



# Soft and hard information in equity crowdfunding: network effects in the digitalization of entrepreneurial finance

Saul Estrin · Susanna Khavul · Mike Wright

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**Abstract** As a digital financial innovation, equity crowdfunding (ECF) allows investors to exploit the complementarity of information provision and network effects in a reduced transaction cost environment. We build on the underlying distinction between soft and hard information and show that ECF platforms create an environment of greater information pooling that benefits from network externalities. We test our hypotheses using a unique proprietary dataset and find that soft information has a greater impact than hard on the likelihood that a financing pitch will be successful. Moreover, the effects of soft information are amplified by the size of the investor network on the platform and network size also positively moderates the effect of information on the amount invested during each pitch. We conclude that ECF platforms can successfully exploit low transaction costs of the digital environment and bring network externalities to

bear on investor decisions. Taken together that these increase the supply of funds to entrepreneurs.

**Keywords** Equity crowdfunding · Entrepreneurial finance · Soft information · Network externalities · Platforms

**JEL Classifications** G23 · L26 · M13

## 1 Introduction

Digital mediation has fundamentally altered the boundaries of market transactions (Lerner & Tirole, 2002; Parker & Van Alstyne, 2005; Nagle et al., 2020). In entrepreneurial finance, digital platforms offer a new mechanism for entrepreneurs to access equity, debt, and non-dilutive capital through crowdfunding (Bruton et al., 2015; Mollick, 2014). Although reduced transaction costs are at the heart of all crowdfunding platforms (Acs et al., 2020; Evans & Schmalensee, 2016), the opportunities and limits of how investment is raised depend on the specific architecture of each type of platform (Goldfarb & Tucker, 2019). In this paper, we focus on equity crowdfunding (ECF) which we define as an open digital marketplace for entrepreneurial equity finance that operates within a social network environment. ECF emerged in the face of known information asymmetries in entrepreneurial finance and relies on reduced transaction costs and network externalities to scale its online marketplace (Estrin & Khavul, 2016). By supplying entrepreneurs with largely illiquid equity

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S. Estrin · S. Khavul  
Department of Management, Centre for Economic Performance,  
London School of Economics, London, England

S. Estrin  
e-mail: s.estrin@lse.ac.uk

S. Khavul (✉)  
Lucas College and Graduate School of Management, San Jose  
State University, San Jose, CA, USA  
e-mail: susanna.khavul@sjsu.edu  
e-mail: s.khavul@lse.ac.uk

M. Wright  
Imperial College, London, England

investments, ECF has the potential to address some of the previous blockages in the supply of finance (Estrin et al., 2018).

Our work builds on the emerging literature on crowdfunding (see Bruton et al., 2015; McKenny et al., 2017; Paoloni et al., 2019; Mochkabadi & Volkmann, 2020 for overviews and reviews). Most academic research on crowdfunding focuses on non-dilutive rewards-based platforms such as Kickstarter (e.g., Chan & Parhankangas, 2017) or peer-to-peer lending platforms such as Prosper (e.g., Hidebrand et al., 2017; Kgoroeadira et al., 2019). Research on ECF emerged more recently but has accelerated to keep up with the scale and diffusion of the phenomenon (e.g., Hornuf & Schwienbacher, 2017; Vismara, 2016, 2018; Cummings et al., 2019; Ralcheva & Roosenboom, 2020). Empirical questions range from the process of preselection of pitches on crowdfunding platforms (Loher, 2017) to the effects of equity retention and social capital (Vismara, 2016, 2018), to the impact of gender (Mohammadi & Shafi, 2018), and the effect of geographic distance between investors and the firms in which they invest (Guenther et al., 2017). Signaling is the most prevalent theoretical perspective (Ahlers et al., 2015; Kleinert et al., 2020) and relies on the argument that entrepreneurs address information asymmetries in entrepreneurial finance with the provision of costly signals, which allow investors to distinguish firms of high and low quality (Connelly et al., 2011; Spence, 1973). However, as has been aptly acknowledged previously, not every piece of information exchanged in the ECF process is a signal, even a costless one (Anglin et al., 2018), yet unlike traditional investment practices, the digitalization of entrepreneurial finance produces, disseminates, and stores an unprecedented deluge of information. In this context, it is possible that a more varied set of investors may use a wider assortment of information for their investment decisions. We see an opportunity for a complementary conceptual perspective that more closely mirrors the wider array of information exchanged during the ECF process. We argue that ECF's virtual two-sided market-place exploits the exchange of diverse information, which, when combined with network effects, facilitates the expansion of this digital market (Goldfarb & Tucker, 2019; Acs et al., 2020).

In this paper, we build on this information perspective and suggest that information on the ECF platform can be categorized into hard and soft (e.g., Ijiri, 1975; Iyer et al., 2013; Stein, 2002; Petersen, 2004). Hard information comprises of facts about which there is

general agreement, which are verifiable, and cannot be easily changed in the investment period (e.g., the entrepreneur's demographics, the firm's age, size, location, and industry) but soft information is open to debate or alternative interpretations of its implications and more difficult to verify (e.g., the firm's valuation or growth potential) (Bertomeu & Marinovic, 2016; Liberti & Petersen, 2018; Liberti, 2018). We adopt this perspective from the finance literature where the classification of information into hard and soft has fruitfully explained the scaling-up of debt (through the codification and use of hard information) and the improvements in the performance of loan portfolios with the inclusion of soft information (Cornée, 2019). We argue that, because of the high levels of uncertainty about the future prospects of entrepreneurial firms, soft information is the main component of the informational asymmetries that limit the ability of entrepreneurs to raise equity. We propose that it is soft information which is crucial for new venture financing, but for investors, it is more costly to obtain soft than hard information about entrepreneurial projects. Indeed, the high transaction costs of acquiring, disseminating, and interpreting soft information restrict the supply of equity capital particularly for early stage ventures. We propose that, because ECF platforms have been designed to facilitate the provision, exchange, and interpretation of soft information, they help potential investors to identify suitable new venture equity.

ECF platforms are two-sided digital marketplaces that are designed to address the information asymmetries underlying the high transaction costs in the market for entrepreneurial finance (Jensen & Meckling, 1976; Lerner, 1995; Gompers, 1995; Myers, 2000; Estrin et al., 2018; Nagle et al., 2020). Consequently, the virtual exchange of information and contracting on ECF platforms means that the costs of information coordination and dissemination are low (Goldfarb & Tucker, 2019) and the virtual market for equity in privately held companies can operate on a greater scale than hitherto. Moreover, as social networks, ECF platforms also benefit from potential knowledge exchange as a result of powerful economies of scale. We build on the ideas of network externalities (Varian et al., 2004) to argue that the benefits of information exchanges in terms of reduced transaction costs are amplified within larger networks (Evans, 2008; Evans & Schmalensee, 2010; Katz & Shapiro, 1994; Parker & Van Alstyne, 2005). Furthermore, because ECF platforms facilitate the rapid exchange of soft

information in a decentralized network, the size of the platform especially amplifies the transmission such soft information.

We test our hypotheses using a proprietary dataset that offers a unique window into choices and behavior on ECF platforms. We use real-time individual-level investment data from each pitch on CrowdCube, one of the largest crowdfunding platforms in the world (Estrin et al., 2016, 2018). Our empirical analysis reflects every transaction within every pitch on the entire network of up to 165,000 investors and 835 pitched projects and 72,315 investment observations between the start of the platform in 2011 and mid-2015. The data capture a significant proportion of all ECF transactions made in the United Kingdom at the critical time when ECF emerged as an alternative source of finance. We use two inter-related models. The first model explores what determines pitch success, a dependent variable considered previously in the ECF and broader crowdfunding literature (e.g., Vismara, 2018; Shafi, 2019; Kleinert et al., 2020; Ralcheva & Roosenboom, 2020). Our approach is distinguished by the focus on the effects of soft as against hard information and how these are amplified by the size of the network. The second model tests scale effects within a dynamic model of funding offers during each pitch. Real time data are used to analyze how the dynamics of investment offers are driven by information exchange amplified by the size of the network. Our estimates of these models show that when entrepreneurs and investors exchange especially soft information, the effect is to increase both the offer of funds and the likelihood of successful funding, effects amplified by network externalities.

