

# Latent Network Capital and Gender in Crowdfunding: evidence from the Kiva platform.

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## Abstract

Our paper provides novel empirical evidence based on 985 projects hosted on Kiva, a platform reaching 3.7 million borrowers, 81 percent of them women, assessing how the interplay between *Latent Network Capital* and gender of a project's proposer affects the Amount of funds raised. To this aim, we develop the notion of a latent network whereby two projects are linked if they share a funder, as they both benefit from the visibility of the funder signalling confidence in them. We then develop novel metrics to capture a project's *Latent Network Capital* through the project's Centrality within this latent network. We find that the *Latent Network Capital's* elasticity of the Amount of funds raised, while remaining positive, is lower for women's led projects than for male's led ones, further extending any pre-existing projects' gender gap.

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## *Keyword*

Crowdfunding, Latent Network Capital, Kiva, Gender Gap, Microfinance, Centrality.

### 1 Introduction

As a distributed system for raising money, Crowdfunding has been practised across disparate geographical regions for several centuries (Tavi, 2014). Due to the diffusion of online crowdfunding platforms, global Crowdfunding is estimated to be worth 14.2 billion in 2019 and is expected to grow to 28.8 billion by 2025 (Market data forecast, 2021). Kiva is a crowdfunding platform that has raised more than 1.5 billion dollars of loans with a 96 percent successful repayment rate. These loans reached 3.7 million borrowers across 76 countries, with 81 percent of them being women (Kiva, 2020). Kiva's funding is especially relevant for micro-enterprises and women in emerging countries. As a platform, it allows investors to back individual projects, either directly or through partnership organisations that assist in the facilitation of the loans. These partnership organisations play an essential role due to the nature of the loans' markets within the emerging world, where there is less access to the internet, and many micro-enterprises may not have the literacy and digital skills and internet access needed to set up an online crowdfunding campaign (Kiva, 2019).

This paper analyses the role of crowdfunding success by a project's latent network capital<sup>3</sup>, a form of social capital relevant for the Kiva micro-projects, built on the direct and indirect relations among funders of micro-projects. This type of micro-projects social *capital* is "*latent*" (i.e., neither *internal* nor *external*). It is based on relations among project funders, not those amongst project proposers since the analysed projects are small and too geographically dispersed to be directly connected among themselves. Secondly, this construct focuses and is operationalised in terms of "Network Capital" (Huggins, 2010) as it is built from the network

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<sup>3</sup> A term only used in a different framework by Shariff, (2018).

properties and metrics based on the direct and indirect connections established among projects by projects' funders. In this context, the Kiva platform plays a crucial role as digital infrastructure, enabling the formation of this latent network capital and potentially lowering the barriers to credit for the projects hosted on Kiva.

In more detail, this paper proposes to model and operationalise the *latent network capital* of a project, based on this project *centrality*, within a *latent network of projects* built around funders' choices to support these projects as publicly displayed on the Kiva crowdfunding platform.

We argue that contrary to other types of social capital analysed in the existing literature, discussed in the next section, *latent network capital* is an essential construct for the analysis of projects that are small and not directly connected among themselves, which is typically the case for micro-projects in emerging countries accessing funding through the Kiva platform.

Hence, in this paper, the *latent network capital* of a project will be captured by considering the set of direct and indirect connections of a project, with other projects latently established by having common backers. These latent network connections will be summarised using standard notions of *Centrality* derived from a *Social Network Analysis* literature.

Therefore, this approach utilises backers' behaviours to generate a latent network, meaning that if the same backer supports two projects, they are considered linked. This novel method is necessary to estimate the impact of *latent network capital* on the amount raised since the micro-projects have no direct way of being linked among themselves. At the same time, the visible support for two projects from a funder can act as a signal, from funders to other funders, of confidence about each of the supported projects, which provides a *latent* link between any pair of projects co-supported by the same funder.

Based on the collected empirical evidence from 985 projects hosted on Kiva, this paper focuses on how the impact of a project's *latent network capital* on the amount of raised loans varies,

depending on the gender of a project proposer. By exploring this key empirical issue, the paper also addresses the essential policy question of whether women, while making up most of the Kiva platform borrowers, might face gender-specific barriers in transforming their projects' *latent network capital* into increased funding. In this case, policy interventions should focus not only on facilitating the formation of *latent network capital* but also on addressing this gender asymmetry in its impact on Crowdfunding.

## 2 Literature Review & Hypotheses Development

Four main types of crowdfunding platforms have been identified, based on differing backer participation rights: reward-based, donation-based, equity-based, and lending-based (Giudici et al., 2013). In Kiva, a lending-based platform, money is returned later, and interest may be accrued.

Six alternative measures are usually considered in the literature to assess success in Crowdfunding: whether a project reaches its funding goal; the number of backers a project obtains, how much funding was raised, the rate at which the venture reached its funding goal (Ahlers et al., 2015), the *pledge per backer* (Kromidha and Robson, 2016), and the number of backing contributions within a given time-period (Boudreau et al., 2021). Given Kiva's rules on the lending process to micro-enterprises, we focus on the amount of funding raised by each project. Two key steps are needed to raise funds: first, the participants supporting the project must draw additional potential backers to the project and, second, these potential backers need to decide to support it financially. Fundamentally, a key aspect of crowdfunding success is whether backers can act as ambassadors to draw in other backers to support the projects (Stanko and Henard, 2017).

Furthermore, unlike the dichotomic decision to purchase a good, the backers of a project are free to support it at multiple different levels. Hence, success results from drawing attention to a project and then convincing potential backers that the project is a viable candidate for lending,

reflecting the funders' confidence about a project's worth. This motivates our focus on *latent network capital* as a key driver for the amount raised by a project, as it captures the confidence signals that funders send about projects.

The relevance of signalling is due to the pervasive presence of information asymmetry in traditional credit markets (Gorton and Winston, 2003), as shown in the seminal contribution by Stiglitz and Weiss (1981) in deriving the conditions for asymmetric information to lead to market failure.

Due to its decentralised platform-mediated decision structure, Crowdfunding is affected by extensive asymmetric information, usually analysed as arising between the funders and the proposers of projects (Belleflamme et al., 2010 and 2013 and Miglo, 2020, Davies and Giovannetti, 2018). A specific feature of asymmetric information in Crowdfunding is that some funders might have a greater knowledge of the quality and potential for success of the campaign than the creator itself, due to a better understanding of the technological limitations of the products available on the market, which implicitly affect the quality of the new product (Ibrahim, 2015). However, even more relevantly, in our case, information asymmetry about the quality of a project might also arise between funders who are knowledgeable about a project; maybe as they have backed it previously or they have invested time in reading the relevant platform dedicated project-page details and reports, and other funders who have not gone through this information processing activities, due to the cognitive cost of these efforts. This informational asymmetry among funders is specific to Crowdfunding due to the decentralised multi-projects-multi-funder nature of the funding platforms, where limited project-specific knowledge is required before choosing the project to invest in, especially for nonprofessional lenders.

To overcome the negative impact of asymmetric information, the better-informed party can signal the quality of a product to the less informed party (Ross, 1977 and Spence, 1978).

Additionally, Spence (1978) argued that signals must also be observable and manipulatable by the sender.

In the Entrepreneurial finance literature (Kim and Aldrich, 2005; Westlund and Bolton, 2003), *social capital*, as the ability to utilise goodwill generated within the fabric of social relations (Adler and Kwon, 2002), is often used in explaining how entrepreneurs benefit from it, in attracting funds for new ventures.

