Credit and Capital Markets, Volume 56, Issue 1, pp. 5 – 26
Scientific Papers

The Impact of COVID-19 on Demand and Lending Behavior in Prosocial P2P Lending

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Abstract

I derive two innovative metrics, capturing the demand and the excess demand for prosocial P2P loans in the US. The measures are based on a data set comprising prosocial P2P loan applications obtained from the US P2P lending platform Kiva for the period of November 2011 to December 2022. Furthermore, I analyze how both indices are influenced by the COVID-19 pandemic. Interestingly, the measures for the current pandemic development show a negative impact on demand while the COVID-19 reproduction rate shows a positive relation, indicating a pro-active behavior of borrowers. On the other side, socially motivated lenders seem to be less generous in providing interest-free loans in times of a worsening pandemic. As it turns out, the risk-free interest level positively impacts demand and excess demand for prosocial lending on Kiva even though the loans were granted without any interest.

Keywords: KIVA, prosocial P2P lending, demand, lending behavior, COVID-19

JEL Classification: G20, G21, G41

I. Introduction

The sudden global spread of COVID-19 in spring 2020 had tremendous and distorting effects on lives and economies around the world (*Goodell* 2020). In May 2020, *International Monetary Fund and World Bank* (2020) highlighted the critical role of the financial sector for mitigating the pandemic shock on the economy by addressing increased liquidity need and loan demand. However, due to regulations, banks' ability for boosting loans in a strained economic situation, and, thus overall increased loan default risk is limited. Lockdowns and

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The contributions to this study represent the author's personal opinions and do not necessarily reflect the views of Deutsche Bundesbank.

Acknowledgement: I am grateful to an anonymous referee and the two guest editors for helpful comments and valuable suggestions.

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other governmental measures affect the distribution of bank loans negatively as banks lack technical tools mandatory for granting loans in the physical absence of borrowers, e.g. online-based loan verification (*Najaf* et al. 2022). Therefore, Peer-to-Peer (P2P) lending, a debt-based form of crowdfunding, has become reasonably popular among borrowers in the first months of the pandemic. The term P2P lending refers to the fact that not a single bank but multiple peers choose to fund a specific loan. A financial technology (fintech) based platform thereby acts as an intermediary body and provides the technical framework for an overall online-based loan process.

This study focuses on a prosocial form of P2P lending, in which P2P loans are granted without interest. It analyzes the effect of the COVID-19 pandemic on the demand and lending behavior in prosocial P2P lending in the US. The issue is important because less is known about the dynamics of prosocial P2P lending in times of a severe crisis. In particular, the USA has been hit hard, shown by a high number of COVID-19 cases[1]. The uncertainty driven by the fast spread of COVID-19 and a quickly rising number of deaths during the first weeks of the pandemic, accompanied by insufficient job securities, led to a significant increase in unemployment[2]. This pandemic shock especially hit poor members of the US society. One approach that might – to some extent – mitigate social needs may be seen in prosocial P2P lending, which helps the poor to start up their own business and, hence, fights poverty. Prosocial P2P lending was introduced by the leading prosocial Peer-to-Peer (P2P) lending platform Kiva (www.kiva.org). Kiva's mission is to provide assistance for poor people who lack access to commercial financial sources in the form of interest-free P2P loans granted by socially motivated lenders (e.g. *Berns* et al. 2020). It combines aspects of P2P-lending (see e.g. *Dorfleitner* et al., 2016; *Berger/Skiera* 2012) with microfinance (e.g. *Dorfleitner* et al. 2020a). Even though the platform works globally and emphasizes the distribution of microloans in developing countries, the platform started in 2011 to distribute actual P2P loans directly and without any intermediary entity in the USA.

In this study, I introduce two innovative metrics which capture the demand and the excess demand for prosocial P2P loans on Kiva US. The latter measures to what extent the demand for prosocial P2P loans exceeds the supply provided by altruistic investors on a specific day. By applying advanced GARCH methodologies, I analyze how both indices are affected by the COVID-19 pandemic. The novel insights of this study shed some light on a still scarcely researched

[1] In August 2022, the USA showed the highest total number of reported Covid-19 cases worldwide valuing 92.739.935 according to the World Health Organization dashboard, http://covid19.who.int/.

[2] The total US unemployment rate soared from 3.5 % in February 2020 to 14.7 % in April 2020 according to the US Bureau of labor statistics, http://www.bls.gov/.

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area in the context of digital transformation in the financial industry. The contribution of this study is twofold. First, I introduce two innovative metrics proxying the demand and the excess demand for prosocial P2P loans on Kiva US. For this, I use a unique data set of risk-free P2P loans directly distributed in the USA. To my best knowledge, this is the first time that P2P loans are researched in an aggregated form. In a first step the resulting time series are analyzed for the period since the start of Kiva US in 2011 to December 2022 to compare index patterns before and after the COVID-19 crisis. Second, I analyze how both indices are affected by the COVID-19 pandemic by utilizing advanced GARCH methodologies for the period between 7th March 2020 to 31st December 2022. Comparing the results of both indices allows one to draw conclusions on how the dynamics of the COVID-19 pandemic influenced the lending behavior of borrowers and socially motivated lenders.

The results reveal that the demand for prosocial loans is negatively related to the magnitude and severity which both measure the pandemic's current development. Furthermore, borrowers seem to act more pro-active because the demand increases in times whenever the reproduction rate predicts a tightening pandemic development in the near future. Regarding the excess demand, the results suggest that the findings are driven more by the supply side. In this context, there is evidence that prosocially orientated investors might hesitate to fund non-interest bearing loans as easily in periods of a worsening pandemic as in normal times. Additionally, I find evidence for the risk-free interest level to impact demand and excess demand for prosocial lending on Kiva positively, even though P2P loans, if granted, are without any interest at all. The reason for this might be seen in opportunity costs obtained from non-prosocial investment or borrowers' increased access-ability of commercial loans when interest rates are low. Overall, the results support the view of the dual nature of prosocial lending behavior, in which investors follow general altruistic motives, while also relying on classical financial criteria, such as default risk.

