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Emergence of Financial Intermediaries in Electronic Markets: The Case of Online P2P Lending

Sven C. Berger, Goethe University & E-Finance Lab Frankfurt, E-mail: sberger@wiwi.uni-frankfurt.de
Fabian Gleisner, Goethe University & E-Finance Lab Frankfurt, E-mail: gleisner@wiwi.uni-frankfurt.de

Abstract
We analyze the role of intermediaries in electronic markets using detailed data of more than 14,000 originated loans on an electronic P2P (peer-to-peer) lending platform. In such an electronic credit market, lenders bid to supply a private loan. Screening of potential borrowers and the monitoring of loan repayment can be delegated to designated group leaders. We find that these market participants act as financial intermediaries and significantly improve borrowers' credit conditions by reducing information asymmetries, predominantly for borrowers with less attractive risk characteristics. Our findings may be surprising given the replacement of a bank by an electronic marketplace.

Keywords: Asymmetric information, intermediation, social lending, electronic markets

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1 Introduction

The evolution of information technology in recent years has led to the development of electronic marketplaces where traditional intermediaries may be less important or even redundant for the economic interaction of market participants (Benjamin and Wigand 1995, Evans and Wurster 1997, Malone, Yates, and Benjamin 1987). Within the financial services industry, the debate about disintermediation and the future relevance of financial intermediaries (Allen and Santomero 2001, Nellis, McCaffery, and Hutchinson 2000, Schmidt, Hackethal, and Tyrell 1999) is fueled by the increasing role of electronic lending markets (*P2P Lending* or *Social Lending*) where an electronic marketplace replaces a bank as the traditional intermediary and enables the brokerage of consumer loans directly between borrowers and lenders (Hulme and Wright 2006, Meyer 2007). A recent study predicts that within the next few years such social banking platforms may have a market share of ten percent of the worldwide market for retail lending and financial planning (Gartner Inc. 2008). For the US, the P2P lending market is estimated to grow to a volume of up to ten billion USD within the next 10 years (Bruene 2007). We examine more than 14,000 credit transactions on the American electronic P2P lending platform *Prosper.com*, covering all transactions that took place in the market between 2005-11 and 2007-09. Our analysis of the P2P credit market starts with the observation that, despite the direct mediation of loans in the marketplace, new types of intermediaries emerge as market participants provide paid intermediary services. In the paper we then focus on the following questions: (1) From a theoretical point of view, how can these intermediaries create value in the interaction between borrowers and lenders? (2) Should all borrowers make use of an intermediary, and can it make sense to pay for intermediary services? (3) From the borrowers' perspective, what is the economic impact of intermediation in the electronic lending marketplace? Our empirical analysis is confirmatory in nature. It is based on the literature on financial intermediation (e. g., Diamond 1984, Leland and Pyle 1976) from which we derive hypotheses on the role of intermediaries in electronic marketplaces.
The electronic lending platform Prosper provides an excellent laboratory for studying intermediaries in electronic marketplaces. Prosper is the

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largest provider with nearly 90 million USD in loans originated in the examination period from 2005-11 to 2007-09, as market participants were permitted to act as paid intermediaries in this period. As of 2008-09-30, Prosper dominated the US market for P2P lending with a total of 176 million USD in issued loans, followed by its competitor *Lending Club* with 19 million USD.[1] At that time, the market share of P2P consumer loans represented a fraction of the around 490 billion USD of non-revolving consumer credit outstanding at commercial banks (Federal Reserve 2008). All loans on Prosper have an identical maturity of 36 months. Our data sample includes detailed information on 14,321 financial transactions as well as the market participants that chose to participate in the market and covers transactions with and without the use of an intermediary. This allows us to test for aspects of the financial transaction and individual factors that might influence the usage of intermediary services. In line with traditional intermediation theory, we find that financial intermediaries on electronic P2P lending platforms have significant impact on borrowers' credit conditions, suggesting that intermediation helps to reduce the prevalent information asymmetries. The intermediary primarily contributes by screening potential borrowers. A mandatory screening process by means of the intermediary's commitment to screen every borrower within the group significantly improves borrowers' access to credit. Following diligent screening, the intermediary's recommendation of a borrower signals better information about creditworthiness and thus leads to better credit conditions. Moreover, bidding on the screened borrower's credit listing has an even stronger impact on the resulting interest rate.

Our results indicate that borrowers should consider the reputation of an intermediary as it serves as a good proxy for the future diligent assessment of borrowers. Intermediation costs can be compensated by lower interest margins for borrowers. These results are robust to self-selection regarding the choice of an intermediary and characteristics of the financial transaction. All in all, our results suggest that financial intermediaries in electronic credit marketplaces may create substantial value for borrowers. Our findings are consistent with a stream of literature suggesting that electronic markets create business opportunities for new intermediaries (Chircu and Kauffman 2000, Methlie and Pedersen 2002, Bakos 1991, Bakos 1998, Sen and King 2003). Despite the electronic credit marketplace enables the direct mediation of loans, new financial intermediaries emerge between borrowers and lenders. There are several reasons why our results are of particular interest also for banks and other financial service providers that face the strategic decision of an active involvement in electronic lending markets. One option could be to participate in these marketplaces and offer financial advisory. Another interesting possibility could be to enter the P2P lending market and to establish a new marketplace to support the existing retail operations and enable cross-selling. Eventually, lending marketplaces are potential customers for banks' transaction services.

Our approach to examining the role of financial intermediaries on electronic lending platforms makes three important contributions to the literature: First, this is one of the first studies analyzing an electronic lending marketplace, and the first study to empirically examine intermediation on an electronic P2P lending platform. We explain how electronic credit markets work, and provide insights into the role of intermediaries in the marketplace. Second, we test theoretical predictions from the literature on financial intermediation with new data. Our sample of more than 14,000 transactions on a P2P lending marketplace includes detailed information on the involved market participants and the loan characteristics. The dataset covers the complete transaction history of the credit marketplace for a time period of almost two years. Third, we quantify the economic impact of intermediation and other transaction characteristics on borrowers' loan spread and show that the usage of financial intermediaries which are neither professional nor institutional but members of the network may significantly improve the terms of trade for the borrowers.

The remainder of the paper is organized as follows: the next section gives an overview of electronic P2P lending platforms and explains the functioning of these marketplaces. Section 3 summarizes the relevant previous literature on financial inter-

[1] The Prosper marketplace temporarily closed at the end of 2008 and is registering with the SEC in order to allow lenders to trade outstanding loans before maturity date (Prosper Marketplace Inc. 2008). This represents a recent development in P2P lending. Lending Club has already successfully registered with the SEC and created a secondary market for loans.

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mediation and derives hypotheses about the role of intermediaries on electronic lending platforms. Section 4 overviews the methodology employed, describes the data, and presents the empirical results of our analyses as well as robustness tests. In section 5 we conclude with a summary and the limitations of our study.

2 Intermediaries in electronic credit marketplaces

2.1 Electronic marketplaces and disintermediation

Markets are essential for economic activity in mediating the demand for and supply of goods and services. Intermediaries help to facilitate transactions between buyers and sellers by (1) providing transaction processing capabilities, (2) bringing enhanced levels of knowledge and expertise, and (3) adding to the transactability of a given good or service (Chircu and Kauffman 2000).

The internet has made e-commerce possible where electronic markets are becoming more important in coordinating supply and demand (Grieger 2003, Segev, Gebauer, and Farber 1999). Electronic markets can facilitate economic activity even under complex and insecure conditions (Cordella 2006), significantly reduce information and transaction costs, and may in this way displace traditional intermediaries (Malone, Yates, and Benjamin 1987). Many authors argue that once electronic markets emerge, traditional intermediaries may be threatened by an electronic brokerage effect also called disintermediation (for a literature overview see Chircu and Kauffman 2000). In sharp contrast to that, the theoretical contributions on electronic markets and disintermediation have not yet been supported by convincing empirical evidence (Chircu and Kauffman 2000, Sen and King 2003). Moreover, the displacement of traditional intermediaries may never occur. Authors like Sarkar, Butler, and Steinfield (1998) or Hagel and Singer (1999) argue that electronic markets may lead to new forms of intermediation.

2.2 Electronic lending platforms

Electronic lending platforms are electronic markets that mediate between borrowers and lenders of loans. We focus here on consumer loans between individual borrowers and lenders and exclude platforms for bonds or syndicated loans (Steelmann 2006). The electronic credit marketplace as a website in the World Wide Web constitutes the general conditions for peer-to-peer lending and provides the administration of current loans. Electronic lending platforms differ in the way loans are originated: Some providers mediate between borrowers and lenders themselves, whereas other providers match borrowers' credit listings and lenders' bids with an auction mechanism (Meyer 2007).

The lion share of participants in the marketplace are private individuals, although there are institutional lenders investing in some, too. There are numerous providers that operate nationally due to differing regulatory frameworks. Table 1 provides an overview of the three major Anglo-American and German providers and their business models. A recent development of the business model of P2P lending marketplaces is that lenders may trade loans prior to maturity, increasing the liquidity of P2P loans. As of February 2009, Prosper is still in the process, whereas Lending Club has already successfully registered with the SEC to create a secondary loan market. Despite differing business models, there is one distinctive feature that these marketplaces have in common: Transactions in electronic credit marketplaces occur anonymously between fictitious "screen names". Therefore, information is asymmetrically distributed between borrowers and lenders. Loans are not collateralized and lenders face the inherent risk of default (Steelmann 2006).

