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Strategic Information Transmission in Peer-to-Peer Lending Markets

Peer-to-peer (P2P) marketplaces, such as Uber, Airbnb, and Lending Club, have experienced massive growth in recent years. They now constitute a significant portion of the world's economy and provide opportunities for people to transact directly with one another. However, such growth also challenges participants to cope with information asymmetry about the quality of the offerings in the marketplace. By conducting an analysis of a P2P lending market, the authors propose and test a theory in which countersignaling provides a mechanism to attenuate information asymmetry about financial products (loans) offered on the platform. Data from a P2P lending website reveal significant, nonmonotonic relationships among the transmission of nonverifiable information, loan funding, and ex post loan quality, consistent with the proposed theory. The results provide insights for platform owners who seek to manage the level of information asymmetry in their P2P environments to create more balanced marketplaces, as well as for P2P participants interested in improving their ability to process information about the goods and services they seek to transact online.

Keywords: asymmetric information, consumer-to-consumer interactions, consumer financial decision making, electronic commerce, P2P platforms

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The Internet and information technology increasingly produce more disintermediated and democratized industries by connecting individual actors in unprecedented ways. Such development fostered the explosive growth of the peer-to-peer (P2P) economy and enabled the rise of many successful P2P platforms. Uber has quickly become the world's largest driving service; Alibaba is now the most valuable retailer; and Airbnb offers more rooms than any other hospitality service (Weed 2015). Similarly, Lending Club, a P2P lending platform, is now the world's largest online marketplace connecting individual borrowers and investors.

Deservedly, the P2P economy and its major societal impacts have attracted substantial research interest as well as calls for more studies that apply decision-making perspectives to these consumer-to-consumer interactions (Kumar 2015; Yadav and Pavlou 2014). In response, a few recent articles in marketing and economics have studied peer-influenced consumer decisions in industries such as music (Sinha, Machado, and Sellman 2010), video games (Landsman and Stremersch 2011), used cars (Lewis 2011), lending (Lin, Prabhala and Viswanathan 2013), and retailing (Backus, Blake, and Tadelis 2015).

Even as P2P platforms expand in various industries, information asymmetry remains a challenge for both participants and P2P platform managers. Without the signals of brand power and other reputational heuristics that consumers often use as proxies for quality, participants in P2P platforms need to make decisions with limited information, causing transaction risks to be higher than those in traditional business settings. On the one hand, buyers need to decide how to interpret the information provided by sellers to infer quality and minimize risk; on the other hand, sellers can strategically reveal or withhold information about themselves to increase their chances of a favorable outcome. In turn, platform managers likely need to weigh the information provided by sellers and create mechanisms to reflect transactional risk accurately and engender more trust in the platform (Schlosser, White, and Lloyd 2006).

In this research, we examine the issue of information asymmetry in P2P markets by studying a social lending platform. We center attention on the Lending Club platform because it is an exemplar P2P marketplace that is gaining substantive importance and in which the effects of asymmetric information can lead to significant consumer losses. P2P lending is a multibillion dollar industry that has experienced staggering 100% annual growth since 2010 (*Economist* 2014) and is expected to reach $150 billion in size by 2025 (PWC 2015). It has

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democratized capital markets by allowing people to bypass traditional banking roadblocks and enabling them to become customers and suppliers of their own financial products. Lending platforms provide verifiable information about borrowers, but a considerable degree of information asymmetry remains, causing lenders to bear significant risk because loans are unsecured. For instance, as of March 2016, Lending Club reports that across all loans, 7.8% of the amount issued to borrowers is charged off. Because lenders shoulder the default losses, it is optimal for them to minimize default risk by looking for borrowers who are most likely to repay their loans.

We consider the Lending Club platform and examine whether the strategic transmission of nonverifiable information by a borrower, represented by the length of the description of the reasons for the loan, offers signaling content that complements other verifiable information, and helps lenders distinguish the likelihood of repayment of each loan. Any mechanism on a P2P lending platform that can further distinguish borrowers more likely to repay a loan has the potential to improve the lending market for both borrowers and lenders. To the best of our knowledge, this is the first study to consider how the mere presence of a description and the length of the description might help borrowers strategically transmit information about their repayment prospects.

According to extant theories on "cheap talk," if the provision of nonverifiable information is costless, then it should not affect a buyer's decision. If the provision has costs in terms of effort, then such information carries a signal that might affect the buyer's decision in a monotonic manner: the higher the effort, the stronger the signal. In contrast with these traditional perspectives, we recognize that nonverifiable communication in P2P platforms is a more complex phenomenon because there are multiple sources of information. Thus, we propose to study the P2P market under the lenses of a theory of *countersignaling* as the potential major force governing P2P interactions under information asymmetry.

Specifically, within the same creditworthiness class, as measured by verifiable information, loan applicants who provide no loan description (i.e., choose not to transmit nonverifiable information) are expected to have a higher likelihood of getting funded and a lower likelihood of delinquency, according to the countersignaling argument. However, when borrowers decide to write descriptions, applications featuring longer descriptions have a greater likelihood of getting funded and a lower likelihood of delinquency than those with short descriptions, a result that is consistent with an effort-as-a-signal argument. We contrast the predictions of countersignaling with those of competing theories. Using a data set of loan applications from the P2P platform Lending Club over three years, we find support for our theory: lenders' funding decisions are influenced by strategic countersignaling by borrowers, and these decisions are confirmed by the borrower's subsequent likelihood of delinquency.