The remaining article is structured as follows: Section II focuses on peculiarities of Kiva and shows the relevant literature. Section III develops measures for the demand and excess demand for direct prosocial P2P loans and describes the resulting time series since the start of Kiva US. Section IV shows the data and methodology used to analyze the impact of COVID-19 on the two demand indices. The results are presented in Section V and Section VI concludes.

II. Prosocial P2P Lending and Relevant Literature

The prosocial lending platform Kiva is a US non-profit organization founded in 2005. The mission of Kiva is to arrange interest-free P2P loans for poor people which are funded by socially motivated investors who neglect receiving any

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financial interest while still accepting the burden of a potential loan loss (see. e. g. *Berns* et al., 2020). For this reason, the platform has applied two different approaches: Kiva's prevailing distribution form in developing countries, the so-called field partner model, and the direct loan approach, which focuses on prosocial P2P loans in the US. As the aim of this study is to analyze the demand for prosocial lending in the US, the empirical focus of this study lies on the direct loan approach. After shedding some light on the peculiarities of Kiva's lending methodologies in Subsections 1 and 2, the relevant literature is shown in Subsection 3.

1. Kiva's Field Partner Loans

A large share of prosocial P2P loans is distributed by Kiva worldwide via the field partner model. Kiva's original lending scheme was the platforms sole distribution method in its first years. One peculiarity of this approach is that a borrower does not apply for an interest-free P2P loan directly. Instead, an inter-mediating entity, which often is a microfinance institution operating in developing countries, tries to pass on a micro loan to socially motivated investors. Often, the interest-bearing loan has already been granted by the microfinance institution to its clients (see e. g. *Dorfleitner* et al. 2021). Consequently, the application for P2P loans on Kiva has become a popular financing source for microfinance institutions (*Bruton* et al., 2015). Note that the inter-mediary microfinance institution plays a profound role in the lenders investment decision (*Berns* et al. 2020).

2. Kiva US's Direct Loans

The second approach comprises the so-called direct lending model which was introduced after the founding of Kiva US in 2011. The direct approach is closely related to classical P2P lending and works without a mediating institution. It mainly focuses on US borrowers lacking access to regular debt. In contrast to the field partner model, the borrowers receive the loan free of any interest.

To protect potential lenders from fraud, Kiva has applied a due-diligence process before a loan application is finally posted on the website. The process is as follows: In a 3-stage process Kiva verifies the identification of a potential borrower and reviews the financial history as well as the loan purpose. Furthermore, applicants need to demonstrate their credit worthiness by being supported either by a trustee or their private network. A trustee is an organization or an individual somehow related to the borrower, e. g., a social worker or a (religious) community. The trustee is per se not reliable for the loan. However, Kiva expects trustees to support 'their' borrowers during the repayment, as potential loan de-

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faults are recorded in the trustees' history. The support of a private network is proved by successfully passing a so-called 'private fundraising', in which family and friends of a potential borrower have to finance the loan to some extent, usually about 10 % to 15 % of the desired loan volume (*Dorfleitner* et al. 2021). Loan applications successfully passing the due diligence[3] are posted on Kiva's website until the loan is fully funded by socially motivated lenders or until an unsuccessful loan application expires on a specific date.

3. Literature Overview

This study combines two fields of research. The first one deals with the impact of COVID-19 on various aspects related to finance. These are, e. g., stock markets (*Szczygielski* et al. 2022), bank lending (*Hasan* et al. 2021; *Colak/Öztekin* 2021), and environmental performance (*Wellalage* et al. 2022). Moreover, *Zheng/Zhang* (2021) show that COVID-19 caused a decrease in the financial efficiency of microfinance institutions, while at the same time the pandemic increased their social efficiency. *Najaf* et al. (2022) examines the effect of COVID-19 on different loan peculiarities on the formerly biggest US P2P lending platform LendingClub by comparing loan applications posted during the early period of the pandemic (January to June 2020) along with those in the year 2019. Using OLS regressions with monthly macro-economic control variables, their results indicate an increased loan volume, maturity, and interest rate.

The second research area comprises prosocial lending. Most of the existing literature in this field addresses the peculiarities of Kiva's so-called field partner model (see e.g. *Ly/Mason* 2012; *Galak* et al. 2011; *Allison* et al. 2013, 2015; *Burtch* et al. 2014; *Moss* et al. 2015; *Dorfleitner* et al. 2020b; *Berns* et al. 2020; *Gafni* et al. 2021; *Gama* et al. 2021), in which the funding of P2P loans is inter-meditated by microfinance institutions. These provide financial services and products, in particular loans, to the poor and usually operate in developing countries. *Dorfleitner* et al. (2017) examine the drivers of loan defaults on Kiva. A focus of the relevant literature lies on motives and considerations of prosocial lenders on Kiva. *Ly/Mason* (2012) focus on the lenders' perception of loan purposes and find that loans with relation to the provision of health services and education are funded faster on Kiva. *Allison* et al. (2015) show that lenders prefer loans that are presented as chance to help other people. *Dorfleitner* et al. (2020b) also underline the altruistic motive of the investors, as they present evidence that loans mediated by microfinance institutions showing a higher social performance are more likely funded. Another example for this 'warm glow effect' among prosocial investors provide *Gafni* et al. (2021) who point out that

[3] More details on Kiva's due diligence for direct loans can be found on Kiva's website: www.kiva.org/about/due-diligence/direct-loans.