Despite anonymous interactions, loan listings contain additional information on potential borrowers. Lenders can evaluate individual creditworthiness through *quantitative* as well as *qualitative* figures. Prosper.com, America's largest peer-to-peer lending marketplace, provides an individual rating and an indicator of indebtedness in cooperation with the credit reporting agency Experian as the two main *quantitative* figures. The informational value of these figures should be considered high, although the degree to which consumer credit reports are accurate, complete or consistent is in dispute (Avery, Calem, Canner, and Bostic 2003). Most platforms give market participants the opportunity to provide additional personal information about their background, their financial standing and the purpose of the loan. This qualitative, "soft" information is mandatory and its validity is a priori not controlled. Borrowers thereby might

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Table 1: Overview of major electronic P2P lending platforms

Provider	Prosper Marketplace Inc.	Lending Club Corp.	Zopa Ltd.	Smava GmbH
URL	prosper.com	lendingclub.com	zopa.co.uk	smava.de
Market	USA	USA	UK, Italy, Japan	Germany
Members	760,000[a]	n. a.	200,000[b]	28,000[c]
Cooperating Credit Reporting Agency	Experian plc	TransUnion LLC	Equifax Inc.	Schufa Holding AG
Loan Processing Bank	Wells Fargo Inc.	WebBank (WebFinancial Corp.)	The Royal Bank of Scotland plc	biw Bank für Investments und Wertpapiere AG
Maximum Amount	25,000 USD	25,000 USD	15,000 GBP	25,000 EUR
Pricing of Loans	Second Price Auction / Determined by BR	7.37% to 20.11% (by credit grade)	Second Price Auction	Determined by BR
Fees	BR initial 1–3% of LA; LN annual 1% of LA outstanding	BR initial 0.75–3.5% of LA; LN 1% of payments received	BR GBP 94.25 (fixed fee); LN annual 0.5% of LA outstanding	BR initial 2–2.5% of LA
Secondary Market	planned	available	available (Italy only)	none

This table presents an overview over the four major Anglo-American and German P2P credit marketplaces and their business models. BR = borrower, LN = lender, LA = loan amount. [a]as of 2008-06-30; [b]as of 2008-07-07; [c]as of 2008-03-24

have an incentive to overemphasize their "quality" (the present value of the prospective projects, their financial standing or payment behavior) in their personal descriptions *(moral hazard)*.

Among the emerging literature on electronic lending marketplaces, a number of working papers examine the role of borrowers' "soft" information that is conveyed in personal pictures and descriptions. A study by Herzenstein, Andrews, Dholakia, and Lyandres (2008) analyzes around 5,000 loan listings on Prosper.com during June 2006 and finds that demographic attributes such as race and gender have only a small effect on the likelihood of the auction's funding success when compared to the impact of borrowers' financial strength and effort when listing and publicizing the auction.

In contrast to that, Ravina (2008) shows that borrowers' characteristics such as beauty and race significantly affect loan fundability and loan pricing. Incorporating nearly 12,000 loan requests from 2007-03-12 and 2007-04-16 she finds that borrowers perceived as beautiful are more likely to get a loan and pay significantly lower credit spreads. Moreover, Ravina finds that black borrowers pay significantly higher spreads even though they are not more likely to default.

A study by Pope and Sydnor (2008) analyzes around 110,000 loan listings on Prosper.com in a one-year period from 2006-06 until 2007-05. There results indicate significant racial disparities on the credit market: Loan listings of black borrowers are less likely to be funded and the spreads paid by blacks are higher than those by comparable whites. In contrast to Ravina (2008), they find that blacks have a higher relative default rate than white borrowers. Of course, it is impossible to evaluate whether P2P lending offers more or less equal access to credit compared to traditional consumer lending: Inherent in an analysis on P2P lending based on transaction data is a potential sample selection bias. Lenders using the online platform might represent those with a high probability of default or lenders whose credit applications have been rejected at traditional banks. For example,

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Agarwal and Hauswald (2008) find that small business lenders strategically self-select into electronic (transactional) lending with respect to the publicly available information on their creditworthiness. It follows that from observed transactions in a P2P marketplace a comparison to loan availability and loan pricing at traditional banking institutions is not possible.

However, none of this is the aim of this paper: We focus on the role of intermediaries that emerge in the interaction between borrowers and lenders in the electronic P2P lending market. Central to our analyses are social networks on the Prosper marketplace called groups.

2.3 Groups on Prosper.com

In addition to personal profiles, borrowers and lenders can form groups. These smaller communities within the marketplace review and assess the creditworthiness of individual members. Groups are potentially beneficial for market participants by providing and verifying information or obtaining additional information about borrowers that is not publicly available. Groups lack distinct ownership and governance features as they typically exist in credit cooperatives (Davis 2001, Taylor 1971). There is no ownership of the groups, and there is no collective decision mechanism on accepting group members or granting loans. Furthermore, groups do not exclusively deal with their members. At any time, lenders from outside the group may invest in a group member's loan listing. This implies that there is no rotation of money within the group, and no specific allocation process. There are two papers that specifically examine the role of groups on the P2P lending website Prosper.com: Freedman and Jin (2008) use transaction data from 2006-01-06 until 2008-07-31 covering around 290,000 loan listings and 25,000 funded loans. They find evidence for the idea that the monitoring within social networks provides a stronger incentive to pay off loans ex-post: Loans with friend endorsements and friend bids have fewer missed payments and yield significantly higher rates of return than other loans. Everett (2008) looks at the influence of group membership on loan default within 13,486 Prosper loans. The dataset covers funded loans from 2006-05-31 until 2007-11-06 and incorporates ex post loan performance information until 2008-05-07. He finds that membership in a group significantly decreases loan default risk if the group enforces real-life personal connections like, e.g., employees of the same company or alumni of a certain university. Both studies presented above look at social networks in the credit market but do not specifically take the group leader into account. It is, however, not the group as an institution per se, but the group leader who decides about membership and plays a substantial role in the lending process.

2.4 Group leaders as financial intermediaries

In order to reduce information asymmetries, lenders must screen potential borrowers. Given the large number of available credit listings, it can be costly or impossible to process the information available about potential borrowers. Therefore, intermediaries emerge in the electronic marketplace offering intermediary services in order to assess and limit credit risk. Every participant in the online lending platform can found a group and become a group leader. Group leaders set membership criteria and administer the group. Groups are smaller communities within the marketplace where group members may share a bond based on employment, geography, education, common leisure activities, or other factors. The principle that people from close communities act more responsibly towards each other aims to lower the risk of defaults and therefore enables lending at better rates. Among the most important tasks of the group leader is the screening of borrowers within the group (a voluntary due diligence known as "vetting"). Within groups, it is common that borrowers send personal documents regarding their identity, income, and other pertinent information to the group leader. The group leader may also establish personal contact with the borrowers' employer to verify the personal income in order to recommend a borrower's credit listing.

The assignment as a group leader may be time-consuming, since a detailed "due diligence" of a potential borrower can take several hours. There are many individual motives for forming a group and becoming a group leader. Intrinsic motivation may result from altruism or related social returns from leading a group. As extrinsic motivation and as a more tangible example, the owner of an Apple computer store may run a group on Prosper

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to promote sales by providing an alternative form of consumer finance. Leading a group can also be even more directly monetarily motivated: Group leaders were permitted to receive remuneration ("fees") for their effort, acting as paid intermediaries. Group leaders collect a fee in the form of additional interest for providing intermediation services until 2007-09-12, when Prosper modified the fee concept (Prosper Marketplace Inc. 2007b). The incentive for borrowers to disclose information to the group leader is to attract more bids on their credit listing for the purpose of better interest rates. Group leaders also supervise the repayment of loans within their group. In the case of default, Prosper informs the group leader who can encourage loan repayment and may arrange limited repayments (called "community payments") on behalf of a member who is not able to do so. Group leaders thus serve as a financial intermediary by acting as middlemen between lenders and borrowers. Even though the electronic lending marketplace displaces the traditional depository institution as a financial intermediary (Datta and Chatterjee 2008), group leaders emerge as new intermediaries. The group leader facilitates the movement of capital from surplus units in the marketplace to deficit units by producing information, providing advice, and monitoring loan repayment. Where intermediary services were concerned, borrowers faced the choice between "free" or "paid" intermediaries. It is a priori not clear if intermediation created value for the electronic marketplace and, in particular, for the borrowers. We focus here on the value of intermediation for borrowers.

3 Development of hypotheses

There is extensive research on financial intermediation. In this section we review the relevant intermediation literature in order to derive hypotheses about the role of intermediaries in electronic credit marketplaces. Traditionally, transaction costs and information problems have provided the foundation for understanding intermediaries (Allen and Santomero 1998, Bhattacharya and Thakor 1993, Dewatripont and Tirole 1994, Santomero 1984). Due to asymmetric information between borrowers and lenders, financial markets can perform poorly or even fail when borrowers know their characteristics (the present value of the prospective projects), but lenders cannot distinguish between them. Market value then reflects average project quality (Akerlof 1970, Leland and Pyle 1976). As a result, "good risks" are driven out of the market and average project quality decreases *(adverse selection)*. This can be the case if borrowers cannot be expected to be entirely straightforward about their characteristics since there may be a substantial reward for exaggerating positive qualities *(moral hazard)*. In his seminal article, Diamond (1984) argues that intermediaries can help to overcome problems of asymmetric information by acting as "delegated monitors". When several lenders in a loan syndicate want to monitor a borrower and monitoring is costly, there will either be inefficiently high monitoring expenditure or a free-riding problem, where no lender has an incentive to monitor. In this case, a financial intermediary as a delegated monitor minimizes the costs of monitoring. In Diamond (1984) the intermediary holds deposits and writes loan contracts to borrowers, which is not the case with the group leader in the electronic lending platform. Nevertheless, the argumentation is applicable to the lending platform Prosper for two reasons. Firstly, the capital of several lenders is syndicated into one loan. Secondly, lenders face a large number of potential borrowers in the marketplace. Lenders benefit from additional private information about borrowers in order to better assess credit risk and the appropriate borrowing rate required. Acquiring private information about credit listings implies a time-consuming (repeated) interaction with the borrower which is costly. Therefore, there are group leaders who act as intermediaries in producing additional private information about borrowers within groups. The intermediary realizes significant economies of scale by producing information for the marketplace. Intermediaries can solve another information problem prevalent in electronic marketplaces. Borrowers might not be willing to disclose proprietary information to a large number of lenders in a public financial market. Following Bhattacharya and Chiesa (1995), an intermediary acts as the facilitator of knowledge sharing, whereby proprietary information is only disclosed vis-à-vis the intermediary.

