interaction terms are statistically significant at specific lags, the absence of a consistent pattern indicates that external media visibility plays a limited role in shaping how investors condition pledge sizes on recent contributions.

The joint significance of the regressors is confirmed by an F-statistic of 405.23 (16, 225), which is statistically significant at conventional levels.

4.8 Two-Way Fixed-Effects Model with Q&A Interaction Effects

Table 8 reports estimates from a two-way fixed-effects regression that allows the association between lagged pledge amounts and current pledge size to vary with cumulative investor Q&A activity. The dependent variable is the natural logarithm of the individual pledge amount. The specification includes campaign and calendar-day fixed effects, five lags of the log pledge amount, interactions between each lag and the standardised Q&A measure, the standardised Q&A main effect, the log of the elapsed time since the previous pledge, an indicator for sophisticated investors, measures of campaign- and platform-level activity, and standardised cumulative news coverage. Standard errors are clustered at the campaign level.

Table 8: Two-Way Fixed-Effects Regression of Within-Campaign Pledge Amounts with Q&A Interaction Effects

Predictor	B	SE	t	p	95% CI
ln Amount (t – 1)	-0.02***	0.00	-4.60	0.00	[-0.03; -0.01]
ln Amount (t – 1) × Q&A (Std.)	-0.00	0.00	-0.18	0.86	[-0.01; 0.01]
ln Amount (t – 2)	-0.01**	0.01	-2.12	0.04	[-0.02; -0.00]
ln Amount (t – 2) × Q&A (Std.)	-0.00	0.00	-0.03	0.97	[-0.01; 0.01]
ln Amount (t – 3)	-0.01*	0.01	-1.93	0.06	[-0.02; 0.00]
ln Amount (t – 3) × Q&A (Std.)	-0.00	0.00	-0.55	0.58	[-0.01; 0.01]
ln Amount (t – 4)	-0.00**	0.01	-1.98	0.05	[-0.02; -0.00]
ln Amount (t – 4) × Q&A (Std.)	0.00	0.00	0.81	0.42	[-0.01; 0.01]
ln Amount (t – 5)	0.01**	0.01	1.97	0.05	[0.00; 0.02]
ln Amount (t – 5) × Q&A (Std.)	-0.00	0.00	-0.54	0.59	[-0.01; 0.01]
Q&A (Std.)	0.00	0.07	0.00	1.00	[-0.14; 0.14]
ln Days Since Prev	0.01	0.01	1.12	0.27	[-0.01; 0.04]
Sophisticated	2.36***	0.03	69.04	0.00	[2.30; 2.44]
Hotness (Std.)	0.00***	0.00	5.26	0.00	[0.00; 0.01]
Intraday Increase	-0.00	0.02	-0.29	0.78	[-0.03; 0.03]
Hotness (Rest Std.)	-0.00	0.00	-0.60	0.55	[-0.01; 0.00]
News (Std.)	0.00	0.01	0.23	0.82	[-0.01; 0.01]
Constant	6.88***	0.14	47.73	0.00	[6.60; 7.17]
Observations	24,394				
Campaigns	226				
Within R^2	0.54				
F (17, 225)	351.89				

Note. Cluster-robust standard errors (by campaign) in parentheses.
*p < .10, **p < .05, ***p < .01.

The model is estimated on 24,394 pledges from 226 campaigns and attains a within R^2 of 0.54, consistent with the baseline two-way fixed-effects specifications. The coefficients on the lagged pledge amounts follow the same sign pattern observed in earlier models. The first four lags enter with negative coefficients; the first, second, and fourth are statistically significant at conventional levels, while the third is marginally significant. The fifth lag is positive and statistically significant at the 5 per cent level. The coefficient on the log of days since the previous pledge remains statistically insignificant.

The interaction terms between lagged pledge amounts and Q&A activity are uniformly small in magnitude and statistically insignificant across all five lags. In addition, the main effect of standardized Q&A activity is statistically negligible and estimated with low precision. Taken together, these results indicate that investor interactions in the campaign's question-and-answer section do not systematically moderate the relationship between recent pledge sizes and current investment decisions.

The sophisticated-investor indicator remains large and precisely estimated. The standardised hotness measure associated with the focal campaign continues to exhibit a positive and statistically significant coefficient. In contrast, the intraday increase indicator and the residual hotness measure capturing activity in other campaigns are not statistically significant after including calendar-day fixed effects. The standardised news variable is also statistically insignificant in this specification.

Overall, the absence of significant interaction effects suggests that Q&A activity, while potentially relevant for information disclosure or engagement, does not systematically shape within-campaign sequential dependence in pledge sizes. The joint significance of the regressors is supported by an F-statistic of 351.89 (17, 225), which is statistically significant at conventional levels.

4.9 Two-Way Fixed-Effects Model with LSV Interaction Effects

Table 9 reports estimates from a two-way fixed-effects regression that introduces the LSV measure and an interaction between LSV and the most recent lag of pledge size. The dependent variable is the natural logarithm of the individual pledge amount. The specification includes campaign and calendar-day fixed effects, five lags of the log pledge amount, the log of the elapsed time since the previous pledge, an indicator for sophisticated investors, measures of campaign- and platform-level activity, standardized information controls (News and Q&A), and the LSV main effect together with the interaction term between the first lag of pledge size and LSV. Standard errors are clustered at the campaign level.

Table 9: Two-Way Fixed-Effects Regression of Within-Campaign Pledge Amounts with LSV Interaction Effects

Predictor	B	SE	t	p	95% CI
ln Amount (t – 1)	-0.02***	0.00	-5.09	0.00	[-0.03, -0.01]
LSV	-0.02***	0.00	-5.30	0.00	[-0.04, -0.01]
ln Amount (t – 1) × LSV	0.00**	0.00	2.19	0,02	[0.00, 0.00]
ln Amount (t – 2)	-0.01**	0.00	-2.14	0,03	[-0.02, -0.00]
ln Amount (t – 3)	-0.01*	0.00	-1.89	0,06	[-0.02, 0.00]
ln Amount (t – 4)	-0.00*	0.00	-1.85	0,06	[-0.01, 0.00]
ln Amount (t – 5)	0.01**	0.00	2.05	0,04	[0.00, 0.02]
ln Days Since Prev	0.01	0.01	0.74	0,45	[-0.01, 0.03]
Sophisticated	2.35***	0.03	69.27	0.00	[2.28, 2.41]
Hotness (Std.)	0.01***	0.00	7.19	0.00	[0.00, 0.01]
Intraday Increase	-0.01	0.01	-0.74	0.45	[-0.04, 0.01]
Hotness (Rest Std.)	-0.00	0.00	-0.74	0.46	[-0.00, 0.00]
News (Std.)	0.00	0.00	0.73	0.46	[-0.00, 0.01]
Q&A (Std.)	-0.01	0.00	-1.51	0.13	[-0.02, 0.00]
Constant	6.86	0.14	46.77	0.00	[6.57, 7.15]
Observations	24,363				
Campaigns	225				
Within R^2	0.54				
F (14, 224)	446.91				

Note. Cluster-robust standard errors (by campaign) in parentheses.
*p < .10, **p < .05, ***p < .001.

The model is estimated on 24,363 pledges from 225 campaigns and attains a within R^2 of 0.54, consistent with earlier two-way fixed-effects specifications. The estimated lag structure of pledge amounts remains stable. The first four lags enter with negative coefficients; the first and second are statistically significant, and the third and fourth are marginally significant, whereas the fifth lag is positive and statistically significant. As in previous models, the coefficient on the log of the number of days since the previous pledge is small in magnitude and statistically insignificant.

The LSV main effect is negative and statistically significant, indicating that periods characterised by greater clustering in pledge arrivals are associated with smaller average pledge sizes, conditional on

campaign and calendar-day fixed effects. The interaction between the first lag of pledge size and LSV is positive and statistically significant at the 5 percent level. This interaction implies that, during periods of heightened clustering, the association between the most recent pledge size and the current pledge becomes stronger.

The sophisticated-investor indicator remains large and precisely estimated. The standardised hotness measure associated with the focal campaign is positive and statistically significant. In contrast, the intraday increase indicator and the residual hotness measure, which capture activity in other campaigns, are not statistically significant in this specification. The standardised news and Q&A variables are also statistically insignificant.

Taken together, these results suggest that elevated levels of herding, as captured by the LSV index, are associated with tighter alignment between consecutive pledges rather than with larger average contributions. In periods of clustered investment activity, investors appear to condition their pledge sizes more closely on the most recent observed contribution, even as overall pledge levels decline. This pattern indicates state-dependent sensitivity to local social information rather than generalised escalation.

The joint significance of the regressors is supported by an F-statistic of 446.91 (14, 224), which is statistically significant at conventional levels.

4.10 Behavioural Synthesis of Results

The empirical results depict equity crowdfunding as a behavioural environment in which investors respond systematically to social information, but not in a manner consistent with simple momentum-following or unconditional imitation. Sequential dependence in pledge sizes is present, yet its structure is asymmetric, state-dependent, and shaped by campaign context and visibility conditions. Rather than generating cumulative escalation, recent actions appear to function primarily as reference points that inform subsequent decisions within clearly bounded limits.

Across specifications, the most robust empirical regularity concerns short-horizon responsiveness to recent pledges once campaign-level heterogeneity and common time shocks are absorbed. The immediate history of contributions matters, but not monotonically. In the two-way fixed-effects specifications, the negative coefficients on the first several lags of pledge size indicate that smaller ones typically follow larger recent pledges. In contrast, the positive coefficient on the fifth lag suggests a delayed adjustment rather than persistent reinforcement. This pattern is inconsistent with naïve imitation or self-reinforcing cascades. Instead, it is consistent with bounded social adjustment, whereby investors anchor on recent visible contributions but modulate their own pledge sizes rather than matching or amplifying them mechanically.