## 2 Theory and hypotheses

### 2.1 Soft and hard information in ECF platforms

Capital markets face well-known information asymmetry and agency problems that create inefficiencies and impede investment decisions (Stigler, 1961; Jensen & Meckling, 1976; Merton, 1987; Spence, 1973; Myers, 2000). Adverse selection and moral hazard problems often result (Akerlof, 1970; Hellmann & Stiglitz, 2000; Myers & Majluf, 1984; Stiglitz & Rothschild, 1976). Consequently, potentially profitable investments may not be made because contracts that assign risks appropriately are difficult to draw up. These problems

apply with particular severity to early stage entrepreneurial finance. In an ideal environment, the availability of information, its ready exchange, and ease of interpretation should reduce uncertainty. However, in early stage finance, investors know less than entrepreneurs about the new ventures in which they seek to acquire equity (Manigart & Wright, 2013). The investment process is information intensive, and investors in entrepreneurial ventures find information costly to acquire, pool, and interpret. Moreover, not only are the transaction costs of collecting accurate and relevant information high but the true risks of investing unfold only over time, often after the investment is made (Parker, 2009; Gompers & Lerner, 2001).

Over decades of collective practice, angels, venture capitalists, and other professional investors in private markets for equity have developed a suite of informal and formal tools to assess the quality of potential investments (Lerner, 1995; Gompers, 1995). The process is highly stylized and curated (Cosh et al., 2009; Parker, 2009; Hellmann et al., 2013; Leboeuf & Schwienbacher, 2018). It also relies heavily on the acquisition and interpretation of information both hard and soft. The conceptual difference between hard and soft information, which we argue is important to develop in the context of crowdfunding, brings into sharp relief the nature of certainty, verifiability, and meaning of underlying facts in the evaluation of new ventures (Bertomeu & Marinovic, 2016; Petersen, 2004; Liberti & Petersen, 2018). As we defined above, information is hard when it represents facts that are generally verifiable and cannot be changed in the short term and about which there is general agreement (e.g., the entrepreneur's demographics data, the firm's age, current size, location, and industry). Soft information (e.g., the firm's valuation, growth potential) is changeable, more difficult to verify, and open to debate or alternative interpretations of its implications. This difference reflects more than the distinction between qualitative and quantitative information (Stein, 2002). That is, even if expressed quantitatively, information that is forward-looking, such as projected financial statements, or intangible and difficult to value such as brands and patents, is soft (Bertomeu & Marinovic, 2016). Hence, in the high uncertainty context of new ventures, successful investors develop industry expertise and syndicate with others not only to spread and diversify risks but also to access broader and deeper reservoirs of knowledge (Barringer & Harrison, 2000; Manigart et al., 2006; Wright & Lockett, 2003) to interpret the

information they receive. Such investor communities engage in a sense-making process under conditions of high uncertainty (Weick, 1995). Sense-making allows investors to reduce complexity and come up with a “plausible understanding” of the investment opportunity. What has evolved is a relatively small, largely closed, and geographically proximate networks of investors with the capabilities to acquire and make sense of largely soft information. The inclusion of soft information in the decision-making process increases the likelihood that such investors will identify potentially successful opportunities, yet the majority of traditional equity investors face high cost of coordinating the acquisition and dissemination of soft information, which creates inefficiencies in the supply of capital to entrepreneurial firms.

Digital platforms, on the other hand, have the potential to greatly reduce the transaction costs of acquiring, disseminating, and interpreting information, including soft information (Goldfarb & Tucker, 2019; Acs et al., 2020). ECF platform architecture allows entrepreneurs and investors instantaneously and nearly costlessly to generate and pool their knowledge about a new venture (Cumming & Hornuf, 2018). Platforms require ventures to provide information about the entrepreneurs, the management team, and the business idea, as well as financial data about the current and future prospects of the company and a video explaining the business opportunity. The open access of the platform environment provides most entrepreneurs with the incentive to reveal as much information as they can and as accurately as possible because what they provide will be scrutinised by large numbers of potential investors. Thus, the architecture of the platform creates an environment where entrepreneurs reveal more hard facts and improve the quality and scale of soft information. Moreover, the information from the entrepreneur is freely available to the entire social network, which is to say to all potential investors. During ongoing pitch processes, investors also provide soft information. They reveal their willingness to pay for equity by pledging towards pitch targets. In doing so, they provide information about the current supply of funds for that project. Soft information can include the frequency with which investors view the pitch site, the number of investors following the pitch, and the nature and volume of discussion about the pitch. The architecture of the platform ensures that the entire network is rapidly informed and a process to make sense and interpret this soft information has the potential to commence.

Unlike the curated processes of traditional early stage entrepreneurial finance, the analysis and interpretation of information on ECF platforms are not constrained by time or location: exchanges can be both synchronous and asynchronous. Moreover, exchanges of information on ECF platforms leave digital traces (Nagle et al., 2020), unlike other investment processes where information is exchanged but is ephemeral that which is captured on ECF platforms is stored as artifacts and codified (Estrin & Khavul, 2016). Notably, such information can become part of the accumulated ECF process history and can influence the investment decisions of all participants in the network in the present and in the future. Nevertheless, uncertainty and information asymmetry remain in the digital space (Adner et al., 2019) and the investment process remains information intensive. However, the architecture of the ECF platform increases the volume and quality of the information provided to potential investors both through the revelation of incremental hard facts but especially by improving the availability and dissemination of soft information, for which transaction costs are inherently higher. As research on banking has shown, soft information, which is difficult to collect and transmit, benefits from a decentralized system because in the transmission across layers in an organization, and between organizations, key soft information insights about borrowers are lost (Cornée, 2019; Filomeni et al., 2021; Liberti & Petersen, 2018; Campbell, et al., 2019). Decentralizing decision-making to loan officers who were able to gather and make sense of the soft information resulted in more loans and higher performing loan portfolios (Liberti & Petersen, 2018; Gropp & Guettler, 2018). The distributed nature of the pitch process on ECF platforms allows that information to be explored, evaluated, and additional data revealed over the course of the investment window. ECF investor communities can engage in the sense-making and co-creation of meaning from the soft information to which they have access. Thus, the low costs of transmitting and exchanging information enable virtually costless transmission to all current and potential investors as well as rapid scaling of particularly soft information flows. On a scale not previously seen in entrepreneurial finance, soft information is easier to identify, disseminate, and subject to interpretation in order to assign to it meaning. Therefore, we argue that in this environment of high uncertainty, the architecture of ECF platforms can reduce the transaction costs of accumulating and interpreting soft information about

new ventures, which helps investors evaluate among competing funding possibilities. We therefore hypothesize:

Hypothesis 1: The likelihood of a firm being funded in an ECF pitch is more sensitive to soft information than hard information.