In the crowdfunding literature, social capital has been captured through online social networks metrics, for example, using projects' Facebook friendships (Ellison et al., 2007), as social networks sites enable users to construct a public or semi-private profile, which can be connected to other users based on a shared connection (Boyd and Ellison, 2007). The effect of social networks on Crowdfunding has been widely discussed in the literature. For example, Lu et al. (2014) found that Twitter promotions are positively correlated with the number of supporters for the crowdfunding project, and Mollick (2014), Moissejev (2013) and Kromidha and Robson (2016) identified a positive impact of social media on project funding. These examples, however, explore social networks that are external to the crowdfunding platform.

Colombo et al. (2015) extended the analysis of social capital by considering that a crowdfunding project can also generate its *internal social capital* by establishing relationships with other backers and funders. They captured this idea by utilising the number of previously backed projects by the creator of the current project as a proxy for *internal social capital*. At the same time, Buttice et al. (2017) further built on this work by examining the number of successfully backed projects by a project's creator. It is also important to acknowledge the related concept of community derived social capital, which Eiteneyer et al. (2019) utilised to explore how social capital was used to engage backers and advance product innovativeness.

*Network capital* was a concept first discussed by Huggins (2010) "to characterise ties held by firms and other organisations, as distinct from social capital's focus on the social interrelations of individual firm members" (Huggins et al. 2012) to enhance economic returns. Also, contrary to social capital, network capital is not location-specific. While this feature was envisaged for the global acquisition of innovation-driven organisations (Huggins, 2010), in our framework, this feature of network capital represents the global nature of the network of funders that support projects on Kiva.

In this paper, we develop metrics to operationalise the *latent network capital*. We postulate that this determines the effectiveness and range of signalling over the Kiva platform, ultimately affecting a project's funds.

Signalling has been used for studying success and future capital acquisition within Crowdfunding (Boudreau et al., 2015, Vismara, 2018 and Roma et al., 2021). In our setting, signals about projects sent by informed backers transmitted through the platform will have a range determined by the intensity of direct and indirect (*latent*) connections among projects, branching off from the original project. Hence, the reach of a signal of confidence in a project sent by a funder is bounded by the set of direct and indirect connections for each project within the latent network. Funding success for micro-entrepreneurs is likely to depend on this *latent* form of *network capital*, signalling the funders' confidence in a project success—to other funders and addressing some of the key informational asymmetries among funders.

#### *Network centrality as a proxy for latent network capital*

To operationalise a project's *latent network capital* in terms of centrality metrics, we define the two building blocks required to describe the Kiva network of projects formally. These are 1) the nodes -projects - and 2) their links. Our key assumption is that any two projects have a latent link when the same backer supports them. The backer is sending a signal that it shares confidence about both projects by supporting these two projects, leading to the publicly visible decision of backing them both. This backing choice is observable within the Kiva platform. This ensuing



link between the two projects acts as a signal sent by the backers to other backers, increasing the *latent network capital* for these two projects and their chances of achieving higher funding levels.

This signal links the two projects since, in a funding environment marred by asymmetric information, a shared signal of confidence by a backer is likely to affect other backers' decisions to fund these same projects.

However, to fully capture this *latent network capital* of a project as network centrality, we need to adopt some well-established social network analysis (SNA) techniques (Borgatti and Halgrin, 2011). *Centrality* has been identified in past work as key in interpreting the effect of social networks (Freeman, 1978), and its relevance can be traced back to Coleman et al. (1957).

Measuring *latent network capital*, based only on the number of direct links between projects, as *degree centrality*, would be missing relevant information, easily available through the network structure analysis, since *degree centrality* does not account for the "connections of my connections" within the network. Hence, to effectively capture the *latent network capital*, we need to focus on *centrality* metrics that also consider a project's *indirect connections*, or the "connections of my connections" that, we argue, are also of relevance. The key idea is that connecting to a poorly connected project is not equivalent to being connected to a well-connected one. Therefore, each project's connection needs to be weighted to reflect these asymmetries.

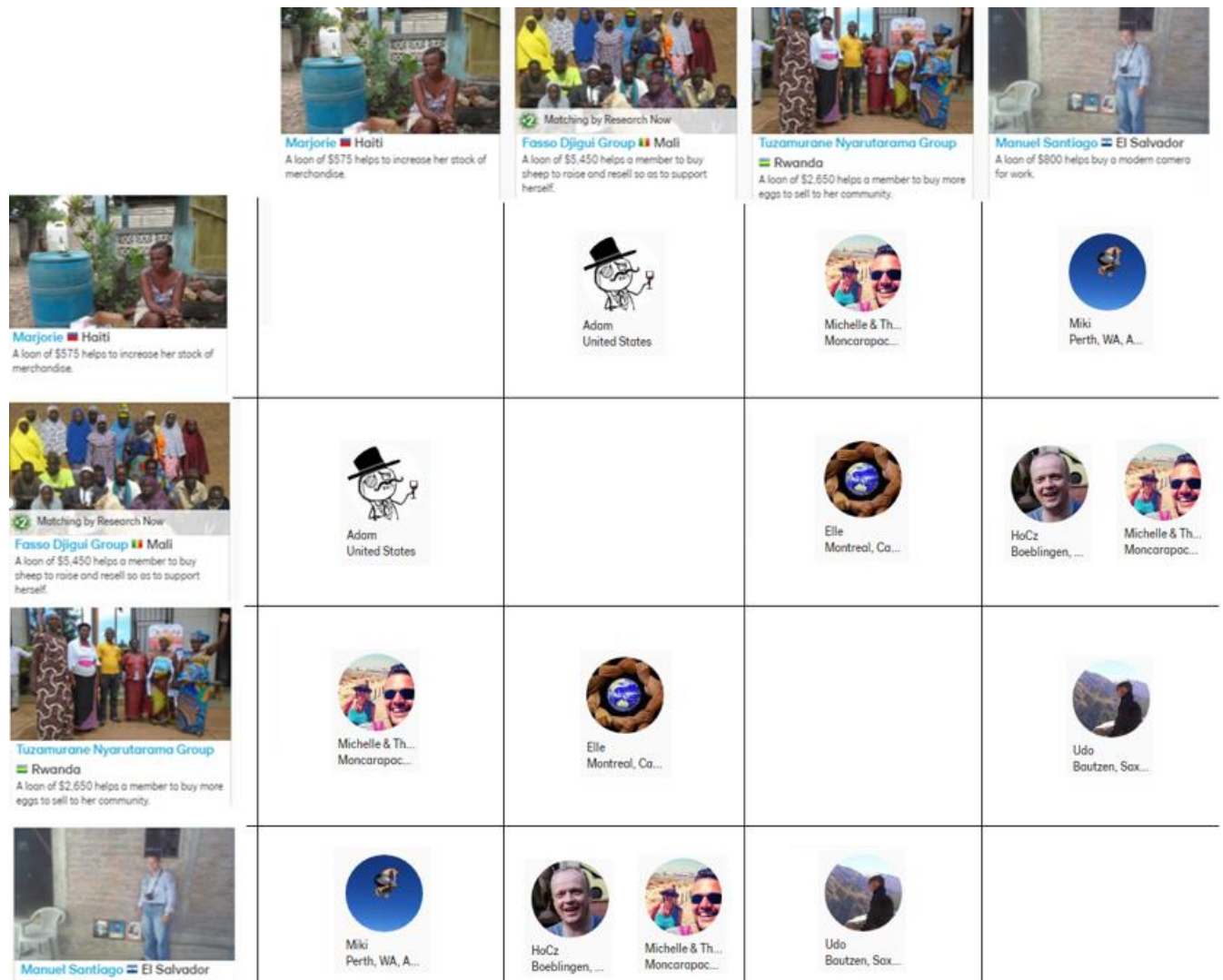
#### *The Adjacency Matrix representation of the network of projects*

As briefly discussed above, the impact of *latent network capital* of a project is examined by considering the latent network of projects sharing the same backers. An Adjacency matrix can represent this latent network displaying which projects are linked and which are not. In this *Adjacency matrix*, if two projects share a backer, the relevant matrix entry, which expresses the potential existence of a direct link between these two projects, will display a value of 1 (or greater if they share multiple backers). If, on the other hand, the two projects do not share at least one

backer, the Adjacency matrix will display a value of 0, as the projects are not directly connected in the represented network.