Instrumental-variables estimates do not provide evidence of a systematic association between the length of the inter-pledge interval and subsequent contribution amounts, even after controlling for endogeneity and common daily shocks. This suggests that temporal clustering primarily reflects coordinated arrivals driven by shared attention or platform-level visibility, rather than contagion operating through time. Investors appear to arrive in bursts, but conditional on arrival, their pledge decisions are linked to others' contributions rather than to the timing of those contributions. This distinction separates coordination in participation from dependence in valuation.

Investor sophistication provides an additional point of reference for interpretation. Across all specifications, sophisticated investors place substantially larger pledges, and this effect is stable and precisely estimated. At the same time, the presence of large or informed contributions does not generate persistent size-based escalation by subsequent investors. While such pledges are salient, they do not induce one-for-one replication. This pattern is consistent with sophisticated investors serving as informative benchmarks rather than as leaders whose actions are mechanically followed.

Campaign visibility and progression further condition behaviour, primarily through level effects. Pledge sizes increase systematically as campaigns progress through funding stages, particularly once they approach or exceed intermediate funding thresholds. These stage effects indicate that investors contribute larger amounts at later stages of the fundraising process, consistent with evolving

perceptions of campaign viability or success. Importantly, this increase arises from higher average pledge sizes rather than stronger sequential dependence. Visibility raises the level of contributions without intensifying imitation dynamics.

External information flows, captured through news coverage and Q&A activity, play a limited role in shaping within-campaign sequential dependence. Main effects are weak, and interaction terms with lagged pledges are largely insignificant or heterogeneous across lags. This indicates that investors do not systematically reinterpret recent pledge information through the lens of external visibility or engagement. Social inference appears to remain primarily endogenous to the campaign's own funding trajectory rather than being reframed by media attention or platform interaction.

The LSV-based analysis provides the clearest evidence of state-dependent herding. Periods characterised by unusually clustered investment activity are associated with smaller average pledge sizes, as well as greater sensitivity to the immediately preceding pledge. During such periods, investors appear to align more closely with local social cues, reducing pledge-size dispersion rather than increasing it. Heightened herding, therefore, manifests as tighter local alignment rather than as aggressive escalation. Behaviour becomes more compressed around recent norms, not more expansionary.

Overall, the results portray equity crowdfunding investors as neither entirely rational signal processors nor passive imitators. Behaviour is shaped by social anchoring, bounded adjustment, and contextual visibility, producing sequential dependence without explosive dynamics. Investors use others' actions as informative benchmarks but retain discretion in their own decisions, resulting in dampened, partially corrective responses rather than self-reinforcing spirals. Herding is present, but it operates through local alignment and reference dependence rather than through unconditional momentum.

The following chapter moves beyond behavioural description to examine the implications of these patterns for theories of information aggregation, the functioning of equity crowdfunding markets, and the institutional frameworks that govern them.

Chapter 5: Discussion

This chapter interprets the empirical results in light of the theoretical and empirical literature on herding in equity crowdfunding, with particular emphasis on how high-frequency, pledge-level evidence refines existing interpretations of sequential dependence and investor coordination. The chapter proceeds in three steps. First, the main findings are reconciled using pledge-level evidence that isolates within-campaign dynamics and distinguishes dependence in valuation from coordination in participation. Second, findings are synthesised into a mechanism-based account of herding under all-or-nothing rules, emphasising how informational signalling, threshold-based coordination, and state-dependent social learning interact over the campaign lifecycle. Third, the Italian evidence is contrasted with prior empirical studies in crowdfunding to clarify which findings generalise across settings, which are context-specific, and how differences emerge when data resolution and identification strategies are strengthened. The chapter concludes by discussing implications for theories of information aggregation, platform design, and investor protection.

5.1 Part I – Interpreting Within-Campaign Herding Dynamics: Pledge-Level Evidence

This part of the Discussion presents a result-by-result interpretation of the empirical findings. The objective is to clarify how the main empirical regularities, short-horizon sequential dependence, temporal clustering, asymmetries in pledge magnitudes, campaign-stage progression, information visibility, and time-varying herding intensity, map onto behavioural mechanisms discussed in the theoretical literature.

Rather than imposing a unified model at this stage, the subsections in Part I evaluate which interpretations are directly supported by the evidence, which become less plausible after controlling for endogeneity and common shocks, and which require refinement in the context of the Italian market and its all-or-nothing funding rules. This structure prepares the ground for the mechanism-based synthesis developed in Part II.

5.1.1 Sequential dependence without escalation

The negative coefficients on the first several lags of pledge size, once both campaign and calendar-day fixed effects are included, indicate that sequential dependence in equity crowdfunding does not exhibit monotonic escalation. Rather than matching or amplifying unusually large recent pledges, subsequent investors, on average, tend to make smaller contributions over short horizons, with a positive association re-emerging only at longer lags.

The pattern of mostly negative coefficients at short lags and positive coefficients at more distant lags diverges from the uniformly positive and statistically significant effects reported in Åstebro et al. (2024). This discrepancy is likely attributable to differences in empirical design. Whereas Åstebro et al. (2024) aggregate prior investments within one-hour time bins, the present analysis models the effect of discrete prior investment instances on subsequent ones, with inter-arrival times that often fall well below one hour. Due to limitations in timestamp precision, it was not possible to replicate an hourly aggregation strategy.

This distinction also helps reconcile the present findings with earlier evidence documenting positive responses of pledge size to recent investment activity (Hornuf & Neuenkirch, 2017; Walther & Bade, 2020; Wang et al., 2019). These studies primarily capture investors' reactions to aggregated or salient funding events, such as cumulative investments over short intervals, conspicuous jump pledges, or daily bidding intensity, rather than to individual preceding pledges. When investment activity is aggregated into coarse time intervals or signalled by large discrete events, accumulated funding is more likely to be interpreted as a strong quality cue, thereby inducing higher subsequent contributions.

By contrast, the present specification isolates how investors respond to individual prior pledges while conditioning their decisions on heterogeneous risk–return considerations and capital constraints. In this setting, investors do not mechanically replicate earlier pledge sizes, particularly following unusually large contributions. Instead, salient investments appear to convey information that affects participation and beliefs, while the monetary response is adjusted downward or smoothed at short horizons. This behaviour is consistent with rational informational herding, in which investors update their beliefs based on observed actions while optimising their own exposure.

More broadly, the non-monotonic lag structure documented here aligns with studies emphasising heterogeneity and constraint-driven responses to social information. Evidence that investors reduce willingness to pay when participation becomes dense (Walther & Bade, 2020) or rely on coarse funding heuristics under cognitive load (Ferretti et al., 2021) suggests that the translation of social signals into investment amounts is neither linear nor uniform.

This pattern is difficult to reconcile with naïve momentum-following or classic informational cascades in which actions converge mechanically once imitation begins (Banerjee, 1992; Bikhchandani et al., 1992). It is more consistent with bounded observational learning, in which recent pledges provide salient information and serve as reference points, while investment decisions remain only partially responsive in magnitude.

In the crowdfunding setting, pledge sizes are publicly observable, but investor constraints and objectives are heterogeneous. Large contributions, often made by better-capitalised or more confident

participants, may therefore convey favourable information about campaign quality or expected success, without implying that subsequent retail investors can or should replicate the same exposure. Under these conditions, social learning is more plausibly expressed through anchoring and adjustment than through quantitative imitation. This interpretation is consistent with theoretical treatments of sequential inference in crowdfunding environments, particularly under all-or-nothing rules, where informative actions can shape beliefs while limiting runaway escalation by preserving individual discretion (Cong & Xiao, 2024; Åstebro et al., 2024).

Accordingly, the observed negative short-lag dependence is best interpreted as disciplined social adjustment rather than contrarian trading. The evidence suggests that investors respond to recent visible actions but do not mechanically increase pledge sizes, which would suppress private judgment or produce self-reinforcing spirals.

While the short-run structure of sequential dependence clarifies how investors react to recent observable actions, it does not, on its own, distinguish between behavioural contagion unfolding through time and responses to the informational content of prior pledges. The following subsection, therefore, assesses whether the timing of contributions exerts an independent influence on pledge size, or whether temporal clustering primarily reflects coordinated attention rather than imitation transmitted through rapid succession.

5.1.2 Timing versus attention coordination

The instrumental-variables results do not provide evidence that inter-pledge timing has a systematic effect on pledge size after controlling for endogeneity. Although pledges cluster in time, variation in the elapsed time between contributions is not associated with economically or statistically detectable differences in the amount invested. This distinction is important because it separates coordination in participation from dependence in valuation: investors may arrive in bursts, yet conditional on arrival, their pledge sizes are not shaped by how rapidly prior investments occurred.

In this case, the results are broadly consistent with those of Åstebro et al. (2024). Shorter elapsed time between consecutive pledges shapes the temporal clustering of investment activity but does not robustly affect pledge size after controlling for endogeneity. This reinforces the notion that, while a behavioural mechanism induces investors to join an offering more rapidly when others are doing so, the amount invested remains largely idiosyncratic and independent of short-run pledge clustering.