## 2.2 Networks effects: amplifying information

As we have seen, the curation of early stage investments in physical space incurs high transaction costs of information acquisition, pooling, and dissemination (Manigart & Wright, 2013). As a result, the scale at which early stage equity markets can operate is limited. In contrast, the architecture of ECF platforms strongly facilitates scaling of the network and can greatly amplify the impact of information flows (Evans & Schmalensee, 2016; Goldfarb & Tucker, 2019). Thus, digitalization of the investment process engages a much larger set of potential investors (Gomber et al., 2017). This allows ECF platforms to exploit economies of scale in the provision of information (Varian et al., 2004) as well as important network externalities (Katz & Shapiro, 1994). In a network, because network effects generate positive feedback loops (Arthur, 1990) and increasing returns to scale (Eisenmann et al., 2006), the value of an individual's membership increases when another user joins. To be successful and stave off competition, social media-based platforms need to scale quickly and grow both sides of their networks. Acs et al. (2020) argue that the architecture of platforms primarily acts to facilitate matching via lower search costs, lower reproduction costs, and lower verification costs, relative to traditional market exchanges. Network effects mean that each of these costs is further reduced by network size (Goldfarb & Tucker, 2019). Network effects have been documented in numerous empirical studies across different industries (Birke, 2009; McIntyre & Subramaniam, 2009), but they are particularly pronounced in digital markets (Lambrecht et al., 2014). Digital two-sided platforms, like ECF, facilitate the matching of one group of users with another and show strong network effects (Evans & Schmalensee, 2016).

Two-sided platforms like ECF generate both direct (same side) and indirect (cross) network effects (Farrell & Saloner, 1988; Katz & Shapiro, 1994). The platform facilitates direct exchanges between investors, on the

one side, and entrepreneurs, on the other (Evans, 2008; Rochet & Tirole, 2003, 2006; Rysman, 2009). Direct, or same-side, network effects in the ECF context occur when, for example, previous successful examples of funding in a sector, region, or peer group encourage other entrepreneurs to pitch or when the increasing size, knowledge, and experience of the investor network attracts more investors. Indirect, or cross network effects occur when a larger number and higher quality of entrepreneurs attract more investors, or the growing scale of the investor pool leads more entrepreneurs to seek funds in this way (Butticè et al., 2017)<sup>1</sup>. Same-side investor network effects may improve members' interpretation of information about the quality of the pitch (Spence, 2002). Such ideas also find resonance in the literature on how crowds or networks, composed of both experts and novices, impact investment decision-making (Budescu & Chen, 2015; Lin & Viswanathan, 2016; Mollick & Nanda, 2016; Müller-Trede et al., 2018; Palley & Soll, 2019). On ECF platforms, as new network members with similar investment goals join, the stock of complementary skills and knowledge within the network increases as does the opportunity for members to communicate with one another. Moreover, because the architecture of ECF platforms increases the ease of communication and reduces its costs, members of larger networks will have more connections through which to engage in pitch evaluation (Evans & Schmalensee, 2016). Hence, as the network size increases, the provision of entrepreneurial and investor information will be amplified. Same-side network effects also benefit from larger numbers of potential investors whose diverse but complementary knowledge can be brought to bear on the interpretation of information from entrepreneurs (Rochet & Tirole, 2003). Larger networks produce more investor generated information which likewise needs to be interpreted. Thus, as its size increases, the capability of the network to evaluate pitch quality also increases (Caillaud & Jullien, 2003). Since ECF platforms are efficient in lowering the cost of pooling and disseminating information (Vulkan et al., 2016), the larger the network, the greater the potential to amplify information.

<sup>1</sup> In the ECF context, most entrepreneurs pitch for equity financing once or only a few times, whereas investors can invest in multiple pitches. Thus, entrepreneurs form a looser network than investors, whose increasing number is more salient to the platform for the potential supply of capital they represent.

However, the impact of network effects is not symmetric between hard and soft information. Moreover, because its collection, storage, and interpretation are standardized, hard information will be less dependent than soft information on the growth of the network. Hard information has less scope for interpretation; hence, there will be fewer benefits through network effects on understanding that type of information. Soft information, on the other hand, is grounded in experience and expressed as opinions, projections, and commentary. Since many firms raising equity capital via crowdfunding have only recently begun to operate, the quality and future profitability of their business model are extremely difficult to judge (Leboeuf & Schwienbacher, 2018) and investor judgements will draw relatively more on interpretation. Whereas hard information requires lower levels of interpretation from multiple perspectives, soft information benefits from a larger and wider pool of potential investors. Collectively, investors can extract meaning about the true nature of the underlying information (Weick, 1995) that soft information transmits and their ability to do so will be increased as network effects become more pronounced. In digital environments, the nonlinear increase in the exchange of information about pitch quality associated with the growth in the size of the network means that the ability of investors to use soft information to evaluate pitches increases with scale. Hence, larger networks amplify the exchange of information and the efficiency of the resulting matching process (Evans & Schmalensee, 2016), and this effect is more marked for soft than for hard information. This leads us to suggest that the complementarities as the network grows between information provision and size of the network will be more pronounced for soft information. Therefore, we hypothesize that,

**Hypothesis 2:** In an ECF pitch, as the size of the network increases, it more strongly amplifies the impact of soft information than hard information on the likelihood of a firm being funded.

### 2.3 Network effects during the pitch

How network size influences investor decisions can also be considered from the perspective of the accumulation of funding offers during each pitch. To some extent, with a focus on the shape of the

accumulation function, this issue has been addressed in the literature. However, our concern is with the complementarities between information exchange and network effects. To this end, we must consider how to characterize the provision of information within the pitch. In capital market theory, this is often captured using an heuristic, adaptive expectations, whereby investors' predictions about future outcomes are based on previously observed choices weighted by their time of occurrence (Barberis & Thaler, 2003; Hirshleifer, 2001). As in other capital market contexts, investors rely on recent historic data and information to help set their expectations (Bauman & Miller, 1997). Thus, the information about the pitch generated up to the date when the investor is making her decision is encapsulated in the history of previous investments and their weighting of previously received information.

As we have seen, an ECF platform taps into the network effects of two-sided platforms to reduce information asymmetries between investors and entrepreneurs. Unlike other early venture financing processes, the platform architecture is highly scalable and information is instantaneously available to all users. The platform can cheaply accommodate and exploit larger and larger networks. As new members join, the information contained within the network increases, as does communication between members. We have shown how same-side or direct network effects can improve the interpretation of information about the quality of the pitch, with network effects operating in a complementary fashion. Information can be amplified more effectively within a larger network. Hence, we propose that during the pitch, network effects can have multiplicative effects on the information from previous investments and further increase the supply of funds offered to entrepreneurs. As previously, this occurs because new information ripples faster and farther: larger networks will improve both the interpretation of information about past investments and the speed with which that information flows around the network. As the network increases in size, the quantity of information generated also increases, along with the opportunity for it to be discussed and evaluated by a set of investors whose expertise is increasingly likely to be more diverse.

Therefore, we expect that as the network increases in size, the quantity of information exchanged will increase

as will the opportunity for it to be discussed and evaluated by investors whose expertise is more likely to be diverse. Moreover, larger networks increase the likelihood that multiple minority opinions will be presented, noticed, and assessed (Parker & Van Alstyne, 2005). Hence, we propose:

Hypothesis 3: During an ECF pitch, the response of investors to previous investments will be amplified as the size of the network increases.

### 3 Methods

#### 3.1 Data

Our dataset captures the complete history of investments made by each of the investors in every equity pitch on the CrowdCube platform, 2011 to mid-2015; a network of 165,000 investors and all 835 pitches. A number of previous quantitative studies have used data gathered externally from the CrowdCube website. The samples vary in terms of the number of pitches included and the observational time period. For example, Vismara (2016) used 187 posted pitches on CrowdCube between 2011 and 2014, Walther-Borm et al. (2018) use a restricted set of 277 firms raising equity finance between 2012 and 2015; Vismara (2018) on 132 equity offerings in 2014; Cumming et al. (2021) 167 offerings between 2013 and 2016; Shafi (2019) used 200 campaigns between September 2015 and August of 2016; Cumming et al. (2019) used a sample of 491 offerings 2011–2015; Nguyen, Cox, and Rich (2019) 104 campaigns that between August 2015 and February 2016. Finally, Kleinert et al. (2020) examine 221 business plans from equity offerings between April 2017 and April 2018, and Ralcheva and Roosenboom (2020) whose observation window is 2012–2017 and includes 1303 CrowdCube campaigns. Our work builds on and extends previous research. We use internal platform archived investment data, which is de-identified for the purpose of the analysis. Thus, all of our variables and especially our dependent variables are actual amounts invested on the platform. Our underlying data are complete and account for such events as reversal of commitments (Meoli &

Vismara, 2021). In addition, our measures of network effects depend on accurate counts of investors and investment events before and during the pitch window.