Figure 1, below, shows an example of how projects could be connected in an *Adjacency matrix*, where columns and rows are identified by a project page's snapshot image and their links, when present, by the image of a common backer's chosen avatar. The lack of a backer's avatar implies that there is no connection between the two projects as they do not share a common backer. The presence of two avatars implies that there are two shared backers between the projects.

Figure 1 Adjacency matrix of Kiva projects with avatars of shared backers



### *Centrality metrics as proxies for latent network capital*

Once the latent network of projects has been generated and represented through its *Adjacency matrix*, the next step is to focus on how to proxy the *latent network capital* of a project through appropriate notions of network centrality. In the following, we consider two different centrality measures: *eigenvector centrality* and *betweenness centrality*<sup>4</sup>, as they capture alternative aspects of the centrality position of a project within the network. The first, *eigenvector centrality*, was selected to measure the *latent network capital* of a project since it captures the full extent of the signalling range among backers within the platform. This is the case as *eigenvector centrality* is calculated by including the indirect connections that each link carries, these connections' indirect connections, and so on. As each link in the network represents a shared backer between two projects, if two projects have multiple links, these represent a group of backers who are signalling support to those two projects. These backers will also be interacting in the surrounding projects (those they are also funding). Therefore, the increased *eigenvector centrality* of a project/node captures greater backer interaction around this project, measuring the confidence in a project, hence providing relevant metrics to measure our variable of interest: a project's *latent network capital*. Hence *latent network capital*, as for social capital, is an essential element in increasing the participation rate for the network users (Wasko and Faraj, 2005). Their interaction and coordination are essential to achieve specific tasks within the network (Marwell and Oliver, 1993).

The second type of network centrality used in our analysis is *betweenness centrality*. This considers the frequency a node is crossed by the most direct paths connecting any two other nodes in the network. *Betweenness centrality* can be used to examine scenarios where the position of a project within the network enables or restricts access to other nodes or to represent the relevance of a

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<sup>4</sup> Their mathematical expressions are provided in Appendix 3.

node's ability to influence the spread of information through the network<sup>5</sup> (Newman, 2005; Brandes et al., 2016). Thus, *betweenness centrality* can capture an additional dimension of the control that can be derived from being at the centre of this signalling network.

To summarise, we characterise the role of *latent network capital* as enabling the signalling range about a project's quality as used by funders to contrast asymmetric information and attract further, less informed funders. We measure *latent network capital* as a project's network centrality within the latent network built on the set of direct and indirect linkages between projects established through the presence of shared backers. These considerations allow us to form our first Hypothesis:

*H1: The latent network capital of a project positively affects the amount of funds it can raise on the platform.*

#### *Gender, latent network capital, and Crowdfunding*

Crowdfunding is considered a means to help overcome gender discrimination as platforms render projects equally visible and more likely to thrive or die based on merit (Slade, 2013). Moreover, project proposers might transcend ascriptive characteristics by representing themselves as they see fit in the online space, overcoming the effect of social bias associated with gender (Yee and Bailenson, 2007). However, in the case of Kiva projects, the gender of the person seeking funds is described and often accompanied by pictures of the project proposer, leaving no space for supposed online freedom to represent oneself as one sees fit. Using data from the Swedish equity crowdfunding platform *FundedByMe*, Mohammadi and Shafi (2018) find that women investors are more likely to invest in projects with a higher proportion of male investors. However, using data from the Kickstarter crowdfunding platform, Greenberg and

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<sup>5</sup> The examination of the rise of the Medici is a key example in which the betweenness centrality is key to identifying why they rose to power. As the Medici had the highest *betweenness centrality* of any family (Padgett and Ansell, 1993)

Mollick (2015) found that women are more likely to succeed at Crowdfunding and based on a laboratory experiment, they discover that this is due to *Active women backers* supporting almost exclusively other women-led projects and that this happens, more evidently, for *high tech* sector projects where women are historically underrepresented.

The impact of the gender of the project proposer on the probability of success in Kickstarter was also estimated by Colombo et al. (2015), who found that males are less likely to succeed than females. Regarding Kiva, different authors found that women have a funding advantage over men (Allison et al., 2015; Anglin et al., 2020; Galak et al., 2011; Moss et al., 2015). However, this growing body of literature focuses on the impact of gender in Crowdfunding. We aim to consider the impact on funding of the relation between gender and a project's *latent network capital*.

A different body of literature, focussing on gender and social networks found that women's networks are structurally different from men's ones in terms of the effectiveness of their connections (Campbell 1988, Moore 1990) and that this might explain genders' wage gap (Smith 2000), supporting the idea that social capital can serve as a mechanism to reproduce social stratification across societies (Lin, 2000). Moreover, the type and the number of connections has been considered relevant, e.g. women knew more women but fewer men than the men did (Erickson, 2004), ultimately having less access to social capital<sup>6</sup>. Closer to our approach, relating network capital to gender is the analysis of Tindall and Cormier (2008) on the role of gender in political participation in British Columbia. These authors focus on network diversity as a key indicator for network capital, emphasising that, to be useful, social capital is produced and channelled through specific network measures (Tindall and Cormier, 2008).

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<sup>6</sup> However, Cross and Lin (2008) challenged the presence of this difference in the proportion of male-female ties.

In our paper, the specific difference in intensity of ties across genders is analysed, not in terms of their gender composition, but in terms of *strength* of the connections of one's connections, captured, as discussed above through the *Centrality* of the nodes, and then linking this Centrality, a project's *latent network capital*, to the gender of the project's proposer, exploring whether the impact of this Centrality exerts a different incremental effect on the amount of funds raised (has a different slope) according to gender.

Hence, in the next hypothesis, we explore how gender and *latent network capital* interact in determining the amount of funding raised by a project. If indeed, the same increase in *latent network capital*, measured through higher Centrality, capturing the signalling range of investors' confidence, has a different impact on the amount of funding raised between genders, this would imply that similarly, strong confidence signals might be less persuasive due to some form of unobservable gender bias. Consequently, equal increases in *latent network capital* would lead to an increase in pre-existing gender funding asymmetry. As previously discussed, Kiva serves primarily women and helps raise funds for women-led projects. While most of the established literature focuses on the complementarities between women-led projects and success in funding, our next hypothesis, *H2*, focuses on the interaction between *latent network capital* and gender in affecting funding, i.e., whether women's projects benefit in the same way as projects led by men from an increase in *latent network capital*.

*H2. The gender gap in the amount raised for a crowdfunding project is increasing in latent network capital.*

The development of this second research hypothesis allows us to better understand the potential channels through which gender impacts crowdfunding success.