This research thus contributes to information transmission and consumer decision-making literature in several ways. Theoretically, we show that the countersignaling mechanism is present in the P2P transaction setting, and it helps resolve information asymmetry. This is a novel finding in light of competing theories based on signaling, cheap talk, persuasion, and psycholinguistics. Empirically, we provide evidence that is consistent with the countersignaling theory and inconsistent with the competing mechanisms. In particular, we show that individuals indeed strategically transmit information to other individuals in an online P2P environment through the effort they exert to write a loan description. This strategic transmission provides an informative signal about loan quality, as evidenced by subsequent loan performance. We show that in equilibrium, individuals on both sides of the platform are sophisticated actors, capable of sending and interpreting quality signals.

Our research also adds to literature on consumer lending decisions, a stream of research that has increasingly received attention from marketing scholars. For instance, research has investigated lenders' reaction to race and appearance of an applicant's uploaded photograph (Galak, Small, and Stephen 2011; Ravina 2012), the number and roles of the members of an applicant's friendship group (Lin, Prabhala, and Viswanathan 2013), lender herding behaviors (Herzenstein, Dholakia, and Andrews 2011; Zhang and Liu 2012), and the impact of type of media on microlending (Stephen and Galak 2012). Our study adds to the literature by showing how borrowers can use loan descriptions to signal quality to lenders. The findings have implications for designers of P2P lending platforms, who should consider countersignaling behavior when they seek to fine-tune their risk/return algorithms. The findings provide guidance to borrowers regarding when to countersignal; for lenders, they reveal how to weight information that goes beyond the verifiable information provided by the platform in order to better identify true risks. A growing industry of hedge funds and algorithm-based services (e.g., Lending Robot) promise that their risk assessments are more comprehensive than those from existing platforms; they select loans on the basis of a borrower's nonverifiable information to boost returns. Our finding reveals an area of information that these companies could productively exploit. Our work not only informs the growing number of P2P marketplaces but also provides new insights into consumer financial decision making in the age of data prevalence.

More generally, our work has managerial implications for various platforms (e.g., eBay, Etsy, Airbnb, Upwork) on which sellers may wish to communicate their quality credibly to buyers. Given the evidence that countersignaling can indeed convey information about quality, managers of P2P platforms should consider opening this avenue of information exchange and incorporate it in their composite seller rating score presented to the buyer in order to reduce information asymmetry and increase efficiency, which, in turn, would build trust among participants. As the P2P economy keeps growing, information asymmetry and trust in the platform will continue to be notable issues. Platforms that can fine-tune their rating system to better reflect risk and to resolve information asymmetry more effectively will instill more confidence among participants and thus gain advantages over their rivals. Sellers (in our case, borrowers) on P2P platforms can use the insights of this research to decide when to rely exclusively on verifiable information provided by the platform and when it is worthwhile to produce nonverifiable information. Buyers in P2P marketplaces can learn how to aggregate platform-provided with participant-provided information about the products and services marketed on the platform. Buyers who are adept at picking up informational cues might achieve higher returns (e.g., buying high-quality products at a lower price) while mitigating risks.

Literature Review

Our work brings together two research streams: asymmetric information in P2P platforms and P2P lending specifically, and the mechanism of countersignaling. We now briefly discuss related research in each stream and our contributions.

Asymmetric Information in P2P Markets

It is well understood that for markets to work efficiently, buyers and sellers need to possess symmetric information. In the presence of information asymmetry, the market will not allocate resources efficiently and may even collapse (Akerlof 1970).

Thus, research on P2P platforms has largely focused on information disclosure and signaling to alleviate asymmetric information. For example, Lewis (2011) studies the P2P marketplace eBay Motors and finds that the disclosure of some degree of verifiable information by a seller, such as pictures and text with specifications of the automobile, can serve to reduce adverse selection, provided sellers are contractually obligated to fulfill products that match the information they provide. Backus, Blake, and Tadelis (2015) identify how participants bargaining on eBay's "Best Offer" listings can signal their level of impatience by posting round-number prices. Li, Tadelis, and Zhou (2016) investigate how sellers can signal quality by offering incentives for consumers to leave feedback in the online P2P marketplace. Taobao, Tadelis, and Zettelmeyer (2015) use a field experiment to investigate how information disclosure about the quality of objects can improve the efficiency of markets. The authors find that the disclosure decreases search costs and thus helps bidders better match their preferences with the quality of the products being offered in the marketplace.

All of these studies find that sellers can alleviate asymmetric information by either voluntarily revealing verifiable information about quality types or sending a costly signal. Our work adds to the literature by recognizing that strategic information transmission in P2P platforms can be a more complex phenomenon in situations in which the P2P platform can serve as an additional source of information. In such cases, the sellers can resolve additional information asymmetry by (1) the voluntary disclosure of unverifiable information (even if unrelated to quality types) and (2) the effort of providing lengthy disclosures. These two elements together can result in a nonmonotonic relationship between the degree of the seller's disclosure and the buyer's interpretation of quality.

Asymmetric Information in P2P Lending

Likewise, P2P lending platforms also experience asymmetric information. Research in this domain has primarily focused on investigating how factors beyond borrower's creditworthiness can influence lender behavior.