Theoretically, this finding challenges interpretations that equate rapid investment sequences with contagious behaviour operating through time itself. A more consistent reading is that temporal clustering reflects synchronised attention driven by platform-level rhythms, visibility shocks, or common patterns in investor availability, rather than imitation transmitted mechanically through short

inter-arrival intervals. In theoretical terms, the evidence refines the application of cascade-style intuition to digital investment settings. Sequential observability remains central for social learning, but the speed of the sequence does not appear to be a separate driver of pledge magnitude. Investors respond to what others have done, not to how recently they have done so, consistent with models in which the arrival process is separable from belief updating. At the same time, observed actions enter the decision problem as informational inputs (Cong & Xiao, 2024).

Given this evidence, the behavioural interpretation of herding in equity crowdfunding is more naturally framed in terms of content-based inference from observable contributions than as time-based contagion. Bursts of activity may therefore be read primarily as attention coordination, while the sizing decision reflects how investors interpret the information embedded in prior pledges.

Having established that temporal proximity does not causally shape investment amounts within this design, attention can be directed more explicitly toward the informational content of observable contributions. The next subsection, therefore, examines the role of unusually large pledges, focusing on how their magnitude may function as a salient signal within campaigns and how subsequent investors respond in the absence of directly observable expertise.

5.1.3 Large pledges as quantity-based signals

The consistently large coefficient on the sophisticated-investor indicator underscores the empirical importance of unusually large pledges in campaigns, consistent with prior evidence that investors condition on salient contributions when forming beliefs about campaign quality (Wang et al., 2019; Åstebro et al., 2024). Even when investor sophistication is not explicitly labelled on the platform, pledge amounts are fully observable in real time, allowing inference to operate through what is staked rather than through who is staking. In this sense, large contributions function as quantity-based signals that convey confidence or favourable private information, particularly in the high-uncertainty early stages of fundraising.

At the same time, the evidence does not suggest that large pledges generate mechanical replication in subsequent pledge sizes. The negative short-horizon lag structure documented in the two-way fixed-effects models indicates that, on average, larger recent pledges are followed by smaller ones. This pattern is consistent with an interpretation in which later contributors acknowledge the informational content of salient investments while adjusting their own exposure in line with heterogeneous risk tolerance and capital constraints. In crowdfunding environments characterised by all-or-nothing rules, early positive-signal actions can affect beliefs about campaign viability at relatively low downside risk, while later investors may benefit informationally without matching quantities (Cong & Xiao, 2024; Åstebro et al., 2024).

This result complements the evidence in Åstebro et al. (2024). While Åstebro et al. (2024) show that the involvement of sophisticated investors in an equity crowdfunding campaign serves as a salient quality signal that attracts subsequent investment activity, the present analysis indicates that later investors do not mechanically replicate those large contributions. Instead, conditional on participating, investors adjust their pledge sizes in line with idiosyncratic risk–return considerations and capital constraints. Thus, whereas Åstebro et al. (2024) document the salience of sophisticated investors' involvement as a social-information signal, our findings shed light on how that salience is translated into heterogeneous monetary commitments.

Therefore, the absence of persistent size escalation suggests that large pledges shape beliefs without establishing a new norm of contribution levels. Social learning, therefore, appears to operate through reference and validation rather than through quantitative imitation. This interpretation reinforces a view of herding in which informational signalling matters, but its expression is constrained by investor heterogeneity and does not rely on deference to publicly identifiable expertise.

While large pledges can convey information about perceived campaign quality, their interpretation does not occur in a static environment. As funding progresses, the strategic context changes, particularly under an all-or-nothing mechanism, in which the likelihood of implementation evolves endogenously. The following subsection, therefore, examines how pledge behaviour varies across funding stages and whether proximity to the target shifts investor responses from informational learning toward coordination around implementation probability.

5.1.4 Campaign-stage effects under all-or-nothing funding rules

The positive and statistically significant coefficients on the campaign-stage indicators indicate that pledge sizes increase systematically as campaigns progress toward and beyond their funding targets, even after controlling for campaign fixed effects, calendar-day shocks, and recent contribution history. Within an all-or-nothing mechanism, this pattern is most naturally interpreted as reflecting changes in incentives associated with the implementation probability, rather than as an intensification of imitation. As cumulative funding rises, the perceived likelihood that the campaign will reach its target increases, thereby reducing the expected participation cost of investing in a project that might otherwise fail to be funded.

This finding adds to the evidence from hourly bins provided by Åstebro et al. (2024), which, due to the research design, does not explicitly disentangle herding dynamics dependent on a series of competing behavioural mechanisms at predefined success thresholds, as illustrated with reference to herding, for example, in Rodríguez-Garnica et al. (2025).

Under this interpretation, larger contributions at later stages primarily reflect a shift in the strategic environment: as the threshold becomes more attainable, the downside risk of committing to a campaign that does not implement declines, and the expected payoff from participation becomes more favourable. This reading is consistent with theoretical models of sequential contribution under threshold rules, which predict that investor behaviour can shift from predominantly informational inference in the early stages toward coordination around the likelihood of implementation as the funding target approaches (Cong & Xiao, 2024). Importantly, the stage effects operate through higher average pledge levels without materially strengthening short-run sequential dependence. This suggests that proximity to the threshold increases willingness to commit but does not produce the mechanically self-reinforcing escalation characteristic of runaway cascades.

Behaviourally, such stage-based increases in pledge size may resemble fear of missing out, but the empirical pattern is also consistent with relatively disciplined coordination under threshold uncertainty. Investors respond to evolving payoff contingencies as campaign success becomes more likely, while still exercising bounded discretion over contribution size.

Although campaign progression alters incentives by changing perceived implementation probability, funding dynamics may also be shaped by external visibility and interactive information channels that operate alongside the contribution history. The next subsection, therefore, examines whether media coverage and investor Q&A activity condition responses to recent pledges, and whether these channels reinforce or reshape within-campaign social learning.

5.1.5 External visibility and on-platform information channels

The weak and largely insignificant effects of news coverage and Q&A activity, both in levels and when interacted with recent pledge sizes, indicate that external visibility and on-platform discussion do not materially reshape within-campaign sequential dependence in pledge amounts. While prior research shows that campaign updates, media attention, and investor engagement can stimulate investment activity at the extensive margin (Block et al., 2018; Xiao et al., 2021), the present results suggest that these information flows do not systematically amplify or attenuate how investors condition pledge sizes on recent contributions once campaign heterogeneity and common shocks are accounted for.

This finding is consistent with a distinction, emphasised in the broader crowdfunding literature, between mechanisms that attract attention or trigger participation and those that shape valuation and investment intensity. Dynamic signals, such as updates and discussion threads, may accelerate arrivals or sustain momentum by keeping campaigns salient, but they appear to provide only limited additional information for determining the size of individual pledges beyond what is already

embedded in observed funding trajectories. In this sense, observable contribution histories remain the primary channel through which social information is incorporated into pledge amounts, whereas external visibility and interactive features mainly operate through coordination and engagement rather than through conditional valuation.

Behaviourally, this pattern suggests that social inference in equity crowdfunding remains predominantly endogenous to the campaign's funding trajectory rather than consistently reframed by external narratives or deliberative exchanges. News items and Q&A interactions may still provide background information, reassurance, or legitimacy cues. Still, the estimates do not indicate that they recalibrate the way recent pledges translate into subsequent pledge amounts. This is consistent with a setting in which investors rely more heavily on salient, low-processing cues, such as visible contribution sizes, funding progress, and contemporaneous campaign "hotness", than on more cognitively demanding signals embedded in textual disclosures or interactive discussion.

In theoretical terms, the evidence is consistent with transmission-based accounts of social influence in which observable actions play a primary role relative to verbal or narrative channels (Raafat et al., 2009; Kameda et al., 2015). The absence of robust interaction effects also aligns with a disciplined, reference-based form of herding: external visibility may affect baseline attention and participation, but it does not appear to convert local social learning into mechanically contagious escalation in pledge magnitudes.

The limited influence of external visibility and interactive discussion suggests that herding dynamics in equity crowdfunding may vary more meaningfully with participation states than with information channels per se. The final subsection of this part, therefore, examines whether social influence intensifies or changes character during periods of unusually clustered investment activity, using the LSV measure to capture state-dependent herding within campaigns.

5.1.6 State-dependent herding and behavioural compression

The interaction between the most recent pledge size and the LSV index indicates that herding in equity crowdfunding is state-dependent rather than uniform over time. Periods characterised by unusually clustered investment activity are associated with smaller average pledge sizes, as reflected in the negative main effect of the LSV index, while simultaneously exhibiting stronger sensitivity to the immediately preceding contribution through the positive interaction term. This combination implies that heightened herding does not take the form of aggressive escalation or momentum-driven amplification.

Instead, the evidence points to a pattern of behavioural compression: when herding intensity is high, investors align their pledge sizes more closely with the most recent observable contribution, reducing

dispersion across pledges without increasing aggregate exposure. This finding is consistent with studies emphasising that herding can operate through convergence rather than escalation, particularly in environments where investors face common uncertainty and rely on salient social cues to calibrate their behaviour (Walther & Bade, 2020; Yi et al., 2024). It also aligns with evidence that dense participation can dampen willingness to pay or constrain investment intensity, even as social sensitivity increases (Ferretti et al., 2021).

More broadly, the state-dependent nature of this effect complements models of rational herding in which investors update beliefs based on recent actions but optimise exposure conditional on perceived crowd behaviour. Rather than generating runaway dynamics, clustered investment periods appear to compress individual decisions around salient benchmarks, reinforcing coordination while limiting excessive risk-taking. This interpretation is consistent with the view that herding in equity crowdfunding reflects adaptive social learning shaped by context and constraints, rather than uniform imitation across all states of market activity.