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investors fund loan proposals, addressing the basic needs, more easily than business related ones. On the other side, *Berns* et al. (2020) find that investors on Kiva – apart from their general prosocial orientation – pursue classical finance goals such as favoring loans that signal low default risk. This view is also supported by *Gama* et al. (2021), who focus on this dual nature of prosocial lenders' decision-making. They find loans associated with modern business sectors to be funded faster. Furthermore, larger modern business loans are even more preferred as they are expected to yield higher project returns. While Kiva's field partner model is already well-researched, there is hardly any empirical analysis focusing on the direct distribution model. *Dorfleitner* et al. (2021) is, to my best knowledge – so far – the only study which analyzes the funding determinants of direct P2P loans on Kiva US and sheds some light on the dynamics of this model. Their results indicate that loan descriptions conveying trust or loans endorsed by a third-party trustee show a better funding. This again underlines the dual nature of prosocial lending behavior. I contribute to this interesting but still under-researched topic.

III. Measuring Demand and Excess Demand on Kiva

In the following, I introduce two innovative measures for the demand and excess demand for Kiva US's direct loans. Moreover, I show the time series of both measures based on the whole Kiva US data set, ranging from its start in November 2011 to the end of 2022. For this purpose, the original loan applications posted on Kiva are used. Kiva provides access to the current and past loan applications via an API[4]. The data used in the following was obtained on 11th February 2023 and comprises 10,956 individual US loan proposals. An obvious limitation is that the data lacks any loan application that has not successfully passed the due-diligence process. However, this also prevents a possible bias caused by fraudulent loan applications.

Let us start our considerations by focusing on a specific loan application. The demand of a prosocial P2P loan is indicated by the publication of the loan proposal on Kiva's website. Thus, the actual demand equals the loan amount of the posted loan on that specific day. However, the demand for the borrowed amount remains constant for the whole maturity of the loan. Hence, I consider a loan to be hypothetically fully funded on the day when the loan's application is posted on Kiva. Following this idea, the loan volume is aggregated each day, comprising all (hypothetically fully funded) loans which have not yet matured.

The resulting Kiva Demand indeX KDX_t for day t is defined as:

[4] Cf. Kiva API, http://build.kiva.org/.

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$$KDX_t = \sum_i LV_i \times 1_{it}^{mat}$$

in which LV_i is the loan volume of loan proposal i and 1_{it}^{mat} is an indicator function equaling 1 if t lies in the period starting with loan proposal being posted and ending after the loan's maturity. For better readability, LV_i and consequently KDX_t are in USD M. Note that *KDX* increases on a specific day if the sum of the new loan applications' volume is larger than the sum of loan volumes of previously posted loans which hypothetically[5] expire on the same day. It decreases vice versa. Anyway, the metric has also one limitation: The loan term of the considered loans ranges from 1 to 60 months, with a median maturity of 25 months. Hence, the metric reacts to shocks quite smoothly.

The time series of the indicator is shown in Figure 1 as black line. For a first analysis, Figure 1 also shows the time series of the yield of a two-year US treasury bond as proxy for the risk-free interest rate (dashed line) as well as the COVID-19 cases (smoothed over a rolling 7-day period, in thousands, gray shaded area)[6]. We observe a steadily increasing demand reaching its first peak in August 2018. Afterwards, a decreasing trend can be observed until the outbreak of the COVID-19 pandemic, when the demand for prosocial loans rises again until the next peak on 16th November 2022. Furthermore, we can observe that the risk-free interest rate level and the *KDX* positively correlate to a higher extent, showing its peaks at similar times. This is economically plausible as, in times with a high interest level on classical credit markets, benefits from borrowing interest-free are higher. However, keep in mind that *KDX* increases also during the COVID-19 pandemic when the risk-free interest rate shows a relatively constantly low level between March 2020 and September 2021. Summarizing, we have some first indication that the prosocial P2P loan demand in the US is positively affected by the risk-free interest level as well as the COVID-19 pandemic. So far, the focus lies on the demand for prosocial P2P loans. For a more comprehensive view, an alternative metric would be desirable which additionally reflects somewhat the supply of prosocial loans. However, this is not straightforward, as it is not possible to measure the whole possible prosocial loan supply directly. The reason is that we can only observe the loan volume of funded loans, which is the equilibrium resulting from supply and demand. A proxy might be seen in the amount of loans that is still funding, to which I refer to as excess demand.

[5] Remember, that 'hypothetically funded' refers to the fact, that the demand for a loan is indicated by the publication of the loan application. Therefore, it is not relevant if or when the loan is actually being funded.

[6] See Section IV for more details on the Covid-19 cases, the yield and data sources.

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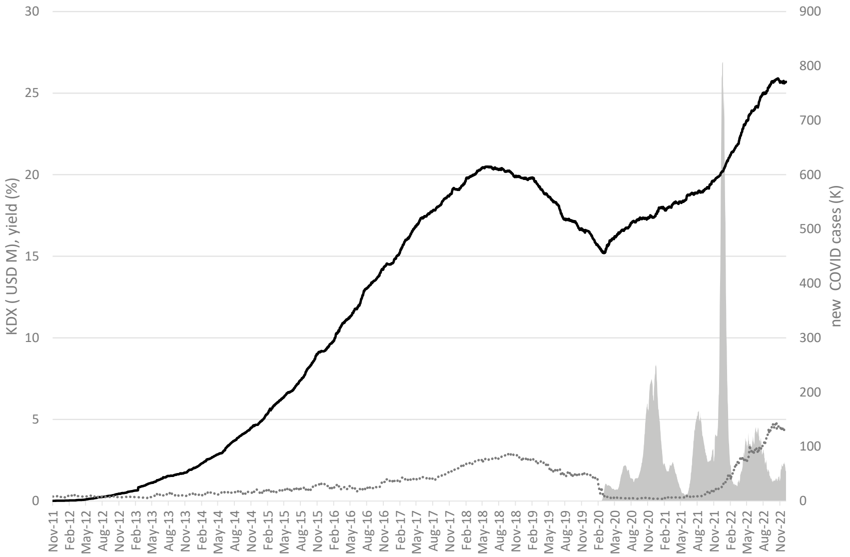