#### 3.2 Specification of estimating equations and dependent variables

We estimate two equations. The first explores how soft information and network size affect the likelihood that a pitch is funded, namely, that offers to invest reach or exceed target of the amount that entrepreneurs request, while the second equation analyzes the impact of network externalities on information flow within each pitch.

The first estimating Equation (1) explores the determinants of success in pitches adding to the literature the unique perspective of the conceptual distinction between soft and hard information and additional data on archived data on networks. We follow the literature and model this process using a probit estimator (Maddala, 1992) to explain the likelihood that a particular pitch reaches (or exceeds) its investment target before the offers to supply funds expire. Variables in Equation (1) distinguish between soft and hard information, which allows us to test hypothesis 1, and include network effects as moderator, which allow us to test hypothesis 2. Thus,

$$\Pr(\text{pitch funded}) = F \left( \text{hard information, soft information, network size} \right. \\ \left. \times \sum \text{informational variables, control variables} \right) \quad (1)$$

Hypothesis 1 is tested via hierarchical model using changes in the log-likelihood and significance of the coefficients on the variables proxying for hard and soft information respectively. We propose that the effect on the probability of funding will be greater for the latter group of variables than for the former. Hypothesis 2 is also tested through Equation (1), by the sign and significance of the coefficients on the moderating effect of network size on the hard and soft information variables respectively. Hypothesis 2 implies that the moderating effects of network size on soft information will be greater than those on hard information.

Equation (2) describes the dynamic process driving the offer of funds by individual investors during each pitch, placed within the context of the pitches against which it was competing and the size of the network at

the time. We propose that the information about the pitch generated up to the date when the marginal investor is making her decision to be encapsulated in the history of previous investments. We use an autoregressive (AR) model where the dependent variable is the daily accumulated funding amount per pitch. We therefore estimate an equation, specified here in a one period lag form<sup>2</sup>, as:

$$I_{it} = aI_{it-1} + B\text{networksize} \times I_{t-1} + e_{it} \quad (2)$$

where  $I$  represent the investment into project  $i$  on day  $t$ , and  $e$  represents an iid error term. Hypothesis 3, concerning the moderating effect of network size on information flows within the pitch, implies that the coefficient  $\beta$  is significantly greater than zero.

### 3.3 Specification of independent, moderator, and control variables

#### 3.3.1 Independent variables

In Equation (1), we operationalize hard and soft information based on the definitions stated earlier. Firm employment, at the time of the pitch (logged to address non-normality); firm age (logged); firm location (Greater London coded as 1, 0 otherwise); firm industry (service coded as 1, 0 otherwise); and entrepreneur's gender (male coded for 1, female as 0) are all treated as hard information. They are verifiable facts that are not easily alterable in the short-term, and about which there is a general agreement. Likewise, information on whether the firm had a previously successful equity crowdfunding raise on the platform (yes coded as 1 and no as 0 in each) and if it has received early investments<sup>3</sup> (yes coded as 1 and no as 0 in each) before the pitch started are both examples of hard information. Each of these is verifiable commitments in the life of the firm and constitutes information that can be codified and stored.

Soft information, on the other hand, includes firm valuation (logged), by which the entrepreneur indicates

<sup>2</sup> In our empirical work, we estimate with up to seven lags to check for robustness of our results to the dynamic specification.

<sup>3</sup> Entrepreneurs often organize for investors who would probably anyway have invested (friends, family, even angels) to pledge investments at the start of the pitch, to try to build early momentum. Over the period that we include in our analysis, entrepreneurs were not required to secure such early investors, but they were given a discount on those transactions if they did. Our dichotomous variable only seeks to capture whether the entrepreneurs brought investors with them in the early stages of the pitch.

their view of the price for the company and therefore the cost of equity investments; this sometimes changes during the pitch.<sup>4</sup> The entrepreneur also has to indicate their view of the growth prospects of the firm; the expected employment growth (logged). Both variables are subjective and have the forward-looking quality that is the hallmark of "loosely" verifiable soft information. Soft information also includes the largest amount invested as a proportion of the amount of funding requested. Investors can invest piecemeal or all at once, and this amount can change during the pitch; thus, it is open to interpretation as to the meaning behind the investment. Similarly, we take account of the number of followers (logged) in the pitch on the platform. Although observable, this measure is soft information because it conveys popularity in a quantitative way, but it does not indicate sentiment nor the actual level of investment interest in the pitch. In a test of robustness, and because of potential collinearity, we also included a related variable which reflects the number of posts per pitch in the chat area of the platform, soft information for similar reasons. Finally, revaluation change (measured as a proportion of the firm's value) captures information about whether during the pitch process there has been an attempt to revalue the firm's equity. Much like valuation information, revaluation provides a forward-looking opinion about the prospects of the firm, but its meaning is soft and subject to dispute. All variables except for those which are dummy coded enter the regressions mean-centered. Finally, in Equation (2), distributed lagged values of amount invested within each pitch on a given day are the independent variables of interest.

#### 3.3.2 Moderator variables

Both equations specify network size as a moderator of the independent variables. Our benchmark measure of network size (specification (1)) is the number of investors in the network at the start of each pitch. This variable enters the regression in logs and is mean-centered. However, as with most social networks, ECF platforms have a large number of members who are either always inactive or become inactive after a single

<sup>4</sup> The entrepreneur has to propose an amount that they seek to raise via the platform and to indicate the proportion of shares being offered in return. Taken together, these determine the valuation of the firm. In practice, the valuation is the most frequently discussed piece of information in most pitches.

bid<sup>5</sup>. Thus, we also test for network effects using specification (2) the number of bidders in the network 3 months prior to the pitch, and specification (3) the number of investors who register on the platform immediately prior to the pitch launch. Moreover, we also tested specification (4) the network size variable scaled by the number of pitches that are trying to raise money at the same time in order to capture the idea that as the network grows the number of entrepreneurs rises as well. We present the results using specification (1); the remaining specifications (2), (3), and (4) were conducted as robustness tests.

### 3.3.3 Control variables

In Equation (1), we control for differences in the macro-economic environment over time by including year dummies as well as the number of competing pitches on each day that the pitch was live on the platform. We opted to minimize the number of controls in the model. However, in the process of testing the robustness of our regressions, we included many of the control variables previously used in the literature (e.g., whether the pitch offered tax incentives, dual class share offering as well as the number of competing pitches on the day the focus pitch was funded, whether the pitch had overfunded, whether it offered rewards). Although a number of these variables had been of focal interest in other studies, in the context of our analysis and our focus on understanding the effects of soft versus hard information and network size, these controls did not alter the results or add explanatory value. In addition, we include the number of competing pitches on each day that the pitch was live on the platform. In Equation (2), we use a daily lag structure.

## 4 Results

In this section, we briefly highlight the descriptive results and report findings from testing our hypotheses based on estimating multiple specifications of equations

<sup>5</sup> For example, friends and family of an entrepreneur who joined the network to watch or participate in a particular pitch or potential investors who enter and watch the platform in search for an opportunity.

