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Herding behaviour in equity crowdfunding and P2P lending markets: A systematic meta-analysis

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ABSTRACT

This paper provides a systematic meta-analysis of empirical research on herding behaviour in equity crowdfunding (ECF) and peer-to-peer (P2P) lending markets. Despite the increasing importance of these fintech-driven entrepreneurial finance models, research on herding remains scattered. Based on a sample of 30 studies, the paper addresses four questions: (1) Is herding behaviour consistently observed in ECF and P2P lending markets? (2) Does herding differ between ECF and P2P lending? (3) Do competing offers impact herding dynamics? (4) Do regional groups (Western vs non-Western countries) and national cultural factors shape herding behaviour? Subgroup analyses reveal that: (1) herding is statistically detectable in these markets, although its magnitude varies widely across studies and contexts; (2) herding is more pronounced in P2P lending than in ECF; (3) herding effects diminish in the presence of competing offerings; (4) herding is more prominent in non-Western markets, with cultural factors also shaping its variation. These findings provide practical insights for platform managers, entrepreneurs, and policymakers.

1. Introduction

Herding behaviour is deeply rooted in human nature. When making financial decisions under high uncertainty and unpredictable outcomes (Nielsen et al., 2024), individuals seldom act in isolation (Cui et al., 2024; Fan et al., 2024; Guo & Wang, 2024; Herzing & Muck, 2024; Li & Lai, 2024; Sheng & Montgomery, 2024; Shi et al., 2024; Spyrou, 2013).

Herding behaviour is defined as the uncoordinated, decentralised alignment of individuals' thoughts and actions within a group (the "herd"), stemming from the accumulation of individual actions rather than centralised decision-making (Raafat et al., 2009).

At its core are information cascades and social proof, which can lead individuals to disregard their private information to conform to the majority (Bikhchandani et al., 1998). Later actors observe predecessors' choices and may interpret these as reflecting superior knowledge (Banerjee, 1992; Eyster & Rabin, 2010). This reliance can lead to accurate or flawed cascades, as decisions are based solely on observable actions without access to underlying information. Consequently, subsequent investors struggle to differentiate between informative and misleading social cues (Nielsen et al., 2024; Tump et al., 2020).

Insights into herding behaviour are especially relevant in environments characterised by sequential decision-making under high uncertainty, such as equity crowdfunding (ECF) and peer-to-peer (P2P) lending platforms (Baumöhl et al., 2024; Di Pietro & Butticè, 2020; Guo et al., 2025; Ho et al., 2024; Sha, 2022; Zhao et al., 2022). ECF enables startups to present their investment proposal, called a "pitch", to retail investors, known as "backers", on platforms called "equity crowdfunding platforms" to raise equity. Each equity offering is referred to as an "equity crowdfunding campaign". In return, startups offer backers an equity stake in the company. An equity crowdfunding campaign is successful if the startup reaches its fundraising target (Belleflamme et al., 2014; Vulkan et al., 2016). Conversely, P2P lending allows entrepreneurs, called "borrowers", to request loans from retail investors, or "lenders", who, in exchange for their funds, secure the right to repayment of principal and interest in instalments (Basha et al., 2021). These two forms of entrepreneurial finance are gaining traction worldwide due to their potential to democratise access to finance for deserving, yet underserved entrepreneurs (Cumming et al., 2021; Jia & Kanagaretnam,

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Table 1
Overview of effect sizes, variable types, and study characteristics.

ID	Paper	DOI	Table	Model	Raw coefficient	DV	IV
1	Åstebro et al. (2024)	10.1111/1756-2171.12474	4	IV-B	0.115	Continuous – monetary amount	Prior amount
2	Bade and Walther (2021)	10.1007/s11846-020-00429-6	5	2	0.000	Binary (investment event)	Prior number of investments
3	Block et al. (2017)	10.1007/s11187-017-9876-4	3	5	0.080	Continuous – monetary amount	Prior amount
4	Caglayan et al. (2021)	10.1016/j.jempfin.2021.05.005	4	1	0.061	Continuous – monetary amount	Prior amount
5	Cai and Polzin (2025)	10.1111/1467-8551.12917	3	1	0.001	Binary (co-investment)	Prior co-investments
6	Chen, Li, Liu, et al. (2021)	10.1007/s10796-020-10006-7	12	5	0.194	Binary (subsequent behaviour)	Prior success
7	Chen, Li, Fan, and Qin (2021)	10.4018/JGIM.20211101.oa36	4	4	0.198	Continuous – ratio/percent funded	Lagged % funded
8	Chen et al. (2022)	10.1016/j.physa.2022.127546	5	8	0.010	Binary (loan success)	Network centrality
9	Ferretti et al. (2021)	10.1016/j.jbef.2021.100506	3	2	0.014	Binary (investment decision)	Competition × amount
10	Gao et al. (2021)	10.1111/manc.12321	4	Count amount (1)	0.011	Continuous – count amount	Prior amount
11	Herzenstein et al. (2011)	10.1016/j.intmar.2010.07.001	2	2	0.810	Binary (follow-on bid)	Prior bids
12	Ho et al. (2024)	10.1016/j.irfa.2023.103056	4	2	0.173	Binary (loan success)	Peer success
13	Hornuf and Neuenkirch (2017)	10.1007/s11187-016-9807-9	3	All bids (1)	0.079	Continuous – price premium	Prior same-day bids
14	Hornuf et al. (2022)	10.1111/jems.12475	4	Panel D (4)	-0.001	Continuous – bias index	Prior investments
15	Jiang et al. (2018)	10.1080/07421222.2018.1440770	2	4	0.291	Continuous – number of investors	Prior investors
16	Jiang et al. (2022)	10.1287/isre.2021.1049	3	1	0.046	Continuous – lending amount	A/Prior cumulative lending
17	Lee and Lee (2012)	10.1016/j.elerap.2012.02.001	8	Only one model	5.381	Continuous – market share	Participation rate
18	Li et al. (2022)	10.1016/j.im.2020.103269	3	H2: IHI → DoO	0.286	Continuous – percentage (overfunding)	Initial herd intensity
19	Lin et al. (2013)	10.1287/mnsc.1120.1560	4	Spec. P5	0.849	Binary (funded or not)	Social network ties
20	Liu et al. (2015)	10.25300/MISQ/2015/39.3.11	C1	6	1.091	Binary (bid yes/no)	Prior bids
21	Lowry et al. (2023)	10.1080/07421222.2023.2229128	6	4	0.131	Continuous – monetary amount	Lagged cumulative amount
22	Mohammadi and Shafi (2018)	10.1007/s11187-016-9825-7	4	2	-0.082	Continuous – number of female investors	Prior investors
23	Walther and Bade (2020)	10.1007/s40685-019-00107-8	4	Only one model	-0.230	Continuous – deviation from usual investment	Prior investments
24	Wang et al. (2019)	10.1016/j.respol.2019.01.003	5	1	-0.013	Continuous – monetary pledge	Cumulative % raised (cascade indicator)
25	Wei and Lin (2017)	10.1287/mnsc.2016.2531	6	Only one model	-0.172	Continuous – daily amount	Lagged cumulative amount
26	Wu et al. (2025)	10.1287/isre.2020.0428	3	1	0.000	Continuous – monetary amount	Prior bids
27	Yi et al. (2024)	10.1108/MD-09-2022-1310	5	2	0.026	Continuous – monetary amount	Prior cumulative investment
28	Yum et al. (2012)	10.1016/j.elerap.2012.05.003	11	Only one model	6.787	Binary (funding success)	Voting ratio
29	Zhang and Chen (2017)	10.1016/j.elerap.2017.04.001	3	4	0.055	Continuous – bid volume	Prior automated bids
30	Zhang and Liu (2012)	10.1287/mnsc.1110.1459	4	1	0.377	Continuous – monetary amount	Lagged total amount

Note. Coefficients represent the raw herding coefficients on their original scales; PCCs derived from these coefficients are used in the meta-analysis. DV and IV classifications follow a harmonised typology developed for meta-analytic comparability and do not replicate the studies' full variable descriptions.

2025).

However, questions remain about whether ECF and P2P lending effectively allocate resources to the most deserving startups and entrepreneurs. This concern stems from widespread information asymmetries in these markets. Given the limited information accessible to ECF backers and P2P lenders when selecting projects to finance, these asymmetries may worsen the existing "market for lemons" problem (Akerlof, 1970; Bollaert et al., 2021), potentially causing significant financial losses for investors (Walthoff-Borm et al., 2018).

Given this information asymmetry, entrepreneurs and borrowers must convey credible signals to backers and lenders to differentiate their ventures from competing alternatives (Ahlers et al., 2015).

While various signals can influence the success of ECF campaigns (Mochkabadi & Volkmann, 2020) and P2P lending listings (Basha et al., 2021), observational learning appears to be among the most influential factors. When later backers and lenders see strong early participation, they might assume that initial investors have superior information that justifies their decision (Åstebro et al., 2024; Lee & Lee, 2012). This cognitive shortcut can trigger an information cascade where early investment signals accumulate and influence subsequent backers and lenders (Vismara, 2018; Zhang & Chen, 2017). As more investors rely on prior actions, herding behaviour is likely to emerge.

Building on observational learning and the need for a deeper understanding of decision-making in this context, research has begun examining herding behaviour in ECF and P2P lending.

Existing studies indicate herding behaviour in both ECF and P2P markets, showing how early funding signals, whether from seemingly genuine peers or anonymous sources (Jiang et al., 2022), affect subsequent investors. Another theme concerns how backers and lenders frame investment decisions, especially when faced with multiple competing offerings.[1] Initial findings suggest that competing investment opportunities can either increase or decrease herding behaviour (Åstebro et al., 2024; Block et al., 2017; Dao et al., 2024; Ferretti et al., 2021; Jiang et al., 2018; Vismara, 2018; Wang et al., 2019). Regarding geographical

[1] Competing offerings are other campaigns running on a given platform at the same time that aim to attract the same investors.

scope, most research on herding in ECF and P2P lending has focused on Western countries, including Germany (Bade & Walther, 2021; Block et al., 2017), Italy (Ferretti et al., 2021), the United Kingdom (Åstebro et al., 2024; Dao et al., 2024; Vismara, 2018; Wang et al., 2019), and the United States (Herzenstein et al., 2011; Wei & Lin, 2017; Zhang & Liu, 2012). Among non-Western nations (Jiang et al., 2022), research has mainly examined China (Caglayan et al., 2021; Chen, Li, Fan, & Qin, 2021; Chen, Li, Liu, et al., 2021; Gao et al., 2021; Jiang et al., 2018; Liu et al., 2015; Lowry et al., 2023; Yi et al., 2024; Zhang & Chen, 2017) and South Korea (Lee & Lee, 2012).