Notes: Kiva Demand indeX (KDX, in USD M) is indicated by the black line and the risk-free interest rate (yield of 2 year US treasury bond, in %) by the dashed line, both are presented via the left axis. The COVID-19 cases (smoothed over a rolling 7-day period, in thousands) are shown as gray shaded area (right axis). The variables are defined in Table 1.

Figure 1: Kiva Demand indeX (KDX) for Prosocial Lending

In this regard, I introduce an innovative measure called Kiva Excess Demand indeX (*KEDX*). The index is defined as:

$$KEDX_t = \sum_i LV_i \times 1_{it}^{fund}$$

in which LV_i is the loan volume of loan proposal i and 1_{it}^{fund} is an indicator function equaling 1 if the loan proposal is currently (at day t) being in funding. Again, LV_i and $KDEX_t$ are in USD M. A loan is regarded as being in funding whenever a loan proposal is posted on Kiva and the loan has not been fully funded so far or the maximum funding time has not expired. *KEDX* increases with the loan volume each time a new loan application is posted and decreases, whenever a loan is being funded or the application expires. Accordingly, whenever a loan has been fully funded at a specific point in time, this indicates sufficient supply for prosocial lending and the loan volume is correctly omitted from the index. Thus, the index *KEDX* covers both, i. e., demand and supply effects, simultaneously as requested. The index increases whenever the additional loan demand exceeds the supply on a specific day. In other words, the excess demand

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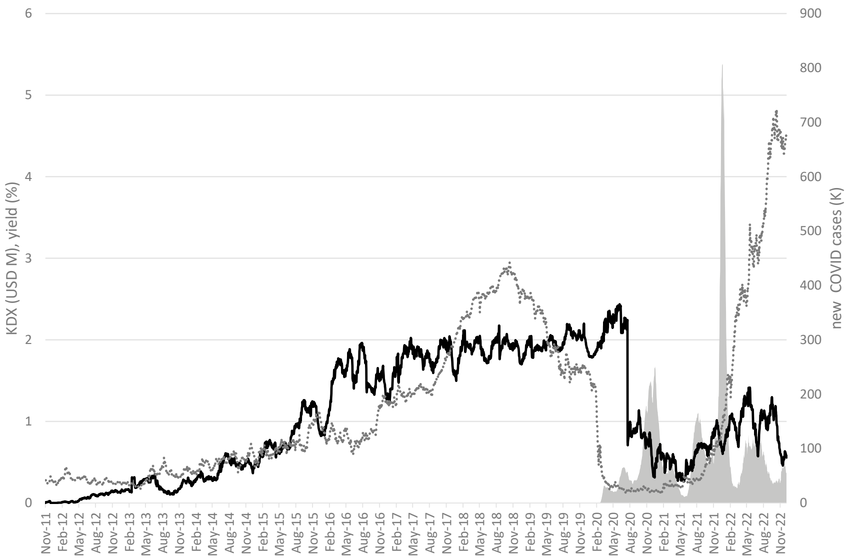
shows how the supply of funds for prosocial P2P loans relates to the demand at a specific day. Consequently, the index does not react whenever an increase in demand is associated with an equal increase in supply. However, the metric has one limitation: Expiring loan applications reduce the *KEDX* like fully funded loans. However, borrowers are allowed to adapt and resubmit an unsuccessful loan proposal. Hence, if a borrower's demand for a (formerly expired) prosocial P2P loan still exists, it is likely that the loan proposal is published again. Therefore, the *KEDX* index should reflect the loan amount again in upcoming observations. Thus, a possible bias should be limited. Comparing both metrics for a specific day, the *KDX* captures the demand of prosocial capital, while the *KEDX* proxies the capital still needed to fully fund all loans currently being in funding.

Figure 2 shows the development of *KEDX* as black line between the start of Kiva US in November 2011 and the end of 2022. What is remarkable is the significant rise of *KEDX* during the first COVID-19 wave in spring 2020. For a short time, the *KEDX* reached its all-time high, indicating an excess demand of prosocial P2P loans of 2.436 USD M on 1st July 2020. Afterwards, a decreasing trend is observable until 2021, with a huge drop in excess demand in August 2020. An increasing trend in excess demand is observable from summer 2021 to



Notes: Kiva Excess Demand indeX (KEDX, in USD M) is indicated by the black line and the risk-free interest rate (yield of 2 year US treasury bond, in %) by the dashed line, both are presented via the left axis. The COVID-19 cases (smoothed over a rolling 7-day period, in thousands) are shown as gray shaded area (right axis). The variables are defined in Table 1.

Figure 2: Kiva Excess Demand indeX (KEDX) for Prosocial Lending

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summer 2022. In contrast to *KDX*, *KEDX* seems to be much less affected by the risk-free interest rate level.

IV. Data and Methodology

Even though the time series of *KDX* and *KEDX* indicate an impact of the COVID-19 pandemic, as shown in the previous section, it remains unclear which aspects of the pandemic are significant drivers of both metrics and how they are related. The following section provides a thorough, multivariate analysis. Therefore, this study focuses on the COVID-19 related period ranging from 7th March 2020 to 31st December 2022.