#### *Control Variables*

Many other factors might affect the amount of funds raised by a crowdfunding project. Here, we briefly discuss three categories that will be used as control variables in our model: *partnership*

*organisations' features*, focussing on the Experience and perception of the partnership organisation sponsoring a project; *sector variables*, capturing sector-specific competitive pressures and *country-specific variables*, capturing localised competition and positive spillovers. In our analysis, we focus on the control of two key contrasting factors on raising funds: the positive effect due to *localised positive externalities*, since projects may benefit from the past *social capital* generated for their specific region, and the negative effect due to *increased localised competition* for limited funds, that might exert a negative impact on funding, given the concentration of projects competing to capture the attention of limited funders.

*Roles of the key actors: a first step in operationalising our hypotheses.*

To address the above hypotheses, we need to clarify the key actors, their roles, and the timing of their interaction.

Table 1, below, represents the key actors: backers, platform, partnership organisations, and project proposers, their role that will be essential in the empirical strategy to test the hypothesised effects in terms of identifying a gender gap in the incremental effect of increased *latent network capital* on the amount of loans successfully funded through the Kiva platform.

*Table 1 Actors and Roles*

<i>Actors</i>	<i>Backers</i>	<i>Platform</i>	<i>Partnership Organisations</i>	<i>Project proposers</i>
<i>Roles</i>	<i>They support a project, and also, through the</i>	<i>It provides both a funding and a signalling channel</i>	<i>They provide key information to</i>	<i>They implement the projects co-prepared with the help of the</i>

	<p><i>visibility of this, they are signalling confidence about a project. Other backers observe these signals through direct and indirect connections within the platform.</i></p>	<p><i>through the visibility of funding decisions. The platform provides the set of latent linkages between projects through shared backers. This is summarised through the Adjacency Matrix, used to represent the network and to calculate Centrality as a proxy for latent network capital of a project,</i></p>	<p><i>backers and services to project proposers</i></p>	<p><i>partnership organisation advertised through the platform. They benefit from the latent network capital generated by the backers funding decisions.</i></p>
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*Timing of the hypothesised effects*

As a first step, based on *proposers* and *partnerships organisations'* information—provided on the project webpage and visible from the Kiva platform—*backers* may find and then decide to fund a project.



1. These funding decisions by the *backers*, also act as signals of confidence about a project, are observable by other potential *backers*, particularly if they share the decision funding of other projects.
2. The Kiva platform allows for projects to be linked by displaying the sharing of backers across projects, therefore acting as a signalling infrastructure.
3. The links and the project nodes form a *latent network* of projects indirectly linked by having at least one shared backer.
4. The *Centrality* of a project within this latent network is utilised as a proxy for capturing its *latent network capital*.
5. The interaction between *latent network capital* and the gender of the project proposer captures different incremental effects of *latent network capital* on funding amount depending on the gender of the project proposer.
6. Finally, a lower incremental effect of *latent network capital* on funding success for women-led projects implies that a gender funding gap widens with increasing levels of *latent network capital*.

### 3 Methodology

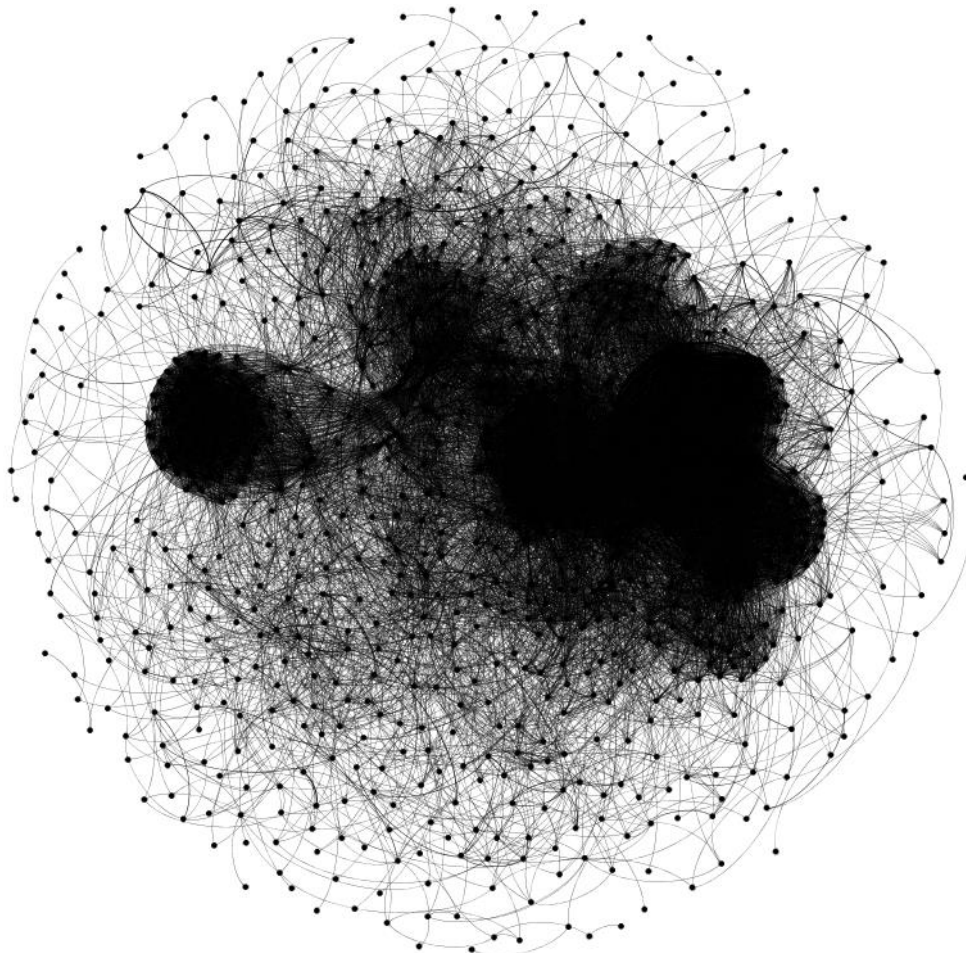
#### *Data Collection*

The data collection was carried out on the 16th of May 2017; at the point of collection, projects had already concluded. The first step of this data collection process was to identify a project that was recently completed on Kiva and then to design selection criteria to capture projects that were completed within the month before the first examined project. The detailed steps and procedures leading to the final collection of our dataset are described in Appendix 1.

The observations units, the rows in our database, are the network nodes, where each node represents a project in our Kiva Database. These observations were then used to construct the latent network of projects, obtained by observing the past behaviour of shared backers supporting any current project. The *Adjacency matrix*, representing this network, was generated by designing a specific crawler to extract the group of backers who supported each campaign; the full description of the procedures used to construct the *Adjacency matrix* is in Appendix 2.

Figure 2, below, provides a visualisation of the full latent network of projects, based on the data collected by the authors from the Kiva platform on the 16th of May 2017.

*Figure 2 Network of Kiva project based on joint connections.*



## *Model Variables*

### **Dependent variable**

The dependent variable is given by the *amount of funding raised* observed for each project in our database and measured in US\$.