However, several issues remain unresolved. While evidence supports the existence of herding behaviour in ECF and P2P lending markets, it comes from studies using different methodologies, samples, and operationalisations of herding. This makes it challenging to determine whether herding genuinely occurs or if its identification is a methodological artefact.

Whether statistically significant differences in herding behaviour exist between ECF and P2P markets remains unclear. Both attract profit-oriented investors but function differently, likely triggering distinct herding dynamics. P2P involves predetermined instalment repayments, whereas ECF does not guarantee dividend disbursements, so following other investors has different implications.

The role of competing offerings in shaping herding behaviour is also uncertain. In both markets, reliance on observational learning increases decision-making complexity when multiple campaigns or listings are available. Some studies suggest that more campaigns promote herding in ECF (Åstebro et al., 2024; Block et al., 2017; Ferretti et al., 2021), while others report conflicting findings (Dao et al., 2024; Vismara, 2018; Wang et al., 2019). Chinese P2P studies show a positive relationship between competing listings and herding (Jiang et al., 2018). The evidence varies across methodologies, making synthesis difficult.

It is also unclear whether herding varies across geographical contexts due to cultural differences. National culture has been shown to influence herding in non-ECF markets (Cho & Kim, 2017; Cicchiello et al., 2023; Shneor et al., 2021; Zheng et al., 2014) and financial markets overall (Spyrou, 2013). It is worth examining whether similar effects occur in ECF and P2P lending, given their greater economic importance and potential investor impacts compared to non-ECF or non-profit P2P operations.

This study aims to answer the following research questions.

RQ1: Is herding behaviour consistently observed in ECF and P2P lending markets?

RQ2: Does herding differ between ECF and P2P lending?

RQ3: Do competing offers impact herding dynamics?

RQ4: Do regional groups (Western vs non-Western countries) and national cultural factors shape herding behaviour?

We conduct a systematic meta-analysis synthesising findings from 30 empirical studies on herding behaviour in ECF and P2P lending to answer these questions. While the method is well-established (Borenstein et al., 2009), it remains underutilised in finance, despite its potential to clarify patterns across studies employing varied samples, methodological designs, and contextual settings (Geyer-Klingeberg, Hang and Rathgeber, 2020). Besides consolidating the fragmented literature on ECF and P2P, a systematic meta-analysis tests theoretical mechanisms that may influence herding dynamics in these markets, such as investors' behavioural responses to competing offerings and the impact of national culture. These features enable a unified examination of behavioural mechanisms that have previously been explored in isolation.

Previous reviews have synthesised evidence on broader themes such as investor attraction in crowdfunding (Geiger & Moore, 2022; Goyal et al., 2024; Liu et al., 2022), the effects of crowdlending practices (Chliova et al., 2015), or what constitutes an effective signal in crowdfunding (Hornuf & Voshaar, 2024). This study compiles and analyses empirical findings on herding behaviour in ECF and P2P lending, an area that remains underserved by systematic integration.

Results show that herding effects are statistically detectable but vary across studies and contexts, with P2P lending exhibiting a significantly stronger effect than ECF. Non-Western markets display a positive and significant herding effect. Studies that do not account for competing offerings show larger herding effects than those that do. Cultural dimensions reveal systematic heterogeneity: herding is positive and significant in high-power-distance, collectivist, and long-term oriented cultures, with suggestive evidence for indulgence-related differences.[2]

This study contributes to entrepreneurial finance by clarifying when herding emerges in ECF and P2P lending, two markets characterised by high information asymmetry. The findings highlight how behavioural mechanisms interact with market design, competitive within-platform dynamics, and cultural context, offering insights relevant to platform managers, entrepreneurs, investors, and policymakers.

2. Literature review and hypothesis development

2.1. Detectability of herding

Whether herding behaviour can be systematically detected in ECF and P2P lending markets remains an open empirical question, due to substantial heterogeneity in study designs (Table 1).

A primary source of variation is the measurement of herding behaviour. Most studies operationalise herding using continuous monetary outcomes, such as pledged or lent amounts at time t, modelling whether higher prior funding predicts later funding flows.

A second group measures herding using count-based outcomes, such as the number of investors participating in a campaign or listing, or the volume of bids in each interval, to capture whether prior participation triggers more.

A third subset uses binary outcomes, such as whether an investor invests, a listing receives follow-on bids, or a loan is funded, examining whether previous investments increase the likelihood of subsequent similar actions.

Finally, some papers employ ratio- or percentage-based measures, such as the cumulative percentage raised or the degree of overfunding, reflecting progress toward funding goals.

Effect sizes reported in the studies, reflecting the strength of herding behaviour, vary widely from negligible to large, with some outliers and negative values. Despite these variations, evidence consistently indicates a positive link between early and subsequent investment behaviour, suggesting herding is detectable in both ECF and P2P markets, albeit with differing effect sizes.

The diversity of strategies highlights the need for a meta-analytic approach to synthesise coefficients across different scales and models. Meta-analysis is specifically designed to reconcile such variation, as it converts regression coefficients into a common effect-size metric, weights each estimate by its precision, and statistically models between-study differences. In doing so, it produces a pooled estimate that reflects the underlying relationship while accounting for differences in sample size, measurement scales, model specifications, and study contexts. Therefore, we hypothesise:

H1. . Herding behaviour can be systematically detected in equity crowdfunding and P2P lending markets.

2.2. ECF Vs. P2P lending

Differences in how the ECF and P2P lending markets operate may lead to distinct patterns of herding behaviour (Hoegen et al., 2018). In ECF, backers acquire an equity stake and are entitled, at least in theory,

[2] The cultural dimensions developed by Hofstede (2001), including power distance, individualism, and long-term orientation, are defined in Section 4.2 and Appendix Table B.1.

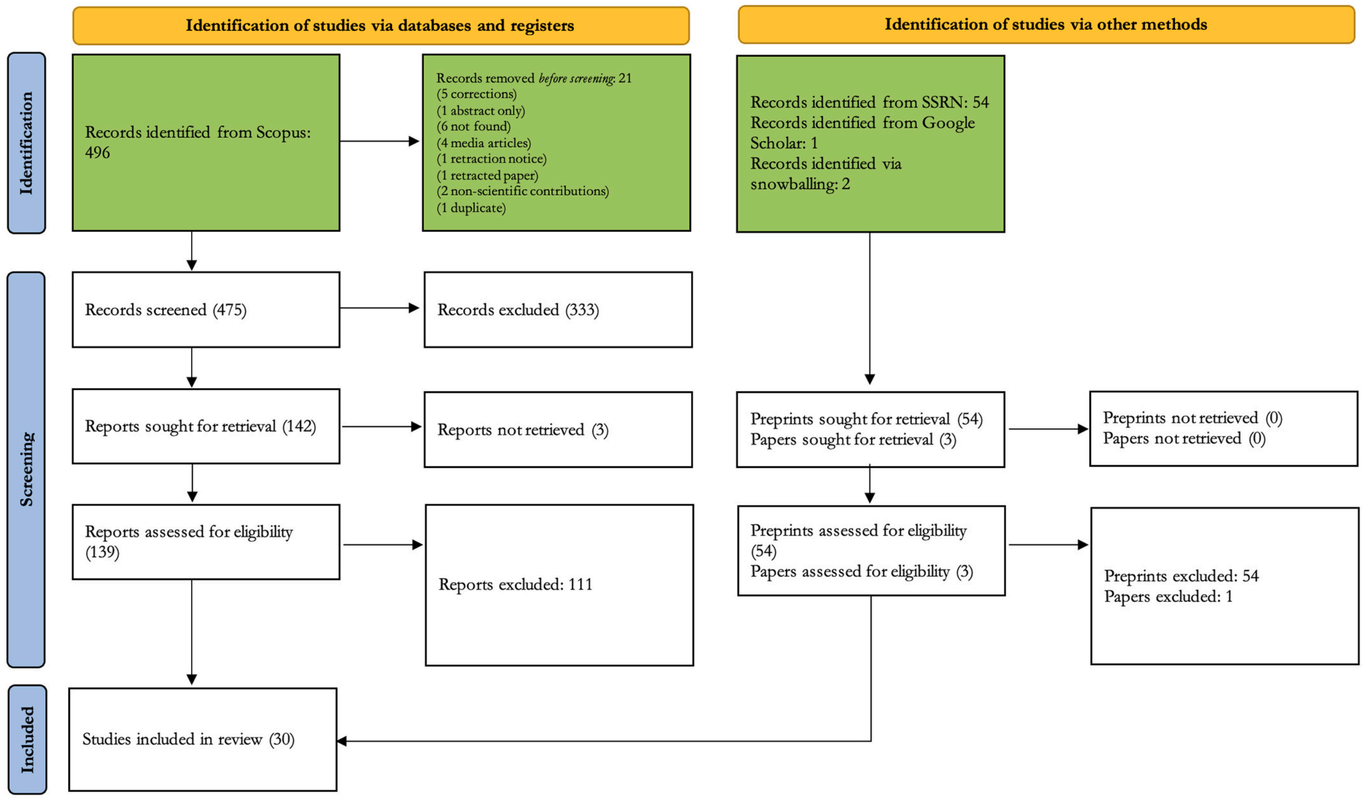

Fig. 1. PRISMA 2020 flow diagram for study identification, screening, and inclusion in the meta-analysis.

to dividends if the startup becomes profitable and distributes earnings. In P2P lending, lenders are entitled to repayment of the principal plus interest through a series of instalments, acting as creditors rather than shareholders.

Another difference concerns exit opportunities. Secondary markets for ECF are underdeveloped (Lukkarinen & Schwienbacher, 2023), limiting investors' ability to exit poorly performing investments. In contrast, P2P markets offer greater flexibility for portfolio adjustments (Caglayan et al., 2020). Consequently, ECF backers are more likely to exit through IPOs, trade sales, management buyouts, or share buybacks, though these options are rarely outlined in ECF pitches (Vismara, 2016).

The timing of returns also varies. ECF backers may benefit from dividends or exit strategies only years after the campaign concludes, while P2P lenders receive repayments much sooner. Since herding varies based on the timing of available options (Buchner et al., 2020; Schmidt et al., 2010), this influences herd behaviour.

Overall, it seems more likely for investors to herd in P2P lending than in ECF, partly because exiting an ECF investment is more difficult, making “following the herd" potentially sub-optimal.

Considering these differences, we hypothesise that:

H2. : Herding behaviour is significantly different between equity crowdfunding and P2P lending. P2P lending exhibits a more substantial herding effect because earlier repayments and greater scope for portfolio rebalancing reduce the cost of following others relative to ECF.

2.3. Competing offerings

Competing offerings influence how backers and lenders allocate their attention. ECF and P2P lending platforms allow investors to observe a campaign's or listing's performance and compare it to others. When a campaign attracts more funding or investors than competitors, subsequent investors may infer that more informed investors have chosen that offering. This creates a strong signal, reinforcing an information cascade and intensifying herding behaviour.