In herd-like states, deviation from the local reference point appears less pronounced, even though investors remain unwilling or unable to match large contributions one-for-one. This pattern is difficult to reconcile with stylised cascade dynamics in which intensified herding suppresses private signals and produces uniform action in a single direction. It is more consistent with bounded social adjustment, in which recent actions serve as focal anchors while investors retain discretion over their magnitude. The LSV results, therefore, refine the interpretation of herding in equity crowdfunding by indicating that excess clustering strengthens conformity to local norms rather than generating directional momentum.

Part I suggest that within-campaign herding in equity crowdfunding is neither the disappearance of independent judgment nor a process of unbounded imitation. Sequential dependence is present but non-escalatory; temporal clustering is more consistent with coordinated attention than with contagion through time; large pledges function as salient but non-binding signals; campaign progression reshapes incentives without strengthening short-run imitation; and heightened herding states compress behaviour rather than amplify it. These regularities point to a common underlying logic: investors rely on social information in disciplined, context-sensitive ways, shaped by institutional design and heterogeneous constraints.

Part II builds on this evidence by reorganising the results around the behavioural mechanisms that can jointly generate these patterns. The focus shifts from coefficient-level reconciliation to a mechanism-based perspective that integrates signalling, threshold-based coordination, and bounded social learning over the crowdfunding lifecycle.

5.2 Part Two – Mechanisms of Herding in Equity Crowdfunding: From Signalling to Coordination

This part of the Discussion synthesises the empirical findings into a mechanism-based account of herding in equity crowdfunding by integrating the evidence around three interrelated behavioural mechanisms: early informational signalling through observable pledge magnitudes; coordination around implementation likelihood under all-or-nothing funding rules; and bounded, state-dependent social learning that governs how investors adjust to recent actions.

Together, these mechanisms explain why herding in equity crowdfunding is neither absent nor uniformly destabilising, but instead operates through disciplined forms of social inference shaped by institutional design, investor heterogeneity, and evolving campaign context. Framing the results in these terms clarifies how crowdfunding-specific features modify the predictions of classical herding models. It helps identify the conditions under which crowd behaviour may support, rather than undermine, information aggregation.

5.2.1 Informational signalling through observable pledge magnitudes

In the early stages of an equity crowdfunding campaign, uncertainty about venture quality is high and verifiable information is limited. In this context, observable pledge magnitudes provide a central channel for informational signalling. Because platforms typically do not label investor sophistication in a way directly observable to other participants, social inference operates primarily through the size of contributions rather than through identifiable expertise or reputational cues. Unusually large pledges can therefore carry disproportionate informational weight by signalling confidence or favourable private assessments without requiring explicit disclosure.

The empirical evidence indicates that such pledges are associated with subsequent adjustments in pledge behaviour, yet do not generate one-for-one imitation in contribution size. This suggests that investors extract directional information from salient investments while remaining constrained by heterogeneous resources and risk tolerance. The resulting pattern is consistent with sequential learning under all-or-nothing rules, where early contributors with positive signals may rationally invest even when campaign success is uncertain, thereby revealing information while limiting downside risk (Cong & Xiao, 2024). Later investors can update their beliefs about campaign prospects and free-ride on the informational content embedded in earlier contributions without matching the quantities of those contributions.

Therefore, informational signalling in equity crowdfunding seems to function through reference and validation rather than through escalation. This mechanism allows the crowd to incorporate dispersed

information into investment decisions while preserving discretion at the contribution margin and limiting the scope for mechanically self-reinforcing size-based cascades.

5.2.2 Coordination under all-or-nothing thresholds and declining participation risk

As campaigns progress and cumulative funding approaches the target, the dominant behavioural mechanism shifts from informational inference toward coordination around the likelihood of implementation. Under an all-or-nothing funding rule, the payoff from contributing is contingent not on interim outcomes but on whether the campaign ultimately reaches its threshold. Consequently, as visible funding accumulates, the perceived probability of implementation rises, reducing the expected participation cost associated with allocating time and attention to a campaign that may fail. The empirical evidence shows that pledge sizes increase systematically at later funding stages, even though short-run sequential dependence remains bounded. This indicates that investors respond to changing payoff contingencies rather than intensifying imitation of recent actions. Large contributions at advanced stages therefore function less as quality signals and more as coordination cues that reinforce expectations of success. Behaviourally, this dynamic resembles fear of missing out, but it is better understood as rational coordination under threshold uncertainty, consistent with theoretical models in which contributors optimally condition on cumulative support rather than on the speed or magnitude of individual pledges (Cong & Xiao, 2024; Åstebro et al., 2024). Coordination under all-or-nothing rules thus raises average commitment levels without destabilising social learning, allowing campaigns to converge toward implementation without generating runaway cascades.

5.2.3 Bounded and state-dependent social learning

Beyond the distinction between early signalling and later coordination, the evidence indicates that social learning in equity crowdfunding is both bounded and state-dependent. The LSV-based results show that periods of unusually clustered activity are not associated with aggressive escalation in pledge sizes. Instead, they are associated with tighter alignment with recent observable actions: sensitivity to the immediately preceding pledge increases, while average commitment levels decline. The combination produces behavioural compression rather than amplification.

This pattern suggests that heightened social influence operates by narrowing the range of behaviour around a local reference point, rather than by suppressing private judgement or producing uniform action in a single direction. Herding, in this sense, is better characterised as reference-based anchoring that intensifies when participation is clustered, while remaining constrained by heterogeneous risk

preferences and capacities. Investors rely more heavily on social cues in high-attention states, yet do not mechanically match large pledges or escalate exposure.

The bounded nature of this adjustment also helps explain why herding can strengthen without destabilising the funding process. Social learning adapts to context, becoming more locally conformist when activity is concentrated, but not overwhelming individual discretion. As a result, collective attention may increase alignment with recent actions without triggering runaway cascades in pledge magnitudes.

5.3 Evidence from Italy in Light of Prior Crowdfunding Research

The preceding sections have developed a mechanism-based interpretation of within-campaign herding grounded in high-frequency pledge-level evidence. This section places those findings in dialogue with the existing empirical literature on equity crowdfunding, which has predominantly relied on more aggregated measures of investment activity. The objective is to clarify how differences in data resolution, modelling choices, and institutional context affect the interpretation of sequential dependence and herding behaviour. By contrasting pledge-level dynamics with aggregate funding patterns, this section highlights where prior findings generalise and where finer-grained evidence leads to more qualified conclusions.

5.3.1 Sequential dependence versus momentum

A substantial share of the empirical literature on herding in equity crowdfunding documents that subsequent investment activity increases following strong prior funding and interprets this pattern as consistent with observational learning and momentum-like dynamics, whereby visible funding cues shape later behaviour (Walther & Bade, 2020; Wang et al., 2019; Li et al., 2022). In these studies, campaigns that attract large or salient early investments tend to experience stronger subsequent inflows, which are often interpreted as evidence that investors condition their decisions on what earlier participants have done.

The pledge-level evidence developed in this thesis is consistent with the relevance of social information but adds nuance regarding how sequential dependence manifests at the intensive margin once within-campaign heterogeneity and common-day shocks are controlled for. In the two-way fixed-effects specifications, short-horizon lag coefficients are negative, indicating that unusually large recent pledges are often followed by smaller subsequent contributions. This pattern does not imply the absence of herding. Instead, it suggests that social influence may operate through anchoring and bounded adjustment, whereby investors respond to the informational content of prior pledges while moderating their own exposure in line with heterogeneous constraints. In this sense, the results

complement earlier findings by showing that aggregate reinforcement in funding trajectories can coexist with non-monotonic adjustment in individual pledge sizes.

Differences in empirical resolution and modelling choices provide a plausible explanation for why studies based on aggregated or daily measures tend to emphasise reinforcement, whereas pledge-level estimates reveal short-run offsetting dynamics. Walther and Bade (2020), for example, relate contribution outcomes to recent campaign activity and interpret stronger subsequent engagement as consistent with momentum in valuations. Still, their unit of observation is not designed to distinguish whether investors match the magnitude of recent pledges or adjust around them within short time windows. Wang et al. (2019) show that large "jump" pledges predict higher subsequent investment, particularly when jumps are associated with investors perceived as more informed; however, this evidence does not separately identify magnitude imitation from broader increases in participation or from changes in investor composition.

A similar point applies to Li et al. (2022), who link early "initial herds" to overfunding and interpret strong early surges as potentially generating inefficient overshooting. The present results do not contradict the possibility that early momentum predicts higher total funding outcomes. Instead, they suggest that one channel through which such outcomes may arise is increased participation and confidence, without requiring escalating pledge sizes at the individual level. Stronger aggregate funding trajectories may therefore reflect investors' interpretation of funding history as a positive signal, while still exhibiting bounded behaviour in their own contribution amounts.

This thesis contributes high-frequency evidence on the within-campaign mechanics of sequential dependence. The results support the broader consensus that investors respond to social information in equity crowdfunding (Walther & Bade, 2020; Wang et al., 2019; Yi et al., 2024), while indicating that such responses need not take the form of mechanical escalation in pledge sizes. This perspective underscores the importance of temporal granularity in empirical analyses of herding and highlights how institutional features and heterogeneous constraints can discipline momentum-like behaviour at the micro level.