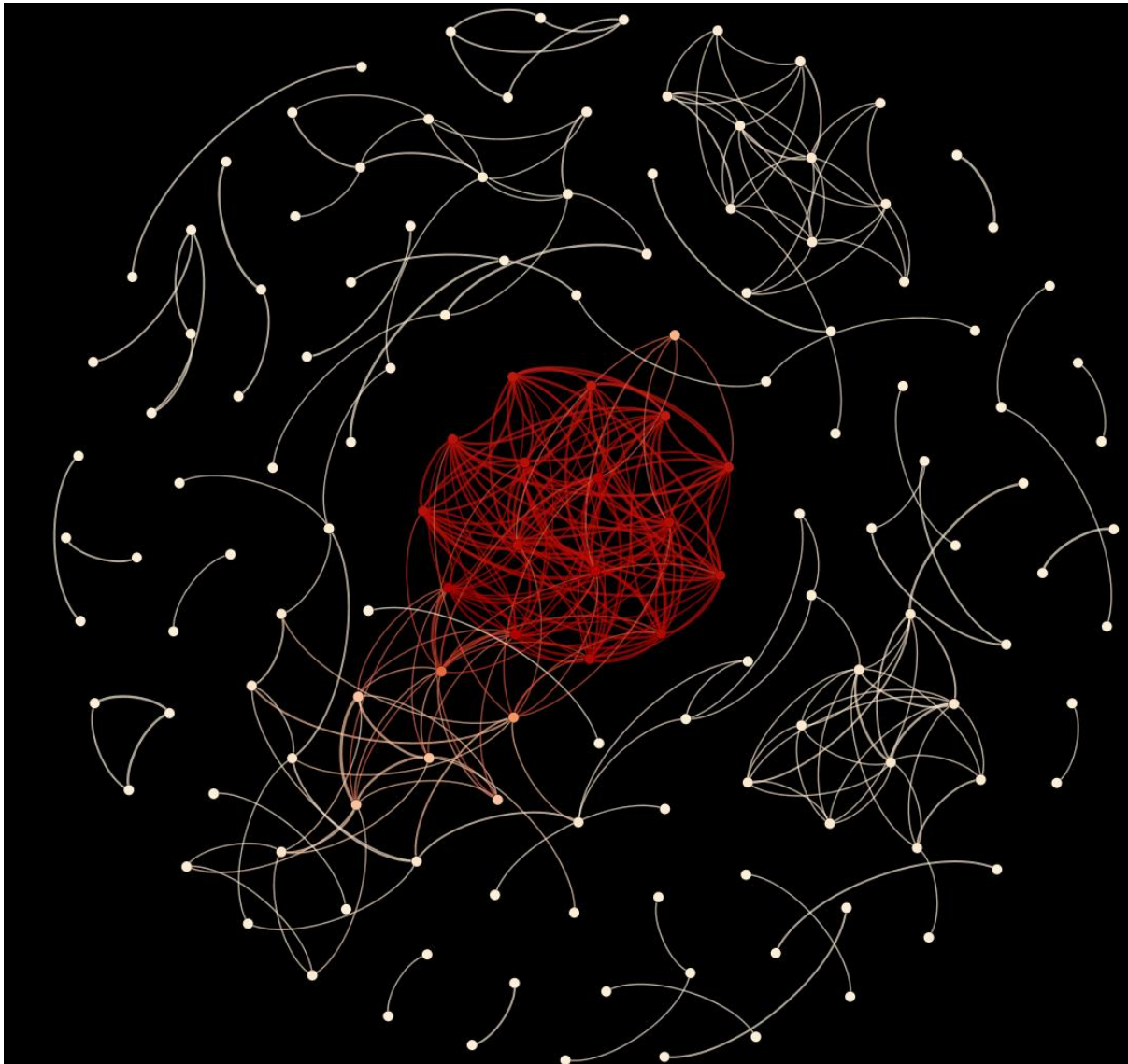
### **Independent Variables**

#### *Latent network capital*

As discussed in Section 2, the impact of the *latent network capital* of a project is examined by considering the *latent network* of projects obtained by observing the past behaviour of shared backers supporting the current project. Once the *latent network* of projects has been generated and represented through its *Adjacency matrix*, the next step was to measure the level of a project's *latent network capital*. The *eigenvector centrality* of a node was selected as a metric for the *latent network capital* of a project since *eigenvector centrality* considers not only the direct, one-hop, connections in the latent network that backers create among projects but also the indirect connections that each link carries, the indirect connections of these connections, and so on. Appendix 3 provides the detailed expressions used to calculate the *eigenvector centrality*, as used in the estimation strategy of this paper.

Figure 3, below, shows the different *eigenvector centrality* from a subset of 142 nodes, where the subset was utilised to provide a clearer representation of the concept. The dark red nodes and edges represent high levels of *eigenvector centrality*, while light orange and white represent low levels of *eigenvector centrality*. The visualisation shows that the highly connected nodes at the centre have very high Centrality levels, while the less connected nodes around the outside have low levels of Centrality.

Figure 3 Visualisation of eigenvector centrality



### *Gender*

To address the impact of *gender* on the *amount of funding raised* by a project, we consider both the gender of the project proposer to capture the average gender effect and an additional variable, where gender interacts with *latent network capital*. This interaction variable is used to test the hypothesis of a significant differential slope/effect of increased *latent network capital* on funding across the genders of project proposers.

### **Additional Covariates**

Additional covariates were obtained from our data, and two specific competition indexes were developed: one based on competition in the sector and the second, based on competition from other projects launched by the same partnership organisation (Wessel et al., 2017, Gallemore et al. 2019, Janku and Kucerova, 2018). Moreover, since our data permit us to classify projects according to sectors, supporting partnership organisation, and geographic region, we were able to consider the following control variables according to three distinct categories:

a) Partnership organisations' features

- *Temporal Experience* is a control variable capturing the time the partnership organisation sponsors a project active on Kiva.
- *Rating* is a control variable capturing the reputation of a Partnership organisation through the rating provided by the platform Kiva on the partnership organisation.

b) Non-geographic sources of competition

- *launch comp*, a control variable capturing the degree of supply-side competitiveness among projects, based on the competitiveness for attention and funding during the day a project is launched.
- *Sector index* is a control variable capturing the degree of supply-side competitiveness among projects within a specific sector.
- *Partner index*, a control variable, captures the degree of competitiveness among projects within the specific partnership organisations sponsored by a project.

c) Country specific effects

- *Country Funds*, a control variable capturing the level of country activity of the Kiva platform, and, finally,
- *Active Loans* is a control variable that captures the current loans currently active within the Country.

Table 2, below, summarises the full set of explanatory variables and covariates utilised in estimating the models used to test the relevant hypotheses developed above.

*Table 2 Full set of variables and covariates*

<b>Explanatory Variables</b>	<b>Definition</b>	<b>Measurement</b>
Female	This variable captures the gender of the person proposing the project.	Dummy variable for Females: 0 for males, 1 for females.
Eigen Centrality	This variable is used as a proxy for the amount of <i>latent network capital</i> generated for a project by the direct and indirect links of its backers within the <i>latent network</i> .	It is captured with the natural logarithm of the <i>Eigenvector centrality</i> of a project node within the <i>latent network</i> .
Betweenness centrality	This variable captures another dimension of the Centrality of a project: the degree of control over the signalling system in the <i>latent network</i> .	It is captured with the natural logarithm of the <i>Betweenness centrality</i> of the project node within the <i>latent network</i> .
Female* Eigen Centrality	This interaction variable captures the difference, due to being a female led project, in the effect of a one percentage increase in <i>eigenvector centrality</i> , as a proxy for <i>latent network capital</i> , on the dependent variable.	Interaction variable between dummy variable Female and the natural logarithm of the <i>eigenvector centrality</i>
<b>Covariates on characteristics of</b>	<b>Definition</b>	<b>Measurement</b>