(1) and (2). Variable means, standard deviations, and correlations are reported in Table 1 for Equation (1). After accounting for missing values, Equation (1) consisted of 800 firm observations and dynamic Equation (2) consisted of 72,315 investment observation points. As Table 1 shows, the average firm is 3.3 years since founding and has 4.3 employees. Approximately 35% of the firms are located in the greater London area and with 15% in central London 58% are in the service industries. Thirteen percent of the entrepreneurs pitching to raise funds are women. The average valuation of a company offering equity is approximately \$3 million. The largest amount per pitch averaged \$37,037. Of the companies that pitched, three percent had raised equity crowdfunding before, and four percent received investment pledges either before or immediately as the pitch opened. From the data for Equation (2), we can report that the average amount raised per pitch on a daily basis is \$2,153 (in the analysis log transformed) and the correlation coefficient between daily amount raised per pitch and network size at the launch of the pitch is  $r=0.212$ . The number of observations in the analysis for Equation (2) is 72,315. There is no significant multicollinearity in the regressions and the average VIF scores are within acceptable norms.

### 4.1 Structure of reported results

The main results are reported in Tables 2 and 3. The specifications of Equation (1) are reported in Table 2. In order to test our hypotheses using hierarchical model testing, we present an expanded regression model set consisting of 9 models, which can be viewed in stages. We estimated a control model (1). Models (2–4) present the probit regressions for the main effects, independent, hard, and soft information variables. Model (5) adds to this the main effect of the network size moderator. Models (6–7) respectively include all hard and soft variable interactions as blocks, and models (8–9) present the fully specified models with all interactions: (model 8), at first, and then a final more parsimonious specification (model 9). The Wald Chi-square test shows that all the models are statistically significant at  $p<.001$ . The pseudo R-squared for all the models is reported and ranges from 0.080 in the control model (1) to 0.531 in the fully specified model (model 8) and 0.526 in the parsimonious model (model 9). The log-likelihood for each model is reported and the difference in log likelihood (chi-squared distributed) is used to test model fit

**Table 1** Descriptive statistics for probit regression

		<i>M</i>	<i>SD</i>	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Funded	0.33	0.47													
2	Firm size	4.31	7.76	0.254												
3	Firm age	3.32	2.93	-0.119	-0.055											
4	Location	0.15	0.35	0.099	0.065	-0.075										
5	Gender	0.13	0.33	0.064	0.031	-0.009	-0.019									
6	Industry	0.58	0.49	-0.204	-0.237	0.135	-0.026	-0.015								
7	Firm valuation	3,013,572	1,369,215	0.099	0.427	0.067	0.053	-0.006	-0.273							
8	Projected growth in employees	6.62	21.3	0.036	0.007	-0.045	0.061	-0.036	-0.051	0.003						
9	Largest amount invested	37,037	200,770	0.409	0.237	-0.115	0.071	0.044	-0.078	0.129	0.025					
10	Early investment in pitch	0.04	0.2	0.145	0.045	0.040	0.006	0.018	0.109	-0.035	-0.005	0.075				
11	Prior crowdfunding raises	0.03	0.17	0.121	0.026	0.058	0.069	-0.004	0.080	-0.018	-0.001	0.049	0.037			
12	Number of investors following pitch	56.42	85.02	0.328	0.100	-0.132	0.135	0.069	-0.011	0.040	0.020	0.546	0.073	0.028		
13	Revaluation offers	0.11	0.31	0.213	0.131	-0.002	0.001	-0.003	0.020	0.033	-0.013	0.184	0.151	0.006	0.171	
14	Network size	66,923	46,941	0.237	0.574	-0.243	0.006	0.011	-0.401	0.334	0.059	0.280	0.006	-0.042	0.022	0.135

*N*=805; *p*<.05 for all *t*>.065Firm valuation and largest amount invested in expressed in USD  
*M*(*SD*) for variables unlogged and uncentered

**Table 2** Probit regression predicting successful equity crowdfunding: moderating effect of network size

	Info type	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)
Firm size (ln)	Hard	0.22*** (0.05)	0.035*** (0.07)	0.36*** (0.07)	0.037*** (0.07)	0.18*** (0.08)	0.28*** (0.09)	0.31*** (0.09)		
Firm age (ln)	Hard	-0.006+ (0.03)	-0.01 (0.04)	-0.01 (0.04)	-0.10 (0.06)	-0.01 (0.04)	0.04 (0.10)	0.00 (0.04)		
Location	Hard	0.24+ (0.14)	0.07 (0.15)	0.06 (0.15)	0.17 (0.17)	-0.05 (0.17)	-0.04 (0.19)	0.07 (0.17)		
Gender	Hard	0.20 (0.14)	0.22 (0.16)	0.26 (0.20)	0.15 (0.18)	0.06 (0.19)	0.16 (0.18)			
Industry	Hard	-0.20+ (0.12)	-0.31* (0.13)	-0.32* (0.130	-0.54** (0.15)	-0.13 (0.15)	-0.27 (0.17)	-0.14 (0.16)		
Early investment in pitch	Hard	1.14*** (0.24)	1.06** (0.22)	1.07*** (0.22)	1.09*** (0.23)	1.30*** (0.23)	1.33*** (0.24)	1.33*** (0.24)		
Prior crowdfunding raises	Hard	1.16*** (0.27)	1.15** (0.28)	1.15*** (0.29)	0.88* (0.35)	1.50*** (0.37)	1.19*** (0.40)	1.20*** (0.40)		
Firm valuation (ln)	Soft	-0.111+ (0.06)	-0.24*** (0.07)	-0.24*** (0.07)	-0.18* (0.08)	-0.45*** (0.08)	-0.59*** (0.10)	-0.60*** (0.10)		
Projected growth in employees (ln)	Soft	0.27*** (0.06)	0.29*** (0.07)	0.30*** (0.07)	0.23*** (0.07)	0.39*** (0.07)	0.33*** (0.08)	0.35*** (0.08)		
Largest amount invested (ln)	Soft	0.18*** (0.04)	0.21*** (0.04)	0.21*** (0.04)	0.29*** (0.05)	0.45*** (0.06)	0.52*** (0.07)	0.50*** (0.06)		
Number of investors following pitch	Soft	0.20*** (0.05)	0.16*** (0.05)	0.16*** (0.05)	0.16*** (0.05)	0.58*** (0.10)	0.61*** (0.11)	0.63*** (0.11)		
Revaluation change percentage	Soft	0.38 (0.25)	0.58* (0.25)	0.58* (0.25)	0.57* (0.28)	0.11 (0.40)	0.02 (0.44)	0.06 (0.43)		
Network size (ln)				-0.11 (0.11)	-1.34*** (0.27)	0.86*** (0.29)	-0.11 (0.39)	0.35 (0.30)		
Firm age × network size	Hard				0.11 (0.07)		-0.05 (0.10)			
Firm size × network size	Hard				-0.34*** (0.06)		-0.37*** (0.10)	-0.43*** (0.10)		
Location × network size	Hard				-0.20 (0.19)		0.30 (0.23)			
Gender × network size	Hard				0.13 (0.25)		0.29 (0.22)			
Industry × network size	Hard				0.29+ (0.17)		0.29 (0.25)			
Early investment in pitch × network size	Hard				0.13 (0.43)		0.19 (0.40)			
Prior crowdfunding raises × network size	Hard				-1.27+ (0.21)		-1.23+ (0.73)	-1.35+ (0.79)		
Firm valuation × network size	Soft					0.21* (0.10)	0.44*** (0.13)	0.47*** (0.13)		
Projected employee growth × network size	Soft					-0.43*** (0.09)	-0.30*** (0.10)	-0.37*** (0.10)		
Largest amount invested × network size	Soft					0.31*** (0.04)	0.34*** (0.06)	0.32*** (0.05)		
Number of investors following pitch × network size	Soft					-0.54*** (0.10)	-0.56*** (0.11)	-0.58*** (0.12)		
Revaluation change percentage × network size	Soft									
Number of competing pitches							1.23+ (0.73)	1.42+ (0.78)	1.33+ (0.77)	
										0.47+ (0.27)
										0.38 (0.27)
										0.30 (0.25)