1. Data

For the analysis, I use data from three different sources. As endogenous variables for demand and excess demand serve the indices *KDX* and *KEDX* as shown in Section III, which were derived from loan application data provided via Kiva's API[7]. Besides, I use several daily COVID-19 measures which have been obtained from Our World In Data (OWID)[8]. OWID is an openly accessible data platform hosted by the Global Change Data Lab, a UK non-profit organization. The time series dates back to 22nd January 2020 when the first COVID-19 case in the US has been reported. However, the data shows many missing values in the first days of the pandemic. Thus, I restrict the observation period to 7th March 2020 to December 2022 as all variables of interest are available for this time span. As financial control, a proxy for the risk-free interest rate is received from Refinitv Datastream[9]. To avoid a possible bias, all values have been transformed to the Eastern Time Zone. In the following, the exogenous variables are described in detail. More information on all variables and measures can also be found in Table 1.

[7] http://build.kiva.org/.

[8] http://ourworldindata.org.

[9] http://refinitiv.com.

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Table 1

Description of Variables

Variable	*description*	*data source*
Demand variables		
KDX	Kiva Demand indeX Indicator measuring the demand in USD M for prosocial P2P loans on Kiva on a specific day. See Section III for more details.	KIVA
KEDX	Kiva Excess Demand indeX Indicator measuring the excess demand in USD M for prosocial P2P loans on Kiva on a specific day. See Section III for more details.	KIVA
COVID-19 metrics		
new_cases	Newly confirmed cases (in thousand) of COVID-19 on a specific day. Might include probable cases where reported. Values are smoothed over a rolling 7-day period.	OWID
new_deaths	Newly confirmed deaths (in thousands) related to COVID-19 on a specific day. Values are smoothed over a rolling 7-day period.	OWID
fully_vaccinated	Share of population who have received all necessary doses of vaccines and are officially regarded as fully vaccinated by the initial vaccination protocol.	OWID
death_rate	*new_deaths* divided by *new_cases*	
COV	Vaccination-adjusted number of cases, derived as $COV = new\_cases \cdot (1 - fully\_vaccinated)$. In the regressions the logarithm of the metric is used.	
R_rate	Effective reproduction rate of COVID-19, estimated in real-time by using Kalman filters. It proxies the average number of people who are infected by one person.	OWID
stringency_index	Government Response Stringency Index, derived on a daily basis by the Oxford Coronavirus Government Response Tracker (OxCGRT) project as mean score of nine individual scores. These capture school and workplace closures, stay-at-home requirements, restrictions on public gatherings and events, public information campaigns, limitations of public transport, and international travel controls. Each sub-score is assigned a value ranging between 0 and 100, which indicates the highest level of government response. In case of locally different policies, the index considers the strictest area. In the regressions the logarithm of the metric is used.	OWID

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(Table 1)

Variable	*description*	*data source*
Control variable		
r_f	Risk-free interest rate, proxied by the yield of US government bonds with 2 year maturity corresponding to the median maturity of Kiva US loan proposals equaling 25 months (interpolated). Missing values for non-trading days are replaced with values of the day before.	refinitiv

2. Exogenous Variables

The COVID-19 pandemic is usually described by various aspects. There are directly related aspects, such as the magnitude (or level of infectiousness) which is commonly measured by the number of infections and the severity tackling the issue of how serious the course of the illness may be. Both aspects constantly changed during the course of the pandemic due to mutations of the virus. Furthermore, the development and distribution of vaccines helped to mitigate the level of severity of COVID-19, as well as the development of new forms of COVID-19 treatments.

Regarding the magnitude, the number of newly confirmed cases is multiplied by the share of population that is not fully vaccinated at a given point in time, to consider the effect of vaccinations. The resulting metric is (*COV*). I proxy the severity by the *death_rate*, which is calculated as the number of new COVID-19 related deaths divided by the number of new cases. Underlying original metrics (new cases and deaths) are applied as a rolling mean of seven days, indicated by the term 'smoothed', to prevent possible biases resulting from lower reporting behavior on weekends.

Both aspects measure the pandemic at a specific point in time. However, I expect possible borrowers and lenders on Kiva to consider expectations about the development of the pandemic in the near future. To tackle this aspect, I use the reproduction rate *R_rate* as a proxy. *R_rate* is a real-time estimation of the COVID-19 transmission rate and describes how many persons are – on average – infected by one contagious person. The measure describes the pandemic situation in the near future.

In the first months, the exponentially rising number of infections could only be stopped by restrictive governmental actions, such as lockdowns, which affected personal lives and income. Thus, I address an important last aspect indirectly related to COVID-19, which is the level of stringency of governmental

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actions. A proxy is provided by the Oxford Coronavirus Government Response Tracker (OxCGRT) project. The *stringency_index* metric is constructed as a mean of nine sub-scores tackling different aspects of government response, such as school and workplace closures or stay-at-home requirements (see Table 1 for more details). Each sub-score is assigned a numeric value ranging from 0 to 100, with 100 indicating the highest possible level of response.

Remember that Figure 1 shows that there might be some positive correlation between *KDX* and the risk-free interest rate. Whenever interest rates are generally high, it is more difficult for Kiva borrowers receive loans from commercial lending sources. This should increase the overall demand. However, it is not clear whether this holds true in times of low interest levels as shown in the period between spring 2020 and summer 2021 when the Federal Reserve kept interest rates low to stimulate the economy during the crisis. Keep in mind that *KDX* even increased during this phase.