Freedman and Jin (2011) show that some of the asymmetric information and adverse selection can be reduced through a learning-by-doing process in which the entire market learns about the risk level of the financial products being offered in the market and gradually excludes low-quality borrowers in favor of higher-quality borrowers. The likelihood of a loan application getting funded can be affected by the race and appearance of an applicant's uploaded photograph (Duarte, Siegel, and Young 2012; Pope and Sydnor 2011; Ravina 2012), the number and roles of the members of an applicant's friendship group (Lin, Prabhala, and Viswanathan 2013), and lender herding behaviors (Herzenstein, Dholakia, and Andrews 2011; Zhang and Liu 2012).

Kawai, Onishi, and Uetake (2014) also study the issue of adverse selection, using data from an earlier version of the Prosper P2P platform, where potential borrowers posted public reserve interest rates to signal their creditworthiness. In our framework and data, interest rates are set by the lending platform according to the borrower's verifiable risk profiles, which is similar to the situation proposed by Milde and Riley (1988). As a result, our borrowers cannot use interest rates to signal their quality and instead rely on unverifiable information to signal and countersignal. When the borrower is required to provide a loan description, Sonenshein, Herzenstein, and Dholakia (2011) demonstrate that, using the perspectives of persuasion, borrowers with poor credit history can improve funding likelihood by explaining and taking responsibility for their financial mistakes. Similarly, the number and content of borrower identity claims influence lenders' decisions (Herzenstein, Sonenshein, and Dholakia 2011; Michels 2012).

Our current research differs from previous P2P lending contributions in two dimensions. First, previous work has only looked at lender's funding decision. We take it a step further and examine whether these decisions are correct in the long run, as measured by loan performance. Second, whereas previous platforms require borrowers to provide loan descriptions, Lending Club offers borrowers the option not to do so. The proposed framework allows us to investigate the differential signaling values of the description length (and its related effort) as well as the value from the mere presence of (or lack of) the description.

Therefore, we can corroborate prior findings that nonverifiable information such as the purpose and the content of the loan description affect loan funding. However, we uniquely provide theory and evidence suggesting that (1) the mere presence and (2) the length of the loan description are signaling mechanisms that can attenuate information asymmetry between the borrower and lender regarding the borrower's ability to repay the loan. Our framework contributes to the P2P lending literature by offering a unified theory of countersignaling, explaining both borrower and lender behaviors, that is likely sustainable in the long run. We show that in equilibrium, individuals on both sides of the platform are sophisticated actors, capable of sending and interpreting quality signals.

Countersignaling

In traditional signaling models, all the information originates from the sender, and the effect of the signaling instrument is monotonic. Research in signaling has examined a broad range of contexts, from education choice (Spence 1973) to advertising decision (Milgrom and Roberts 1986) and pricing (Desai 2000).

The P2P lending context features a mix of verifiable information, screened and provided by the platform (e.g., credit score, debt level, public records), and nonverifiable information provided by the borrower (e.g., loan purpose, loan description). When borrowers prepare their applications, they do not know with certainty how their verifiable information (compiled by the P2P lending platform) will appeal to lenders, according to the platform's underwriting model. This reality more closely relates to the countersignaling theory, in which there are two sources of information: one provided by the sender and the other provided by a trusted third party (Feltovich, Harbaugh, and To 2002).

Prior research theorizes that when additional sources of information are available, high-quality senders countersignal by choosing not to provide information about course grades Feltovich et al. (2002), by using low-quality packaging (Clements 2011), spending less on advertising (Orzach, Overgaard, and Tauman 2002) or engaging in either image or informative advertising (Mayzlin and Shin 2011). Countersignaling creates a nonmonotonic relationship between sender quality and signaling effort, and this relationship can hold even if there is heterogeneity in how consumers process information (a common phenomenon, as noted by Bart et al. [2005] and Zhu and Zhang [2010]).

Our research is one of the very few studies to empirically investigate countersignaling. We do so in the growing field of P2P lending. We now describe our theory, followed by an empirical test of the theory.

A Theory of Countersignaling in Peer-to-Peer Lending

In this section, we put forth a theory in which loan descriptions serve as an instrument for countersignaling, formalize hypotheses associated with this theory, and contrast its predictions with competing theories regarding the role that loan descriptions serve on peer-to-peer lending platforms. In the P2P marketplace, informational asymmetry exists regarding a borrower's type. Borrowers' inherent quality may not be expressed perfectly in the available verifiable information (e.g., credit scores), and borrowers have superior knowledge about their own likelihood to pay back a loan, relative to lenders. Lenders may attempt to infer the true quality of the loan from the information that borrowers provide on their applications. Thus, a borrower might try to use the loan request or description as a signaling instrument, to facilitate the exchange of information from the prospective borrower (sender) to the potential lenders (receivers). Countersignaling theory offers predictions about a lender's behavior in response to a borrower's communication of such nonverifiable information.

Intuition

Consider first a stylized P2P social lending situation in which there are three types of borrowers for a given asset class: high-quality, medium-quality, and low-quality, where quality indicates borrowers' unobservable likelihood to repay the loan. Each loan has a level of risk and an interest rate that compensates the lender for taking that risk. The lender's goal is to choose the asset classes that match his or her portfolio objectives and within each class identify the quality of the loans. The signaling mechanism (i.e., loan description, in our case) does not differentiate applicants across verified credit grades; this classification already has been done by the credit grade itself. Instead, the loan description functions to differentiate among the loans within the same credit grade. All potential lenders know that a loan with credit grade A (best), priced at an interest rate of 5%, has a lower risk of default than a loan with credit grade G (worst), priced with an interest rate of 21%. The informational problem is the differentiation among loans within a range of similar credit grades and interest rate combinations. Thus, high-, medium-, and low-quality types refer to the types *within* the same credit grade (e.g., among three A-grade borrowers or three G-grade borrowers).