In the marketplace, participants can voluntarily disclose additional private information regarding their credit listing. Within groups, borrowers may disclose proprietary information regarding their financial standing solely to the group leader. As

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group members, borrowers can thus avoid disclosing private information to the marketplace. Group leaders assess and recommend a borrower's credit quality based on additional private information, and at the same time preserve the privacy of proprietary information. Groups enable a better assessment of the borrowers' credit quality, resulting in potentially lower rates for borrowers.

Finally, group leaders not only screen potential borrowers, but also monitor ongoing loan repayment in place of the potentially large number of lenders. In cases of loan default, Prosper informs the group leader who may encourage loan repayment and even arrange limited repayments by the group. If a borrower's loan is more than one month late, lenders can make what is called a "community payment" on behalf of a borrower who is temporarily not able to do so. These payments can be compared to a mutual insurance mechanism.

All in all, the intermediary reduces uncertainty for lenders, which should be reflected in lower required risk premiums. The arguments provided above lead us to the first fundamental hypothesis:

Hypothesis H1: Borrowers within groups are able to borrow at lower credit spreads.

Next, we formulate three hypotheses that enable us to decompose the role of the group leader in the lending marketplace. With imperfect information about borrowers' credit quality, lenders can use publicly observable signals to assess credit risk (Riley 1975, Rothschild and Stiglitz 1976, Spence 1973). Observable characteristics or actions can serve as signals. On the electronic lending platform Prosper, the recommendation of a credit listing by a group leader is a strong observable signal of credit quality. Borrowers can voluntarily provide additional private information regarding their financial standing to their group leader. Group leaders can then recommend credit listings within their groups. This observable recommendation serves as a signal of good credit quality for the marketplace.This leads to:

Hypothesis H2: The recommendation of a credit listing by the group leader leads to lower credit spreads.

The reliability of information produced by an intermediary is a prevalent problem in the intermediation literature. Group leaders might recommend credit listings within their group without prior diligent screening. It may be difficult or impossible for potential lenders to distinguish good information from bad. Group leaders can signal credibility of a recommendation by bidding on the recommended credit listing. The potential investment of the group leader is an observable signal for information quality (Leland and Pyle 1976). We derive:

Hypothesis H3a: A group leader's bidding serves as a credible signal for the quality of the credit listing and results in lower credit spreads.

Hypothesis H3b: A group leader's bidding on a credit listing signals information quality and has a stronger impact on credit spreads than a recommendation by the group leader.

We derive two additional hypotheses about the reputation and the size of groups. Past activities within a group, especially regarding the diligent assessment of individual borrowers by the group leader, are only imperfectly observable. In contrast, the reputation of a group in the electronic marketplace is observable from its group rating. The group rating is a measurement of a group's performance in paying back its loans in comparison with expected (historical) default rates. A defaulted loan worsens a group's rating and therefore its reputation. Tirole (1996) shows analytically how a group's good reputation positively influences individual behavior. The group rating reflects a group's ability to assess borrowers' credit quality, and serves as a proxy for the group leader's behavior in the future.

In addition to a group leader's general ability, we argue that group reputation serves as an effective mechanism to prevent collusion between the group leader and a borrower within the group. The phenomenon of collusion (see, e.g., Tirole 1991) could be a major concern for participants in the electronic lending marketplace. This would be the case if a potential borrower could "bribe" the group leader in order to receive a recommendation and a bid. With an increasing probability for such collusive behavior, the credibility of the observable actions of the intermediary would be significantly reduced. This would be reflected in a decreasing group rating due to higher than expected defaults within the group. We deduce:

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Hypothesis H4: A higher group rating leads to lower credit spreads.

When deciding to join a group, market participants face the choice of group size. At first sight, a smaller group seems to offer a potentially close-knit community in the marketplace that facilitates the interaction and closer collaboration of group members with the group leader. This is fairly comparable to the stream of literature on *relationship lending* that emphasizes the exchange and evaluation of "soft information" within small banks (Petersen and Rajan 1994, Elyasiani and Goldberg 2004, Berger, Miller, Petersen, Rajan, and Stein 2005). On closer examination, and presumably more important, borrowers and lenders might prefer larger groups because they generate more opportunities for exchange, collectively provide more funds for loans, and, thus, offer easier access to credit. From an investor's perspective, in addition to a larger network, bigger groups are attractive because they may enable effective "peer-monitoring" which lowers credit risk. The concept of peer-monitoring, where group members have better information and intra-group monitoring leads to greater rates of repayment, is formalized in a large body of academic literature dealing with the optimal design of group lending agreements in the context of developing economies (Stiglitz 1990, Varian 1990, Chowdhury 2005, Besley and Coate 1995). Armendariz de Aghion (1999) provides tentative arguments in favor of a positive correlation between group size and the peer-monitoring effort. Within groups in the electronic lending marketplace, even though there is no joint liability as it typically exists in group lending (see, e.g., Prescott 1997), there are several incentive mechanisms in place to create peer pressure and induce peer-monitoring. First of all, groups comprise of individuals that share a common background or interest, based on, e.g., employment, geography, education, or leisure activities. The group can be viewed as a community where anonymity is reduced and relationships are established. In those relationships lies the potential for social sanctions (see Besley and Coate 1995 for a succinct intro- duction), resulting in peer pressure. Moreover, in cases of loan default, limited repayments ("community payments") may be arranged. This is, to a certain extent, comparable to a joint liability. Hence, we argue that, beyond the group leader's functions, there are peer-monitoring effects increasing with group size. These effects are perceived and valued by lenders, resulting in a lower demanded risk premium.
This leads to:

Hypothesis H5: Increasing group size leads to lower credit spreads.

4 Empirical Study

4.1 Methodology

We apply OLS regression analysis in order to determine the factors that impact the credit spreads as the outcome of the credit transactions in the marketplace and test the hypotheses H1 through H5. As a robustness test to control for a potential estimation bias due to self-selection in the choice of an intermediary, we further apply the matching method explained in section 4.5. Econometric matching techniques were developed by Rosenbaum and Rubin (1983) and extended by Heckman and Robb Jr (1985). The methods take into account the fact that the characteristics of group members may differ significantly from those of non-group members and ensure that such observed characteristics are not biasing the regression estimations.

4.2 Dependent and Independent Variables

In our empirical analysis of intermediaries on an electronic P2P lending platform, the interest rates measure how successfully borrowers can access capital. Lower interest rates indicate better access to capital. The interest rates on Prosper should generally be interpreted with respect to market interest rates (de Bondt 2005). As the dependent variable we therefore analyze the spread over three-year interest rate swaps (on the use of swap rates as a proxy for the risk-free rate see Zhu 2006), measured in basis points (i.e. one hundredth of one percent) in order to control for differing market interest rates in our data. This ensures matching maturities since all loans on Prosper have a maturity of 36 months. We employ Borrower Rate, representing borrowers' total loan cost, and Borrower Rate Net which excludes a potential group fee in order to evaluate the net effect of intermediation. Daily time series of these swap rates were obtained from the website of the Federal Reserve.

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To facilitate the testing of our hypotheses from Chapter 3, we employ listing- and group-specific variables. We present an overview of our variables in Table 2.

In order to test hypotheses H1, H2, H3a and H3b we rely on the group-related variables Group Affiliation, Certification, Group Leader Bid, and Mandatory Review. They measure the effect of group membership, a group leader's screening of potential borrowers, and the group leader's bid for a recommended loan listing. To be able to assess the usage of a paid intermediary, we look at Paid Group as well as Group Fee. In order to evaluate the effect of a group's reputation in hypothesis H4, we use the independent variable Group Rating. Group Size measures the potential effect hypothesized in hypothesis H5.

We incorporate a number of borrower and transaction characteristics into our analyses. First we look at four criteria based on individuals' credit reports commonly used by by traditional lending institutions (Avery, Bostic, Calem, and Canner 1996). As a proxy for probability of default (PD) and loss given default (LGD), we use Credit Grade and Debt-to-Income (DTI) Grade. Both variables are provided by Prosper in cooperation with the credit reporting agency Experian. Credit grades are derived from the individual credit score, where 40 points on the credit grade scale represent one rating notch. Therefore, Credit Grade can be included as a metric variable in our regression models. Amount and Homeownership serve as additional risk characteristics.

We include two important transaction characteristics related to internet-based e-commerce: As self-disclosure may reduce uncertainty in electronic marketplaces (Tidwell and Walther 2002), we control for Visual Self-Disclosure in borrowers' loan listings with the provision of personal photographs. We include Auction as a control variable reflecting use of the auction mechanism on Prosper as this may significantly influence price determination (Klemperer 2004). Borrowers can choose the auction mechanism if they want to give lenders the chance to bid down the interest rate. Not using the auction mechanism will close a loan listing as soon as the requested loan amount is met by bidders. We include quarter dummies into each regression model to control for the eve of the sub-prime crisis in 2007. Moreover, this allows to control for the fact that consumers tend to adopt innovations in a process over a certain time (Olshavsky 1980) which could cause a distortions in the database by consumers' hesitant use of intermediaries in the marketplace.

Table 3 presents Pearson's correlations of our independent variables. We further display *Cramér's V coefficient* (Cramér 1991), as it "is probably the best-known measure of association for contingency tables" (Kline 2004, p. 151). In the case of two dichotome variables, Cramér's V simplifies to the *Phi coefficient* ϕ.