**Table 2** (continued)

Info type	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)
Constant	-0.93** (0.26)	-0.33 (0.30)	-0.02 (0.29)	0.94* (0.37)	0.74+ (0.43)	0.98+ (0.59)	-0.13 (0.62)	-1.56+ (0.85)	-1.37+ (0.81)
Pseudo R-squared	.080	0.152	0.252	0.320	0.321	0.372	0.500	0.531	0.526
Log likelihood	-466.79	-427.02	-377.12	-340.19	-339.81	-314.00	-250.17	-234.52	-237.38
Change in LL from model (1)									
Change in LL from model (3) to model (4)									
Change in LL from model (5)									
Change in LL from model (7) to model (8)									
Model Wald Chi-square									

N= 800 B(SE) clustered by pitch; LLO= 500.3. All changes in LL (-2LL) are significant at  $p<.001$ ; ; year effects included. + $p<.1$ ; \* $p<.05$  \*\* $p<.01$  \*\*\* $p<.001$

**Table 3** Linear regression of daily amount bid in pitch: moderating effect of network size at launch

Variables	Model (1)	Model (2)	Model (3)
Lag daily amount bid in pitch (ln)	0.560** (0.0128)	0.560** (0.0128)	0.515 ** (0.0133)
Network size at launch of pitch		0.00238 (0.0115)	0.211** (0.0436)
Lag daily amount in pitch $\times$ network size at launch of pitch			0.10688 (0.0156)
R-squared	0.344	0.344	0.352
F	688.5	573.3	510.9

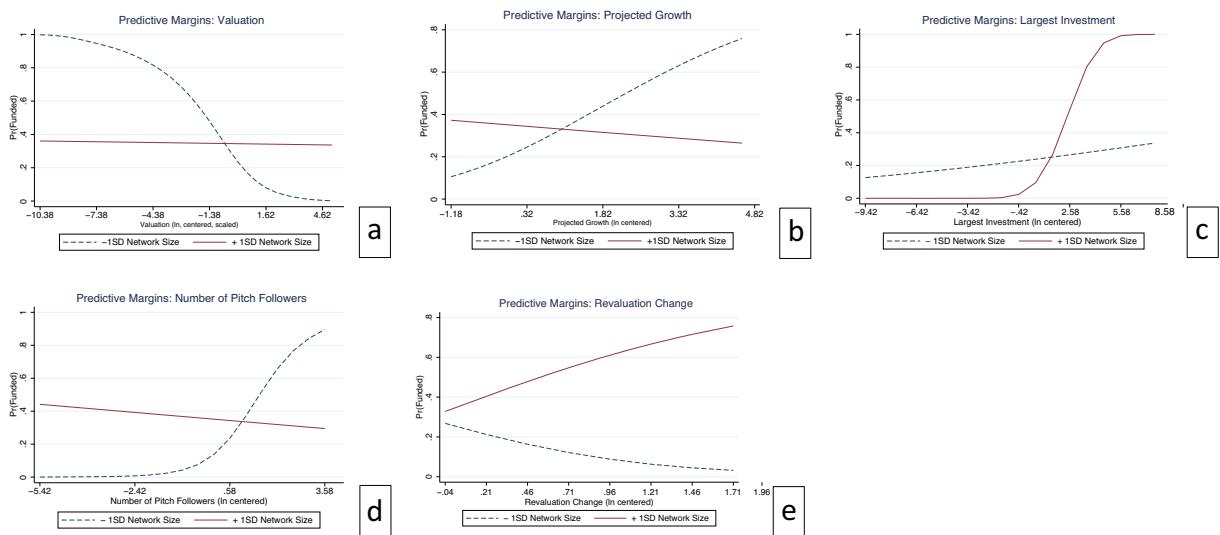
N=72,315 + $p<.1$ ; \* $p<.05$ , \*\* $p<.01$

for hierarchical groups of variables. In addition, Figures 1–5 show plots based on margins and help to interpret the interaction effects.

Table 3 contains the estimates for Equation (2). The table reports three models where the lagged investment amounts are captured in a single lag, as specified in Equation (2). In the second model, we add the direct effect of network size. In model (3), we further add the moderating effects of network size on the lagged dependent variable.

## 4.2 Summary of results

In Table 2, model (1) provides the baseline control model; model (2) adds the hard information independent variables as a group; model (3) adds the soft information as a block; and model (4) combines both. We test the relative effect of hard and soft information by comparing the change in log-likelihood between the baseline, model (1); the hard information variables in model (2) (79.77; 7df); and the soft information variables in model (3) (179.34; 5df). This reveals that at  $p<.001$ , model (2) is a significant improvement on the baseline model (1) but that model (3) fits significantly better than model (2). Thus, whether considered by itself in model (3) or jointly with hard information in model (4), soft information more significantly impacts the likelihood of a pitch being funded. Moreover, as the change in pseudo  $R^2$  shows, the addition of soft information offers substantial incremental explanatory power to the model; the pseudo  $R^2$  is 0.8 in model 1; 0.152 in model 2; 0.252 in model 3 and 0.32 in model 4. Thus, variables capturing soft information add more to the explanation of successful pitches on the ECF platform than variables capturing



**Fig. 1** Predictive margins: **a** valuation, **b** projected growth, **c** largest investment, **d** number of pitch followers, **e** revaluation change

hard information, though they both have significant effects on the outcomes.

Looking at the coefficients of the variables, we note that larger firms (in terms of employee numbers) are more likely to be funded, as are firms that have raised money through crowdfunding before and have early investors in the pitch. However, the majority of hard information variables, such as the industry to which the firm belongs, the location of the firm, the gender of its founders, and the age of the firm, do not significantly affect the likelihood of the firm being funded. On the other hand, we observe that most of the indicators of soft information do significantly affect the likelihood of the pitch outcome. Firm valuation is negatively related (with  $p < .01$ ) to the probability of pitch success. Firms that project a future of better business prospects as reflected in terms of projected employment growth are also more likely to be funded. Likewise, the largest amount invested during the pitch and the total number of investors who follow the pitch significantly predict funding (all at  $p < .01$ ). Revaluation of the firm's valuation during the pitch is significant when considered in model (4).

Hypothesis 2 proposes that the effects of the information generated on the likelihood of a firm being funded increases with the size of the network, more markedly for soft than hard information. We test this on estimates of Equation (1) in Table 2, models 6–9, and find strong support for the hypothesis. Model (6) additionally enters the hard information variables moderated

by network size; model (7) does the same with soft information; model (8) includes both; and model 9 is a parsimonious representation of model 8. We observe that a number of the interactive effects between hard and soft information and network size are statistically significant. In terms of hard information variables, only firm size significantly interacts with network size to affect the likelihood of a pitch being funded. More consistently, we see that the interactions between network effects and soft information variables such as valuation, projected employment, largest amount invested, numbers following pitch, and revaluation of equity are significant. Assessing hard and soft information from a hierarchical approach, we find that the change between model (5) and model (6) is significant (51.62; df 7) but a corresponding change between model (5) and model (7) reflecting soft information suggests a much better fit of the model (179.28; df 5). Moreover, the addition of soft information to model (6) results in a clear improvement to the fully specified model 8 (158.85; df 5). Correspondingly, the change in pseudo  $R^2$  moves from 0.371 to 0.372 between model 5 and 6, but to 0.500 in model 7. However, both soft and hard information are relevant in explaining pitch outcomes: the pseudo  $R^2$  is even higher in model 8 at 0.531. Overall, the models are notable for explaining a significant portion of the variance in the likelihood of a pitch being funded.

Hypothesis 3 concerns the moderating effects of network size on lagged investment, which we argue

encompasses the new information in the system during the pitch. It is tested on the results reported in Table 3, in which model 1 is the base model including a single lagged investment variable; model 2 adds the moderator, network size; and model 3 adds the interaction effect between the lagged investment and network size. We test hypothesis 3 using the results from model 3 of Table 3. We note that the coefficient on the interactive term between lagged investment and network size is positive and significant ( $p < .001$ ) providing strong support for hypothesis 3.