It is important to note that Lending Club loans are unsecured personal loans, so their creditworthiness is supported only by and is a direct function of the creditworthiness of the borrower. The credit grade, however, is not a completely deterministic measure of creditworthiness (e.g., 95% of A-grade borrowers honor their loans, but 5% do not), nor is it the only verifiable information reported by the Lending Club. The platform also reports additional verifiable information such as FICO score and number of previous hard credit inquires. Credit grades largely depend on FICO scores, though, as we demonstrate empirically later in this article.

In our data set, Lending Club borrowers apply for loans and may write loan descriptions *before* the platform performs the formal creditworthiness assessment (e.g., checking credit scores, employment, public records) and reveals this third-party-verified information to lenders on the platform. At that point, borrowers know that the third-party-verified information correlates positively with their identified type, but they do not know the exact information.

Borrowers seek to maximize their payoff when choosing whether to write a loan description and how long to make it.[1] A borrower is willing to incur the cognitive cost (effort) of creating a loan description if the benefits outweigh the costs. Thus, the loan description can facilitate a lender's inference of borrower quality. Medium-quality borrowers cannot be confident about whether the information provided by the third party will be viewed positively. Thus, they exert effort to send a signal to differentiate themselves from low-quality borrowers and write long descriptions. Low-quality borrowers recognize that the verifiable information is unlikely to benefit them, so it is unprofitable to attempt to overcome the negativity of this information by exerting a high level of effort to provide a lengthy loan description. They thus exert less effort describing the loan than medium-quality borrowers do. High-quality borrowers recognize that the third-party information has a high probability of distinguishing them from a low-quality borrower. That is, they have a low probability of being confused with low-quality borrowers, and by providing no loan description, they can profitably draw a distinction from medium-quality borrowers.

Formal Model for a Continuum of Borrower Types

Assume that, in accordance with their previous portfolio allocation decisions,[2] two lenders on the platform wish to invest some of their money into a certain risk–reward category of loans offered in the platform. Because each risk–reward category has

[1]Prior research reveals the cognitive cost of writing text. For example, Greiner and Wang (2010) report that prospective borrowers need to invest effort to write high-quality loan requests. Shavell (2010) also asserts that people usually experience some disutility for writing well-crafted works, and Liebowitz and Margolis (2005) even suggest that the act of writing may be subject to opportunity costs.

[2]Fabozzi (2013, p. 464) states that the first decision portfolio managers should make is the asset allocation decision, that is, the decision of how much to invest in each asset class. Brus (2010) provides the example of the Oklahoma Teachers Retirement System, which has an executive directive to invest 70% in the equity market and 30% in the bond market. Bodie, Kane, and Marcus (2009, p. 218) report that even sophisticated investment companies may adopt a multistage decentralized approach by first deciding between asset-class allocations and then performing security section within each class, because of the overwhelming complexity of optimizing an organization's entire portfolio decision in one stage. Our analysis is abstracting from higher-level asset-class allocation and concentrates on the security selection of loans within the same risk–reward category.

fixed interest rates, it is optimal for lenders to infer the quality of the loans within each asset class and to allocate higher shares of their budget to the loans that are less likely to default (i.e., have higher quality).[3]

The quality of the loans within a risk–reward category is linked to the quality of the borrower, which can be represented by a parameter $\theta \in [\underline{\theta}, \overline{\theta}]$, with $0 < \theta < 1$. Higher values of θ represent higher-quality borrowers in terms of the likelihood of on-schedule loan repayment. Both borrowers and lenders have common knowledge about the distribution of borrowers in the market, but ex ante, only a particular borrower knows his or her own true quality.

The independent platform compiles verifiable information and sends a noisy signal, $x = \theta + \varepsilon$, where ε is a random variable distributed uniformly in the interval $[-a, a]$. This signal represents a measure of all the verifiable information provided by the lending platform, such as monthly income, delinquencies, credit inquiries, and so on. Ex ante, the borrower knows his or her own type θ but not the realization of x. Without loss of generality, we assume that the interval $[-a, a]$ is such that $\underline{\theta} - a \geq 0$ and $\overline{\theta} + a \leq 1$.[4]

Before x is revealed on the platform, borrowers can write descriptions of a length s (with $s > 0$) to send a signal to the market. To send the signal, borrowers experience a cognitive cost of effort s, where k is a cost parameter. We consider that a proportion λ of lenders are sophisticated and make decisions based on the verifiable information x and on their own inferences from the signal s. The likelihood these sophisticated lenders will fund a loan is equal to $\mu_s = \Phi(s, x)$, where $\Phi(s, x)$ represents the lenders' belief function as they rationalize both the verifiable and nonverifiable information. As discussed above, this assumption is consistent with the optimal portfolio allocation of rational lenders who consider a mean-variance trade-off, as these lenders should allocate higher shares of their budget to higher-quality loans and consequently be more likely to fund higher-quality loans.