We see that a group's mandatory review process correlates positively with the recommendation by the group leader (Certification) and the group leader's bid. There is also a significant and positive correlation between certification and Group Leader Bid. Interestingly, we find that Group Size correlates negatively with Certification, Group Leader's Bid, and a mandatory review process. As expected, Credit Grade is negatively correlated with Amount and Homeownership. Between the variables that are used within the same regression models there is no significant correlation above 0.5 which is a first indicator that there is not any multicollinearity issue with the data. In line with our expectations, we document a significant and high correlation of 0.75 between Paid Group and Group Fee. This is not an issue since these two variables will not be included simultaneously into our multivariate analyses.

4.3 Description of data set

Our empirical analysis of financial intermediaries in the electronic P2P lending platform Prosper is based on 14,321 credit transactions between 2005-11 and 2007-09, covering all transactions that took place in the market in this time period. As of 2007-09-12, the marketplace consisted of a total of 385,161 registered users.

Our data set includes detailed information about these credit transactions, and there is also comprehensive information about the course of the loan-originating auction, including individual bidding and its impact on interest rates. At this point in time the data set is still heavily right censored with respect to subsequent information on ex-post-realized loan defaults. For this reason we adopt the borrowers' perspective and focus our analyses on the credit spreads realized. We begin with a closer look at the borrowers and the lenders in the mar-

Table 2: Definition of variables

Variable	Description
Listing-specific variables	
BORROWER RATE	Total loan cost for borrowers defined as spread over three-year interest rate swaps in basis points.
BORROWER RATE NET	Loan cost for borrowers excluding the group fee, defined as spread over three-year interest rate swaps in basis points.
CREDIT GRADE	Assessment of credit provided by credit reporting agency Experian. Credit grades assigned are AA, A, B, C, D, E and HR.
AMOUNT	Loan amount (in USD).
DTI GRADE	Debt-to-Income ratio as percentage of consumer's income that goes towards paying non-housing debts. Based on credit report.
VISUAL SELF-DISCLOSURE	Dummy variable equals 1 if borrowers included at least one picture in loan listing, else 0.
HOMEOWNERSHIP	Dummy variable equals 1 if borrower is home owner, else 0.
AUCTION	Dummy variable equals 1 if loan listing in "auction" format. Allows for bidding on interest rate, else 0.
Group-specific variables	
GROUP AFFILIATION	Dummy variable equals 1 if borrower is member of a group, else 0.
PAID GROUP	Dummy variable equals 1 if borrower is member of a group that imposes a fee, else 0.
GROUP RATING	Group's historic repayment performance against expected (historical) default rates. Rating from 1 to 5 rating notches.
CERTIFICATION	Dummy variable equals 1 if group leader recommends a credit listing within the group, else 0.
GROUP LEADER BID	Dummy variable equals 1 if group leader bid on loan listing, else 0.
GROUP FEE	Optional fee group leader can impose as additional interest in basis points.
GROUP SIZE	Number of group members.
MANDATORY REVIEW	Dummy variable equals 1 if a credit transaction requires prior approval by the group leader, else 0.

ketplace. Borrowers (lenders) are defined quite literally as market participants that were involved in transactions solely as borrowers (lenders).

As we can see from Table 4, the sample of 14,321 credit transactions involved almost twice as many lenders as borrowers (32,996 vs. 16,778). This reflects the fact that on Prosper, several lenders collectively syndicate a loan in order to diversify their investments among many borrowers.

We see that nearly 90 percent of lenders in the marketplace held a stake in at least two loans, with an average bid size of 96.22 USD (whereas most of the bids amount to the minimum, resulting in a median of 50 USD). Every second lender was invested in more than 10 loans, and the average lender held 32.7 loan shares. We rarely observe repeated borrowing in the marketplace. Only 4.6 percent of borrowers have a second, and 0.2 percent of borrowers have a third loan.

Borrowers and lenders can form groups or become

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Table 3: Correlations and measures of association for independent variables

	Certification	Group Leader Bid	Mandatory Review	Group Affiliation	Paid Group	Group Fee	Group Rating	Group Size	Credit Grade	DTI Grade	Amount	Homeownership	Visual Self-Disclosure	Auction
Certification	1 (1)													
Group Leader Bid	.46* (.4362)	1												
Mandatory Review	.46* (.3836)	.31* (.2881)	1 (1)											
Group Affiliation	—	—	—	1 (1)										
Paid Group	.13* (.1074)	.16* (.1690)	.01 (-.0019)	.58* (.5803)	1 (1)									
Group Fee	-.01 (.2363)	.16* (.2404)	-.09* (.1721)	.43* (.5803)	.75* (1)	1								
Group Rating	.11* (.2363)	.06* (.1146)	.07* (.1177)	— (1)	.11 (0.590	.8 (.2722)	1 (1)							
Group Size	-.27* (.3273)	-.14* (.1776)	-.49* (.5746)	—	.01* (.2086)	.08* (.2361)	-.37* (.2815)	1						
Credit Grade	.01 (.0552)	.09* (.1013)	-.05* (.0582)	.19* (.2002)	.11* (.1243)	.31* (.2451)	-.15* (.1175)	.03* (.0978)	1 (1)					
DTI Grade	.07* (.2734)	.05* (.3087)	.06* (.3026)	.03* (.2894)	.03* (.3019)	.01 (.4732)	.02 (.3167)	-.04* (*n.a.*)	-.03* (.3217)	1				
Amount	.12* (.3016)	.06* (.2615)	.11* (.2854)	-.02* (.2191)	.04* (.2297)	-.08* (.2075)	.01 (.2269)	- 0.0297 (*n.a.*)	-.39* (.2907)	.08* (*n.a.*)	1			
Homeownership	.01 (-.0025)	-.02* (-0.0273)	.01 (0.0125)	-.07* (-.0704)	-.01* (-.0186)	-.08* (.1436)	.01 (.0776)	.01 (.0554)	-.35* (.3634)	.03* (.2096)	.24* (.3308)	1 (1)		
Visual Self-Disclosure	.12* (.1208)	.09* (0.093	.10* (0.1001	.16* (.1682)	.11* (.1167)	.08* (.1248)	.01 (.1709)	-.02 (.0379)	.04* (.0584)	.03* (.2903)	.08* (.2514)	-.04* (-.0443)	1	
Auction	.18* (.1743)	.21* (.2067)	.10* (.1023)	.13* (.1370)	.13* (.1312)	.07* (.2213	.09* (.1495)	.01* (.0510)	-.26* (.2545)	-.01 (.2959)	.11* (.0551)	.05* (-.0443)	.13* (.1294)	1

This table shows the correlation matrix for our independent variables. $*$ indicates significance of correlations at the 5% level. We display the Cramér's V coefficient in parentheses (ranging from 0 to 1), in the case of two dichotome variables it is reduced to ϕ ranging from -1 to $+1$.

group members. We argue in section 2 that group leaders serve as financial intermediaries in the marketplace. Figure 4.3 presents the composition of groups by group size.

We find that, in terms of member share, groups are dominated by lenders. The share of lenders within groups ranges from 45 to 68 percent and tends to increase with group size. We calculate the share of internal financing for each group as the percentage of the last 12 months' loan amount that is provided by members of the same group. Even with an increasing group size and an increasing absolute number of lenders within a group, only a fraction of loans are syndicated within groups. With the exception of very small groups, the share of internal financing is between 0.8 and 2.2 percent. We can subsume that groups are dominated by lenders and that borrowers' loans are funded primarily by lenders outside of their group. This supports our interpretation of group leaders as financial intermediaries that produce and signal information about potential borrowers for lenders outside the group.

Table 5 presents descriptive statistics for loan amount and borrower rate by borrowers' credit grade as well as borrowers' group affiliation. Several interesting patterns emerge from this table.

Out of a total sample of 14,321 loans, 9,187 transactions were carried out by group members and 5,134 transactions without group affiliation. 58 percent of total group-affiliated borrowers were members of paid groups. We find borrowers of all credit grades in paid and unpaid groups as well as without group affiliation. Borrowers with the best credit grades AA, A and B were in relative terms more frequent in the sub-sample of borrowers without group affiliation (40 percent vs. 25 of all group-affiliated borrowers).

The average loan amount over the total sample was 6,102 USD. Borrowers with a better credit

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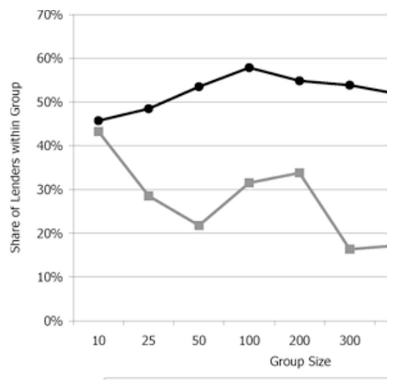
Table 4: Descriptive statistics for borrowers and lenders

	Market Participants	Average Number of Loans
Borrower	16,778 (32%)	1.05
Lender	32,996 (63%)	32.7
Borrower and Lender	2,731 (5%)	—
Average Bid Size (USD)	96.22	
Median Bid Size (USD)	50.00	

Market participants involved in at least	% Borrowers	% Lenders
1 loan	100	100
2 loans	4.56	89.59
3 loans	0.18	81.40
5 loans	0.01	71.30
10 loans	—	55.08
50 loans	—	15.83
100 loans	—	7.02

We present the distribution of borrowers and lenders involved in the observed 14,321 credit transactions. The table also gives an overview of the average number of loans of borrowers and lenders. Borrowers (lenders) are defined as market participants that were involved in transactions solely as borrowers (lenders).

Figure 1: Share of lenders within groups and internal financing



This figure presents the share of lenders and the share of internal financing by group size. The abscissa shows ten deciles of group size, measured by the number of group members. Each decile contains the same number of groups. The left ordinate belongs to the black line and presents the share of lenders within the groups as of 2007-09. The right ordinate belongs to the grey line and indicates the historical share of internal financing within the groups. The share of internal financing for each group is calculated as the percentage of the last 12 months' loan amount that is provided by members of the same group.

grade borrowed higher loan amounts. We see a mean loan amount in the total sample for borrowers with the best credit grade AA of 8,264 USD whereas for "high risk" borrowers (credit grade HR) the amount was only about one third of that. The average loan amount was higher for borrowers without group affiliation. However, when comparing by credit grades, we find higher average loan amounts for group members than for borrowers without group association. When comparing unpaid and paid groups, we find that borrowers with better credit grades borrowed significantly higher amounts in groups with a paid group leader than in unpaid groups.