The literature on competing offerings is fragmented: some studies suggest that a higher number of campaigns positively impacts funding in the UK ECF market (Åstebro et al., 2024; Block et al., 2017; Ferretti et al., 2021), while others report conflicting results regarding the number of active campaigns (Dao et al., 2024; Vismara, 2018; Wang et al., 2019). Similarly, studies on China's P2P lending market find a positive relationship between the number of competing listings and herding dynamics (Jiang et al., 2018).

Based on this theoretical and empirical evidence, we hypothesise that:

H3. : Competing offerings moderate herding behaviour in equity crowdfunding and P2P lending markets.

2.4. Geographical scope and cultural differences

National culture influences behavioural patterns in financial markets, leading, among other things, to herding among stock investors (Chang & Lin, 2015). As a theoretical construct, culture encompasses the implicit norms and behaviours shaping various aspects of life (Galariotis & Karagiannis, 2021). A key distinction in herding lies between Western and non-Western Confucian cultures. Empirical finance research supports this view (Chiang & Zheng, 2010; Hakmaoui & El Jebari, 2023; Loang, 2025), revealing significant differences in herding between these cultures.

Confucian societies typically exhibit higher power distance and lower individualism, reflecting more interdependence among individuals and a greater regard for others' actions (The Culture Factor Group Oy, 2025). In contrast, Western cultures emphasise individual achievement. The reduced focus on collective achievement in Western cultures is believed to lower herding behaviour compared to non-Western societies (Chang & Lin, 2015). Additionally, features of Confucian cultures tend to intensify market overreactions (Loang, 2025). Based on this background, we hypothesise that:

H4. : Herding behaviour in equity crowdfunding and P2P lending markets differs significantly between Western and non-Western countries, with non-Western markets exhibiting more substantial herding effects.

3. Methodology

3.1. Overview of meta-analysis approach

A meta-analysis is a set of statistical procedures used to combine data from multiple studies to determine whether a phenomenon is consistently observed, to estimate the magnitude of the effect[3] and its expected range, and to provide an estimate of where future studies might fall if they sampled from the same population and conducted comparable research. The growing adoption of meta-analyses in finance research reflects their capacity to consolidate findings within a given field (Bessler et al., 2019; Białkowski & Perera, 2019; Campos et al., 2019; Gehlen & Lucey, 2017; Geyer-Klingeberg et al., 2020; Gric et al., 2023; Hussaini, 2025; Papadamou et al., 2019; Pérez-Calero et al., 2019).

Prior meta-analyses in crowdfunding and P2P lending focus on platform and fund-provider characteristics (Goyal et al., 2024), campaign determinants of success (Geiger & Moore, 2022), and broader drivers of crowdfunding outcomes (Liu et al., 2022). However, none examined herding behaviour specifically, despite it being a primary mechanism influencing investment dynamics in both ECF (Åstebro et al., 2024) and P2P lending (Lee & Lee, 2012).

The meta-analysis here has a systematic component, which is why we refer to it as a "systematic meta-analysis". Besides synthesising findings across multiple empirical studies, it also aims to test specific theoretical mechanisms.

The analyses presented here were conducted using the "*meta*"[4] R package.

3.2. Study selection

We conducted a systematic search to identify studies for the meta-analysis. The main search was performed in Scopus, with additional searches conducted in Google Scholar. Also, we employed a snowballing procedure to ensure that no relevant papers were missed (Gric et al., 2023; Malovaná et al., 2025). We also expanded the search to include SSRN preprints (Gerrish, 2016; Grewal et al., 2018). The screening process, summarised through the PRISMA statement (Page et al., 2021), is reported in Figure 1.

On 6 October 2025, we conducted a pilot search in Scopus to identify keywords related to herding behaviour. The advanced search string was: (TITLE-ABS-KEY("herd") AND TITLE-ABS-KEY("crowdfund")). This query returned 82 results, including journal articles, book chapters, conference proceedings, editorials, and other document types. Sixty-four were accessible. We reviewed these documents, extracting herding-related keywords from each, and compiled a table listing the source, keywords, and passages. A total of 239 non-unique keywords were collected; duplicates and morphological variants were consolidated using wildcards, preserving hyphenated and unhyphenated forms, as well as UK and US spelling variants (see Appendix Table A.1). Related concepts were grouped under broader wildcard terms, e.g., the "*information cascade*" family under "*cascad**". This process resulted in a final list of 31 distinct keywords (Appendix Table A.2). This preliminary literature analysis to identify the most suitable keywords is similar to that used in recent meta-analyses (e.g., Bajzik et al., 2025). To build the final search string, we combined the terms "*crowdfunding*", "*peer-to-peer lending*", "*peer to peer lending*", and "*P2P*" with the 31 keywords using the Boolean operator "AND", restricting the search to document titles only. As of 27 October 2025, the search yielded 550 results: 496 published documents and 54 preprints, retrieved through Scopus's preprints function. We screened 475 of the 496 published documents, excluding corrections, retractions, duplicates, and non-academic content. Of these, 139 were accessed and assessed for eligibility.

To be included, a study had to estimate herding as a sequential dependence of investment outcomes on prior peer activity ($t-1$ to t), captured either by within-offering momentum cues or by relational peer signals that enter the model to generate sequential dependence. Studies that modelled fundraising dynamics across discrete stages or imposed quadratic time patterns were excluded to maintain comparability (e.g., Dao et al., 2024; Vismara, 2018).

Applying this criterion excluded 111 papers, leaving 28 published studies. The 54 SSRN preprints were assessed with the same criteria and were excluded for the same methodological reasons.

Additionally, one paper was identified through Google Scholar, and two others through snowball sampling. One of the papers identified through snowballing was not deemed suitable for inclusion in the meta-analysis and retrieved because insufficient statistical data were available, specifically the absence of standard errors, t-statistics, or z-statistics in regression tables (Hornuf & Schwienbacher, 2018). The final sample comprises 30 papers.

3.3. Effect size calculation

We employed partial correlation coefficients (PCCs) as the effect size measure (Gustafson, 1961), calculated from the regression coefficients reported in the papers, while adjusting the degrees of freedom used in their calculations to minimise any remaining bias in the meta-analysis (Stanley et al., 2024). PCCs allow results to be compared across models that use different measurement units (Malovaná et al., 2024). Details on the calculation of PCCs are provided in Appendix A. After computing the PCCs, we determined whether to use a fixed or random-effects meta-analysis model (Borenstein et al., 2009).

The fixed-effects model assumes that all studies are based on a single population, so any observed variation in effect sizes across them is attributed solely to sampling error. Under this model, the true effect size is assumed to be the same for all studies, and the findings apply only to that population.

In contrast, the random-effects model assumes that the included studies are drawn from different populations and exhibit meaningful variation. Here, the true effect size is expected to differ across studies, each representing a unique population. This approach allows the results to be generalised. Given the heterogeneity of the populations under examination, we employed the random-effects model for the primary meta-analysis.

When moving on to subgroup analyses, one important consideration is the estimation of tau-squared (τ^2), which reflects the variation in true effect sizes across studies. In a meta-analysis involving a single set of studies, τ^2 is computed once based on the entire dataset. However, when subgroups are introduced, τ^2 must be calculated separately for each subgroup, resulting in two distinct estimates.

At this stage, we faced a methodological choice: either pool the τ^2 estimates across subgroups and apply a single pooled estimate to both groups, or use separate estimates of τ^2 for each subgroup.

We opted to pool the estimates. Estimates of τ^2 based on a few studies can be unreliable. While pooling might result in a minor loss of information, the error introduced by pooling is smaller than that from estimating τ^2 from small samples (Borenstein, 2009).

Thus, we applied a mixed-effects model for subgroup analyses,

[3] The term "effect", or more precisely, "effect size", refers to "*a number that reflects the magnitude of the relationship between two variables*" (Borenstein, 2009a, p. 222). Depending on the context, effect size can be interpreted in various ways, including an unstandardised or standardised mean difference, a response ratio, a risk ratio, an odds ratio, a risk difference, or a correlation coefficient.

[4] https://cran.r-project.org/web/packages/meta/index.html

Table 2
Descriptive Statistics of PCCs by Study Subgroups.

Variable	Category	n	Mean PCC	SD of PCC
Market	ECF	12	–0.0064	0.0574
	P2P	18	0.0656	0.0851
Culture	Western	14	–0.0003	0.0572
	Non-Western	16	0.0693	0.0887
Competition	Accounted for	6	0.0034	0.0234
	Not accounted for	24	0.0452	0.0898

Note. Means and standard deviations are computed across all effect-size estimates within each subgroup. n denotes the number of effect-size estimates. Subgroup categories follow the coding scheme used in the meta-analysis: Market (equity crowdfunding vs. peer-to-peer lending), Culture (Western vs. Non-Western), and Competition (studies explicitly modelling competitive structure vs. those that do not).

combining random effects within subgroups and fixed effects across subgroups. In this context, the term "fixed" does not imply that the subgroups are homogenous, but rather that they have been predefined (Borenstein, 2009).

While subgroup analyses are widely employed in meta-analyses to uncover otherwise unobservable differences within a sample, they are not without limitations. The most significant one is that these analyses ideally require dozens to hundreds of studies to achieve sufficient statistical power. Subgroup analyses risk inflating Type I and Type II errors when sample sizes are inadequate.

To mitigate these risks, it is necessary to limit subgroup analyses to a predefined set of comparisons grounded in theoretical reasoning and prior empirical evidence (Cuijpers et al., 2021). We therefore restricted our subgroup analyses to a predefined set based on theory and prior evidence: ECF vs. P2P lending, Competition vs. No Competition, and Western vs. Non-Western countries.

Subgroup analyses conducted in the crowdfunding domain have employed comparable numbers of studies per subgroup to those in the present systematic meta-analysis (Geiger & Moore, 2022; Goyal et al., 2024).

4. Results

4.1. Descriptive statistics

Table 2 summarises the PCCs across studies by market, culture, and competition.

Studies on P2P lending show a positive mean PCC (0.0656) with higher variability (SD = 0.0851), while those on ECF report an average near zero (–0.0064). Non-Western samples exhibit a positive mean PCC (0.0693), whereas Western markets exhibit near-zero values (–0.0003). Studies that do not account for competition display higher mean correlations (0.0452) and greater dispersion (SD = 0.0898) than those that do (0.0034; SD = 0.0234).

4.2. Pooled meta-analysis and subgroup results

Table 3 reports the random-effects systematic meta-analysis estimates for the full sample and each subgroup, and Figure 2 presents the corresponding forest plot.