We also allow for a proportion $1 - \lambda$ of lenders to be naïve lenders who myopically believe in the nonverifiable information. Our treatment of naive individuals is similar to Inderst and Ottaviani (2012), who also allow for individuals who do not properly account for the strategic incentives behind the information they receive. For these lenders, their belief of borrower quality increases directly with the amount of nonverifiable information and with the quality of the platform's provided noisy signal (subsequently, we discuss the ensuing outcomes when these types of lenders are absent from the market).

The likelihood that naive lenders will fund a loan is equal to $\mu_n = [s/(1 + s)]x^{\gamma}$, where x^{γ} reflects the importance of verifiable information to the naive lenders and captures the effect that borrowers who have good objective information have a better basis to write enticing descriptions (for instance, a borrower who has a prestigious job or high income can write a description that highlights these facts). The parameter γ allows for a nonlinear interaction. Whereas this functional form nicely captures the possibility that naive lenders are more easily swayed by nonverifiable information when the verifiable information is positive, we note the countersignaling equilibrium result is robust to modifications to this function.[5] Our assumption about the likelihood that a naive lender funds a loan is also in line with portfolio allocation decisions of lenders who consider a mean-variance trade-off. In the same vein as sophisticated lenders, the naive lenders should be more likely to fund the loans that they perceive to be of higher quality. The difference between these two types of lenders is the way they form beliefs about the quality of the loans.

Notice that the presence of naive lenders may provide an incentive for some borrowers to convince these lenders via description length. As will be seen later, in the section on equilibrium results, for any type θ, both too little and too much effort investment in the description can be costly. If borrowers invest too much, their disutility for writing descriptions overpowers the benefit of convincing lenders; if borrowers invest too little, they leave too much "money on the table" from naive lenders.

Assuming that borrowers get a value V from obtaining a loan,[6] and recalling that x is a function of θ, we can write the borrowers' expected utility as

$$\text{(1)}\quad E[U(s,\theta)] = E\left[V\left(\lambda\Phi\left(s, x(\theta)\right) + (1-\lambda)\frac{s}{1+s}x(\theta)^{\gamma}\right) - k\,s\right].$$

Given that x is the only random variable, we can rewrite this expression as

$$\text{(2)}\quad E[U(s,\theta)] = V\left(\lambda E[\Phi(s, x(\theta))] + (1-\lambda)\frac{s}{1+s}E\left[x(\theta)^{\gamma}\right]\right) - k\,s.$$

Since we are interested in whether the amount of nonverifiable information can signal the quality of the borrower, we will be looking for an informational equilibrium that satisfies the following perfect Bayesian equilibrium conditions:

$$\text{(i)}\qquad E[U(s^*, \theta)] \geq E[U(s', \theta)] \text{ for any } s' \in S.$$

$$\text{(ii)}\qquad E[\Phi(s^*, x(\theta))] = \theta \text{ for all } \theta \in \left[\underline{\theta}, \overline{\theta}\right].$$

The first condition states that each borrower type θ sends a signal s^* that maximizes his or her own utility. The second condition states that the sophisticated lenders' beliefs about the borrowers' types are confirmed in equilibrium. In other words, $E[\Phi(s^*, x(\theta))]$ will capture the derived belief supports our countersignaling equilibrium.

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[3]A straightforward portfolio analysis in which loans have fixed interest rates and differ in their likelihood of default will conclude that lenders should be more likely to fund loans they believe to be less likely to default. Such an analysis is available from the authors upon request.

[4]The intervals for the values of the borrower quality θ and the noise ε can be constructed from a simple normalization in which alternative parameters θ' and a' are members of $\mathbb{R}_+$, with $\underline{\theta}' > a'$. The normalization is formed by choosing a large enough number M, ($M = \overline{\theta}' + a'$ is sufficient) and making $\theta = \theta'/M$ and $a = a'/M$.

[5]The countersignaling equilibrium that arises in our model is robust to other specifications that preserve the standard single-crossing property. For instance, the effect of signaling on naive borrowers can be independent of borrower type, and the signaling cost can be a function of borrower type, as in Feltovich, Harbaugh, and To (2002).

[6]In an extension of this model in Web Appendix 1, we show that results are preserved even if the value V is dependent on the borrower's type θ, provided that the single-crossing property is preserved.

Because $E[\Phi(s, x(\theta))]$ is ultimately a function of s and θ, we can define $\Phi_x(s, \theta) \equiv E[\Phi(s, x(\theta))]$. In addition, we can compute the expectation $E[x(\theta)^\gamma]$ by integrating over the random noise ε:

$$E\left[x(\theta)^\gamma\right] = \int_{-a}^{a} x(\theta)^\gamma \frac{1}{2a} d\varepsilon = \frac{(\theta + a)^{\gamma+1} - (\theta - a)^{\gamma+1}}{2a(\gamma + 1)}.$$

Hence, we define the function

$$\xi(\theta) \equiv E\left[x(\theta)^\gamma\right] = \frac{(\theta + a)^{\gamma+1} - (\theta - a)^{\gamma+1}}{2a(\gamma + 1)}$$

to be this expectation.

Following Condition i, we maximize Expression 2 with respect to s. We take derivatives with respect to s and find the first-order condition

$$(3) \qquad V\left(\lambda \Phi'_x(s^*, \theta) + (1 - \lambda)\frac{\xi(\theta)}{(1 + s)^2}\right) - k = 0,$$

where s^* denotes the equilibrium signaling effort.