Table 5 also lists the average borrower rate by credit grade as the spread over three-year interest rate swaps. We see that the average spread was 1,011 basis points (= 10.11 percent). Comparing borrowers with and without group affiliation, we find that average spreads by credit grade were lower for borrowers with group affiliation. Table 5 documents significant differences in average spreads between paid and unpaid groups. Borrowers in unpaid groups on average borrowed at lower spreads than borrowers in paid groups or borrowers without group affiliation. When comparing paid groups to borrowers without group affiliation,

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Table 5: Descriptive statistics for loan amount and borrower rate

	Credit Grade	Total Sample	No Group (36%)	Group Members (64%)		
				Total	Paid Group	Unpaid Group
	AA	8,264 (5,000)	7,924 (5,000)	8,624 (6,000)	10,321 (8,500)	7,181 (5,000)
	A	9,170 (7,000)	8,431 (6,000)	9,835 (8,000)	10,089 (8,100)	9,466 (7,000)
	B	8,681 (7,000)	8,172 (6,000)	9,057 (7,500)	9,596 (8,000)	8,157 (6,100)
Mean (Median)	C	7,143 (5,100)	6,402 (5,000)	7,588 (6,000)	7,877 (6,500)	7,104 (5,000)
Loan Amount	D	5,630 (4,750)	5,045 (4,000)	5,952 (5,000)	6,228 (5,000)	5,454 (4,500)
	E	3,917 (3,000)	3,897 (3,000)	3,926 (3,000)	3,965 (3,100)	3,872 (3,000)
	HR	2,629 (2,500)	2,616 (2,500)	2,632 (2,500)	2,625 (2,500)	2,641 (2,500)
	Total	6,102 (4,000)	6,226 (4,300)	6,033 (4,000)	6,406 (4,800)	5,506 (3,500)
	AA	130 (64)	123 (54)	137 (74)	233 (175)	55 (0)
	A	340 (275)	341 (265)	339 (284)	384 (322)	274 (224)
Mean	B	605 (553)	611 (555)	601 (542)	662 (605)	499 (445)
(Median)	C	891 (805)	928 (875)	868 (775)	943 (870)	743 (675)
Borrower	D	1,205 (1,175)	1,297 (1,280)	1,154 (1,125)	1,212 (1,175)	1,051 (990)
Rate	E	1,591 (1,600)	1,701 (1,819)	1,545 (1,575)	1,584 (1,575)	1,492 (1,575)
	HR	1,604 (1,675)	1,667 (1,975)	1,589 (1,670)	1,635 (1,670)	1,537 (1,675)
	Total	1,011 (975)	922 (825)	1,060 (1,025)	1,116 (1,110)	981 (875)
	AA	1,472 (10)	756 (15)	716 (8)	329 (6)	387 (10)
	A	1,363 (10)	645 (13)	718 (8)	425 (8)	293 (8)
Absolute	B	1,768 (12)	751 (15)	1,017 (11)	636 (12)	381 (10)
(Relative)	C	2,494 (17)	937 (18)	1,557 (17)	975 (18)	582 (15)
Number of	D	2,592 (18)	920 (18)	1,672 (18)	1,075 (20)	597 (16)
Transactions	E	2,167 (15)	638 (12)	1,529 (17)	885 (17)	644 (17)
	HR	2,465 (17)	487 (9)	1,978 (22)	1,048 (20)	930 (24)
	Total	14,321 (100)	5,134 (100)	9,187 (100)	5,373 (100)	3,814 (100)
Share of	% AA,A,B	31%	40%	25%	24%	26%
Credit Grades	% D,E,HR	50%	38%	55%	55%	55%

This table displays descriptive statistics for loan amount and borrower rate by borrowers' credit grade for the total sample of 14,321 credit transactions as well as by borrowers' group affiliation. The first part reports statistics on loan amount by credit grade, with median loan amount given in parentheses. The second part reports statistics on borrower rate in basis points by credit grade, with median borrower rate in parentheses. The third part presents the distribution of borrowers among credit grades, with relative frequencies in parentheses. Percentages may not add up to 100% due to rounding. For details on variable definition see Table 2.

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Table 6: Descriptive statistics for loan funding over time

Year	Quarter	Mean	Median	Sum	No. of Loans
2005	4	3,576.682	3,000	78,687	22
2006	1	4,872.394	3,001	1,680,976	345
	2	4,490.887	3,000	5,986,352	1,333
	3	5,003.916	3,200	9,727,613	1,944
	4	4,896.718	3,000	12,134,066	2,478
2007	1	6,629.019	4,562.5	20,775,344	3,134
	2	7,426.593	5,000	22,695,669	3,056
	3	6,812.083	5,000	14,530,173	2,133

This table provides sample statistics on the temporal distribution of the loan origination and the originated volume.

we find that borrowers with credit grades of AA, A, B and C (credit grades of D, E, and HR) borrowed at higher (lower) spreads in paid groups.

Table 6 provides sample statistics on the temporal distribution of the loan origination and the originated volume. We observe 22 transactions in the fourth quarter of 2005, and document an increase in transactions to more than 3,000 loans in the first and second quarter of 2007. We also see an increase in mean loan volume from between 4,500 and 5,000 USD in 2006 to between 6,500 and 7,500 USD in the first and second quarter of 2007.

To gain a better understanding of the patterns documented in Table 5 and 6, we offer some further insights into the role of groups in the electronic lending platform in Table 7.

The first three rows in Table 7 represent the distribution of variables based on individuals' credit reports by group membership. As already presented in the last rows of Table 5, the median credit grade of borrowers without group affiliation tends to be better. Group-affiliated borrowers are on average more indebted which is reflected in the Debt-to-Income (DTI) Grade. We find an average DTI Grade of 40 percent within groups compared to 32 percent with transactions outside groups. Within the sample, 41 percent of borrowers owned a house, and homeownership was more frequent in transactions outside groups (45 percent). Average Credit Grade and DTI Grade, as well as the distribution of Homeownership seem to confirm the finding that borrowers with better risk characteristics are more frequent in the sub-sample of borrowers without group affiliation.

Regarding the characteristics of the transaction, we find that two out of three bidders within the sample reveal personal photographs (Visual Self-Disclosure). This is far more often the case with transactions involving groups (71 vs. 55 percent). This corresponds with anecdotal evidence that group leaders often encourage group members to include personal pictures in their loan listings.

Table 7 shows that 63 percent of all transactions within the sample made use of the marketplace's auction mechanism. Borrowers with group affiliation use the auction mechanism more often (68 vs. 54 percent in transactions out of groups), and auctioned transactions are more frequent in paid groups. An auction enables lenders to bid down the interest rate and may lead to lower credit spreads for borrowers. Not using the auction mechanism may accelerate the access to credit by potentially reducing the time until a loan is fully funded, since the loan listing is closed once the required loan amount is fully funded. Facing this trade-off, borrowers outside groups decide to use the auction mechanism less often. There are two possible explanations for this finding: It could be that borrowers with better credit grades expect to benefit less from an auction of their loan listing. As an alternative explanation, group leaders might encourage borrowers to make use of the auction mechanism.

Table 7 further presents the distribution of five group-related variables. Table 7 strongly indicates that group leaders create value by serving as intermediaries in the electronic marketplace in order to help overcome problems of asymmetric information. The majority (55 percent) of groups enforces a mandatory review process and commit to screening of every borrower within a group. Yet there is evidence of important differences in the role of group leaders in unpaid and paid groups. We find that certification of screened loan listings as well as group leaders' bidding is more frequent in paid

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Table 7: Descriptive statistics for independent variables

	Total Sample	No Group	Group Members		
			Total	Paid Group	Unpaid Group
Observations	*14,321*	*5,134*	*9,187*	*5,373*	*3,814*
CREDIT GRADE: Median	D	C	D	D	D
DTI GRADE: Mean (Median)	37% (18%)	32% (17%)	40% (19%)	43% (17%)	38% (17%)
HOMEOWNERSHIP	40.9%	45.4%	38.3%	39.7%	36.4%
VISUAL SELF-DISCLOSURE	65.4%	54.7%	71.4%	72.7%	69.7%
AUCTION	63.2%	54.3%	68.1%	71.3%	63.5%
MANDATORY REVIEW			55.3%	55.7%	54.7%
CERTIFICATION			30.8%	35.8%	23.7%
GROUP LEADER BID			48.3%	55.3%	38.5%
GROUP SIZE: Median			433	458	316
GROUP FEE: Mean Basis Points				109.7	

This table reports descriptive statistics for the group related variables as well as the control variables. Statistics are presented for the total sample as well as by borrowers' group affiliation. For details on variable definition see Table 2.

groups. Group leaders assess and then observably signal borrower's credit quality (Certification) in 36 percent of transactions in paid groups compared to 24 percent in unpaid groups. Furthermore, paid group leaders bid for more than every second recommended loan listing and thus credibly signal information quality (Group Leader Bid).

Comparing the average size of unpaid and paid groups we find that unpaid groups tend to be smaller (median of 316 vs. 459 members). Finally, Table 7 presents the average costs inherent in the choice of a paid intermediary. The average fee that group leaders impose amounts to 110 basis points or about one additional percentage point of interest for the borrower. So far it is not possible to draw conclusions on the net value creation of a (paid) intermediary for the borrowers. In a next step we analyze the role of intermediation in the electronic marketplace in a multivariate set-up.