<b>the partnership organization</b>		
Temporal Experience	This variable captures the temporal Experience of a partnership organisation sponsoring the project, based on the time it has been active on Kiva.	It is the natural logarithm of the months a partnership organisation has spent on Kiva.
Rating	This variable captures the relevance of the reputation of a partnership organisation through the <i>rating</i> provided by the platform Kiva on the partnership organisation.	The rating is between 0-5 stars and is provided by Kiva to all partnership organisations.
<b>Covariates on Competitiveness</b>	<b>Definition</b>	<b>Measurement</b>
Launch competition	This variable captures the degree of supply-side competition among projects and is based on the competitiveness for attention and funding on the day a project is launched.	Launch competition was captured via the natural logarithm of the number of other projects launched within the same day as the examined project.
Sector index	This variable captures the degree of supply-side competitiveness among projects within the specific sector a project belongs to.	It is captured with the natural logarithm of the amount of competition within the sector. This is measured as an index value measuring competition between projects on Kiva within the same sector. Index values are between 0 and 10000, with higher

		index values showing lower levels of competition.
Partner index	As each partnership organisation is funding multiple projects, these can be seen to compete with each other for funding and attention. This variable captures the degree of competitiveness among projects, within the specific partnership organisations a project is sponsored by.	It is captured with the natural logarithm of the amount of competition for each partnership organisation. This is an index value measuring competition between projects on Kiva within the same partnership organisation. Index values are between 0 and 10000, with higher index values showing lower levels of competition.
<b>Covariates on Country specific effects</b>	<b>Definition</b>	<b>Measurement</b>
Country Funds	This variable captures the level of country activity of the Kiva platform.	It is captured with the natural logarithm of the amount of funds Kiva has lent within the Country of the individual seeking funds.
Active Loans	This variable captures the level of current loans currently active within the Country.	It is captured with the natural logarithm of the amount of active loans, loans that have been funded and were currently being repaid within the specific Country of the individual seeking funds.

### *Descriptive Statistics*

An initial exploration of the data, reported in Table 3 below, provides the key summary statistics on the amount raised on the platform according to gender. It shows that while the Kiva platform targets women, with more than 75% of the projects led by women, on average, loans for women



are smaller by more than 100 US\$, and the median value is also smaller for women by 100 US\$. Similarly, the distribution of *latent network capital* shows that men-led projects have 47% more latent network capital than women's ones, indicating that projects led by men are better connected to (better connected) projects than women-led ones. This initial evidence, discussed in detail in the next section, indicates that while the Kiva platform mainly targets women and plays a critical role in providing finance to their projects, on average, women's projects raise less funds than men's and generate a lower level of *latent network capital*, measured in terms of the Centrality of their projects within the Kiva network.

Table 3: Summary statistics on gender and latent network capital

Male	Observations	Standard deviation	Mean	Median	Sum	Variance
Loan amount	243	496.169	611.42	500	148575	246183.62
Latent network capital	243	.27	.207	.045	50.406	.073
Females						
Loan amount	742	425.31	507.985	400	376925	180888.41
Latent network capital	742	.217	.141	.031	104.862	.047

Source: Data Extrapolated from the authors' Kiva dataset

### *Analytical Strategy*

This section introduces the econometric model utilised to assess the paper's main hypotheses; their detailed discussion will be in the next section. As previously discussed, the observation units in this model are the network nodes, where each node represents a micro-project. The *amount of funding raised* is the dependent variable; thus, we want to understand the impact of increased *latent network capital* on the *amount of funding raised* and how this might differ according to gender.

### *Truncated regression*

Allison et al. (2015) have used an OLS regression approach to examine how different factors impact the time it takes for Kiva projects to reach their funding goal. Similar approaches based on OLS regression have been utilised within the wider crowdfunding literature (Calic and Mosakowski, 2016; Mollick and Nanda, 2015). However, Kiva's projects cannot raise negative amounts of money. Thus, the dependent variable of the models is truncated at 0, which could cause a critical model misspecification error (Heckman, 1979). Colombo et al. (2015) used a Tobin regression to address this source of potential misspecification; in a related way, we implement a robust *truncated regression* approach<sup>7</sup> that overcomes this misspecification error by

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<sup>7</sup> Consider an unobserved relationship of the form:

$$y_i^* = x_i' \beta_i + u_i$$

With  $u_i \sim N(0, \sigma^2)$ , where the observed dependent variable is linked to the unobserved one, via a function assuming positive values when the unobserved variable is positive and zero otherwise.

$$y_i = 1(y_i^* > 0)$$

restricting the sample and the residuals to values that are positive. Utilising log values restricts all values of the amount raised above 1 dollar.

The full model, estimated below, focuses on *eigenvector centrality*, *betweenness centrality*, gender and the interaction variable between *eigenvector centrality* and gender, in addition to the other control variables, briefly discussed in section 2. In detail, for  $Y_i$  = Amount of money raised for project  $i$ ,

The hypothesised population regression model to be estimated is given by<sup>8</sup>:

$$\begin{aligned}
 \text{Log } Y_i &= \alpha + \beta_1 \text{Female} \\
 &+ \beta_2 \text{Female} * \text{Eigen Centrality} \\
 &+ \beta_3 \text{Eigen Centrality} + \beta_4 \text{Betweenness Centrality} \\
 &+ \beta_5 \text{Temporal Experience} + \beta_6 \text{Country Funds} + \beta_7 \text{Active Loans} \\
 &+ \beta_8 \text{Rating} + \beta_9 \text{Launch Competition} + \beta_{10} \text{Sector index} \\
 &+ \beta_{11} \text{Partner index} + \varepsilon_i
 \end{aligned}$$

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In this case, it would be inappropriate to estimate this model on the entire sample using the observed information on  $y$ , since for censored observations, we cannot consider the censoring rule as a true realization of the underlying relationship.

<sup>8</sup> Considering the restriction that  $\text{Log } Y_i > 1$  and  $\text{Log } \bar{Y}_i > 1$

From on this full model, we have estimated five different models based upon the number of variables considered, with later models including fewer variables.

## 4 Results

Table 4, below, reports the estimates from the truncated regression of 5 nested models. These estimates are discussed in relation to the hypotheses developed in section 2.

*Table 4 Kiva results by model*

	<b>Dependent Variable log of the loan amount raised by a project</b>				
<b>Variables on Gender and Internal Social Capita</b>	Model 1	Model 2	Model 3	Model 4	Model 5
Female	-.137 **	-.204 ***	-.142 **	-.197***	-.177 **
Female*Eigen Centrality	-.033 **	-.04 **	-.032 **	-.0236	-.021
Eigen Centrality	.122 ***	.132 ***	.128 ***	.117***	.148* **
Betweenness centrality	.016 ***	.018 ***	.015 ***	.021***	
<b>Covariates</b>					
Temporal Experience	.248 ***	.258 ***	.254 ***		
Country Funds	.045 **	.013	.028		
Active Loans	-.145***	-.171 ***	-.139 ***		
Rating	.02 ***	.011			
Launch Competition	-.032	-.053 ***	-.039 ***		
sector index	.041 *	.063 ***	.046 **		
partner index	.16 ***		13 *		
Constant	4.239 ***	5.908 ***	4.692 ***	6.483***	6.75***
sigma	.558 ***	.573 ***	.565	.644	.681***
AIC	1655.452	1705.90 9	1689.339	1941.754	1964.448