By solving the ordinary differential equation given by Expression 3, we find that $\Phi_x(s^*, \theta)$ can be expressed as

$$(4) \qquad \Phi_x(s^*, \theta) = \frac{k(1 + s^*)}{V\lambda} + \frac{(1 - \lambda)\,\xi(\theta)}{\lambda + \lambda s^*} + C,$$

where C is a constant to be determined by the appropriate boundary condition.

As in Milgrom and Roberts (1982) and Daughety and Reinganum (1995), we consider that a Pareto-efficient outcome requires that in a separating equilibrium, the lowest quality borrower $\underline{\theta}$ has no incentive to distort his or her optimal amount of nonverifiable information. Hence, we rewrite the borrower's expected utility function in Expression 1 as

$$(5) \qquad E[U(s, \underline{\theta})] = V\left(\lambda \Phi_x(s, \underline{\theta}) + (1 - \lambda)\frac{s}{1 + s}\xi(\underline{\theta})\right) - ks.$$

By maximizing this expression with respect to s, we find that the optimal (undistorted) amount of nonverifiable information sent by a $\underline{\theta}$ borrower is

$$(6) \qquad s^*(\underline{\theta}) = \frac{-k + \sqrt{(1 - \lambda)Vk\,\xi(\underline{\theta})}}{k}.$$

By using Expression 6 as a boundary condition and solving the equality

$$\underline{\theta} = \frac{k(1 + s^*(\underline{\theta}))}{V\lambda} + \frac{(1 - \lambda)\xi(\underline{\theta})}{\lambda + \lambda s^*(\underline{\theta})} + C,$$

we can determine the constant C and rewrite Expression 4 as

$$(7) \qquad \Phi_x(s^*, \theta) = \frac{k(1 + s^*)}{V\lambda} + \frac{(1 - \lambda)\xi(\theta)}{\lambda + \lambda s^*} + \frac{-2k(1 - \lambda)\xi(\underline{\theta}) + \lambda\,\underline{\theta}\,\sqrt{(1 - \lambda)Vk\,\xi(\underline{\theta})}}{\sqrt{(1 - \lambda)Vk\,\xi(\underline{\theta})}}.$$

By observing Condition ii in our signaling equilibrium that $\Phi(s^*, \theta) = \theta$, we solve

$$\theta = \frac{k(1 + s^*)}{V\lambda} + \frac{(1 - \lambda)\xi(\theta)}{\lambda + \lambda s^*} + \frac{-2k(1 - \lambda)\xi(\underline{\theta}) + \lambda\,\underline{\theta}\,\sqrt{(1 - \lambda)Vk\,\xi(\underline{\theta})}}{\sqrt{(1 - \lambda)Vk\,\xi(\underline{\theta})}}$$

for the optimal signaling amount s^*. Inverting the equation, we find that the curve

$$(8) \quad s^*(\theta) = \frac{1}{2k}\Bigg(\lambda V(\theta - \underline{\theta}) - 2k + 2\sqrt{(1 - \lambda)Vk\,\xi(\underline{\theta})} + \sqrt{V\Big(4(1 - \lambda)k\big(\xi(\underline{\theta}) - \xi(\theta)\big) + \lambda(\theta - \underline{\theta})\big(V\lambda(\theta - \underline{\theta}) + 4\sqrt{(1 - \lambda)Vk\,\xi(\underline{\theta})}\big)\Big)}\Bigg)$$

can represent the optimal amount of nonverifiable information s^* for a borrower of type θ.

Finally, we prove that a countersignaling equilibrium is possible in this model. By observing Condition i in our signaling equilibrium, we find that a countersignaling equilibrium is possible if the higher types find it optimal to switch from the function described in Expression 8 to the curve $s = 0$ (i.e., to provide no description). Hence, we compute the higher-quality-type borrowers' expected outcome when following the belief function given by Expression 7:

$$(9) \qquad U^{s^*} = E[U(s^*(\theta), \theta)] = V\left(\lambda\theta + (1 - \lambda)\frac{s^*(\theta)}{1 + s^*(\theta)}\xi(\theta)\right) - ks^*(\theta).$$

On the other hand, the higher-quality-type borrowers' expected outcome when they exert zero signaling effort is simply

$$(10) \qquad U^{s0} = E[U(0, \theta)] = V\left(\lambda\theta + (1 - \lambda)\frac{0}{1 + 0}\xi(\theta)\right) - 0k = V\lambda\theta.$$

The belief $\Phi_x(0, \theta) = \theta$ is rational only for types that prefer the outcomes given by Expression 10 over those given by Expression 9.