4.4 Empirical results

Table 8 presents our analyses on the role of intermediation in the electronic lending platform. In three different regression models we look at the influence of (1) general group membership, (2) the use of a paid intermediary, and (3) the hypothesized functions of intermediation on borrowers' credit conditions. The dependent variable in regression model (1) is *Borrower Rate*, borrowers' total loan cost including a potential group fee. This allows for the comparison of borrowers' credit spread with and without the use of an intermediary. In regression models (2) and (3), the dependent variable *Borrower Rate Net* excludes the group fee in order to evaluate the net effect of intermediation. Several interesting patterns emerge.

The results from regression model (1) regarding Group Affiliation as well as from model (3) regarding the group-specific variables confirm our fundamental hypothesis H1: the use of an intermediary in the electronic marketplace significantly lowers borrowers' loan spread. Group affiliation ceteris paribus lowers the credit spread by 25 basis points. In regression models (2) and (3) we shed more light on the function and value creation of the intermediary.

Does the choice of the intermediary matter? Should borrowers make demands on paid intermediary services? In order to be able to compare the net impact of unpaid and paid groups, we analyze *Borrower Rate Net* in regression model (2) and find that intermediation significantly lowers borrower's cost of credit overall. However, we document a difference in the net impact of group membership of 42 basis points: An unpaid intermediary reduces borrower's credit spread by 107 basis points, a paid intermediary by 65 basis points. It follows that the group fee can turn the case for a paid intermediary borderline. The average group fee of 110 basis points (Table 7) will more than counter the net

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Table 8: Effect of intermediation and characteristics of the transaction

	(1)	(2)	(3)
AMOUNT	0.025***	0.025***	0.027***
	0.214	0.220	0.244
	(39.840)	(40.378)	(33.258)
CREDIT GRADE	280.430***	270.291***	267.192***
	0.813	0.803	0.812
	(139.810)	(136.602)	(100.376)
DTI GRADE	22.948***	23.065***	27.073***
	0.043	0.044	0.058
	(8.738)	(8.911)	(9.031)
HOMEOWNERSHIP	-1.370	-3.488	-10.466**
	-0.002	-0.005	-0.017
	(-0.398)	(-1.028)	(-2.476)
VISUAL SELF-DISCLOSURE	-61.559***	-59.151***	-59.730***
	-0.045	-0.044	-0.044
	(-9.017)	(-8.789)	(-6.882)
AUCTION	-291.247***	-302.584***	-242.808***
	-0.215	-0.228	-0.185
	(-41.093)	(-43.288)	(-26.661)
GROUP AFFILIATION	-24.586***		
	-0.018		
	(-3.519)		
PAID GROUP		-65.287***	
		-0.050	
		(-8.560)	
UNPAID GROUP		-106.746***	
		-0.074	
		(-12.687)	
GROUP RATING			-32.135***
			-0.055
			(-8.335)
CERTIFICATION			-19.562*
			-0.014
			(-1.853)
GROUP LEADER BID			-83.293***
			-0.069
			(-9.059)
GROUP FEE			0.103*
			0.013
			(1.874)
GROUP SIZE			-0.010***
			-0.041
			(-5.075)
MANDATORY REVIEW			-52.851***
			-0.043
			(-5.408)
INTERCEPT	174.022***	207.291***	137.650***
	(12.227)	(14.777)	(6.333)
No. of observations	13,556	13,556	8,575
F	2,672.4	2,379.1	1,027.2
Prob>F	0.000	0.000	0.000
R^2	0.685	0.678	0.658
Adj. R^2	0.684	0.678	0.657

This table reports results of OLS regression models where the dependent variable is Borrower Rate, *defined as spread over the risk-free rate in basis points (in models (2) and (3)* Borrower Rate Net *which excludes the group fee). Reported are regression coefficients and standardized coefficients underneath, t-ratios in parenthesis. For details see Table 2. Significance levels are given as ***, **, and * indicating significance at 1%, 5% and 10% level, respectively. All regressions include quarter dummies (not reported).*

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Table 9: Effect of intermediation with credit grade sub-samples

Credit Grade	(AA)	(A)	(B)	(C)	(D)	(E)	(HR)
AMOUNT	0.018***	0.023***	0.023***	0.030***	0.039***	0.032***	0.076***
	0.554	0.603	0.438	0.442	0.432	0.223	0.229
	(29.287)	(27.830)	(20.440)	(22.674)	(20.735)	(9.930)	(11.241)
DTI GRADE	32.078***	24.014***	31.739***	36.340***	25.012***	19.495**	12.280
	0.216	0.130	0.143	0.137	0.093	0.045	0.022
	(11.963)	(6.319)	(6.868)	(7.334)	(4.669)	(2.054)	(1.150)
HOMEOWNE	-11.100**	-5.468	2.904	-2.984	-21.311**	-24.928**	-34.208***
	-0.041	-0.019	0.009	-0.008	-0.050	-0.053	-0.053
	(-2.270)	(-0.933)	(0.416)	(-0.434)	(-2.493)	(-2.429)	(-2.749)
VISUAL SELF-	-29.446***	-28.939**	-30.023*	-88.939***	-103.919***	-80.493***	-89.280***
DISCLOSURE	-0.056	-0.046	-0.040	-0.113	-0.119	-0.089	-0.077
	(-3.136)	(-2.197)	(-1.902)	(-5.967)	(-5.800)	(-4.007)	(-3.951)
AUCTION	-79.013***	-126.373***	-197.591***	-264.066***	-266.131***	-272.747***	-254.254***
	-0.110	-0.161	-0.233	-0.317	-0.309	-0.327	-0.249
	(-6.046)	(-7.805)	(-10.937)	(-16.606)	(-14.627)	(-13.503)	(-11.405)
GROUP RATING	-5.563**	-7.874*	-6.791	-19.135***	-32.375***	-46.692***	-53.679***
	-0.039	-0.036	-0.022	-0.052	-0.077	-0.089	-0.087
	(-1.985)	(-1.680)	(-1.043)	(-2.735)	(-3.839)	(-3.931)	(-4.423)
CERTIFICATI	19.497*	-21.964	-13.742	-6.468	-57.040***	-7.789	-65.837**
	0.036	-0.035	-0.018	-0.008	-0.067	-0.008	-0.057
	(1.698)	(-1.386)	(-0.718)	(-0.362)	(-2.726)	(-0.307)	(-2.333)
GROUP LEADER	-14.721	17.947	7.394	-44.091***	-80.237***	-67.475***	-103.066***
BID	-0.030	0.032	0.011	-0.060	-0.101	-0.082	-0.101
	(-1.551)	(1.331)	(0.464)	(-2.822)	(-4.253)	(-2.942)	(-4.042)
GROUP FEE	0.975***	0.846***	0.516***	0.797***	0.342**	-0.164	-0.332***
	0.103	0.083	0.078	0.122	0.048	-0.039	-0.070
	(5.270)	(3.767)	(3.500)	(6.188)	(2.385)	(-1.633)	(-2.864)
SIZE	-0.002	-0.003	-0.001	-0.001	-0.007*	-0.002	-0.009*
	-0.021	-0.027	-0.009	-0.005	-0.042	-0.013	-0.055
	(-0.981)	(-1.080)	(-0.375)	(-0.233)	(-1.778)	(-0.499)	(-1.954)
MANDATORY	-20.015*	-19.730	23.346	-21.942	4.416	-84.179***	-103.899***
REVIEW	-0.041	-0.035	0.034	-0.030	0.006	-0.102	-0.102
	(-1.889)	(-1.355)	(1.325)	(-1.266)	(0.222)	(-3.648)	(-4.025)
INTERCEPT	333.761***	516.963***	776.650***	1,162.328***	1,602.209***	2,148.142***	1,975.435***
	(15.160)	(18.112)	(22.557)	(35.375)	(42.520)	(43.466)	(42.489)
No. of observations	626	644	929	1,456	1,590	1,450	1,880
F	90.847	63.864	47.769	64.169	52.227	35.693	33.924
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.705	0.620	0.456	0.416	0.347	0.285	0.226
Adj. R^2	0.697	0.610	0.446	0.410	0.340	0.277	0.219

This table reports results of our OLS regression model (3) from Table 8, where the dependent variable is Borrower Rate Net, *separately for each credit grade. Missing values resulted in the exclusion of some observations (compared to descriptive statistics in Table 5).*
*Reported are regression coefficients and standardized coefficients underneath, t-ratios in parenthesis. For details on dependent variable definition see Table 2. Significance levels are given as ***, **, and * indicating significance at 1%, 5% and 10% level, respectively. All regressions include quarter dummies (not reported).*

reduction in credit spread. Taken together, intermediation has a positive net impact but the choice of intermediary matters. We hereby do not comment on the overall impact of paid groups, since this analysis does not incorporate the intermediary's role in overall access to credit or the long-run performance of the loan thus originated.

In model (3) we analyze in greater detail how the intermediary creates value for the borrower. Again, we look at the net impact of intermediation *(Borrower Rate Net)* and control for the fee of a paid intermediary *(Group Fee)*. All group-specific variables in regression model (3) have significant impact on credit spreads. The variables *Certification* and *Group Leader Bid* in regression model (3) significantly reduce borrowers' loan costs. Hypotheses H2 and H3a cannot be rejected: An important function of the intermediary is the screening of a potential borrower. The intermediary may then recommend the borrower's credit listing. There is further evidence for the hypothesized creation of value by the intermediary: We find significant lower credit spreads in groups where the group leader was committed to screening every potential borrower *(Mandatory Review)*.

Regression model (3) also shows that "actions speak louder than words": the group leader's bid for the borrower's credit listing exerts a significant stronger impact on borrowers' credit conditions than a recommendation. Moreover, *Certification* is only significant at the 10-percent level. We can confirm Hypothesis H3b: the regression coefficient of *Group Leader Bid* exceeds *Certification*.