5.3.2 Timing, bursts, and the interpretation of temporal clustering

A recurrent theme in the equity crowdfunding literature is that investments tend to arrive in bursts, with periods of intense activity followed by relative lulls. Several empirical studies implicitly interpret such temporal clustering as evidence of behavioural contagion, in which rapid sequences of contributions amplify social influence and accelerate herding dynamics (Block et al., 2018; Walther & Bade, 2020; Yi et al., 2024). In these accounts, short inter-arrival times are often treated as

indicative of imitation pressure, under the assumption that closely spaced investments reinforce one another and trigger further participation.

The instrumental-variables evidence in this study supports a more cautious interpretation of these patterns. Once endogeneity in inter-pledge timing is addressed, variation in the elapsed time between consecutive pledges does not exert a statistically detectable effect on pledge size. This result suggests that, although pledges cluster in time, the speed at which contributions arrive does not independently shape the intensity of investment decisions. Rather than indicating contagion transmitted through rapid succession, temporal clustering appears more consistent with coordinated attention driven by platform-level rhythms, shared availability of investors, or common visibility shocks.

This interpretation aligns with a conceptual separation between arrival processes and valuation decisions. Investors may arrive in synchronised waves, yet condition their pledge amounts on the informational content of prior contributions rather than on their temporal proximity. In this respect, the results refine the interpretation of timing in crowdfunding settings, where high-frequency observability and platform design can generate clustered arrivals without implying imitation in contribution magnitude.

The findings complement, rather than contradict, existing empirical evidence. Block et al. (2018), for example, show that campaign updates and other visibility-enhancing events are followed by increased investment activity over subsequent days, which they interpret primarily as attention-driven responses. Walther and Bade (2020) document that periods of high platform activity coincide with stronger funding outcomes, but their empirical design does not isolate whether shorter inter-pledge intervals affect pledge magnitudes. Yi et al. (2024) show that investors rely more heavily on public signals when private information is weak; however, their analysis does not explicitly disentangle timing effects from the informational content embedded in prior investments. The instrumental-variables strategy employed here addresses this gap by exploiting predetermined variation in inter-pledge duration, allowing a more direct assessment of whether timing itself constitutes a behavioural channel.

The absence of a timing effect refines the behavioural interpretation of bursts commonly observed in crowdfunding data. It indicates that such bursts should not be automatically interpreted as evidence of escalating imitation or contagion over time. Instead, they are more plausibly understood as coordination at the participation margin, where multiple investors simultaneously attend to the same campaign and make decisions based on shared social information. Temporal clustering, in this sense, reflects synchronised attention rather than amplification of valuation responses.

The results presented in this thesis support a cautious interpretation of the temporal clustering patterns documented in earlier studies, indicating that while clustering is a salient feature of crowdfunding

markets, it does not, by itself, imply behavioural contagion operating through rapid succession. This distinction underscores the importance of separating attention-driven coordination from imitation in contribution magnitudes when interpreting high-frequency investment dynamics.

5.3.3 Large pledges, expertise, and quantity-based signalling

A prominent finding in the equity crowdfunding literature is that unusually large or salient contributions exert a disproportionate influence on subsequent investment behaviour. Several studies interpret this pattern as evidence that investors attribute greater informational content to specific contributors, either because of observable characteristics such as business angel status or because the size of the investment itself signals confidence and favourable private information (Wang et al., 2019; Walther & Bade, 2020; Yi et al., 2024). In this view, large pledges function as focal signals that shape beliefs about project quality and can stimulate further investment.

The evidence from the present thesis is consistent with a signalling role for large pledges, but points to a more restrained response at the intensive margin. The sophisticated-investor indicator, defined ex post but corresponding to an ex ante observable pledge magnitude, captures a persistent and economically large difference in contribution size. At the same time, the negative short-run dependence in pledge amounts indicates that subsequent investors typically do not replicate these large contributions on a one-for-one basis. Instead, they appear to incorporate the informational content of salient pledges while adjusting their own commitment levels downward, reflecting heterogeneous wealth constraints, risk tolerance, and portfolio considerations. This pattern is indicative of quantity-based signalling without proportional imitation.

These findings complement existing evidence and help refine its behavioural interpretation. Wang et al. (2019) show that large "jump" pledges predict higher subsequent investment, particularly when such jumps are made by investors perceived as more informed, and interpret this as evidence that investors condition on contributor expertise. The present results do not contradict this interpretation but suggest that part of the observed effect may operate through increased participation or confidence rather than through larger individual pledge sizes. Similarly, Yi et al. (2024) document that investors rely more heavily on public signals when private information is weak, consistent with rational herding. The pledge-level dynamics documented here indicate that such reliance can coexist with bounded adjustment in magnitude, especially in settings dominated by retail investors.

The Italian evidence also relates to the interpretation offered by Ferretti et al. (2021), who argue that investors may rely on accumulated funding as a heuristic in complex platform environments. While the present analysis confirms that investors closely attend to salient funding cues, it shows that this reliance does not necessarily translate into the mechanical imitation of large pledges. Instead, large

contributions appear to validate campaigns and discipline beliefs, while leaving room for individual discretion in the size of contributions. Quantity-based signalling thus operates as a coarse but informative input into decision-making rather than as a norm-setting device that redefines acceptable pledge magnitudes.

From a theoretical perspective, this pattern is consistent with sequential learning under all-or-nothing funding rules, in which early contributors with favourable private signals reveal information at relatively low downside risk, and later investors optimally free-ride on this information without matching contributions (Cong & Xiao, 2024; Åstebro et al., 2024). The absence of persistent size escalation suggests that observable pledge magnitudes function primarily as validation signals rather than as anchors for quantitative imitation. This interpretation helps reconcile the widespread empirical finding that large pledges matter with the absence of runaway cascades.

The results indicate that large pledges play an important informational role in equity crowdfunding, but that their influence is mediated by heterogeneous investor constraints and institutional design. Social learning operates through reference and confirmation rather than through deference to identifiable experts or unconditional replication of contribution sizes, refining existing interpretations of how expertise and signalling function in crowdfunding markets.

5.3.4 Herding intensity, overfunding, and behavioural compression

Recent work has increasingly focused not only on whether herding occurs in equity crowdfunding but also on how its intensity varies over time and on the consequences for funding outcomes. In particular, Li et al. (2022) introduce the notion of an "initial herd" and show that campaigns characterised by earlier, stronger, and more persistent surges in funding are more likely to experience overfunding. They interpret this pattern as suggestive of potential inefficiency, whereby social influence amplifies early signals and leads investors to allocate capital beyond what fundamentals alone would justify. This interpretation aligns with broader concerns in the literature that herding dynamics in crowdfunding may, under certain conditions, contribute to misallocation.

The evidence from the present study offers a complementary perspective by examining how herding intensity interacts with individual pledge behaviour within campaigns. Using an LSV-type measure adapted to the crowdfunding context, periods of unusually clustered investment activity are identified as states of heightened herding. Consistent with stronger social influence, these states are associated with greater sensitivity to the most recent pledge. At the same time, the main effect of herding intensity is negative: average pledge sizes are smaller during periods of high clustering. Together, these results indicate that intensified herding is accompanied by tighter alignment with recent observable behaviour, but not by an increase in overall exposure at the individual level.

This combination contrasts with interpretations that equate stronger herding with exuberant overreaction. While Li et al. (2022) document that early herds predict higher final funding ratios, the present findings suggest that one mechanism underlying such outcomes may be increased participation and behavioural alignment rather than systematic growth in individual pledge sizes. Campaigns may therefore accumulate capital more rapidly, or attract a larger number of contributors, during herd-like phases without requiring investors to commit progressively larger amounts. Such distinctions are difficult to detect in campaign-level or aggregate data, but become visible once pledge-level dynamics are modelled explicitly.

The concept of behavioural compression also helps reconcile heightened herding with the absence of destabilising cascades observed in earlier sections. In herd-like states, investors appear less willing to deviate from recent contribution norms, thereby reducing pledge-size dispersion. However, this conformity operates around a local reference point rather than pushing contributions upward. The resulting pattern is consistent with bounded social learning, in which investors place greater weight on social cues when uncertainty or participation intensity is high, yet remain constrained by individual risk considerations and platform design. Importantly, this mechanism does not require investors to abandon private judgment altogether, nor does it imply that herding necessarily generates inefficient outcomes.

From a broader perspective, these findings suggest caution in interpreting measures of herding intensity as direct indicators of excess exuberance or misallocation. While elevated herding states are associated with greater local conformity, they need not imply increased commitment or deterioration in decision quality. Instead, they may reflect periods in which social information becomes more salient, and investors coordinate more tightly around recent norms. This interpretation complements existing evidence on overfunding by highlighting that similar aggregate outcomes can arise from distinct micro-level behaviours, and that herding intensity can manifest through compression rather than amplification.

The LSV-based analysis adds nuance to the emerging literature on herding intensity in equity crowdfunding. It supports the view that social influence varies across participation states, while indicating that its behavioural expression depends critically on institutional features and investor constraints. In the Italian setting examined here, heightened herding reinforces alignment rather than escalation, providing additional evidence that herding in crowdfunding can be disciplined rather than destabilising.

5.3.5 What this evidence adds to the herding literature

This thesis has examined herding in equity crowdfunding through a pledge-level perspective that isolates within-campaign dynamics, separates attention from imitation, and integrates multiple behavioural channels within a single empirical framework. By combining high-frequency transaction data with two-way fixed effects and an instrumental-variables strategy, the analysis provides a granular account of how investors respond to social information in environments characterised by high uncertainty and limited transparency. Rather than overturning existing findings, the results refine their interpretation by showing how aggregate patterns often attributed to momentum or contagion can emerge from disciplined and bounded adjustments at the individual level.