To verify existence, consider that the difference in utilities $U^{s^*} - U^{s0}$ (Expressions 9 and 10) must be positive for the lowest-quality borrower $\underline{\theta}$. This difference is

$$U^{s^*}\big|_{\theta=\underline{\theta}} - U^{s0}\big|_{\theta=\underline{\theta}} = (1 - \lambda)V\xi(\underline{\theta})\frac{s^*(\underline{\theta})}{1 + s^*(\underline{\theta})} - ks^*(\underline{\theta}).$$

Next, consider that the difference in utilities $U^{s*} - U^{s0}$ for the highest-quality borrower $\overline{\theta}$ must be negative. The difference is

$$U^{s^*}\big|_{\theta=\overline{\theta}} - U^{s0}\big|_{\theta=\overline{\theta}} = (1 - \lambda)V\frac{s^*(\overline{\theta})}{1 + s^*(\overline{\theta})}\xi(\overline{\theta}) - ks^*(\overline{\theta}).$$

Countersignaling occurs when the two conditions above are satisfied. They can be combined in the condition

$$(11) \qquad \frac{(1 - \lambda)V\xi(\overline{\theta})}{1 + s^*(\overline{\theta})} < k < \frac{(1 - \lambda)V\xi(\underline{\theta})}{1 + s^*(\underline{\theta})}.$$

One can verify that because $s^*(\theta) > \theta$, there are parameter values that satisfy Condition 11. Furthermore, because both $\xi(\theta)$ and $s^*(\theta)$ are strictly increasing in θ, there exists a cutoff borrower-quality level θ^* such that types $\theta > \theta^*$ find it better to countersignal by sending $s^* = 0$ because $U^{s^*}\big|_{\theta>\theta^*} - U^{s0}\big|_{\theta>\theta^*} < 0$, whereas types $\theta < \theta^*$ find it unprofitable to do so because $U^{s^*}\big|_{\theta<\theta^*} - U^{s0}\big|_{\theta<\theta^*} > 0$ (the types

$\theta < \theta^*$ thereby optimally choose to send a signal s^* according to Equation 8).

Thus, it follows that the equilibrium amount of nonverifiable information as a function of borrower type is

$$s^{*countersignal} = \begin{cases} s^*(\theta) \text{ for } \theta \in [\underline{\theta}, \theta^*] \\ 0 \text{ for } \theta \in [\theta^*, \overline{\theta}]. \end{cases} \quad (12)$$

Notice, however, that if there were no naive consumers, and thus $(1 - \lambda) = 0$, it would be impossible to find any values for the parameters that satisfy Condition 11. In such a case, a countersignaling equilibrium could not be sustained, and the optimal for all players would be to write no description. The intuition is that if the benefit of writing a description cannot be rationalized and the cost of writing a description still exists, then the optimal is for all borrowers to simply avoid the cost of writing a description (thus setting $s^{*no-naives} = 0$).

Figure 1 illustrates our theory's prediction about the relationship between the equilibrium amount of nonverifiable information sent by the borrowers and the likelihood that a loan will be funded. The figure shows that loan requests with no description are interpreted as being sent by higher-quality borrowers and are rewarded by a high likelihood of being funded. For the remaining borrowers, the likelihood that a loan request is funded is increasing in the amount of signaling effort.

In summary, in the P2P lending setting, in which information asymmetry regarding the quality of the borrowers plays a significant role, if potential lenders are able to account for countersignaling when inferring the quality of a loan, the effect of loan description on funding will be nonmonotonic. Specifically, the absence of a loan description should increase the likelihood that the loan gets funded relative to the presence of a loan description. However, once a borrower provides a loan description, the likelihood of getting funded should be higher when the description is lengthy than when the description is short. Furthermore, no borrower has an incentive to pretend to be of a different quality by mimicking the strategy of other borrowers. The implications of the analytical model are synthetized in four testable hypotheses:

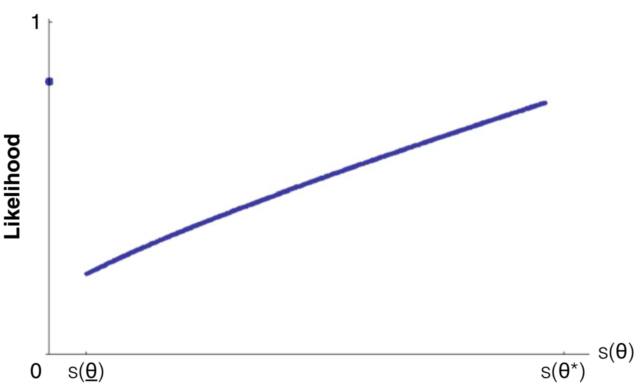
H_1: The absence of a loan description has a positive effect on the likelihood of a loan being funded.

H_2: The absence of a loan description has a negative correlation with the ex post likelihood of a loan being delinquent in repayment.

H_3: Given that a loan has a borrower-provided description, the likelihood of a loan being funded increases with description length.

H_4: Given that a loan has a borrower-provided description, the ex post likelihood of a loan being delinquent in repayment correlates negatively with its description length.

FIGURE 1
Countersignaling Theoretical Prediction for the Relationship Between Signaling Effort (Description Length) and Probability of Funding



Notes: The parameter values used for this graph are λ=.7, k = 1/2,000, V = 200, γ = 1/2, $\underline{\theta}$ = .1, $\overline{\theta}$ = .9, and a = 1/20. The appearance of the graph is robust to an array of parameter values.

At this point, it is useful to compare our hypotheses with competing theories. If providing a lengthy loan description were costless to borrowers, a model of cheap talk would predict that it would have no effect on lender behavior (e.g., Crawford and Sobel 1982). Thus, if loan descriptions are costless to borrowers, H_1–H_4 would not be supported, and we would not be able to reject the null hypotheses.