Across 30 studies, the pooled effect is small but positive (PCC = 0.0375, 95% CI [0.0065, 0.0683], $p < 0.001$). Heterogeneity is substantial ($\tau^2 = 0.0067$; $I^2 = 100\%$). The 95% prediction interval from the random-effects model is wide, implying that a new comparable study could plausibly find a negative effect or a moderately positive one. Figure 2 illustrates this pattern clearly: most estimates lie close to zero but show wide dispersion, reflecting the considerable variability across studies. This confirms that herding effects are statistically detectable but vary markedly across studies and contexts.

Market-level differences persist (Figure 3). P2P lending shows a

Table 3
Random-effects meta-analysis of PCCs (Overall and by Subgroup).

Group	Subgroup	k	Pooled PCC	95% CI	τ^2	τ	Q	I^2 (%)	p-value
Main	All studies	30	0.0375	[0.0065; 0.0683]	0.0067	0.0821	82,016.82	100.0	<0.001
Market	ECF	12	–0.0060	[–0.0399; 0.0278]	0.0023	0.0478	161.06	93.2	<0.001
	P2P	18	0.0661	[0.0232; 0.1087]	0.0074	0.0861	77,086.35	100.0	<0.001
	Between groups						8.02		0.0046
Cultural region	Western	14	–0.0001	[–0.0312; 0.0310]	0.0025	0.0498	697.05	98.1	<0.001
	Non-Western	16	0.0701	[0.0223; 0.1176]	0.0080	0.0896	76,875.16	100.0	<0.001
	Between groups						6.92		0.0085
Power distance (Hofstede)	Low	13	–0.0028	[–0.0361; 0.0305]	0.0026	0.0510	690.75	98.3	<0.001
	High	16	0.0696	[0.0216; 0.1173]	0.0081	0.0898	76,867.08	100.0	<0.001
	Between groups						10.74		0.0047
Individualism (Hofstede)	Individualist	10	–0.0062	[–0.0460; 0.0335]	0.0025	0.0500	146.90	93.9	<0.001
	Collectivist	19	0.0598	[0.0174; 0.1020]	0.0077	0.0878	77,099.40	100.0	<0.001
	Between groups						8.88		0.0118
Masculinity (Hofstede)	Masculine	26	0.0323	[0.0041; 0.0605]	0.0048	0.0696	81,352.05	100.0	<0.001
	Feminine	3	0.0769	[–0.3811; 0.5046]	0.0366	0.1914	189.24	98.9	<0.001
	Between groups						0.92		0.6318
Uncertainty avoidance (Hofstede)	Low	20	0.0302	[–0.0097; 0.0701]	0.0071	0.0845	76,956.03	100.0	<0.001
	High	9	0.0527	[–0.0128; 0.1178]	0.0072	0.0846	820.78	99.0	<0.001
	Between groups						0.68		0.7121
Long-term orientation (Hofstede)	Short-term orientation	14	–0.0001	[–0.0312; 0.0310]	0.0025	0.0498	697.05	98.1	<0.001
	Long-term orientation	15	0.0717	[0.0204; 0.1227]	0.0086	0.0925	76,867.04	100.0	<0.001
	Between groups						10.74		0.0047
Indulgence (Hofstede)	Indulgent	7	–0.0142	[–0.0753; 0.0471]	0.0041	0.0636	478.86	98.7	<0.001
	Restrained	22	0.0538	[0.0166; 0.0907]	0.0070	0.0834	81,488.45	100.0	<0.001
	Between groups						5.80		0.0550
Competition specification	Not accounted for	24	0.0460	[0.0078; 0.0841]	0.0080	0.0896	81,451.75	100.0	<0.001
	Accounted for	6	0.0016	[–0.0219; 0.0251]	0.0004	0.0209	94.77	94.7	<0.001
	Between groups						4.64		0.0312

Notes. k differs across Hofstede moderators because one study's country-sample lacks Hofstede scores. "Pooled PCC" is the estimated average true partial correlation within each subgroup. τ^2 is the between-study variance; τ is the standard deviation of true effects. Q is Cochran's heterogeneity statistic; I^2 measures the proportion of total variability due to between-study heterogeneity. p-values in subgroup rows refer to within-subgroup heterogeneity tests; "Between groups" rows report Q^B and its p-value for moderator-level differences. Hofstede dimensions (power distance, individualism, masculinity, uncertainty avoidance, long-term orientation, and indulgence) are coded as binary cultural profiles (low vs. high).

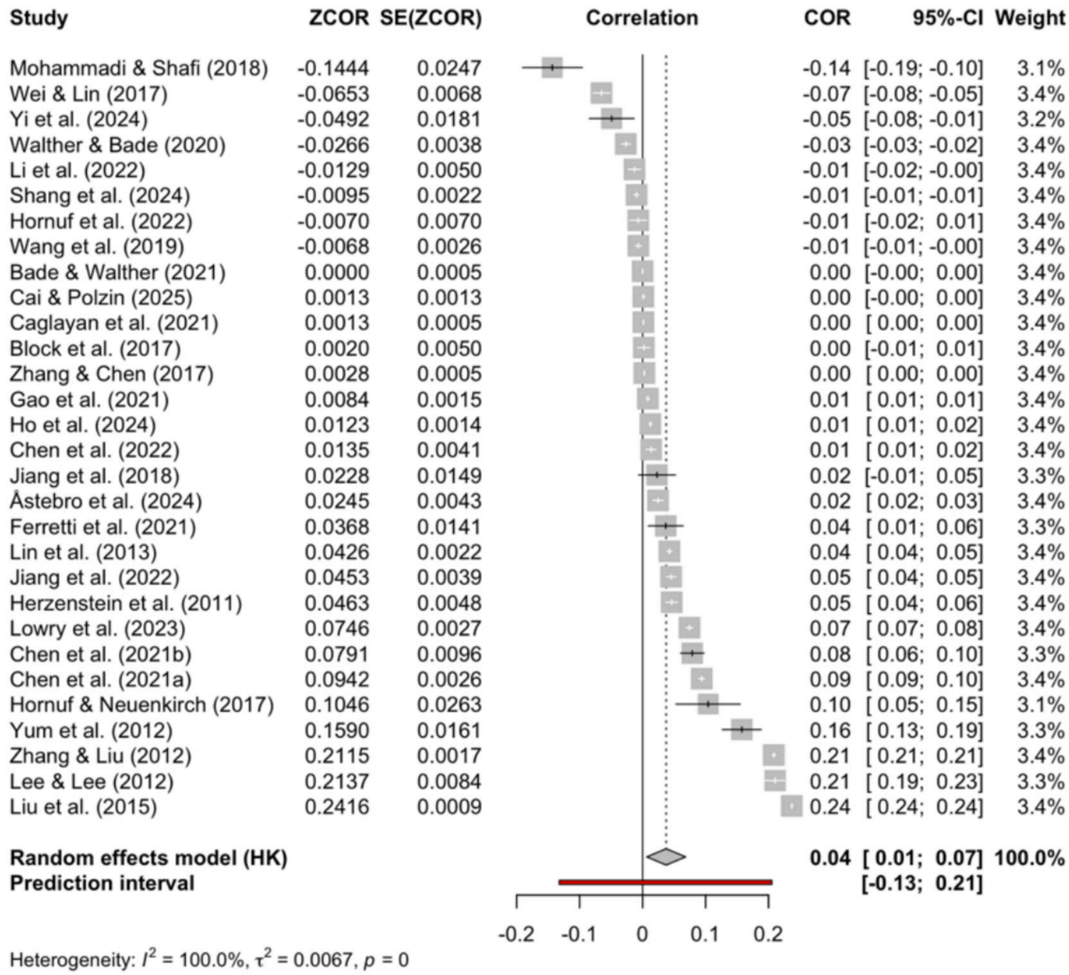

Fig. 2. Forest plot – Overall random-effects meta-analysis.
Note. The figure displays individual Fisher's z-transformed correlation estimates and their 95% confidence intervals for all 30 studies included in the meta-analysis. Squares represent point estimates scaled by inverse-variance weights, and horizontal lines denote confidence intervals. The vertical dashed line marks the pooled random-effects estimate.

significantly stronger correlation (0.0661) than ECF (–0.0060), with the between-group test indicating a meaningful divergence ($Q^B = 8.02$, $p = 0.0046$).

Geographical contrasts follow a similar pattern (Figure 4). Non-Western markets display a positive and significant effect (0.0701), whereas Western samples yield a near-zero estimate (–0.0001), with between-group heterogeneity again significant ($Q^B = 6.92$, $p = 0.0085$).

Competition continues to attenuate herding (Figure 5).

Studies accounting for competitive dynamics show near-zero pooled effects (PCC = 0.0016), while those without competition controls exhibit substantially larger correlations (PCC = 0.0460). The difference remains statistically significant ($Q^B = 4.64$, $p = 0.0312$).

We employ Hofstede's (2001) national culture indices, covering power distance, individualism, masculinity (also termed "motivation towards success and achievement"), uncertainty avoidance, long-term orientation, and indulgence. Power distance reflects how much inequality and hierarchy are expected and accepted; individualism captures whether people see themselves mainly as autonomous individuals or as members of loyal in-groups; masculinity describes whether competition and winning or care and quality of life are the dominant social values; uncertainty avoidance indicates how threatened people feel by ambiguity and how strongly they rely on rules to reduce it; long-term orientation contrasts pragmatic future focus with respect for tradition and present stability; indulgence measures how freely desires are gratified versus restrained by social norms (The Culture Factor Group Oy, 2025). Each dimension is coded as high or low based on the median score across countries in our sample. Results suggest that herding varies across several of Hofstede's (2001) cultural dimensions[5].

Power Distance reveals a clear divide: herding is virtually absent in low-hierarchy settings (PCC = –0.0028, 95% CI [–0.0361, 0.0305]) but positive and significant in high-power-distance contexts (0.0696, 95% CI [0.0216, 0.1173]; $Q^B = 10.74$, $p = 0.0047$).

Similarly, Individualism moderates the effect: collectivist environments (low individualism) show stronger correlations (0.0598, 95% CI [0.0174, 0.1020]) than highly individualistic ones (–0.0062, 95% CI [–0.0460, 0.0335]; $Q^B = 8.88$, $p = 0.0118$).

Long-Term Orientation follows a similar pattern, with forward-looking cultures exhibiting greater herding (0.0717, 95% CI [0.0204, 0.1227]) than short-term-oriented cultures (–0.0001, 95% CI [–0.0312, 0.0310]; $Q^B = 10.74$, $p = 0.0047$).

Indulgence also differentiates outcomes: restrained cultures (low indulgence) display moderate positive correlations (0.0538, 95% CI [0.0166, 0.0907]), while indulgent societies show no effect (–0.0142, 95% CI [–0.0753, 0.0471]; $Q^B = 5.80$, $p = 0.0550$).

By contrast, Masculinity and Uncertainty Avoidance do not produce

[5] One study (Jiang et al., 2022) lacks information on the country where it was conducted; it remains in the overall model but is excluded from subgroup analyses.