Regarding the effect of the interest rate on the *KEDX*, Figure 2 shows no clear indication. As a positive relation between the demand and the interest rate is likely, possible effects on the supply of prosocial loans have to be discussed in more detail: Even though lenders on Kiva forego to receive interest from borrowers, their lending decision may be influenced by alternative investments. Hence, a low interest rate level goes hand in hand with low opportunity costs for potential lenders whenever they choose to lend money via Kiva. However, prosocial lenders also follow – at least to some extent – philanthropic motives and may provide more social capital in times of high interest rates to alleviate poverty. Overall, I expect interest levels in an economy to have an impact on the excess demand of prosocial lending. I control for this effect by considering the risk-free interest rate r_f as a proxy. As the median maturity of all P2P loans used to derive *KEDX* is 25 months, I regard the yield of 2-year US government bonds as suitable.

Summarizing, I expect an positive relation between *KDX* and the interest rate level. Yet the direction of the relation between *KEDX* and r_f depends on the extent of the investors' social motivation.

3. *Methodology*

The development of both indices *KDX* and *KEDX* clearly indicates the time series as non-stationary and to be subject to auto-correlation. This is supported by Augmented Dickey-Fuller (ADF) tests and Box-Ljung tests. Therefore, the application of OLS regressions is not appropriate. Keep in mind, that the focus of this study is to analyze the impact of different exogenous variables on the demand indices, rather than to derive a highly predictive model. In other words, I want to explain the (non-stationary) pattern of the indices to some extent by the

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explanatory variables. Thus, differencing, which is the standard procedure in time series analysis, is not suitable here. The reason is that it removes the trend/pattern and, hence, would obviously lead to insignificant results and would make the analysis obsolete. Furthermore, differencing would distort the demand indices. For example, differencing *KDX* results in the total loan volume of all new loan applications from a specific day and does not account for the fact that the demand for those loans continues during the suggested maturity.

As differencing is not possible, the issues of non-stationarity and auto-correlation are addressed by the exogenous variables as well as Auto-Regressive (AR) and Moving-Average (MA) components. The respective ARMA components are carefully derived by analyzing and testing the residuals of various specifications. In doing so, I followed two criteria: First, the residuals should be stationary, as proven by ADF tests and free of auto-correlation as shown by Box-Ljung tests. Second, I choose ARMA in order to obtain a model with a low Bayes Information Criterion (BIC).

The residuals of simple ARMA-models still show patterns of heteroscedasticity which typically occurs when a time series is influenced by differently stressed periods. Thus, I consider a GJR-GARCH approach as introduced by *Glosten* et al. (1993) and typically used in the context of stock returns *(Sun/Tong*, 2010; *Hudson* et al., 2020; *Kreuzer* et al., 2022). The desired peculiarity of the GJR-GARCH (1,1) model is that error terms may deviate in an asymmetric way with respect to positive and negative error terms. In particular, I apply the following specification:

$$Y_t = \alpha_0 + \sum_{k=1}^{AR} \alpha_{1,k} Y_{t-k} + \sum_{l=1}^{MA} \alpha_{2,l} \varepsilon_{t-l} + \vec{\alpha} \cdot CO_t + \alpha_c \cdot C_t + \varepsilon_t$$

$$h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 \varepsilon_{t-1}^2 + \beta_3 \varepsilon_{t-1}^2 I_{t-1}$$

in which Y_t is the the endogenous variable (in this case *KEDX*), while Y_{t-k} comprises the *k*'th previous index value, and ε_{t-l} the *l*'th previous index error term. While CO_t represents a vector of COVID-19-related variables, C_t represents the control variable r_f (see Table 1 for details) and ε_t the residual at time *t*. In the second equation, h_t describes the conditional variance of ε_t. I_{t-1} is a dummy variable, which equals 1 if $\varepsilon_{t-1} < 1$, and 0 otherwise. Due to the specification process, I find that the GJR-GARCH model is more suitable for modeling the *KEDX* than the *KDX*. Therefore, a standard GARCH (1,1) is used in case of *KDX*. Thus, the GJR component (term including β_3) is neglected for *KDX*.

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Table 2

Descriptive Statistics for Metric Variables

	Mean	*S.D.*	*Min*	*Q25 %*	*Median*	*Q75 %*	*Max*
Endogenous variables							
KDX	19.80	3.17	15.19	17.35	18.84	22.21	25.91
KEDX	0.99	0.57	0.26	0.61	0.83	1.10	2.44
Original COVID-19 metrics							
new_cases	97.66	117.88	0.05	38.60	65.00	112.83	806.96
new_deaths	1.06	0.77	0.00	0.43	0.79	1.57	3.38
fully_vaccinated	37.91	29.71	0.00	0.00	51.77	66.46	69.09
stringency_index	51.31	17.10	20.37	32.01	52.36	68.98	75.46
COVID-19 variables							
log(COV)	3.55	1.04	–2.92	3.03	3.58	4.06	5.67
death_rate	0.02	0.01	0.00	0.01	0.01	0.02	0.08
R_rate	1.08	0.38	0.52	0.91	1.02	1.13	3.61
log(stringency_index)	1.24	1.49	0.12	0.20	0.30	2.43	4.82
Control							
r_f	1.24	1.49	0.12	0.20	0.30	2.43	4.82

Notes: Q25 % and Q75 % refer to the 25 % and 75 % quantiles, respectively. The observation period ranges from 7th March 2020 to 31st December 2022, resulting in 1030 observations for all variables. The variables are defined in Table 1.

V. Results

1. *Descriptive Analysis*

The descriptive statistics for all variables are displayed in Table 2 and describe the analyzed COVID-19 period ranging from 7th March 2020 to 31st December 2022. The table's first section shows the demand (*KDX*) and excess demand index (*KEDX*), which serve as endogenous variables. The *KDX* has its minimum value on 30th March 2020, indicating a demand of 15.192 USD M following a rise in demand during the COVID-19 pandemic. The minimum value of the *KEDX* is 0.264 USD M and was observed on 19th June 2021 whereas the maximum equals 2.436 USD M on 1st July 2020. About 50 % of all observed values are between 0.61 and 1.10 USD M as indicated by the lower and upper quartile.