Across specifications, herding does not appear to be either the absence of independent judgment or a process of unbounded imitation. Sequential dependence is present but non-escalatory; temporal clustering reflects coordinated attention rather than causal contagion; large pledges function as salient but non-binding signals; and campaign progression reshapes incentives without mechanically strengthening imitation. Periods of heightened herding intensity further compress behaviour around local reference points without inducing systematic escalation. Overall, these regularities support an interpretation of herding as context-dependent social learning, shaped by institutional design, investor heterogeneity, and the evolving informational content of observable actions.

At the same time, the scope of these conclusions is necessarily bounded. The evidence is drawn from a regulated equity crowdfunding market operating under all-or-nothing funding rules, characterised by limited liquidity and a predominantly retail investor base. These features condition both the availability of social information and the costs of imitation, and they are likely to play a role in disciplining herding dynamics. While several mechanisms identified here, such as quantity-based signalling, threshold-driven coordination, and state-dependent alignment, are plausibly relevant to other digitally mediated investment environments, their strength and expression may vary across institutional settings. The results should therefore be read as conditional refinements of existing herding theories rather than as general statements about crowd behaviour.

By clarifying how herding operates at the micro level, this chapter proposes a foundation for moving beyond descriptive patterns toward broader implications. The following section builds on this synthesis to discuss the implications of these findings for theoretical models of social learning and information aggregation, for the design of crowdfunding platforms, and for regulatory approaches to investor protection in digital financial markets.

5.4 Implications

5.4.1 Theoretical implications

The results presented in this thesis carry several implications for how herding and social learning could be conceptualised in environments characterised by high uncertainty, sequential observability, and institutional thresholds. A first implication concerns the nature of herding itself. The negative short-run dependence in pledge sizes documented in the two-way fixed-effects models indicates that herding need not take the form of monotonic escalation or cumulative reinforcement. Instead, investors appear to respond to social information in a bounded manner, using recent observable actions as reference points while retaining discretion over the magnitude of their own commitments. This pattern refines standard interpretations of herding that emphasise convergence and amplification, suggesting that sequential dependence can coexist with disciplined adjustment rather than crowd-driven escalation.

The findings also inform the mechanics of observational learning. Classical accounts of social learning emphasise the risk that early actions may dominate later decisions by crowding out private information. The pledge-level evidence presented here points to a more nuanced process. Large or salient contributions influence subsequent behaviour, but they do not redefine acceptable contribution levels for later investors. Observable actions inform beliefs about project quality while leaving scope for heterogeneous responses. This suggests that observational learning in crowdfunding operates through anchoring and partial updating rather than by suppressing private judgment. Theoretical models of herding may therefore benefit from explicitly incorporating constraints on quantitative imitation, particularly in settings where agents differ substantially in resources and risk tolerance.

The absence of a causal role for inter-pledge timing further refines how sequential processes should be modelled. Although temporal clustering is a prominent feature of crowdfunding data, the instrumental-variables results show that the speed of arrival does not independently shape pledge sizes. From a theoretical perspective, this supports a distinction between coordination in participation and imitation in valuation. Investors may arrive in bursts owing to shared attention or platform-level rhythms, yet condition their valuation decisions on the content of observed actions rather than on their temporal proximity. Herding models should therefore be cautious in treating rapid sequences as evidence of contagion per se and instead allow for arrival processes that are exogenous to belief updating.

The campaign-stage results underscore the role of institutional design, particularly threshold-based funding rules, in shaping social learning. Under an all-or-nothing mechanism, the informational content of observed contributions evolves. Early in the campaign, pledges primarily convey information about perceived project quality, whereas later contributions increasingly affect beliefs

about the likelihood of implementation. The finding that pledge sizes rise systematically with campaign progress, without a corresponding strengthening of short-run sequential dependence, points to a shift from informational inference toward coordination around payoff contingencies. This pattern supports theoretical accounts in which herding dynamics are endogenously shaped by proximity to a threshold, and in which coordination motives become more salient as collective success becomes attainable.

The state-dependent evidence provided by the LSV interaction further highlights that herding is not a uniform phenomenon. Periods of heightened clustering are associated with greater sensitivity to recent actions but smaller average pledge sizes, indicating tighter behavioural alignment without escalation. This pattern suggests that intensified herding may operate by narrowing the range of acceptable actions rather than by pushing behaviour in a particular direction. From a theoretical standpoint, this implies that herding intensity should not be equated mechanically with exuberance or inefficiency. Models of herding may therefore need to accommodate states in which social influence increases conformity while remaining constrained by individual decision rules.

Taken together, these findings have implications for theories of information aggregation. The evidence suggests that social learning in crowdfunding can facilitate the aggregation of dispersed private information without necessarily generating runaway cascades. Observable actions convey coarse but informative signals, while bounded responses limit the extent to which individual judgment is crowded out. This perspective aligns with the idea that markets characterised by limited disclosure and high uncertainty may rely on social cues as substitutes for fundamentals, yet still retain mechanisms that discipline behaviour. Notably, the results caution against interpreting the presence of herding as prima facie evidence of inefficiency; the form that herding takes is central to assessing its welfare implications.

Finally, while these implications are grounded in equity crowdfunding under all-or-nothing funding rules, they may extend, with appropriate caution, to other digital investment environments that share similar features, such as sequential observability, heterogeneous participants, and threshold-like payoffs. The evidence suggests that when actions are observable but costly to imitate quantitatively, social learning is likely to remain bounded rather than explosive. Future theoretical work could usefully explore how institutional constraints, participant heterogeneity, and state dependence jointly shape herding dynamics across such settings.

5.4.2 Platform design implications

The empirical findings of this thesis carry several implications for how equity crowdfunding platforms design information environments and structure investor interaction. A first implication

concerns the visibility of contribution histories. The evidence shows that investors respond systematically to observable pledge sizes, using recent contributions as reference points while avoiding mechanical imitation. Making individual pledge amounts transparent can support information aggregation by allowing investors to infer confidence and perceived quality from prior actions. At the same time, the absence of escalation and the presence of bounded adjustment indicate that such transparency does not necessarily induce destabilising cascades. From a design perspective, this supports the continued disclosure of contribution magnitudes, while cautioning against interface features that excessively amplify single large pledges or frame them as normative benchmarks.

A second implication relates to how platforms present temporal information and activity bursts. Although investments cluster in time, the instrumental-variables results indicate that inter-pledge timing does not affect pledge size. This finding suggests that design elements emphasising speed, such as countdowns to the last investment, real-time "recent activity" tickers, or alerts highlighting rapid succession, may primarily influence attention rather than valuation. While such features can increase engagement, they risk being misinterpreted by investors as signals of quality or urgency. Platforms may therefore wish to differentiate more clearly between indicators of attention (e.g. current traffic or number of viewers) and indicators of informed commitment, reducing the likelihood that temporal clustering is perceived as evidence of superior project fundamentals.

Campaign-stage effects also point to the importance of how funding progress is communicated. The results show that pledge sizes increase as campaigns approach and exceed their funding targets, consistent with coordination around the likelihood of implementation under all-or-nothing rules. This implies that cumulative funding displays are not merely informational but actively shape investor incentives by altering perceived downside risk. From a design standpoint, platforms should be aware that progress bars and milestone indicators can encourage larger commitments at later stages, even in the absence of new quality information. While this mechanism can help viable campaigns reach completion, it also places greater responsibility on platforms to ensure that early-stage information is sufficiently explicit, so that later coordination does not rest solely on inferred momentum.

The limited role of news coverage and Q&A activity in conditioning responses to recent pledges has further design implications. Although updates, media links, and interactive discussions are often promoted as tools to enhance investor understanding, the evidence suggests that these channels do not materially reshape within-campaign social learning at the intensive margin. This does not imply that such features are unimportant; rather, their influence may operate primarily on participation decisions rather than on contribution size. Platforms may therefore consider integrating these informational elements more closely with financial cues, for example, by linking updates to specific

funding milestones or clarifying how new information relates to prior contributions, rather than treating them as parallel streams of engagement.

Finally, the state-dependent herding results suggest that platform design choices may have different effects under different participation regimes. During periods of heightened clustering, investors become more sensitive to recent actions while reducing average commitment levels, leading to behavioural compression. This implies that design features that intensify social visibility may have more substantial conformity effects precisely when activity is already high. Platforms and regulators may therefore wish to consider adaptive design elements that temper social salience during peak periods, for instance, by aggregating recent activity over longer windows or reducing the prominence of single recent pledges, to preserve individual discretion without eliminating informative cues.

These implications highlight that platform design is not neutral with respect to herding dynamics. Visibility, timing cues, and progress indicators shape how investors interpret social information and coordinate their actions. The evidence from this thesis suggests that carefully calibrated transparency can support disciplined social learning, whereas excessive emphasis on speed or salience risks conflating attention with information. Designing platforms that distinguish between these dimensions may help balance engagement with informed decision-making in equity crowdfunding markets.

5.4.3 Regulatory and policy implications

The findings of this study also carry implications for regulatory frameworks governing equity crowdfunding, particularly in jurisdictions where platforms operate under detailed investor-protection rules but markets remain thin, and information asymmetries are pronounced. A first implication concerns how herding behaviour itself is interpreted by regulators. The results suggest that the presence of sequential dependence or clustered investment activity should not automatically be read as evidence of behavioural excess or market failure. Once pledge-level dynamics are examined, herding appears largely bounded, context-dependent, and shaped by institutional features such as all-or-nothing funding rules. From a policy perspective, this cautions against regulatory responses that treat all forms of herding as destabilising and instead calls for more nuanced assessments of how social influence manifests in investor behaviour.