Log pseudolikelihood	-814.7261	-840.954	-832.6697	-964.87724	-977.22397
Wald $\chi^2$ (11),	785.50,	634.83	764.69	333.09	316.35
Prob > $\chi^2$	0.000	0.000	0.000	0.0000	0.000
H0: Eigen Centrality =0 & Betweenness centrality =0 & Female*Eigen Centrality=0	$\chi^2$ (3) = 359.75 Prob > $\chi^2$ = 0.000	$\chi^2$ (3) = 373.80 Prob > $\chi^2$ = 0.000	$\chi^2$ (3) = 372.70 Prob > $\chi^2$ = 0.000	$\chi^2$ (3) = 308.57 Prob > $\chi^2$ = 0.000	$\chi^2$ (2) = 292.13 Prob > $\chi^2$ = 0.000
H0: Female =0 & Female*E. Centrality=0	$\chi^2$ (2) = 5.33 Prob > $\chi^2$ =0.069	$\chi^2$ (2) = 9.32 Prob > $\chi^2$ =.009	$\chi^2$ (2) = 5.16 Prob > $\chi^2$ = 0.076	$\chi^2$ (2) = 8.28 Prob > $\chi^2$ =0.016	$\chi^2$ (2) = 6.47 Prob > $\chi^2$ =0.039
Number of observations	975	975	980	985	985

\*\*\* p<.01, \*\* p<.05, \* p<.1

Our first hypothesis was on the impact of *latent network capital*:

*H1: The latent network capital of a project positively affects the amount of funds raised on the platform.*

This hypothesis is supported by our empirical evidence, given the positive and significant value of the estimated coefficient for the variable *eigenvector centrality*, used as a proxy for the *latent network capital* raised for a project through the set of direct and indirect connections based on the definition of a link in this latent network. This indicates that a common backer links two separate projects. Indeed, by focusing on Model 1, the model displaying the lowest *Akaike Information Criterion (AIC)* score and the highest value of the *pseudo loglikelihood*, the estimated parameter,  $\hat{\beta}_3$  capturing the *impact of latent network capital* is positive and significant at 1%, indicating that a ten percent increase in *latent network capital*, as captured by the *eigenvector centrality* of a project, leads to a 1.22 % increase in the *Amount of funds raised* by a project.

Moreover, again from the lower part of Table 4, we can see that the joint test of significance of the three different *centrality* variables: H<sub>0</sub>: *Eigen Centrality = 0* & *Betweenness Centrality = 0* & *Female\* Eigen Centrality = 0*, is also rejected, since, in Model 1, these three variables are jointly significant below the 1% significance level ( $\chi^2$ (2) = 359.75 and Prob >  $\chi^2$ =0.000).

The Centrality of a project, which captures its *latent network capital*, as seen with the interpretation of the *eigenvector centrality*, is highly significant in affecting the capacity of a project to raise funds through Crowdfunding on Kiva. The same applies to the degree of control of the signalling system within the platform, expressed by the project *betweenness centrality*,

The second hypothesis of the paper focused on the possibility of observing *an increasing gender gap* in the platform's ability to transform projects' *latent network capital* into an additional *percentage of funds raised*.

H2. *The gender gap in the amount raised for a crowdfunding project is increasing in latent network capital.*

From the estimates of Model 1, in Table 4, we can see that the gender variable has a negative and significant ( $\hat{\beta}_1 = -.137^{**}$ ) coefficient. Moreover, by looking at the interaction variable *Female\*Eigen Centrality*, one can see that this gender gap is increasing in the percentage of *latent network capital*, captured by the *eigenvector centrality*, as shown by the value of the estimated parameter for the interaction variable,  $\hat{\beta}_2 = -.033^{**}$ .

Hence, we can see that, for women-led projects, while an increased percentage of *latent network capital* still exerts positive effects on the *percentage of funds raised* (since:  $\hat{\beta}_2 + \hat{\beta}_3 = -0.33 + 0.122 = 0.089$ ) this increased *latent network capital* leads to an increasing *gender gap*. This is evident as the positive effect of an extra 10 percent of *latent network capital* (captured by the *eigenvector centrality*) induces an increase of 1.22 percent in the amount raised for projects led by men. In comparison, the same 10 percent of *latent network capital* only leads to a smaller increase of 0.89 percent for women-led ones.

This evidence supports H2, that the gender gap in the amount raised for a project increases *latent network capital*.

Moreover, we can also see the joint significance of the gender-related variables, captured by the test reported in Table 4, under the null hypothesis,  $H_0: \text{Female} = 0 \ \& \ \text{Female*Eigen Centrality} = 0$ ,

since in Model 1, these two variables are jointly significant below the 7% level of significance, ( $\chi^2(2) = 5.33, \text{Prob} > \chi^2 = 0.069$ )<sup>9</sup>

#### *Other covariates.*

In this paper, we have used additional control variables to better specify a model focusing on gender and *latent network capital*. The detailed analyses of the remaining covariates can be developed based on our estimates. These address very important factors, such as the effects of geographic and non-geographic and competition and positive externalities, and the role of the partnership organisations. While we did not develop specific hypotheses on these factors, it is easily seen that, in Model 1, these variables are all significant apart from *Launch Competition*. They are essential controls as they improve the AIC score of the specification.

## 5 Discussion and conclusions

Crowdfunding platforms are an increasingly relevant source of funds for ventures and projects across the globe, including developing countries, after gaining influence across developed economies as a response to the limited capital available after the financial crash (Bruton et al., 2015) and more recently providing increased financial resilience, during the Covid-19 pandemic (Farhoud et al. 2021). Kiva plays a crucial role, filling a gap due to the credit market failures typically associated with pervasive asymmetric information. Signalling has been advocated as a strategy to overcome the damaging effects of asymmetric information, and Kiva addresses this problem by providing an effective signalling infrastructure. Its governance structure allows *partnership organisations* to collect and represent projects, pooling the demand for funds and reducing the fixed and cognitive costs to participate in the platform for microprojects often located in areas of high digital exclusions. In this context, funders with Experience of a project

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<sup>9</sup>This significance going below 1% in the estimates of specification of Model 2.

become more informed than the project proposers themselves since they have access to more resources necessary to understand the project's economic environment better.

#### *Key contributions*

In this context, our paper identified the key signalling activity by the funders—the informed party—directed to the *crowds* of other potential funders. Instead, we considered the project's proposers as playing a more passive role in this process, only needing to represent themselves on the platform. We introduced a novel way to model a *latent network* whose building blocks are the links among the project's nodes provided by funders. I.e. if a backer funds two different projects, they signal confidence linking the two projects as co-beneficiaries of their trust. After adopting this novel representation of the platform as a signalling infrastructure, whereby the project's nodes are linked through their shared backers, we were in the position to assess our research question on how the *latent network capital* of a project affects the amount of funds it can raise through Crowdfunding on this platform.

While the *latent network capital* of a project might be captured in different ways, we focussed on *eigenvector centrality* as a proxy for the *latent network capital* of a project, since this notion of Centrality also accounts for the connections of a connection, their connections, and so on, capturing the full extent of the signalling reach for the funders' support to a project within the *latent network* we constructed. These metrics were expected to exert a positive impact on the *amount of funds raised* by a project within the platform, and our findings confirm this hypothesis, providing new empirical evidence about the role of *latent network capital* as an effective signalling strategy to overcome the adverse effects of asymmetric information in Crowdfunding.

The next question we addressed was whether there was an *increasing gender gap* that might raise invisible barriers for women-led projects. Increased *latent network capital* provides fewer benefits in terms of additional funds raised for women-led projects than for those led by men. In our findings, projects led by women, while retaining a positive effect from increased *latent network*



*capital*, face a widening funding gap *vis-à-vis* men-led projects, as increased *latent network capital* shows lower returns in the amount raised by their projects.