We find that a group's reputation serves as a proxy for the future diligent assessment of borrowers by the group leader. Lenders increasingly bid down the interest rate in groups with a good reputation, resulting in lower credit spreads for borrowers. Hypothesis 4 cannot be rejected as a group's reputation *(Group Rating)* significantly lowers borrowers' spread. Table 8 shows further evidence for the negative effect of group size on loan spreads. This finding statistically confirms our hypothesis H5. We find evidence for a perceived lower credit risk within larger groups due to more effective peer-monitoring. When comparing estimated coefficients, we see that this effect is far less important than the group leader's role in screening and monitoring of borrowers. This can be regarded as a certain restriction in the confirmation of H5 from an economist's point of view. Nonetheless, it confirms the important role of the group leader as the financial intermediary. An analysis of the effect of intermediation with credit grade sub-samples in Table 9 confirms our main findings and yields some interesting additional insights. Controlling for borrowers' risk characteristics and the group fee we find that intermediation may significantly reduce borrowers' credit spread and that the reputation of a group has a strong impact across credit grades. Interestingly, a mandatory review process, the recommendation of a loan listing by the group leader, or a group leader's bid on a screened loan listing have a significant impact mostly for borrowers with lower credit grades "D", "E", and "HR". These credit grades represent 57 percent of all group members. This finding highlights that the intermediary may create significant value by screening and monitoring of borrowers who represent more risky investments. We conclude that intermediation is particularly valuable for borrowers with less attractive risk characteristics.

Overall, our results show that even though the electronic P2P lending platform leads to disintermediation by enabling the direct brokerage of loans between borrowers and lenders, a new type of financial intermediary emerges. Market participants become group leaders and provide intermediary services, reducing the information asymmetries prevalent in the electronic marketplace. The intermediary primarily creates value by screening potential borrowers with lower scores, representing investments with higher risk a priori. This finding is supported by the significant reduction in borrowers' credit spread by a mandatory screening process as well as the intermediary's recommendation of a borrower *(Certification)*. Moreover, bidding on the screened borrower's credit listing has an even stronger impact on the resulting spread. Given a mandatory screening process, the recommendation of a borrower and the group leader's bid for the recommended loan listing, the credit spread will ceteris paribus be 156 basis points lower (see model 3 in Table 8). This more than compensates for the average required fee of 110 basis points (as shown in Table 7). These results are stable when controlling for borrowers' credit history as well as transaction characteristics. In all regression models in Table 8 and 9 we find that the variables based on individual credit reports significantly influence credit conditions, and that a borrower's *Credit Grade* as a proxy for Probabil-

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ity of Default has the strongest impact. In model (1) in Table 8 for example, we find that ceteris paribus a decline in credit grade by one grade is associated with an average of 280 basis points increase in credit spread. Increasing indebtedness *(DTI Grade)* which proxies for Loss Given Default or a higher loan amount *(Amount)* significantly increases credit spread. We cannot find a consistent significant impact of *Homeownership*. This result is intuitive since a house does not serve as collateral for loans on the Prosper marketplace. Hence, homeownership does not per se serve as information on borrowers' creditworthiness. There is initial evidence that this somewhat changed in the climax of the sub-prime crisis (Crowe and Ramcharan 2009), which exceeds our period of analysis.

We further control for use of the auction mechanism *(Auction)* and find a significant and negative impact on credit spreads. One obvious interpretation of this result is that the auction mechanism allows for competition among bidders which improves the conditions for borrowers. Another possible interpretation is that not using the auction mechanism serves as a negative signal of creditworthiness where the marketplace requires a significant risk premium for loan listings that are not auctioned.

4.5 Robustness tests

4.5.1 Tests for self-selection bias

Economic agents participating in capital markets are subject to self-selection (Alexander, Jones, and Nigro 1997). Self-selection arises if those participating in an activity are systematically different from those who do not participate (Bjorklund and Moffitt 1987). Each OLS regression analysis involving any such participation (including voluntary group memberships) can suffer from an endogeneity bias through the existence of variables that simultaneously influence the decision to choose the group membership as well as the dependent variable (Heckman 1979, Rubin 1979).

In financial transactions, self-selection in choosing an intermediary may arise from different levels of expertise as well as transaction characteristics (Alexander, Jones, and Nigro 1997, Zumpano, Elder, and Baryla 1996). Self-selection might be present in electronic marketplaces when individuals turning to intermediaries might differ significantly from those not using intermediary services. This could be the case if, for example, borrowers with weak market access, i. e. bad credit history resulting in a low credit score, use group membership as mitigation. Transaction characteristics like loan amount might also lead to self-selection towards using intermediary services. One possible way of easing the problem lies in the matching method (Rubin and Waterman 2006), by which one can construct pairs of comparable credit transactions with and without using intermediaries. Pairs are selected from both groups that do not differ in their relevant characteristics, i. e. they are identical ("statistical twins") or close to identical. It is most relevant for creating the pairs that the characteristics are linked with the relevant measure which determines the outcome of the credit transaction. Due to the similarity of the pairs with and without using intermediaries one can assume that self-selection bias can be excluded from the analysis.

As there are usually a lot of explanatory variables on interest rates (Avery, Calem, and Canner 2004), we need to find adequate partners matching in terms of several variables. This is also a multi-dimensional problem, which complicates the search for adequate partners for every credit transaction. As a solution, Rosenbaum and Rubin (1983) propose the use of a balancing score, i. e. a function of all relevant characteristics. The matching partners selected are similar with respect to that balancing score. The propensity score, as a special balancing score, equals the probability of using a group as an intermediary. The propensity score is usually determined using Logit or Probit models (Titus 2007).

When constructing matching pairs, all relevant characteristics of the customer are implicitly taken into consideration by the propensity score. Therefore, when searching for the matching partner, one has to consider only one dimension in terms of the propensity score (D'Agostino 1998). An in-depth discussion of the method as well as adequate search algorithms is provided by Gensler, Skiera, and Böhm (2005) and Titus (2007), the method has recently become established in finance research (e.g., Drucker and Puri 2005).

Table 10 presents our estimates for the matched sub-sample, where we used a Logit model for propensity score estimation. Controlling for self-

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Table 10: Robustness test: matched sub-sample

Variable	($1^{matched}$)	($2^{matched}$)	($3^{matched}$)
INTERCEPT	-120.867***	-158.274***	-146.152***
	(-7.686)	(-9.060)	(-5.678)
CREDIT	275.828***	267.782***	267.614***
GRADE	*0.795*	*0.791*	*0.782*
	(117.131)	(115.203)	(85.496)
AMOUNT	0.026***	0.026***	0.028***
	0.221	*0.226*	*0.251*
	(35.541)	(35.785)	(29.757)
DTI GRADE	24.947***	25.365***	30.261***
	0.047	*0.049*	*0.065*
	(8.212)	(8.427)	(8.666)
VISUAL SELF-	-69.163***	-63.302***	-65.832***
DISCLOSURE	*-0.051*	*-0.048*	*-0.025*
	(-8.830)	(-8.181)	(-3.218)
HOME-	-9.618	-14.742	-31.802***
OWNERSHIP	*-0.007*	*-0.011*	*-0.025*
	(-1.191)	(-1.854)	(-3.218)
AUCTION	-293.646***	-294.751***	-247.522***
	-0.218	*-0.224*	*-0.192*
	(-35.980)	(-36.012)	(-23.463)
GROUP	-16.671**		
AFFILIATION	-0.012		
	(-2.050)		
PAID GROUP		-60.588***	
		-0.046	
		(-6.854)	
UNPAID GROUP		-87.252***	
		-0.058	
		(-8.524)	
GROUP			-24.124***
RATING			*-0.046*
			(-5.963)
CERTIFICATION			-24.664*
			-0.018
			(-1.913)
GROUP			-76.679***
LEADER BID			*-0.062*
			(-7.082)
GROUP FEE			-0.001
			0.000
			(-0.038)
GROUP SIZE			-0.011***
			-0.047
			(-4.936)
MANDATORY			-46.965***
REVIEW			*-0.038*
			(-3.798)
No. of observations	9,542	9,542	5,786
Prob > F	0.000	0.000	0.000
R^2	0.834	0.831	0.830
Adj. R^2	0.695	0.691	0.688

*This table presents coefficient estimates from OLS regressions (cf. Table 8) with a matched sub-sample as robustness test (see section 4.5). The sub-sample is compiled through a propensity-score matching. The dependent variable is Borrower Rate, defined as spread over the risk-free rate in basis points (in models (2) and (3) Borrower Rate Net, which excludes the group fee). Reported are regression coefficients and standardized coefficients in italics, t-ratios in parenthesis. For details on variable definition see Table 2. Significance levels are given as ***, **, and * indicating significance at 1%, 5% and 10% level, respectively. All regressions include quarter dummies (not reported).*

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selection, all regression model estimates remain largely unchanged and significant. We do not find any support for a self-selection-driven estimation bias through the use of intermediary services in the electronic credit marketplace which corroborates our prior findings.

4.5.2 Tests for multicollinearity

The estimates from our multivariate analyses could be inaccurate in the presence of multicollinearity. As a first counter-argument we see from Table 3 that there are no unusually high pairwise correlations between our independent variables. To address residual concerns about multicollinearity, we calculate the variance-inflation factors (VIF) (Freund and Littell 2000, p. 98) for our models. As we see in our analysis (e.g., Table 11 presents the collinearity diagnostics for the third regression model in Table 8), there is no evidence of a high inter-correlation. As an additional measure of collinearity, we present the Condition Number in the same table. Belsley, Kuh, and Welsch (1980) propose 10 as a beginning and 100 as a serious point where collinearity affects estimates, Paris (2001) recognizes "deleterious effects when Belsley's Condition Number is around 30". Therefore, our Condition Number of 14.737 indicates only a very small degree of multicollinearity.

4.5.3 Tests for fixed effects

As market participants are typically involved more than once in the transactions on the market place, one can assume that fixed effects may exist that could distort the results of our analysis. Therefore, we conduct an additional robustness test on this issue.