A second implication relates to disclosure requirements and the regulation of social information. Most crowdfunding regimes mandate transparency regarding cumulative funding and recent investment activity, on the premise that such disclosure enhances market discipline. The evidence here supports this premise in a qualified sense: observable pledge histories facilitate social learning and coordination without generating systematic escalation in individual commitments. At the same time, the findings indicate that investors rely primarily on coarse, salient cues, such as contribution sizes

and funding progress, rather than on detailed textual disclosures. Regulators may therefore wish to complement existing disclosure rules with guidance on how information is framed and presented, so that visibility supports informed inference rather than conflating attention with underlying project quality.

The absence of a causal role for inter-pledge timing also has regulatory relevance. Policymakers sometimes express concern that rapid investment sequences may reflect undue pressure on retail investors or manipulation through artificial urgency. The instrumental-variables evidence suggests that, in this setting, temporal clustering reflects coordinated attention rather than imitation transmitted through speed itself. This implies that regulatory scrutiny should focus less on the pace of contributions per se and more on whether platforms deploy design features that create misleading cues of urgency. Rules aimed at limiting countdown effects or real-time pressure tactics may therefore be justified not because speed directly causes imitation, but because it can blur the distinction between attention and information for less experienced investors.

Campaign-stage effects under all-or-nothing rules raise additional policy considerations. As campaigns approach their funding targets, larger pledges become more common, reflecting coordination around the likelihood of implementation rather than new quality information. While this mechanism can be efficiency-enhancing by helping viable projects reach completion, it also increases reliance on cumulative funding as a coordination signal. Regulators may therefore wish to ensure that early-stage disclosures are sufficiently robust, given that later investment decisions increasingly draw on inferred momentum. Strengthening upfront disclosure standards or requiring clearer communication of risks early in campaigns could mitigate the informational asymmetries inherent in threshold-based mechanisms.

The state-dependent nature of herding also has implications for investor protection. Periods of heightened clustering are associated with stronger conformity to recent actions, even though average pledge sizes decline. This suggests that social influence intensifies precisely when participation is most visible, potentially reducing behavioural diversity. While the evidence does not indicate harmful escalation, it does point to moments when retail investors may be more susceptible to social cues. Regulators could therefore consider whether platform-level safeguards, such as standardised risk reminders or cooling-off prompts, might be activated during such high-activity periods, not to suppress participation, but to reinforce reflective decision-making.

Finally, the Italian context highlights the interaction between regulation and market structure. Despite relatively strong formal investor protections, social learning remains a central mechanism for aggregating information. This suggests that regulation alone cannot eliminate reliance on social cues in opaque markets. Effective policy should instead recognise herding as an endogenous feature of

entrepreneurial finance and aim to channel it toward informative and disciplined forms. By distinguishing between bounded social learning and destabilising imitation, regulators can better align oversight with the behavioural dynamics observed in equity crowdfunding markets.

These implications point toward a regulatory approach that is attentive to how information is framed and interpreted, rather than one that seeks to suppress social influence altogether. The evidence suggests that well-designed disclosure and platform rules can accommodate herding as a mechanism of information aggregation, while limiting the risk that attention-driven cues or excessive salience undermine investor judgment.

Also, the implications highlighted in this section should be interpreted in light of the analysis's institutional and empirical context scope. The results are derived from a regulated equity crowdfunding market operating under all-or-nothing funding rules, with limited secondary liquidity and a predominantly retail investor base. While several mechanisms identified here are likely relevant to other digital investment environments with similar features, their strength and expression may vary with platform design, disclosure regimes, and investor composition. Accordingly, the implications outlined above should be understood as conditional insights that refine existing policy discussions rather than as universal prescriptions.

Chapter 6: Conclusion

This thesis has examined how herding behaviour operates in equity crowdfunding when investment decisions unfold sequentially, social information is salient and continuously observable, and fundamental uncertainty is substantial. Rather than approaching herding as a binary condition, the analysis has treated it as a behavioural process whose form and consequences depend on institutional design, investor heterogeneity, and the structure of information transmission within campaigns. The empirical objective has been to identify, at high temporal resolution, how investors condition their decisions on others' observed actions in a digital entrepreneurial finance setting.

A central premise motivating the analysis is that correlations in crowdfunding investments are intrinsically ambiguous. Aggregate funding trajectories may reflect imitation in valuation, coordination in participation, common attention shocks, or strategic responses to threshold-based payoffs. Much of the existing literature documents sequential dependence and interprets it as consistent with observational learning or momentum. However, empirical designs based on daily or campaign-level aggregation often struggle to cleanly distinguish these mechanisms. This thesis has therefore sought to refine the interpretation of herding by disentangling the behavioural content of social influence from confounding sources of correlation, and by separating informational inference from attention synchronisation and other platform-wide dynamics.

To this end, the empirical analysis uses data from over 25,000 pledges across 226 Italian campaigns hosted on one of Italy’s leading equity crowdfunding platforms, Crowdfundme, spanning from 2015 to 2025, and examines the full ordering of individual contributions campaigns. The modelling strategy combines high-dimensional fixed effects to isolate within-campaign dynamics from time-varying shocks, with an instrumental-variables design to address potential endogeneity in inter-pledge timing. This framework enables a more precise behavioural interpretation of crowdfunding sequences than is possible when inference is drawn primarily from aggregate measures. In particular, it allows the analysis to separate the role of what is observed, specifically recent pledges and their magnitudes, from the role of when actions occur, such as bursts and lulls in activity, and to assess whether observed clustering reflects causal contagion or coordinated attention.

The evidence from this approach suggests that herding in equity crowdfunding is best understood as a disciplined, context-dependent form of social learning. Investors respond systematically to observable pledge histories, yet these responses do not take the form of mechanical escalation in contribution size, nor do they appear to be driven by the speed at which investments arrive. Instead, social information functions as a salient reference point that shapes behaviour while remaining constrained by heterogeneous resources, risk tolerance, and the institutional environment of all-or-

nothing fundraising. During periods of heightened activity, social influence intensifies, with individuals aligning more closely with recent observable actions, but this manifests primarily as behavioural compression rather than unbounded amplification.

These patterns are closely linked to the institutional architecture of equity crowdfunding, particularly to threshold-based payoffs. Under all-or-nothing rules, the meaning of observed contributions evolves as a campaign progresses. Early contributions primarily convey information relevant to perceived project quality when uncertainty is high. In contrast, later contributions increasingly facilitate coordination around implementation likelihood as the perceived probability of success rises and the perceived risk of participation declines. The thesis therefore situates herding within a dynamic campaign lifecycle in which informational inference and coordination motives interact, and in which social learning is shaped, and plausibly disciplined, by the market's underlying incentive structure.

The purpose of this concluding chapter is to consolidate the thesis's empirical and conceptual insights and to clarify their implications. It proceeds by (i) summarising the main findings and their behavioural interpretation, (ii) articulating the thesis's contributions to the literature on herding and social learning in crowdfunding markets, and (iii) outlining a focused set of directions for future research that build directly on the empirical framework developed in this study.

In doing so, the chapter positions the Italian equity crowdfunding market not merely as an additional empirical context, but as a setting that is informative for theory. The evidence presented here suggests that herding in equity crowdfunding should not be characterised exclusively as a source of inefficiency or fragility. Under certain institutional conditions, it may instead reflect an adaptive response to uncertainty that supports coordination and partial information aggregation, while remaining bounded by heterogeneity and by the constraints embedded in platform-mediated entrepreneurial finance.

6.1 Main Findings

This thesis presents a set of interrelated findings that collectively refine the understanding of herding behaviour in equity crowdfunding. At a broad level, the results confirm that investors condition their decisions on observable actions taken by others. At the same time, they show that the form this conditioning takes is more nuanced and constrained than is often assumed. Herding emerges not as a process of monotonic imitation or unbounded escalation, but as a structured pattern of social learning shaped by campaign context, institutional design, and investor heterogeneity.

A first central finding concerns the nature of sequential dependence in pledge sizes. Once unobserved campaign characteristics and common time shocks are absorbed, the immediate history of contributions continues to matter, but in a non-monotonic manner. Large recent pledges are not

typically followed by equally large or larger contributions. Instead, short-horizon responses tend to be offsetting, with subsequent investors adjusting their pledge sizes downward before partial reversal occurs at longer lags. This pattern is inconsistent with naïve momentum-following or simple cascade dynamics in which actions converge mechanically once imitation begins. Rather, it suggests that investors use recent pledges as informative reference points while exercising bounded discretion over their own exposure. Social learning therefore operates through anchoring and partial adjustment rather than through quantitative replication.

A second key finding is the absence of a causal role for inter-pledge timing in shaping pledge sizes. Although investment activity clusters in time, instrumental-variables estimates indicate that variation in the elapsed time between consecutive pledges does not meaningfully affect the magnitude of subsequent contributions. This result draws a clear distinction between coordination in participation and imitation in valuation. Investors may arrive in bursts, reflecting platform-level rhythms, shared attention, or common visibility shocks, but, conditional on arrival, their valuation decisions respond to others' actions rather than to how recently those actions occurred. Temporal clustering thus reflects synchronised attention rather than behavioural contagion transmitted through rapid succession.

Third, the analysis highlights the informational role of unusually large pledges. Contributions made by investors identified ex post as sophisticated are consistently and substantially larger, and such pledges function as salient quantity-based signals within campaigns. Subsequent investors respond to these signals, yet do not replicate them one-for-one. Instead, they appear to extract directional information regarding perceived campaign quality while scaling their own commitments in line with heterogeneous resources and risk preferences. This finding underscores that observable pledge magnitudes convey information even in the absence of publicly identifiable expertise, but that the influence of such signals is mediated by constraints that limit mechanical imitation.