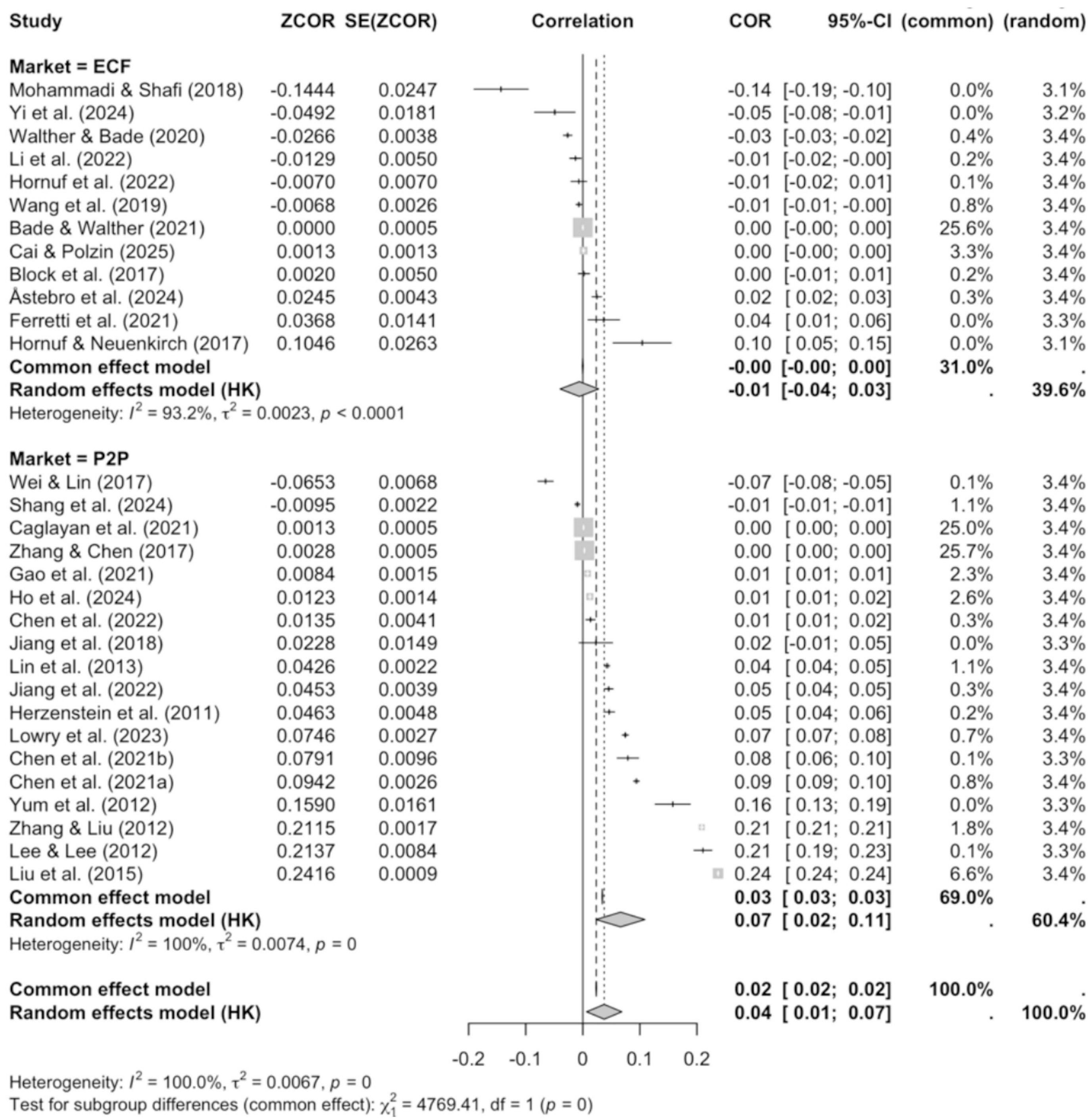

Fig. 3. Forest plot of herding estimates by market (ECF vs. P2P).
Note. Confidence intervals and pooled subgroup estimates are shown under the Hartung–Knapp random-effects specification.

statistically distinct subgroups under the random-effects model (Q^B = 0.92, p = 0.632; Q^B = 0.68, p = 0.712, respectively).

4.3. Robustness and influence diagnostics

Leave-one-out analysis confirms the stability of the pooled estimate (Table 4).

Sequential exclusion of each study yields estimated correlations ranging from approximately 0.030 to 0.043. In all cases, the pooled effect remains positive, and its confidence interval excludes zero. Heterogeneity remains high ($I^2 \approx 100\%$), showing that no paper drives the dispersion across estimates. The most significant shifts occur when Liu et al. (2015) and Mohammadi and Shafi (2018) are omitted, resulting in the lowest and highest pooled correlations, respectively. Nonetheless, the conclusion of a persistent herding effect remains unchanged.

Influence diagnostics in Table 5 further confirm the robustness of the results.

Standardised residuals are small for most studies, but a limited set of papers stands out with very large values, notably Lee and Lee (2012), Liu et al. (2015), Yum et al. (2012), and Zhang and Liu (2012), with Mohammadi and Shafi (2018) also exceeding conventional |2| thresholds. DFFITS and Cook's D are generally low across the sample, though

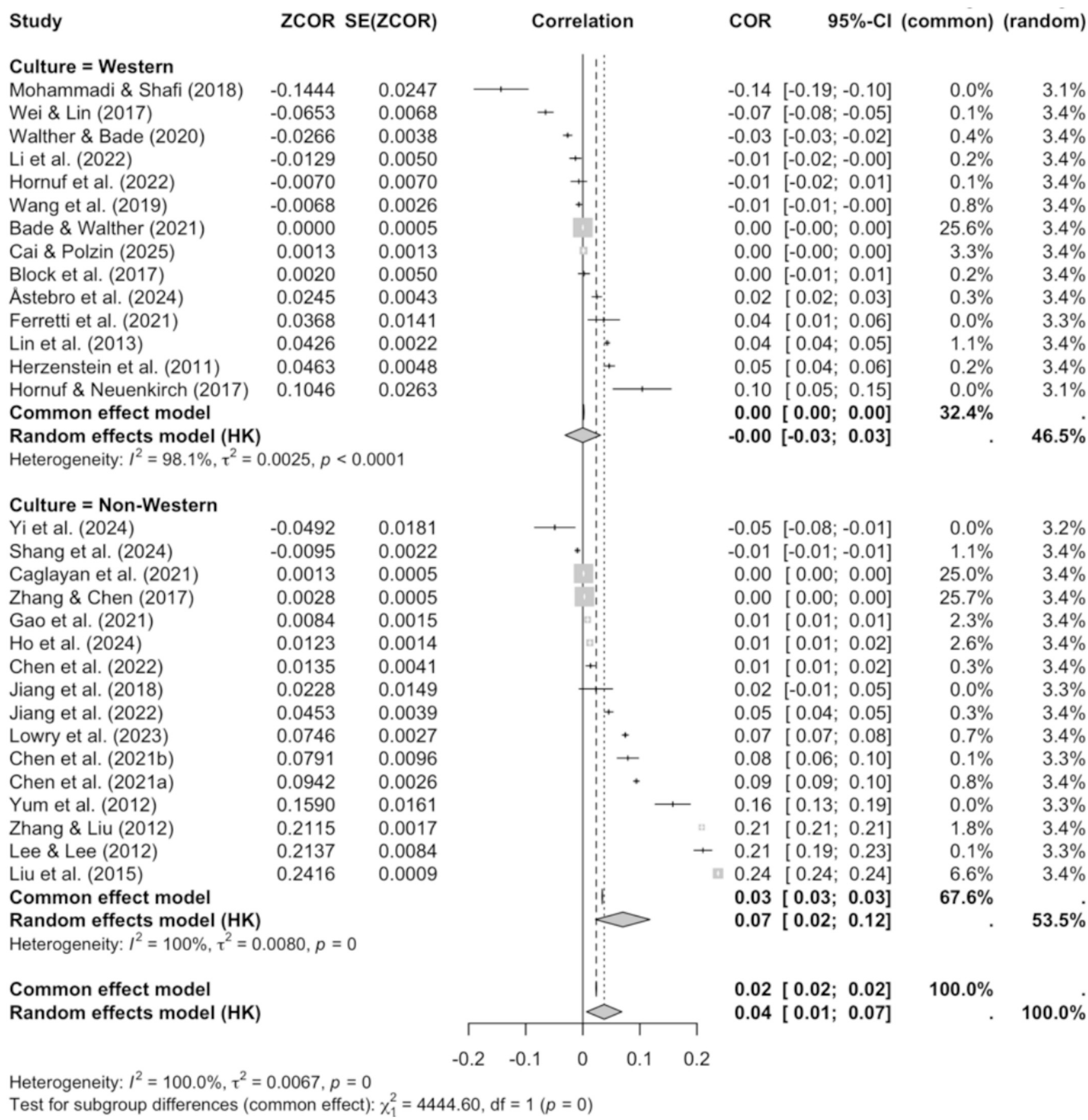

Fig. 4. Forest plot of herding estimates by geographical context (Western vs. Non-Western).
Note. Confidence intervals and pooled subgroup estimates are shown under the Hartung–Knapp random-effects specification.

they rise for these same studies, indicating a comparatively more substantial influence on fitted values and the pooled estimate. Covariance ratios are close to their typical benchmark for most cases but deviate more strongly for the influential studies, signalling localised effects on estimate precision. Deletion-based heterogeneity measures remain broadly similar to the full-sample values, with τ^2[deleted] changing only modestly across omissions, although Q[deleted] drops sharply when Liu et al. (2015) is removed, suggesting this study contributes disproportionately to overall dispersion.

4.4. Publication bias

Publication bias tests (Table 6) and visual inspection of the funnel plot (Figure 6) provide consistent evidence against small-study or selective-reporting bias.

The funnel plot in Figure 6 is broadly symmetric. Studies cluster around the pooled effect, with larger samples forming the expected narrow spread at the top of the plot. Smaller studies display wider dispersion, but without a directional pattern on either side of the mean. No visual outliers or pocket-patterns suggestive of selective reporting are evident.