#### 4.3 Robustness checks

We undertook a number of additional tests based on Equation (1). For example, within each category of information, we included the interactive effects singly as well as jointly as reported in Table 2. As noted above, we also ran specifications which excluded singly the soft and hard information variables within each category which were found not to be significant within this dataset. More importantly, the specification of the direct and moderating effects did not alter the sign and significance of the other main effects, despite the complexity of the specifications the structure of the results remains the same.

We conducted additional tests with soft information variables that are interesting operationalisations of the construct but are highly correlated with the soft variables we already included. For example, the number of forum posts that was offered for a given pitch is meaningful soft information but is highly correlated ( $r = .74$ ) with the number of followers. In addition, we tested alternative specifications which instead of valuation use target amount of the raise and equity that the company is willing to give up. These additional variables all have predictable signs, but unsurprisingly given the collinearity, are sometimes not statistically significant. Finally, for the estimates of Equation (2), we investigated singly and jointly lag structures up to seven and have undertaken regressions including interactive effects for all lag structures up to five. The pattern of results was not affected, so we report the one lag structure.

Importantly, we also tested alternative specifications of the network size variables. These include the number of bidders in the network 3 months prior to the pitch, and specification; the number of investors who register on the platform immediately prior to the pitch launch. Moreover, we also tested the network size variable scaled by the number of pitches that are trying to raise

money at the same time in order to capture the idea that as the network grows the number of entrepreneurs rises as well. These variables address concerns that the entire network built over four years may include many dormant members, who therefore do not contribute. The results from the specification of recent bidders are similar to network size, but the results for recent registrants are slightly stronger than for the other two. The conclusions with respect to our hypotheses are the same in these specifications.

## 5 Discussion

Three questions guided our inquiry in the effects of ECF platforms. First, we wanted to establish the central role of the exchange of soft information. Next, we focused on the size of the network, asking whether increasing numbers of investors on the platform amplifies the effects of soft information on the likelihood of a project receiving funding. Finally, we explored network effects during the pitch, searching for evidence that the dynamic path of investment was sensitive to the size of the network.

The empirical results show support for all our hypotheses. In brief, we find support for the impact of information generation on the likelihood of a pitch success, more markedly for soft than hard information. We also find evidence for the existence of network effects that amplify the role of soft information. Moreover, we find that the effect of previous decisions on current investments is amplified as the network size increases. These results hold for a variety of measures of soft information, of network size, and for the number of lags in the autoregressive investment Equation (2). We elaborate on the findings and limitation in this section and implications in the concluding section.

### 5.1 How do investors behave in the presence of hard and soft information?

We have argued that ECF is best understood as an innovation in the digitalization of entrepreneurial equity markets (Belleflamme et al., 2015; Rysman, 2009; Goldfarb & Tucker, 2019). We have identified how the microstructure of ECF reduces transaction costs and addresses market failures caused by informational asymmetries between entrepreneurs and investors (Nagle et al., 2020). While previous work has

concentrated on signals, we focus on the distinction between soft and hard information. We argue that ECF reduces transaction costs via exchange of the latter because this is the informational problem caused by the uncertainty about the future prospects of entrepreneurial businesses, as well as by being scalable at low cost, allowing the investor community to benefit from network externalities. As a result, ECF platforms improve the matching between entrepreneurs looking for funding and investors looking for investments.

Our findings are consistent with these arguments. Soft information increases the probability of pitch success more than hard information. Soft information about the projected growth of the firm, the largest amount invested, and the number of investors following a pitch all have a positive effect on the likelihood of a pitch being funded. For example, as found in other studies (e.g., Moedl, 2020), the entrepreneur's valuation of their business has a negative effect on the likelihood of pitch success. A higher valuation implies that the investor is paying more per share and is therefore being invited to accept a more ambitious business plan from the entrepreneur. In addition, a higher valuation implies that relatively more shares are offered for sale at a given price (Hornuf & Schwienbacher, 2017). This suggests that the dispersion of ownership will be larger, and the influence of any particular investor on the entrepreneur will be lower, which raises agency issues and might de-motivate investors who seek to influence entrepreneurial activity. As mentioned above, we made a preliminary exploration of agency effects by considering the effect of dual class shares (A and B shares) (see also Cumming et al., 2019). In some pitches, only if an investor purchased more than a minimum stake set by the entrepreneur would those shares be voting (A) shares. We included the A share threshold in our regressions, but the coefficient was not significant. This is probably because the lower the threshold for A shares, the greater the dispersion of effective ownership but at the same time, the more influence would be purchased from a given (below the threshold) share, and these factors are offsetting.

*The moderating effects of network size* We argued that network size would amplify the impact of informational exchange on the likelihood of the pitch. ECF platforms are designed for rapid scaling, and as a two-sided network, they create the positive network effects that increase with the number of network members (Rochet & Tirole, 2003; Varian et al., 2004). We argued that this

effect would be stronger for soft rather than hard information signals because as additional members join, the stock of complementary skills and knowledge increases as would the opportunity for members to communicate. Soft information requires interpretation and meaning making, which benefits from larger and wider pool of potential investors. Our empirical evidence supports this hypothesis. Increasing network size amplifies soft information more markedly than hard. This result holds for a variety of measures of network size.

We use interactions plots in Fig. 1a–e to explore network size effects more thoroughly. Using the results in the more parsimonious model (9) of Table 2, we plotted the interactions of network size (moderator) with firm valuation, projected growth, largest amount invested, number of investors following pitch, and re-valuation change percentage (independent variables). In each figure, network size is set at one standard deviation above and below the mean (+1SD/-1SD). Figure 1a shows the interaction of firm valuation with network size. This effect is large: the graph suggests that in smaller networks the decrease in probability of being funded drops steeply with increasing valuation, whereas in larger networks, the decrease is more gradual. This is supportive of the view that the additional expertise associated with network size assists investors in evaluating the soft information in entrepreneurs' valuations of their own prospects. Figure 1b shows the interaction of network size and another soft variable, projected firm growth. The graph again illustrates how interpretations of soft information are sensitive to the size of the network. Hence, we observe that in smaller networks, the probability of getting funded increases with projected growth, but in larger networks, the probability gradually declines with growth projections. Once again, the greater expertise available to the larger networks dampens the impact of high entrepreneurial growth aspirations on the probability of being funded.

Figure 1c shows the interaction of largest amount funded and network size. Interestingly, these results suggest that the impact of above average offers of capital only become influential on pitch outcomes when the network size is larger, and even then, only when the largest amount invested is above the average. Thus, this shows little effect from the largest amount invested in smaller networks. However, in larger networks, while there is only a small effect from below average amounts invested, there is a steep rise in the impact of the largest amount invested on the probability of a pitch being funded above the mean

value of largest amount. Figure 1d shows that there is a trade-off between soft information generated through the pitch and the size of the network, indicated by the interaction of the number of investors following the pitch and network size. The graph suggests that, in smaller networks, increasing numbers of followers greatly improves the probability of a pitch being funded; this graph indicates the impact of additional exchanges of soft information on the likelihood of a pitch being funded. However, the effect does not hold in larger networks; indeed, the probability of being funded slightly falls as the number of followers increases.

Finally, we explore, in Fig. 1e, the impact of another important element of information revealed during the pitch—valuations of the business—and how this is affected by network size. Revaluations represent specific information revealed during the pitch about the future prospects of the business (Moedl, 2020). One might therefore expect that they would be associated with an increased likelihood of a pitch being funded. However, this is not always the case. In fact, the revaluation is, as expected positive in larger networks, but is actually negative in smaller ones. These offsetting forces probably explain why the overall interaction effect is only marginal in significance ( $p < .1$ ). One interpretation is that smaller networks find it hard to evaluate revaluations of the business: while perhaps, bringing valuation closer to expectations, they also undermine confidence in the entrepreneur and therefore bring the reputation of the business into question (Nagle et al., 2020). However, the greater availability of expertise in larger networks, and the greater information exchanges associated with this, helps investors to interpret the information better and therefore improve matching.