A fourth finding relates to the dynamic role of campaign progression under all-or-nothing funding rules. Pledge sizes increase systematically as campaigns move closer to, and beyond, their funding targets. This effect persists after controlling for recent contribution history and other confounding factors, indicating that it reflects a shift in incentives rather than intensified social imitation. As cumulative funding rises, the perceived probability of campaign implementation increases, lowering the expected participation cost associated with investing. Contributions at later stages therefore facilitate coordination around implementation likelihood rather than conveying new information about underlying quality. Importantly, this stage-dependent increase in pledge sizes does not coincide with stronger short-run sequential dependence, suggesting that coordination and imitation operate through distinct behavioural channels.

Fifth, the results show that external visibility and interactive information channels play a limited role in shaping within-campaign herding dynamics at the intensive margin. Measures of media coverage and investor Q&A activity exhibit weak direct effects and do not materially condition responses to recent pledges. This suggests that investors rely primarily on salient, easily interpretable social cues, such as visible pledge sizes and cumulative funding, rather than on more complex or cognitively demanding information sources when adjusting their contribution amounts. External information may influence participation decisions or baseline attention, but it does not systematically amplify or dampen sequential dependence in pledge sizes.

Finally, the analysis provides evidence that herding intensity is state-dependent. Periods characterised by unusually clustered investment activity are associated with greater sensitivity to the most recent pledge, yet with smaller average pledge sizes. This combination implies that heightened herding manifests as behavioural compression rather than escalation. In such states, investors align more closely with recent observable actions, reducing dispersion in contribution sizes without increasing overall exposure. Herding thus intensifies in form, but not in magnitude, reinforcing the view that social influence in equity crowdfunding operates through bounded conformity rather than exuberant amplification.

Overall, these findings depict equity crowdfunding investors as neither entirely independent optimisers nor passive imitators. Observable social information matters, but its influence is disciplined by institutional thresholds, heterogeneous constraints, and evolving campaign context. Herding is present, but it operates through local alignment, anchoring, and coordination rather than through runaway cascades. This behavioural configuration provides the empirical foundation for the contributions and implications discussed in the remainder of this chapter.

6.2 Contributions to the Literature on Herding and Social Learning

This thesis contributes to the behavioural finance and entrepreneurial finance literatures by refining the conceptualisation of herding and social learning in environments characterised by sequential observability, high uncertainty, and institutional thresholds. The analysis consolidates and extends existing frameworks by showing how widely documented aggregate patterns can arise from disciplined and bounded adjustments at the micro level. In doing so, it clarifies both the mechanisms through which social influence operates in equity crowdfunding and the conditions under which herding remains constrained rather than destabilising.

A first contribution lies in the distinction between sequential dependence and escalation. Prior empirical work has established that investors respond to observable funding activity, often interpreting reinforcement in campaign trajectories as evidence of imitation or momentum. By

exploiting pledge-level data and isolating within-campaign and within-day variation, this thesis shows that such responsiveness does not necessarily imply monotonic amplification in individual decisions. Short-horizon sequential dependence is present, but it is typically offsetting rather than reinforcing, with investors adjusting around recent reference points instead of replicating them quantitatively. This finding refines standard interpretations of herding by demonstrating that observable reinforcement at the aggregate level can coexist with non-escalatory behaviour at the individual level. It therefore helps reconcile evidence of social influence with the absence of runaway cascades observed in many regulated crowdfunding markets.

A second contribution concerns the separation of attention coordination from imitation in valuation. Temporal clustering of investments is a pervasive feature of crowdfunding data and is frequently interpreted as behavioural contagion. By addressing endogeneity in inter-pledge timing, this thesis shows that the timing of investments does not independently shape pledge sizes. This result sharpens the interpretation of bursts commonly observed in crowdfunding markets, suggesting that they reflect synchronised attention rather than imitation transmitted through time. Conceptually, this distinction matters for herding theory, as it implies that arrival processes and valuation decisions can be analytically separated, and that rapid sequences should not automatically be treated as evidence of contagion. The contribution is therefore not to downplay the importance of timing, but to delimit its behavioural role.

A third contribution relates to the informational content of observable actions in the absence of identifiable expertise. Much of the literature emphasises the role of experts, lead investors, or certified signals in shaping crowdfunding dynamics. The evidence presented here shows that even when investor sophistication is not publicly labelled, observable pledge magnitudes function as effective quantity-based signals. At the same time, the bounded response to such signals indicates that social learning operates through directional inference rather than quantitative imitation. This contribution clarifies how information can be aggregated through actions alone, without requiring explicit reputation mechanisms, while remaining constrained by heterogeneous investor capacities.

A fourth contribution concerns the role of institutional design, particularly all-or-nothing funding rules, in shaping the expression of herding. By documenting systematic increases in pledge sizes as campaigns approach their funding targets, without a corresponding strengthening of short-run sequential dependence, the analysis highlights a shift from informational learning toward coordination around the likelihood of implementation. This finding integrates herding theory with models of threshold-based participation, showing that what may appear as intensified herding at later stages is more accurately interpreted as rational coordination under changing payoff contingencies.

The contribution lies in embedding herding behaviour within the institutional logic of crowdfunding, rather than treating it as a uniform behavioural response across campaign phases.

Finally, the thesis contributes to emerging work on herding intensity and state dependence. Using an LSV-based measure adapted to the crowdfunding context, the analysis shows that periods of heightened clustering are associated with stronger local conformity but lower average commitment. This pattern introduces the notion of behavioural compression as a distinct manifestation of herding, complementing interpretations that focus on exuberance or overreaction. By demonstrating that intensified herding can narrow behavioural dispersion without escalating exposure, the thesis refines how herding intensity should be interpreted and cautions against equating stronger social influence with inefficiency.

These contributions consolidate a view of herding as context-dependent and bounded social learning rather than as mechanical imitation. In doing so, the thesis helps bridge behavioural finance and entrepreneurial finance by showing that herding in equity crowdfunding can support information aggregation without necessarily undermining individual judgment or market discipline.

6.3 Scope, Limitations, and Directions for Future Research

The conclusions drawn in this thesis should be interpreted in light of the institutional, empirical, and methodological scope of the analysis. The evidence is drawn from a regulated equity crowdfunding market operating under all-or-nothing funding rules, characterised by limited secondary liquidity and a predominantly retail investor base. These features shape both the availability of social information and the costs of imitation, and they are likely to play an essential role in disciplining herding dynamics. While several mechanisms identified here are plausibly relevant beyond this setting, their strength and expression may vary in markets with different institutional architectures.

A first limitation concerns external validity across platforms and funding mechanisms. The Italian equity crowdfunding market differs from reward-based crowdfunding, peer-to-peer lending, and secondary financial markets in terms of disclosure requirements, investor composition, and payoff structures. In particular, the all-or-nothing rule conditions both incentives and beliefs in ways that may attenuate escalation and promote coordination. Platforms operating under keep-it-all rules, with continuous payoffs or tradable claims, may exhibit stronger momentum effects or different patterns of sequential dependence. Extending the pledge-level approach developed here to alternative crowdfunding models would help clarify which aspects of bounded herding are general and which are specific to threshold-based environments.

A second limitation relates to the measurement of investor information and heterogeneity. Investor sophistication in this study is inferred from relative pledge size rather than from observable

credentials or historical behaviour, reflecting the information environment faced by actual participants. While this approach is consistent with the platform's design, it necessarily abstracts from richer dimensions of investor identity, experience, and portfolio considerations. Future research could combine transaction-level data with investor-level histories, where available, to examine how learning dynamics evolve as participants accumulate experience or repeatedly interact within the same market.

A third limitation concerns the temporal resolution of social information. Although the analysis exploits high-frequency pledge sequences, it does not directly observe investor attention, browsing behaviour, or exposure to off-platform information in real time. As a consequence, coordination in participation is inferred indirectly from observed clustering rather than measured explicitly. Linking transaction data with clickstream information, notification logs, or experimental variation in information exposure would allow future studies to disentangle attention-driven arrivals from valuation-driven responses more directly.

A fourth consideration concerns the interpretation of herding-intensity measures. The LSV-based index developed in this thesis captures excess clustering relative to a Poisson benchmark and provides evidence of state dependence in social influence. However, alternative measures of herding may emphasise different dimensions, such as directional imbalance, persistence, or investor overlap. Future work could assess whether behavioural compression persists when herding intensity is measured using complementary approaches and whether different indices capture distinct behavioural regimes within the same campaigns.

Finally, the empirical design adopted here focuses on within-campaign dynamics, abstracting from cross-campaign portfolio choice and capital allocation across opportunities. While this focus is appropriate for isolating sequential learning, it leaves open questions about how investors reallocate attention and funds across competing campaigns and whether campaign-level herding aggregates into broader platform-level patterns. Extending the analysis to model joint campaign-choice and pledge-size decisions would provide a more comprehensive picture of how social learning shapes capital allocation in crowdfunding ecosystems.

These limitations do not undermine the central findings of the thesis, but they delineate the conditions under which they apply and point to promising avenues for further research. By documenting that herding in equity crowdfunding is bounded, context-dependent, and shaped by institutional design, the thesis establishes a framework that future work can extend across platforms, mechanisms, and data environments. In doing so, it contributes to a more precise and empirically grounded understanding of social learning in digitally mediated financial markets.

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