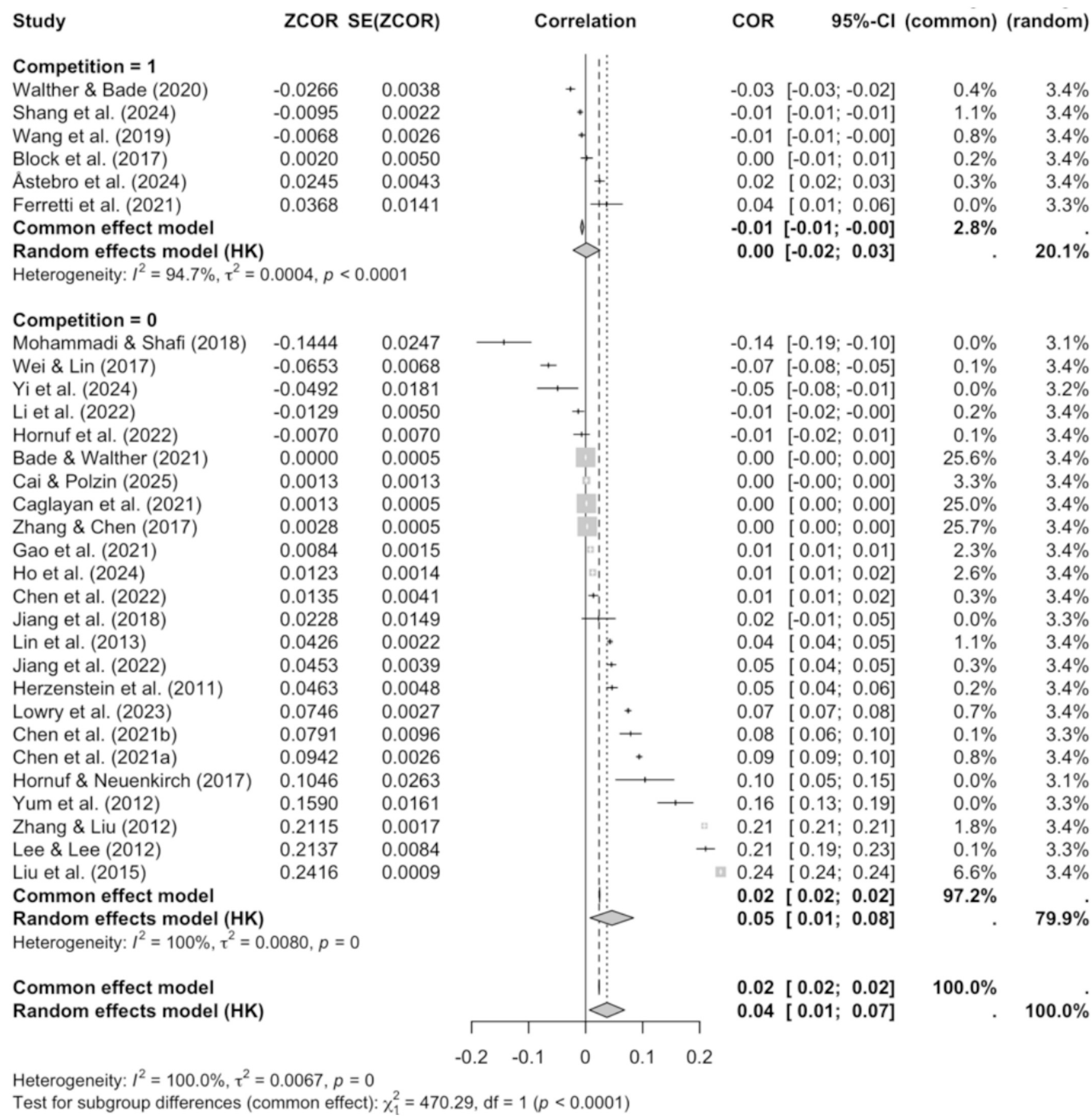

Fig. 5. Forest plot of herding estimates by competition control (accounted for vs. not accounted for).
Note. Confidence intervals and pooled subgroup estimates are shown under the Hartung–Knapp random-effects specification.

In line with previous meta-analytic syntheses (e.g., Bajzik, 2021; Bajzik et al., 2020; Bhaskar et al., 2023; George et al., 2019; Huang et al., 2020; Siegel et al., 2022), we performed a series of additional tests to assess publication bias. Begg's rank-correlation test is non-significant (Kendall's $\tau = 0.20$, $p = 0.1257$), and Egger's regression test likewise indicates no funnel asymmetry ($t = 0.87$, $p = 0.3924$). Equivalent procedures implemented in the specialised R package for meta-analysis (*metafor*) lead to the same conclusion (Kendall's $\tau = 0.20$, $p = 0.1257$; $t = 0.869$, $p = 0.392$).

As an additional sensitivity check, we applied Duval and Tweedie's trim-and-fill procedure (Table 7). The method imputes seven potentially missing studies on the right side of the funnel and yields a slightly higher adjusted pooled effect ($r = 0.062$) relative to the original estimate ($r = 0.037$). This pattern is inconsistent with upward selective reporting bias; if anything, it suggests that small studies with stronger positive effects may be underrepresented. Because heterogeneity is substantial ($I^2 \approx 100\%$), trim-and-fill can overestimate missing studies and should be interpreted with caution. PET–PEESE is more informative here, and both PET and PEESE, reported later in Table 9, show no small-study effects and produce bias-adjusted PCCs close to the main estimate.

To assess whether the overall trim-and-fill signal was driven by cross-study heterogeneity, we re-estimated the procedure within the main

Table 4
Leave-one-out Random-Effects Meta-Analysis of Herding PCCs.

Omitted study	Pooled PCC	95% CI	p-value	τ^2	τ	I^2 (%)
Åstebro et al. (2024)	0.0379	[0.0073; 0.0684]	0.0152	0.0070	0.0835	100.0
Bade and Walther (2021)	0.0388	[0.0083; 0.0692]	0.0127	0.0069	0.0833	100.0
Block et al. (2017)	0.0387	[0.0082; 0.0691]	0.0129	0.0069	0.0833	100.0
Caglayan et al. (2021)	0.0387	[0.0082; 0.0691]	0.0128	0.0069	0.0833	100.0
Cai and Polzin (2025)	0.0387	[0.0082; 0.0691]	0.0128	0.0069	0.0833	100.0
Chen, Li, Liu, et al. (2021)	0.0355	[0.0051; 0.0657]	0.0219	0.0069	0.0828	100.0
Chen, Li, Fan, and Qin (2021)	0.0360	[0.0056; 0.0664]	0.0204	0.0069	0.0832	100.0
Chen et al. (2022)	0.0383	[0.0077; 0.0688]	0.0141	0.0070	0.0834	100.0
Ferretti et al. (2021)	0.0375	[0.0069; 0.0680]	0.0163	0.0070	0.0835	100.0
Gao et al. (2021)	0.0385	[0.0079; 0.0689]	0.0135	0.0070	0.0834	100.0
Herzenstein et al. (2011)	0.0371	[0.0066; 0.0677]	0.0173	0.0070	0.0836	100.0
Ho et al. (2024)	0.0383	[0.0078; 0.0688]	0.0139	0.0070	0.0834	100.0
Hornuf and Neuenkirch (2017)	0.0353	[0.0051; 0.0655]	0.0218	0.0068	0.0826	100.0
Hornuf et al. (2022)	0.0390	[0.0086; 0.0693]	0.0120	0.0069	0.0831	100.0
Jiang et al. (2018)	0.0379	[0.0074; 0.0684]	0.0159	0.0070	0.0835	100.0
Jiang et al. (2022)	0.0372	[0.0066; 0.0677]	0.0172	0.0070	0.0836	100.0
Lee and Lee (2012)	0.0314	[0.0035; 0.0593]	0.0276	0.0058	0.0762	100.0
Li et al. (2022)	0.0392	[0.0088; 0.0695]	0.0114	0.0069	0.0830	100.0
Lin et al. (2013)	0.0373	[0.0067; 0.0678]	0.0170	0.0070	0.0836	100.0
Liu et al. (2015)	0.0304	[0.0035; 0.0572]	0.0268	0.0054	0.0733	100.0
Lowry et al. (2023)	0.0362	[0.0057; 0.0666]	0.0201	0.0069	0.0833	100.0
Mohammadi and Shafi (2018)	0.0432	[0.0151; 0.0713]	0.0026	0.0059	0.0769	100.0
Walther and Bade (2020)	0.0391	[0.0087; 0.0694]	0.0118	0.0069	0.0831	100.0
Wang et al. (2019)	0.0397	[0.0094; 0.0699]	0.0101	0.0068	0.0826	100.0
Wei and Lin (2017)	0.0390	[0.0086; 0.0694]	0.0120	0.0069	0.0831	100.0
Wu et al. (2025)	0.0410	[0.0113; 0.0707]	0.0068	0.0066	0.0811	100.0
Yi et al. (2024)	0.0403	[0.0104; 0.0702]	0.0084	0.0067	0.0819	100.0
Yum et al. (2012)	0.0334	[0.0040; 0.0627]	0.0261	0.0065	0.0803	100.0
Zhang and Chen (2017)	0.0387	[0.0082; 0.0691]	0.0130	0.0069	0.0833	100.0
Zhang and Liu (2012)	0.0314	[0.0035; 0.0593]	0.0277	0.0058	0.0763	100.0
Full model (all studies)	0.0375	[0.0065; 0.0683]	0.0195	0.0067	0.0821	100.0

Note. Each row reports the pooled herding PCC from a random-effects meta-analysis after omitting the study listed in the first column (leave-one-out analysis). The "Full model (all studies)" row reports the estimate using all 30 studies. τ^2 is the estimated between-study variance, and τ is its square root (the standard deviation of true effects). I^2 denotes the percentage of total variability attributable to between-study heterogeneity. p-values test the null hypothesis that the pooled PCC equals zero in each leave-one-out model.

moderator strata (Table 8). For *Market*, no imputed studies were detected in either ECF or P2P, and adjusted effects were identical to the originals. For *Culture*, the Western subset showed no imputation. In contrast, the Non-Western subset imputed one study on the right side, resulting in only a negligible increase in the pooled effect ($\Delta r \approx +0.008$). For *Competition*, the 'Accounted for' subset showed no imputation, whereas the 'Not accounted for' subset imputed four right-side studies, raising the pooled effect modestly ($\Delta r \approx +0.022$). Overall, trim-and-fill provides no evidence of effect inflation due to selective reporting; if anything, any residual asymmetry would bias estimates downward. These moderator-specific results indicate that the aggregate trim-and-fill adjustment reflects heterogeneity across study designs rather than publication selection, corroborating the non-significant Begg/Egger tests and the visually symmetric funnel plot.

We further evaluated small-study effects using PET–PEESE meta-regression (Table 9). In the PET specification, the standard-error slope was not significant ($\beta = -1.41$, $p = 0.530$), indicating no systematic association between effect size and study precision. The PET intercept remained positive and significant, with a PCC of 0.046. Results were unchanged in the PEESE specification: the SE^2 slope was also non-significant ($p = 0.474$), and the adjusted intercept implied PCC = 0.043. Overall, PET–PEESE provides no evidence of publication selection bias and yields bias-adjusted effects that are virtually identical to the main estimate.