Potential borrower fixed effects: As borrowers are on average involved in 1.05 transactions (see Table 4), we cannot assume that there are fixed effects.

Potential lender fixed effects: Lenders, in contrast, are involved in 32.07 transactions, whereas the general existence of such effects on the market place cannot be rejected a priori. Nevertheless, our hypotheses and the variables employed in our multivariate analysis in this article do not cover lender-specific aspects; hence this issue is not of concern in this context.

Potential group fixed effects: Lenders and borrowers organize in groups, which indeed might be a source of unobserved effects, although we cover a lot of group-specific variables in our regression models. This lowers the potential distorting impact of any unobserved effects. Nevertheless, we test for the robustness of our primary analysis by estimating a fixed effect model for our non-group-specific variables (see Table 12).

We observe a decrease in degrees of freedom, naturally, but the coefficients of our control variables do not change signs and keep rather stable.

4.5.4 Tests for operationalization of variable credit grade

The credit grade represents the variable of highest influence in all regression models. As introduced in section 4.2, this variable represents the credit grade which is provided by an external rating agency. In their credit scoring model, 40 score points are equivalent to one notch on the credit grade scale. Therefore, credit grade can be included as a metric variable in our regression models. We control for residual concerns that our results might be primarily driven by the operationalization of this variable by conducting several robustness tests. First, we conducted the same regression models with dummy variables for each credit grade, which produced the same results in terms of coefficients, t-statistics, and goodness-of-fit measures (not displayed here, therefore). Furthermore, we operationalized the credit grades with the corresponding historical probabilities of default that were published by Experian (Prosper Marketplace Inc. 2007a) as displayed in Table 13. The results of these regressions are shown in Table 14. Again, the results are comparable to the analyses in Table 8. In regression model (3), Certification is no longer statistically significant, which is in line with our overall finding, that "actions speak louder than words". Nonetheless, our overall results remain unchanged.

4.5.5 Tests with sub-samples per year

In unreported results, we conducted our regression analyses for the sub-samples of the transactions of 2006 (a total of 5,440 loans) and of 2007 (8,189 loans). We can address residual concerns that temporal effects such as the eve of the sub-prime crisis in 2007 bias our results: estimates for these sub-samples remain basically unchanged to the results presented. There is recent evidence for an impact of the subprime crisis beginning with the fourth

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Table 11: Collinearity diagnostics

Variable	VIF	$\sqrt{VIF}$	Tolerance	R-Squared
CREDIT GRADE	1.62	1.27	0.616	0.384
AMOUNT	1.34	1.16	0.745	0.255
DTI GRADE	1.02	1.01	0.983	0.017
HOMEOWNERSHIP	1.15	1.07	0.869	0.131
VISUAL SELF-DISCLOSURE	1.04	1.02	0.960	0.040
AUCTION	1.18	1.08	0.850	0.150
GROUP RATING	1.09	1.04	0.918	0.083
CERTIFICATION	1.46	1.21	0.685	0.315
GROUP LEADER BID	1.40	1.18	0.714	0.286
GROUP FEE	1.23	1.11	0.8130	0.187
GROUP SIZE	1.57	1.25	0.639	0.361
MANDATORY REVIEW	1.57	1.25	0.636	0.364
Mean VIF	1.31			
Condition Number	14.737			

This table shows the results of our collinearity analysis for regression model (3) in Table 8.

Table 12: Robustness test: fixed effect regression model

Variable	Coefficient	T-ratio
CREDIT GRADE	275.853	101.73***
AMOUNT	.026	31.25***
DTI GRADE	25.534	3.020***
VISUAL SELF-DISCLOSURE	-49.750	8.755***
HOMEOWNERSHIP	-12.066	4.216***
AUCTION	-241.144	9.184***
N	8,729	
Prob > F	0.000	
R^2	0.649	
ρ	.504	

*This table reports results of a group fixed effect regression model which serves as a robustness test. The dependent variable is borrower rate, defined as spread over the risk-free rate in basis points. Reported are regression coefficients and t-ratios, just as in Table 8, but for non-group-specific covariates. For details on variable definition see Table 2. Significance levels are given as ***, **, and * indicating significance at 1%, 5% and 10% level, respectively. The regression includes quarter dummies (not reported).*

quarter of 2007 (Crowe and Ramcharan 2009), which is beyond our period of analysis.

4.5.6 Tests with robust standard error erstimation

To check the robustness of our models against some common types of misspecification, we applied a regression with Huber/White/Sandwich estimation (Kent 1982)("regression with robust standard errors"). The estimation results show exactly the same coefficients, as expected by definition. More important, there is not a relevant change in t-ratios, i.e., all levels of significance remain unchanged (therefore, table not shown here).

Table 13: Probability of default from credit rating agency

Credit Grade	Probability of default
AA	0.20%
A	0.90%
B	1.80%
C	3.30%
D	6.20%
E	10.40%
HR	19.10%

Historical probabilities of default for each credit grade provided by Prosper Marketplace Inc. (2007a).

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Table 14: Robustness test: *Average Probability of Default* instead of *Credit Grade*

	(1)	(2)	(3)
AMOUNT	0.026***	0.025***	0.026***
	0.222	0.217	0.234
	(44.025)	(35.950)	(32.766)
PROB. OF DEF.	119.117***	102.096***	105.027***
	0.845	0.742	0.821
	(155.614)	(114.980)	(106.364)
DTI GRADE	29.220***	26.905***	28.951***
	0.054	0.051	0.062
	(11.929)	(9.472)	(10.020)
HOMEOWNERSHIP	-25.629***	-25.139***	-25.533***
	-0.039	-0.039	-0.041
	(-7.977)	(-6.791)	(-6.256)
VISUAL SELF-DISCLOSURE	-81.666***	-68.892***	-81.032***
	-0.059	-0.051	-0.060
	(-12.749)	(-9.296)	(-9.603)
AUCTION	-346.010***	-332.277***	-291.366***
	-0.255	-0.251	-0.222
	(-53.181)	(-43.309)	(-33.484)
GROUP AFFILIATION	-16.294**		
	-0.012		
	(-2.506)		
PAID GROUP		-19.341**	
		-0.015	
		(-2.303)	
UNPAID GROUP		-93.720***	
		-0.065	
		(-10.055)	
GROUP RATING			-41.392***
			-0.071
			(-11.142)
CERTIFICATION			3.809
			0.003
			(0.380)
GROUP LEADER BID			-46.279***
			-0.038
			(-5.247)
GROUP FEE			0.221***
			0.029
			(4.263)
GROUP SIZE			-0.012***
			-0.051
			(-6.685)
MANDATORY REVIEW			-29.413***
			-0.024
			(-3.145)
INTERCEPT	756.044***	862.374***	820.006***
	(82.733)	(65.803)	(56.360)
No. of observations	13,556	13,556	8,575
F	5,444.2	1,649.3	1,591.6
Prob>F	0.000	0.000	0.000
R^2	0.738	0.613	0.690
Adj. R^2	0.738	0.613	0.690

This table reports results of OLS regression models similar to Table 8, just with Average Probability of Default instead of Credit Grade, see Table 13.

5 Conclusions

This paper presents new empirical evidence on electronic markets for consumer loans. We analyze the role of financial intermediaries in the American electronic P2P lending platform *Prosper.com.*

The marketplace enables the direct mediation of loans without an intermediary between borrowers and lenders. Our analysis of an electronic credit lending platform provides differentiated results: We find that there are participants in the electronic marketplace acting as financial intermediaries, and that intermediation services significantly improve borrowers' credit conditions.

We apply a new data set to analyze theoretical predictions from the literature on financial intermediation and find that, as suggested by traditional intermediation theory, the intermediary creates value by reducing information asymmetries between borrowers and lenders. We document the positive impact of the intermediary's screening activities for the borrowers. When looking at credit grade sub-samples, we recognize these effects predominantly for borrowers with less attractive risk characteristics. Based on superior private information, the recommendation of a credit listing significantly improves borrowers' credit conditions. Moreover, the intermediary's bid has an even stronger impact on the resulting credit spread. Our results indicate that intermediation costs could be more than compensated for by lower credit spreads for borrowers. Borrowers should also consider the intermediary's reputation. These results are robust to self-selection regarding the choice of an intermediary as well as other control variables relevant to the electronic lending platform. Based on our analyses, one can quantify the effect of each possible listing feature on the credit spread.

Our results contribute to the existing literature on financial intermediation and electronic credit markets and yield some interesting implications for the setup of online credit lending platforms and the behavior of their participants. However, the deduction of broad conclusions from our study is limited in so far as our sample is restricted to individuals who chose to participate in the marketplace. Additional data on market participants' banking relationships and an assessment of the individual alternative cost of credit would enable the evaluation of the overall macro-economic impact of internet-based lending platforms such as the displacement or crowding out of traditional banks, or industry-economic effects such as the reactions of traditional banks in response to these online platforms. Also, we focus mainly on the impact of intermediation on borrowers' credit conditions. It would be interesting to include ex-post-realized loan defaults into further analyses. Moreover, our data sample consists of consumer credit transactions on an American marketplace. Generalization to electronic markets for corporate or governmental debt, to other electronic markets, and to markets in other countries may provide interesting avenues for future research.

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Biographies

Sven C. Berger is a trained bank official and studied business administration with a focus on information systems at the Frankfurt School of Finance & Management, the Indian Institute of Management in Ahmedabad/India and the Goethe University Frankfurt. He is a doctoral candidate and research assistant at the chair of electronic commerce at the Goethe University in the industry-academic research project E-Finance Lab. His research focuses on customer management and value creation in retail banking.

Fabian Gleisner recently obtained a doctor's degree from the Goethe University for his dissertation on retail financial services. He studied business administration with a focus on finance and accounting at this university. As a research assistant at the chair of banking and finance and at the E-Finance Lab, his work covered bank M&A, higher education finance, and financial advisory.