#### *Limitations and further research*

Our findings are limited to the extent of the data they are based on. We started by considering 1000 projects, marginally reducing their number based on simple eligibility criteria, and reached a large *adjacency matrix*. We considered the inclusion of centrality metrics as proxies for *latent network capital* as an essential element of the originality of our contribution. While this somewhat limits the number of observations that can be used, the dimensionality of working with networks of observations increases dramatically. Moreover, different notions of network centrality capture alternative aspects of a project's positioning within the *latent network*; by choosing to focus on *eigenvector centrality*, other aspects might have been overlooked. In particular, we considered and modelled the impact of *betweenness centrality*, as this captures how a project is positioned in the network flows of information signals, as an additional measure of the project's relevance within the entirety of the platform seen as a signalling infrastructure. However, we did not focus on additional specific features/drivers this metric can be a proxy for, apart from its natural role of expressing the relevance of a node within a system of information flows. Future research should further explore the different aspects of this and additional centrality metrics.

Our findings confirmed our hypothesis that women receive less incremental benefits from increased *latent network capital* within the platform. Clearly, the crowds seem to be displaying a collective bias that negatively affects women 's-led projects' capacity to raise funds, mitigating the positive effects of *latent network capital* on funding. Further research should focus on the drivers underlying this bias that emerged from our empirical evidence.

A more detailed analysis of the role of other control variables used in the estimations only as controls would bring further insights if explored in future analysis. An extension addressing a more detailed geographical analysis of the different projects would be of particular interest.

We started from a set of completed projects at a given date and worked backwards to reconstruct the set of other relevant projects. Our network is thus a snapshot of existing, latent links, and a dynamic network analysis would add interesting aspects of the phenomena studied. The study of the morphological changes of an *Adjacency matrix* might indeed provide a natural extension of this work, and our data collection techniques might allow such future challenging work. Finally, our findings are also limited to the specific crowdfunding platform analysed, Kiva, which, although relevant, might have specific internal governance aspects that affect the generalisability of our results. An extension that includes different loan-based crowdfunding platforms might add diverse insights to our analysis and provide interesting avenues for future research.

#### *Policy implications*

While developing our second hypothesis, H2, we considered, rather than only considering gender in itself, we focussed on distinguishing whether the *latent network capital* impact on the amount of raised funds differs across genders. Our key question was whether *latent network capital* might have a differential impact on Crowdfunding across genders. The main policy implication we can derive from our findings is that the dimensionality of the gender gap in Crowdfunding cannot be limited to the observation that women represent most of the projects funded. A deeper understanding is needed of *why* women-led projects raise fewer funds and how this can be linked to key organisational features of the platform as a signalling infrastructure. Where and how does the gap emerge in the process? Is it through the initial signals sent by the backers or during the formation of the projects' *latent network capital* as captured by the centrality metrics? These questions remain difficult to ascertain given the available data on the micro-funding choices. However, our evidence shows that the incremental effects of additional *latent network capital* vary according to the gender of the project's proposer, increasing existing gender gaps if remedies and balancing actions are not considered. Kiva provides funds mainly for women-led

projects and allows online matching possibilities that would not otherwise take place between investors and microbusinesses, substituting the missing credit markets that are probably too *consciously biased* against micro-projects even to exist. Finding solutions to mitigate this, possibly unconscious, bias of the crowds would further improve the *public good* aspects of this platform, which operates as a digital signalling infrastructure to facilitate access to credit.

## Appendix 1: Data Collection procedure

The first project was selected manually, then moving to the most recent project, which was also completed. Then, additional projects which had finished before the project were also identified and selected. This is possible as Kiva has an Identifier (ID) for each project contained within its URL, to find the project which occurred before the last project the ID simply had to be changed by 1 digit for example if the ID was 1400, the project before that would have the ID 1399.

Therefore, utilising Excel and the *Concatenate* command enabled the URL of the past 1000 projects to be created, over 1000 specific projects URLs were created.

Due to restrictions in the *Import.io* crawler software utilised for this process, 985 observations, from the 1173 project originally captured, were retained, and examined. Once the final list of projects' URLs had been obtained, *Import.io* was utilised again to retrieve additional project's specific information from the actual project page. Additional secondary data were also collected on the partnership organisations through the utilisation of Postman and the Kiva application programming interface (API) (Postman, 2019; Kiva, 2019c). Finally, only projects which utilise partnership organisations were considered, since over 99 percent of the projects utilised them and it was better not to include additional data heterogeneity

## Appendix 2: The Adjacency matrix

Our empirical *Adjacency matrix*, representing this network, was generated by designing a specific crawler to extract the group of backers who supported each campaign. These backers had the choice to keep their identity anonymous or to openly back the campaign. The crawler did not extract backers who had chosen to keep their identity anonymous as, in this case, private backing was not a signal and hence did not increase the *latent network capital* of a project. The key to achieving this was the use of *manual x-path*, a system for identifying key elements of a web within the *Import.io* framework. Then, a multi-step process utilising *Countifs* functions within Excel was used to create the resulting (985x985) *adjacency matrix* which showed which among the 985 projects shared joint backers. Finally, the links in the *adjacency matrix* were weighted by the number of joint backers shared between any two projects.

## Appendix 3: Centrality metrics

This step requires the data to be represented in vector form, based on three columns capturing: 1) source project, 2) target project and 3) weight, given by the number of connections between source and target. These data were then imported into the *Gephi* software for network visualisations, see Figure 3, and to calculate alternative measures of *Centrality*, for each node, as discussed below.

Formally, let  $C_e(g)$  denote the eigenvector centrality from network  $g$ , whose nodes are the selected Kiva projects, and links occur if two projects share a backer.

Furthermore, consider a proportional factor  $\mathcal{L}$ . Thus, eigenvector centrality for node  $i$ , can be written as:

$$\mathcal{L}C_i e(g) = \sum_j g_{ij} C_j e(g)$$

Where  $g_{ij} = \begin{cases} 1 & \text{if } i \& j \text{ are linked} \\ 0 & \text{if } i \& j \text{ are not linked} \end{cases}$

Capturing the eigenvector centrality of a node  $i$ , as a weighted sum of the centralities of its direct neighbours, i.e., those adjacent nodes/ project for which  $g_{ij} = 1$ , themselves weighted by their own centralities,  $C_j e(g)$

In matrix notation this can be represented as:

$$\mathcal{L}Ce(g) = gCe(g)$$

Where  $g$ , is the *Adjacency matrix*, representing the network of direct connections among the project/nodes and  $Ce(g)$  is the vector of *eigenvector centralities* for all the projects.

Thus  $Ce(g)$ , is an eigenvector of  $g$ , with  $\mathcal{L}$  being the eigenvalue. There can be multiple *eigenvalues* and normally the highest *eigenvalue* is used (Jackson, 2010)<sup>10</sup>.

The second notion of network centrality used in our analysis is that of *betweenness centrality*. This considers the relative frequency a node is crossed by, most direct, paths connecting any two other nodes in the latent network:

$$Betweenness(d_i) = \frac{\sum_{k \neq j: i \in [k,j]} p_{kj}}{(n-1)(n-2)/2}$$

Where  $p_{kj}$  represents the number of shortest paths between any pair of nodes  $k$  and  $j$ , within the network which pass through the project/node  $d_i$ .

*Betweenness centrality* can be used to examine scenarios where the position of a project within the *latent network* enables or restricts access to other nodes' i.e. to represent a node's ability to influence the spread of information through the network (Newman, 2005).

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<sup>10</sup> *Eigenvectors'* usefulness in capturing the effects of *social capital* within a network are discussed in detail in Bonacich, (1972) and Borgatti et al., (1998).

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