5. Discussion

This study aimed to answer four questions: (1) Is herding behaviour consistently observed in ECF and P2P lending markets? (2) Does herding differ between ECF and P2P lending? (3) Do competing offers impact herding dynamics? (4) Do regional groups (Western vs non-Western countries) and national cultural factors shape herding behaviour? Subgroup analyses show that: (1) herding can be consistently identified in these markets, though it varies across studies and contexts; (2) herding is more pronounced in P2P lending than ECF; (3) herding effects decrease when competing offers are present; (4) herding is more prominent in non-Western markets, influenced by specific cultural factors, namely power distance, individualism, and long-term orientation, with suggestive evidence for indulgence.

While the systematic detectability of herding and its varying magnitude across ECF and P2P lending markets represent relevant empirical insights, the findings related to competing offerings and the role of national culture also offer worthwhile theoretical implications.

Incorporating the competitive environment into the empirical specification results in herding becoming notably weaker on average, and its estimated magnitude is more uncertain. The inclusion of negative values within the interval further illustrates that, across studies, sequential investment behaviour can be attenuated or offset when investors consider the broader platform activity surrounding the focal campaign.

A key source of heterogeneity lies in how the literature operationalises competition. Some studies define competition strictly within a single platform, exposing investors only to the performance of concurrently active campaigns on that portal. This narrower information environment, as in Åstebro et al. (2024), may intensify attention to intra-platform momentum signals, leading to stronger herding patterns. By contrast, studies such as Block et al. (2017), which measure competition across multiple platforms, situate investors in a more complex, information-rich environment. When evaluating a campaign's traction relative to offerings on several portals, the process becomes more demanding and may reduce reliance on simple sequential cues.

However, this single-platform-versus-multi-platform distinction does not fully explain the observed variation. Ferretti et al. (2021), despite measuring competition within a single platform, report a lower herding coefficient than Block et al. (2017). Wang et al. (2019), operating in the same setting as Åstebro et al. (2024), find a negative coefficient. These discrepancies highlight the importance of platform design. Competing

Table 5
Influence diagnostics from the random-effects meta-analysis.

Study	Std. residual	DFFITS	Cook's D	Cov. ratio	τ^2 (deleted)	Q (deleted)	Leverage	Weight	DFBETAS
Åstebro et al. (2024)	−0.1576	−0.0288	0.0009	10.718	0.0070	82,016.76	0.0337	3.37	−0.0288
Bade and Walther (2021)	−0.4573	−0.0850	0.0074	10.647	0.0069	78,425.11	0.0338	3.38	−0.0850
Block et al. (2017)	−0.4322	−0.0802	0.0066	10.653	0.0069	81,998.53	0.0336	3.36	−0.0802
Caglayan et al. (2021)	−0.4413	−0.0820	0.0069	10.653	0.0069	78,915.55	0.0338	3.38	−0.0820
Cai and Polzin (2025)	−0.4423	−0.0822	0.0070	10.652	0.0069	81,692.94	0.0338	3.38	−0.0822
Chen, Li, Liu, et al. (2021)	0.6963	0.1304	0.0173	10.543	0.0069	81,252.04	0.0337	3.37	0.1304
Chen, Li, Fan, and Qin (2021)	0.5052	0.0942	0.0091	10.623	0.0069	81,983.28	0.0333	3.33	0.0942
Chen et al. (2022)	−0.2912	−0.0538	0.0030	10.694	0.0070	82,010.98	0.0337	3.37	−0.0538
Ferretti et al. (2021)	−0.0079	−0.0009	0.0000	10.709	0.0070	82,015.93	0.0328	3.28	−0.0009
Gao et al. (2021)	−0.3550	−0.0658	0.0045	10.679	0.0070	81,914.73	0.0338	3.38	−0.0658
Herzenstein et al. (2011)	0.1069	0.0205	0.0004	10.723	0.0070	81,994.73	0.0337	3.37	0.0205
Ho et al. (2024)	−0.3064	−0.0567	0.0033	10.692	0.0070	81,953.34	0.0338	3.38	−0.0567
Hornuf and Neuenkirch (2017)	0.7861	0.1401	0.0199	10.448	0.0068	82,007.32	0.0306	3.06	0.1400
Hornuf et al. (2022)	−0.5423	−0.1006	0.0104	10.610	0.0069	81,997.79	0.0335	3.35	−0.1006
Jiang et al. (2018)	−0.1754	−0.0317	0.0010	10.695	0.0070	82,016.81	0.0327	3.27	−0.0317
Jiang et al. (2022)	0.0955	0.0184	0.0004	10.725	0.0070	81,985.90	0.0337	3.37	0.0184
Lee and Lee (2012)	23.364	0.4318	0.1612	0.8945	0.0058	81,500.26	0.0334	3.34	0.4318
Li et al. (2022)	−0.6169	−0.1147	0.0135	10.578	0.0069	81,964.39	0.0336	3.36	−0.1147
Lin et al. (2013)	0.0624	0.0122	0.0002	10.728	0.0070	81,941.53	0.0337	3.37	0.0122
Liu et al. (2015)	28.323	0.5265	0.2210	0.8278	0.0054	18,361.96	0.0338	3.38	0.5257
Lowry et al. (2023)	0.4534	0.0851	0.0075	10.650	0.0069	81,662.67	0.0337	3.37	0.0852
Mohammadi and Shafi (2018)	−2.2876	−0.4072	0.1473	0.9075	0.0059	81,970.65	0.0310	3.10	−0.4092
Walther and Bade (2020)	−0.5754	−0.1071	0.0118	10.599	0.0069	81,787.62	0.0337	3.37	−0.1071
Wang et al. (2019)	−0.7880	−0.1469	0.0219	10.488	0.0068	81,843.59	0.0337	3.37	−0.1469
Wei and Lin (2017)	−0.5419	−0.1008	0.0104	10.614	0.0069	81,882.15	0.0337	3.37	−0.1008
Wu et al. (2025)	−1.2847	−0.2397	0.0562	10.112	0.0066	81,847.89	0.0335	3.35	−0.2397
Yi et al. (2024)	−1.0500	−0.1915	0.0366	10.295	0.0067	82,000.74	0.0322	3.22	−0.1916
Yum et al. (2012)	15.075	0.2753	0.0728	0.9909	0.0065	81,946.19	0.0325	3.25	0.2755
Zhang and Chen (2017)	−0.4237	−0.0787	0.0064	10.659	0.0069	79,196.75	0.0338	3.38	−0.0787
Zhang and Liu (2012)	23.203	0.4317	0.1610	0.8955	0.0058	69,497.48	0.0338	3.38	0.4313

Note. "Std. residual" reports externally studentized residuals for each study. "DFFITS" and "Cook's D" measure each study's influence on fitted values and the overall meta-analytic effect, respectively. "Cov. ratio" is the covariance ratio, with values farther from 1 indicating greater impact on the precision of the pooled estimate. "τ^2 (deleted)" and "Q (deleted)" are the between-study variance and heterogeneity statistic after exclusion of the given study. "Leverage" quantifies the study's influence on model fit, and "Weight" is the (random-effects) inverse-variance weight on the Fisher z scale. "DFBETAS" capture each study's influence on the pooled PCC.

Table 6
Publication-bias tests (Begg and Egger).

Test	Test statistic	df	p-value	Intercept / bias estimate (Egger only)	95% CI of intercept
Begg (rank correlation)	Kendall's τ = 0.2000		0.1257		
Egger (linear regression)	t = 0.8688	28	0.3924	0.0149	[−0.0174, 0.0473]

Note. The Begg test evaluates the rank correlation (Kendall's τ) between standardised effect sizes and their variances; no intercept estimate is defined. The Egger test regresses standardised effect sizes on their standard errors; the intercept term reflects potential funnel-plot asymmetry.

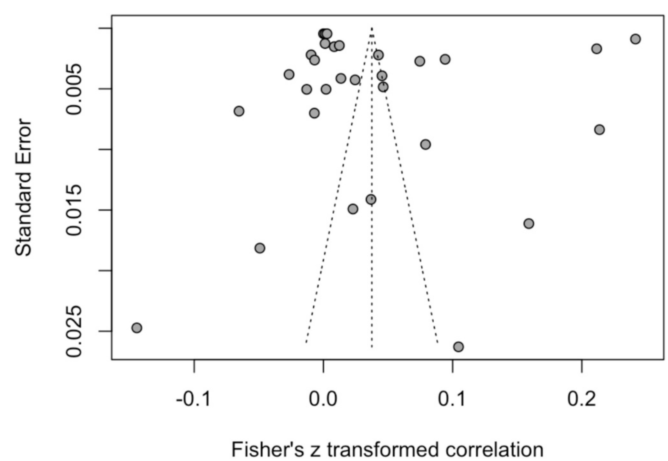

Fig. 6. Funnel plot of Fisher's z-transformed herding correlations.
Note. The figure displays effect sizes (horizontal axis) plotted against their standard errors (vertical axis), with the pooled random-effects estimate shown as a vertical dashed line and pseudo 95% confidence region indicated by dashed diagonal lines.

offerings influence investor decisions only to the extent that their performance is salient. Platforms differ in whether and how they display real-time fundraising trajectories, rankings, or visibility of concurrent campaigns. High visibility may intensify evaluation and amplify momentum when the focal campaign performs well, but it can also dampen herding when competing offerings draw more attention. Limited visibility weakens these benchmarks and may mute the effect of sequential cues.

These findings suggest the need for further research on how platforms frame competition through campaign presentation, ranking systems, real-time indicators, and cross-platform comparisons, and how such design choices influence behavioural responses in ECF and P2P lending markets. As research expands, understanding how competition shapes investor heuristics will be key to explaining when and why herding emerges or dissipates in digital finance environments.

Regarding differences in herding behaviour across cultural contexts, investors in high-power-distance societies exhibit greater conformity to collective behaviour. In contrast, those in more individualistic contexts are less inclined to follow the crowd. This pattern suggests that deference to authority and collective orientation heighten the perceived informational value of others' actions. In such environments, investors respond more strongly to peer signals, consistent with the role of social expectations in shaping financial decisions. Conversely, in individualistic settings, decision-making is driven more by the sense of personal efficacy, thereby dampening imitation dynamics. These results align

Table 7
Trim-and-fill publication bias test (Duval & Tweedie).

Statistic	Estimate
Number of observed studies (k)	30
Estimated missing studies	7 (right side)
Original pooled effect (r)	0.0375
Trim-and-fill adjusted pooled effect (r)	0.0619
Change in pooled effect (Δr)	+0.0244
Adjusted pooled effect (Fisher's z)	0.0619
Standard error (Fisher's z)	0.0152
95% CI (Fisher's z)	[0.0322, 0.0917]
z-value	4.0842
p-value	< 0.0001
τ^2 (REML)	0.0084
τ	0.0917
I^2 (%)	99.97
Q (df = 36)	87012.94
Q-test p-value	< 0.0001

Note. The trim-and-fill procedure (Duval & Tweedie) imputes potentially missing studies to restore funnel-plot symmetry and recomputes the random-effects pooled estimate. "Right-side" imputation indicates that missing studies are those with more positive effects, implying no upward selective-reporting bias. Effects are estimated on Fisher's z scale and back-transformed to partial correlations (r) for interpretation. Random-effects estimation uses REML for τ^2.

with prior evidence on how cultural orientations condition the relative influence of subjective norms and perceived behavioural control on intentions to participate in fintech markets (Shneor et al., 2021).