The second panel shows the descriptive statistics of the original COVID-19 measures as obtained from OWID, while Panel 'COVID-19 variables' comprise

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the variables used as exogenous variables in the following regression. Note that vaccination programs started in late 2020 and, hence, first data on fully vaccinated people was first reported on 13th December 2020. This explains why 28.16 % of all observations show the value 0. Thus, adding the original value as a control in the regression model might have a distorting effect. This finding supports the view of considering the level of vaccination as interaction with *new_cases* in the form of the log(*COV*) metric.

Table 3 shows the Bravis-Pearson correlation coefficients of the demand indices *KDX*, *KEDX*, and all metrics used as explanatory variables. All pairwise correlations of the COVID-19 metrics are negatively correlated with the *KDX*. Noteworthy are the high correlations of *KDX* with log(*stringency_index*), valuing –0.92 and r_f, which is 0.95. However, the correlation of *KEDX* with log(*stringency_index*) is much lower and the one with r_f is not even significant. Obviously, *KEDX* is driven less by interest rate movements of classical debt markets than the *KDX*. As the *KEDX* comprises the interest-free loan demand as well as the prosocial loan supply, this may be seen as a fist indication that Kiva investors have dual motives. Namely, comprising a distinctive prosocial lending behavior while focusing on opportunity costs.

Table 3

Bravis-Pearson Correlation Coefficients for KDX, KEDX and all Explanatory Variables

	(1)	(2)	(3)	(4)	(5)	(6)
(1) *KDX*						
(2) *KEDX*	–0.27***					
(3) *log(COV)*	–0.20***	–0.20***				
(4) *death_rate*	–0.53***	0.48***	–0.22***			
(5) *R_rate*	–0.21***	0.26***	–0.43***	–0.07**		
(6) *log(stringency_index)*	–0.92***	0.14***	0.43***	0.46***	–0.03	
(7) r_f	0.95***	–0.05	–0.32***	–0.39***	–0.07**	–0.90***

Notes: The symbols ***, **, * indicate a significance level of 1 %, 5 %, and 10 %, respectively. The observation period specification ranges from 7th March 2020 to 31st December 2022, resulting in 1030 observations for all variables. The variables are defined in Table 1.

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Regarding the explanatory variables, the high correlation between r_f and log(*stringency_index*) equaling –0.90 has to be addressed. The negative relation can be explained through the monetary actions taken by the Federal Reserve that caused a reduction of r_f by 40 BP in March and April 2020 when (at the same time) many governmental actions have been enforced. Nevertheless, as there is a clear indication for multicollinearity, I refrain from using both metrics simultaneously in the following regressions.

Apart from that, the coefficients of all other explanatory variables are far below 0.8 which indicates the absence of multicollinearity in the respective data (*Kennedy*, 2008). The negative correlation between *R_rate* and log(*COV*) can be explained by the fact that *R_rate* captures the future development of the pandemic. Thus, a low value of *new_cases* today accompanied by a high level of *R_rate* often leads (a few weeks later) to a situation in which *new_cases* is high and governmental response resulted in a decreased *R_rate*.

2. *Regression Analysis*

I analyze the effect of four aspects of the COVID-19 pandemic –magnitude, severity, the expectation regarding the development, and stringency of governmental response– on the demand and excess demand of prosocial P2P loans on Kiva. The results of the regressions are shown in Table 4.

Specifications D.1 and D.2 show the results of GARCH (1,1) regressions explaining *KDX*. Due to multicollinearity issues r_f is used in Specification D.1 apart from log(*stringency_index*) in D.2. As a single loan application's volume is considered by the *KDX* over the whole (hypothetical) maturity of the loan, the *KDX* reacts quite smoothly to external effects and shows a strong auto-correlation. Consequently, higher degrees of AR|MA orders are necessary. The specification process proved AR = 9 and MA = 4 as suitable. Specifications ED.1 and ED.2 present the regressions results for the *KEDX* as endogenous variable. Like for the *KDX*, ED.1 incorporates r_f, whereas Specification ED.2 applies log(*stringency_index*) instead. As already motivated in Section IV, a GJR-GARCH (1,1) approach is used. Note that the coefficient of the GJR-component leverage parameter (β_3) is highly significant in both specifications, which highlights the suitability of the GJR-GARCH model. As the *KEDX* is less affected by auto-correlation compared to *KDX*, a simple AR = 2, MA = 0 model serves well to control for auto-correlation.

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Table 4

Results of the GARCH Models

	KDX		*KEDX*	
	D.1	D.2	ED.1	ED.2
COVID-19 variables				
log(COV)	−0.0616***	−0.0379***	−0.0516***	−0.0463**
death_rate	−0.6681***	−0.5326	1.2287***	1.5870
R_rate	0.0271***	0.0223	0.3255***	0.2859***
log(stringency_index)		−0.0453**		−0.1453*
Control				
r_f	0.0205***		0.0438***	
GARCH-parameters				
intercept (α_0)	15.2359***	15.4581***	0.5512***	1.1624***
variance intercept (β_0)	1.70E-05	1.50E-05***	3.70E-05***	0.0001
β_1	0.9556***	0.9609***	0.9371***	0.8485***
β_2	0.0225	0.0201***	0.1294***	0.2673***
leverage parameter (β_3)			−0.1435***	−0.3091***
AR|MA	9|4	9|4	2|0	2|0

Notes: Specifications D.1 and D2 show the results of a GARCH(1,1) model with *KDX* as endogenous variable. Specifications ED.1 and ED.2 present the results of a GJR-GARCH(1,1) model with *KEDX* as endogenous variable. The observation period for each specification ranges from 7th March 2020 to 31st December 2022, resulting in 1030 observations. AR refers to the auto-regressive and MA to the mean average components used. ***, **, * indicate a significance level of 1 %, 5 %, and 10 %, respectively. All variables as shown in Table 1.