## 5.2 How do network effects impact the supply of funds during the pitch?

We turn next to analyzing the internal dynamics of the pitch. We suggest that information within the pitch can be modelled through an autoregressive process and propose that these dynamics are sensitive to network size; in particular that the impact of prior information is enhanced in larger networks. Our empirical work confirms this prediction: for example, in the single lag specification, the interaction between the lagged endogenous variable and network size has a significant positive effect. This finding is consistent with our previous results about the impact of the interaction between

network size and the provision of information on the probability that a pitch will be funded. The result further strengthens the argument that factors acting to enhance the provision of information, whether they be via network externalities or larger actual information flows reduce the asymmetries of information between entrepreneurs and potential investors and enhance the prospects of successful matching.

The fact that larger networks are subject to economies of scale might lead to a concern that the investment dynamics during a pitch might be explosive as network size increases. By this, we mean that as the network grows, any initial investment gets more strongly taken up by other investors, so that the first investment generates a stream of subsequent ones, at an accelerating rate. For example, Agrawal et al. (2011) argue that, because the process of investment is sequential, with funders drawing on accumulated capital as a signal of quality, the pitch process may create an information cascade (Bikhchandani et al., 1992; Anderson & Holt, 1997; Zhang & Liu, 2012; Vismara, 2018). For Easley and Kleinberg (2010), information cascades represent a form of irrational herding behavior because they entail people making decisions on the basis of other peoples' actions rather than their own information and judgement. Parker (2014) also highlights some of the irrational outcomes that may occur with path dependence in an equity crowdfunding context.

Our results are not consistent with that view. As one would expect, larger network size is associated with an increase in the effects of previous on current investment, but the effect tapers over time; the coefficient on the lagged endogenous variable(s) is always less than unity. For example, in model 3 of Table 3, the sum of the direct and interactive effects is  $0.515 + 0.106 \times$  network size. Within our sample, the network size is centered and in logs. At the maximum size of the network (1.67 in logs and centered), the sum of the adjustment effects is 0.692, which is much less than unity. This is again consistent with the argument that increased network size would also bring increased diversity of opinion and expertise.

## 6 Future research directions and implications

The development of equity crowdfunding has generated significant public debate. For some, ECF represents a dramatic new opportunity for early stage entrepreneurial

funding while for others the dangers of inappropriate investor choices and fraud loom large (Cumming & Hornuf, 2018). The rapid expansion in the number of platforms and the amounts raised (Dushnitsky et al., 2016; Dushnitsky et al., 2020; Estrin et al., 2018) suggests that ECF is managing to exploit new technologies to fill a gap in the market. We aimed to analyze how platforms are doing so.

We have developed a conceptual framework building on the way that digital platforms reduce transaction costs (Goldfarb & Tucker, 2019) and drawing on the specific architecture and microstructures of ECF platforms. Our aim has been to identify the mechanisms by which crowdfunding reduces the asymmetries of information which raise transaction costs in the market for early stage entrepreneurial equity finance. We have proposed that two characteristics of ECF platforms act to ameliorate these problems: first, increases in the provision and flow of soft information between entrepreneurs and potential investors; second, the interaction between the size of the network and the information flows which acts to amplify the impact of such information. The richness of our dataset has then allowed us to specify measures of these concepts, as well as to link them to investor behavior. We have been able to consider the investment process in depth, both in terms of the supply of funds made available each day within every pitch separately, as well as explaining the factors leading some pitches to succeed in reaching their financing targets while others fail.

Our findings confirm the relevance of our hypotheses in understanding the ECF process. Investors invest more within each pitch and pitches are more likely to be successful when information, especially soft information, is exchanged via the pitch processes. This is consistent with the view that it is indeed the lack of information that constrains socially beneficial investment, and that the cheap web-based provision and transmission of that information through the ECF platform can counteract the market failure. Moreover, our research unpacks the differences in the types of information that entrepreneurs and investors exchange. The distinction in a digital platform environment between soft and hard information has been occasionally invoked in the context of debt financing but not actively in the context of equity crowdfunding. Second, we confirm the relevance of network effects in identifying the advantages brought to the early stage investment process by ECF. This operates as a moderating effect; the size of the network

enhances the power of soft information in the pitch process and therefore leads investors to supply more funds and pitches to be more likely to succeed. We therefore conclude that the way in which equity crowdfunding platforms have designed their processes to exploit the low transaction costs characteristics of the web and to bring network effects to bear on investor decisions does increase the supply of funds to entrepreneurs in the early stages of their projects.

Clearly, there are a number of important directions for future research. We advanced to the equity crowdfunding literature ideas about the nature of information, soft and hard. To illustrate our theoretical point, we drew on a set of variables that, based on our definitional criteria, conform with the classification of soft or hard information. However, albeit important and accessible, these are not the only variables that could be tested. Entrepreneurs and investors exchange other soft information on discussion boards, through documentation. In addition, entrepreneurs offer soft information through press releases, various social media platforms, and through virtual or virtually disseminated meetings and seminars. Each of these provides a raft of soft information which the network of investors can analyze. Although we chose to stay within the bounds of structured soft information variables that were more easily accessible to the entire network, future research should consider in more detail the effects of unstructured information conceptualized as soft e.g., Ivanov & Knyazeva, (2017). Indeed, a robust stream of research in crowdfunding focuses signals from unstructured and visual presentations on all sorts of platforms (e.g., Cappa et al., 2020). This could be further considered in the context of soft and hard information. Furthermore, it is entirely plausible to release and test some of the definitional parameters distinguishing soft and hard information. For example, future researchers could ask questions about the extent of verifiability of soft and hard information, the time horizons in which such information can be changed, and the degree of consensus or agreement that can be expected in interpreting the information. Finally, it strikes us as possible that the dichotomy between soft and hard information may not be the lived reality of such information. We urge further theoretical development to consider and then test the distinct possibility that soft and hard information is laid out on a continuum with degrees of softness and hardness in between. Ours is the first attempt at taking the soft and hard information criteria and extending it to the

crowdfunding literature. Likewise, we urge more research into the properties of entrepreneur and investor networks on ECF platforms. In this paper, we argued that growing networks can amplify the effects of information processes and outcomes in digital entrepreneurial finance. We tested multiple operationalizations of networks to support our findings, yet additional work on the structure and evolution of the network would be of significant interest.

If detailed datasets can be identified, it would be interesting to explore other key implications of the transaction cost approach for ECF platforms. Our work has indicated intriguing relationships, for example, some degree of substitutability between network size and the provision of information within each pitch that merit further analysis. More generally, the framework could be extended to consider the impact of reputation effects, both concerning investors and entrepreneurs. Future research should build on current work (e.g., Eldridge et al., 2021) to consider the performance of entrepreneurial firms receiving ECF finance versus non-recipients: it will be important here to distinguish between the selection effect and the impact of the incremental funding.

Finally, one could say that we only consider the activities of one crowdfunding platform situated within a particular regulatory environment. Certainly, the ECF market has already seen the emergence of several organizational models and specializations. Alternative approaches include the use of nominee structures, fund structure, and investor led platforms. However, CrowdCube is the largest and one of the oldest and most important ECF platforms operating in the world today. Its model is diffusing across the globe and set to consolidate in the UK. Its scale and experience are hard to match and hold many generalizable insights about investor behavior. We acknowledge that there are differences which may play out differently on other platforms and in other geographies and hence propose future researchers also consider.

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