Countries with higher long-term orientation tend to exhibit stronger herding. In fintech markets with limited exit options, forward-looking investors are more willing to wait and learn from accumulated social signals to reduce uncertainty and evaluate credibility. In more short-term oriented cultures, investors may place greater weight on immediate cues, thereby dampening reliance on crowd signals and counteracting herding. Additionally, more restrained, norm-bound societies may exhibit greater herding, but the evidence for indulgence-based differences is only marginal in our meta-analysis and should be interpreted cautiously.

Taken together, these findings indicate that herding in ECF and P2P lending is shaped not only by the structural features of these markets but also by culturally embedded decision heuristics that influence how investors interpret and respond to others' behaviour. By presenting this evidence, we contribute to the ongoing academic debate by underscoring the role of sociocultural factors in shaping herding dynamics under conditions of market uncertainty, conditions in which greater reliance is placed on crowd wisdom (shown by the statistical significance of collectivism), early backers are interpreted as authoritative signals (indicated by the statistical significance of power distance), and the inclination to act independently in the face of noisy information is reduced (in line with Spyrou, 2013).

This systematic meta-analysis makes a significant contribution to the existing ECF and P2P lending literature. It provides statistically robust evidence that herding behaviour exists in these markets and that its economic impact is substantial enough to determine the success or failure of a campaign or listing. Although the observed effect appears small, it should be considered in the context of sequential decision-making: ECF and P2P lending offerings attract hundreds of investments daily and last several days. Therefore, an apparently modest correlation may translate into meaningful economic effects over the course of a campaign.

The analysis also reveals that herding behaviour differs between ECF and P2P lending markets. Although previous research has extensively documented the unique features of these markets, no comparative assessment of herding dynamics has been undertaken until now.

Additionally, the study provides statistical support for the moderating role of competing campaigns, showing that the presence of multiple investment opportunities affects herding dynamics. This builds on initial studies suggesting such an effect, but these lacked confirmation through aggregated evidence.

Finally, the research provides evidence that herding behaviour varies significantly between Western and non-Western countries and depends on specific cultural dimensions. While prior research has explored herding behaviour across cultures, few studies have explicitly compared Western and non-Western contexts, leaving regional differences under-explored. This systematic meta-analysis addresses that gap and offers new insights into how cultural factors shape investment dynamics in fintech markets.

Despite its contributions to the ECF and P2P lending literature, this study presents certain limitations.

First, the sample is relatively modest, indicating that effect sizes may

Table 8
Moderator-specific trim-and-fill results (Duval & Tweedie).

Moderator	Group	Observed studies (k)	Imputed studies (k_e)	Side of imputation	Original pooled r	Adjusted pooled r	Δr
Market	ECF	12	0	Right	−0.0060	−0.0060	0.0000
Market	P2P	18	0	Left	0.0661	0.0661	0.0000
Culture	Western	14	0	Right	−0.0001	−0.0001	0.0000
Culture	Non-Western	16	1	Right	0.0701	0.0778	+0.0077
Competition	Accounted for	6	0	Left	0.0016	0.0016	0.0000
Competition	Not accounted for	24	4	Right	0.0460	0.0680	+0.0220

Note. The trim-and-fill procedure (Duval & Tweedie) was re-estimated within each moderator subgroup. "Imputed studies" indicates the number of potentially missing effects added to restore funnel symmetry; "side" refers to whether missing studies are estimated to lie to the left (more negative) or right (more positive) of the observed mean. Effects are computed on Fisher's z scale and back-transformed to partial correlations (r). Positive Δr indicates the adjusted pooled effect is larger than the original.

Table 9
PET–PEESE meta-regression tests for small-study effects.

Model	k	Bias term	Bias estimate	SE	z	p	95% CI	Intercept (Fisher's z)	SE	z	p	95% CI	Bias-adjusted r (intercept)
PET	30	SE	−1.4071	2.2391	−0.6284	0.5297	[−5.7956, 2.9815]	0.0465	0.0210	2.2183	0.0265	[0.0054, 0.0876]	0.0465
PEESE	30	SE^2	−65.2489	91.1213	−0.7161	0.4740	[−243.8434, 113.3456]	0.0432	0.0172	2.5144	0.0119	[0.0095, 0.0769]	0.0432

Note. PET regresses Fisher's z effect sizes on their standard errors, while PEESE uses squared standard errors. The bias term tests for small-study effects; non-significant slopes indicate no evidence of publication selection related to precision. Intercepts represent bias-adjusted pooled effects, reported on Fisher's z scale and back-transformed to partial correlations (r). Both models are mixed-effects meta-regressions estimated with REML.

evolve as more empirical evidence becomes available. Future meta-analyses should expand the dataset and examine additional moderators. Second, while we detected statistically significant and theoretically grounded differences in herding behaviour between ECF and P2P lending markets, a logical follow-up analysis would involve testing the identified moderators separately within each market. We did not conduct this analysis to avoid results driven by small subgroup sizes. Future research could refine the analysis by conducting moderation tests on distinct subsamples. Finally, this meta-analysis excluded studies on other forms of crowdfunding, such as donation-based and reward-based models. Investigating herding behaviour across profit and non-profit platforms could reveal whether financial motivations moderate herding tendencies.

The topic of herding behaviour in ECF and P2P lending markets remains a promising area for future research. Some potential directions are outlined in the following section.

5.1. Future research directions

5.1.1. Institutional settings

A primary direction for future research is to expand the evidence on herding in ECF and P2P lending beyond the currently dominant settings of China, the UK, the US, and selected European markets. From an institutional perspective, future studies could investigate how different regulatory regimes influence the number and types of active platforms, and how these configurations impact market-wide herding. Additionally, it would be useful to examine whether herding varies with platform maturity by comparing markets that include both new and established platforms, rather than simply considering the number of operational portals. Further research should also analyse how country differences in demographics, educational attainment, financial literacy, and the age structure of active investors moderate the likelihood or magnitude of herding.

Cultural norms also warrant scrutiny. Such analyses would enable the extension of current frameworks describing information cascades in fintech markets (Cong & Xiao, 2024) by providing evidence on factors that influence herding beyond mere observation of others' investment behaviour.

5.1.2. Platform design

A second avenue for future research concerns the role of platform design and transparency settings. Empirical studies often overlook the influence of interface features that are likely to influence investors' cognitive processes. For example, real-time visibility into funding progress may alter how investors evaluate social information, leading them to focus on how close a campaign is to its funding threshold rather than reacting only to the most recent investment or the time since the last contribution. Similarly, ranking mechanisms that highlight "hot" or fast-growing campaigns can direct attention to a small subset of offerings, potentially creating new herding flows and reinforcing self-reinforcing trajectories.

Another design element worth examination is the visibility of competing campaigns when an investor views a specific campaign page. If investors can observe the funding progress of other live campaigns, cross-campaign spillovers may occur (Belleflamme et al., 2025), with herding influenced by both the focal project's trajectory and the relative performance signals. Controlled experiments could isolate these effects.

5.1.3. Investor heterogeneity and the rationality of herding

A third avenue for future research is to examine how investor demographics and behavioural heterogeneity influence herding dynamics. While some studies have explored gender affinity, much remains unknown about how characteristics such as age, education, financial literacy, income, investment experience, risk tolerance, or personality traits affect susceptibility to herding. Experimental research would be especially valuable in this context, as current empirical work primarily relies on secondary data.

Another important area concerns differentiating rational from irrational herding. Classifying herding as rational or irrational requires understanding investors' motivations, which cannot be inferred solely from observational data. Future studies could conduct experiments to better understand why individuals follow social signals.

5.1.4. Culture and herding mechanisms

The present meta-analysis indicates that non-Western investors tend to exhibit stronger herding tendencies. Exploratory analyses suggest that factors such as individualism, power distance, long-term orientation, and indulgence may drive these differences. Several questions arise: Do collectivist societies amplify information cascades due to social norms that increase conformity? Do cultures with high power distance elevate the perceived authority of early investors, thus strengthening the informational weight of initial signals? Do long-term oriented cultures rely more on social cues when exit options are limited, or project quality is hard to assess? Addressing these questions would require cross-country experiments, multi-level empirical studies, or mixed methods combining survey data with platform-level behavioural evidence. Such research could refine existing theories by illustrating how culturally influenced cognitive processes interact with structural market features to affect the emergence, strength, and persistence of herding behaviours.

6. Conclusion

This systematic meta-analysis of 30 papers shows that herding is statistically detectable in these markets, though its magnitude is highly heterogeneous across studies. It is more pronounced in P2P lending than in ECF, and reported herding effects diminish with increased competition. Herding is also more evident in non-Western markets, and varies with cultural factors such as power distance, individualism, and long-term orientation, with suggestive evidence for indulgence. Aside from their academic significance, these findings also carry practical implications. Herding in ECF and P2P lending warrants examination because it directly affects startup survival rates. When funds flow to less deserving startups that nonetheless gain more traction, the most deserving ones risk being excluded from the market. The "market for lemons" problem here is genuine and warrants policy attention not only for startup survival but also for investors' savings. Retail savings may be mobilised in an inefficient market where secondary negotiations are largely absent, especially in ECF. If such savings are also diverted away from the best entrepreneurs, the loss is twofold: retail investors lose their savings and are trapped in poor investments, while less deserving startups may receive funding.

What should policymakers do to reduce the adverse effects of a potential "market for lemons"? First, promote the development of secondary markets. This intervention would enable the correction of suboptimal investment decisions and increase public scrutiny of entrepreneurs both during and after the fundraising, particularly if such secondary markets facilitate the buying and selling of securities or debt repayment rights across borders. Second, the rationality or irrationality of herding hinges on individuals' financial literacy. Policymakers should ensure investors are supported in recognising behavioural biases that may emerge when investing in fintech markets. Ideally, such educational initiatives could complement existing risk and knowledge assessment questionnaires administered to platform users.

As disintermediation advances in fintech markets and social pressure in the digital era intensifies, a closer examination of herding dynamics, given their real impact on financial markets, merits attention.

Declaration of generative AI in scientific writing

While preparing this work, the authors used OpenAI's GPT, ChatGPT, to enhance the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as necessary, taking full responsibility for the publication's content.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.irfa.2026.105101.

Data availability

The data that has been used is confidential.

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