The results show a negative and significant relation between the magnitude of the pandemic, measured by log(*COV*), and both demand indices (with exception of ED.2). Thus, the magnitude of the pandemic decreases the demand (*KDX*) for prosocial loans, as well as the loan volume that is currently funding (*KEDX*), indicating a moderate effect on the supply.

The severity of the pandemic shows a negative effect on the *KDX* in Specification D.1, but a positive relation with the *KEDX* in ED.1. A rise of *death_rate* by 1 % leads, on average, to a decrease in demand of 6.681 USD, while simultaneously excess demand increases by approximately 12.287 USD. This indicates that, in times of more severe phases of the pandemic, investors hesitate to provide capital for prosocial loans. Apart from that, the coefficient of *death_rate* is insignificant when log(*stringency_index*) is used.

The coefficient's sign of *R_rate* capturing future expectations is positive in all specifications and, hence, the expectation of an intensifying pandemic leads to

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an increased excess demand. Please note, the coefficient in ED.1 is approx. 12 times larger than in D.1, which indicates that an increase of *R_rate* by 1 % increases excess demand by approx. 12 times the rise in demand. Thus, investors seem to be less generous in granting prosocial loans in times of greater uncertainty. However, the results show significance only for Specifications D.1, ED.1, and ED.2.

According to the coefficients regarding log(*stringency_index*), I find that, in phases with more restrictive governmental measures, the excess demand is increased on average. However, the result is significant only on the 10 % level. Regarding the *KDX*, the effect is also negative and significant on the 5 % level. Hence, by comparing the coefficients, there is weak evidence that the supply increases when more restrictive governmental actions are in place.

An interesting result concerns the control variable r_f. Its coefficient is positive and significant for *KDX*, which is not surprising as this finding is already revealed by the high correlation between *KDX* and r_f equaling 0.95 %. More interesting is the positive coefficient of r_f in ED.1. Keep in mind that an insignificant or negative coefficient would have indicated that investors tend to follow more philanthropic motives than considering opportunity costs. The highly significant positive coefficient shows that this is not the case. Thus, borrowers and lenders on Kiva seem to consider the current overall interest rate level the same way. Hence, in times with higher interest rate levels, the opportunity costs for potential lenders to provide interest-free loans are higher. At the same time, loans on Kiva become more attractive for potential borrowers, leading to an increased demand. Both result in a higher excess demand.

Please be aware that there is no indication in the results that causality behind the development of the excess demand does come from the interest rate level. This –at a first glance– plausible idea might be rooted in the observation that the Federal Reserve lowered interest rates at the beginning of the pandemic to support the economy. This motivates the rationale that the COVID-19 pandemic impacts the interest level via central bank actions which in turn (solely) effects the *KEDX*. However, the significant coefficients of the COVID-19 measures in Specification ED.1 clearly demonstrate their explanatory power in addition to r_f. Furthermore, applying r_f as the sole explanatory variable yields no significant results. This is economically sound as r_f should capture to a greater extent the previous pandemic development as central banks are not expected to act instantaneously on new pandemic developments.

VI. Conclusion

The behavior of borrowers and prosocial lenders is still an under-researched topic. This study is the first to introduce demand and excess demand indices

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based on loan application data from the leading prosocial P2P-lending platform Kiva. The index for the demand reveals that the demand for prosocial P2P loans rose steadily during the pandemic after a phase of decreasing demand. The index for excess demand shows higher time dynamics and focuses on the critical issue, i. e., whether altruistic investors are capable of and willing to supply social loans in case of a severe crisis when the need for interest-free loans is high among the poor.

By analyzing the impact of different COVID-19-related aspects on the demand and excess demand utilizing GARCH and GJR-GARCH approaches, I shed some light on the issue of how the prosocial lending market is being affected by the COVID-19 pandemic. Summarizing, I observe a significant influence of several COVID-19 measures on the demand and the excess demand after controlling for the prevalent interest rate level. The impact of COVID-19 metrics on the demand as well as on the excess demand of prosocial P2P loans is not rectified. Demand is negatively affected by the vaccination-adjusted number of cases and the mortality rate which proxy current situations in terms of magnitude and severity. Thus, potential borrowers seem to abstain from asking for new prosocial loans in times when the pandemic situation becomes worse. However, there is a positive effect of reproduction rate on demand. This indicates a pro-active behavior of borrowers trying to receive prosocial loans before circumstances exacerbate. Excess demand is negatively affected by the magnitude of the pandemic or restrictive governmental actions and positively by death rate and reproduction rate. The results suggest that the findings are driven more by the supply side. Comparing the results of both indices shows an indication that the lending behavior of prosocial investors is affected by pandemic effects. Hence, investors seem to be more reluctant to provide social capital in stronger pandemic phases or when the pandemic might worsen in the near future.

Furthermore, I find evidence that borrowers and lenders on Kiva consider the current risk-free interest level when they decide to borrow or to lend. The reason for this might be seen in investors' opportunity costs associated with the foregone interest that is obtained from non-prosocial investment or borrowers' access-ability of commercial loans. This is an important new finding as it indicates an important control variable for further studies.

Overall, the results are in favor of the dual nature of prosocial lending behavior: All investors on Kiva, to some extent, follow socially oriented motives as they relinquish to receive interest rate payments. Yet the investors behavior is also influenced by financial considerations and the uncertainty arising from the pandemic instead of acting purely out of philanthropic motivation.

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