Literature on persuasion and compliance (Langer, Blank, and Chanowitz 1978) would predict that a lender is more likely to comply with a funding request when a reason is offered, whether that reason is legitimate or not. In contrast with H_1, this account would predict a negative effect of the absence of a loan description on loan funding. Moreover, we would not be able to reject the null version of H_2. Research that predicts an effect of the number of persuasive arguments (e.g., Petty and Cacioppo 1984) predicts that more arguments tend to improve persuasion. This prediction is consistent with H_3, but it implies the opposite of H_1. Moreover, we would not be able to reject the null hypotheses associated with H_2 and H_4.

Finally, we compare our theory's predictions with psycholinguistics theory, which predicts that in asynchronous computer communications, liars produce more words when lying than when telling the truth (e.g., Hancock et al. 2008). This theory would predict that ex post loan delinquency increases monotonically with description length, in conflict with H_4, and if lenders rationally infer this relationship, loan funding monotonically decreases with description length, in contrast with H_3.

In summary, in the P2P lending context that we study, the countersignaling model generates four testable hypotheses that capture the nonmonotonic effects of loan descriptions on funding and ex post delinquency. Competing theories based on models of cheap talk, persuasion, and psycholinguistics generate one or more predictions that conflict with H_1–H_4. Thus, we can test whether countersignaling governs how borrowers and lenders use the loan description or whether this relationship instead can be explained better by one of the competing theories.

Institutional Details, Data, Empirical Model, and Results

In this section, we describe the institutional settings that govern the theory construction and the empirical model. We first discuss the data used to test our hypotheses and provide some model free evidence, then present the tests of the impact of borrowers' provision of nonverifiable loan information on attracting funding and the ensuing relationship between nonverifiable loan information and ex post loan performance.

Institutional Details of the P2P Lending Platform

We examine loan requests on Lending Club. The two dependent variables of interest are whether the loans are funded by lenders and their subsequent performance. The loan application process is as follows: First, the borrower fills out an online form with his or her name, address, date of birth, annual income, and requested loan amount. Second, Lending Club immediately makes an *initial* nonbinding offer that includes information about the monthly payment. This offer is based on the information provided as well as publicly available information about the borrower; it is known as a "soft credit pull." Borrowers are reminded to be truthful in providing the information because false information will lead to denial of the loan. Third, once the borrower agrees with the initial terms, he or she fills out another online form, providing additional information that can be used for credit verification and displayed to lenders (e.g., employment, loan description, home ownership, Social Security number). At this point, the borrower also can write the loan description. All of this occurs before Lending Club performs the final creditworthiness verification. Fourth, after the borrower decides whether to write nonverifiable information in the form of a loan description, Lending Club conducts further identity verification by checking additional paperwork (e.g., recent tax returns), conducting phone call verifications, and making inquiries into the borrower's credit history. Finally, if the borrower passes Lending Club's underwriting review, the loan request will be posted online, along with the verified information (credit score, debt-to-income ratio, number of delinquencies) and any borrower-provided information about the purposes and description of the loan. Once the loan is funded, Lending Club deposits the money in the borrower's bank account.

Several details make Lending Club unique relative to other P2P platforms (e.g., Prosper.com), such that it offers a cleaner venue in which to study countersignaling. First, borrowers are anonymous and are unable to communicate with lenders offline; lenders, in turn, have no capability to identify whether a particular borrower is a first-time or repeat borrower. In our data set, we observe the same information that is available to lenders when they make funding decisions; it seems implausible that lenders could gain any private, unobserved information about borrowers. Second, some factors included in prior research, such as applicant photos, borrower groups, and borrower history, are not available to lenders on this platform. Lenders thus cannot be influenced by heuristics based on borrowers' looks, group associations, or prior repayment history. Third, borrowers cannot set their own interest rates, which are set solely at Lending Club's discretion. The platform's website states that interest rates are a result of Lending Club's base rate plus an adjustment for risk and volatility, depending on creditworthiness scores.[7] Borrowers thus cannot signal their quality using interest rates.

The sequence of events in this loan application process may motivate borrowers to engage in signaling/countersignaling: Borrowers need to provide loan descriptions prior to Lending Club performing the verification and publishing the verifiable information. Borrowers have private information about their true quality, which they expect will correlate positively with Lending Club's published, verifiable information. However, they do not know this with certainty or a priori. Because the interaction is anonymous, and borrowers cannot communicate with lenders or entice lenders with higher interest rates, the only action they can perform is writing a loan description.

Data Description

The source of data is Lending Club archives, which feature all loan applications from 41 consecutive months, May 2007–September 2010, providing a total of 26,314 applications. During this period, the platform was open only to individual instead of institutional lenders.[8] To be considered for a loan, borrowers must have a valid bank account, valid Social Security number, a sufficiently high credit score (640 or above), and a debt-to-income ratio below 25% (excluding mortgage). After the verifiable information is authenticated, the loan request is listed on the site for two weeks or until it gets funded, whichever happens first.

The Lending Club platform provides verifiable credit history information collected from the major credit bureaus and reports. The following information thus is reported about each application: the borrower's FICO credit score range, number of open lines of credit, earliest credit line, credit line utilization, revolving credit balance, number and timing of delinquencies, home ownership status, physical location of the applicant (state), number of credit inquiries in the last six months, and other relevant public records such as public records on file, months since last record, and months since last major derogatory report. Potential borrowers are also required to select a purpose of the loan (e.g., debt consolidation, home improvement) and have the option to provide a loan description and state why lenders should lend them money (for samples of loan descriptions of varying lengths, see Web Appendix 2), which is nonverifiable information. Interested lenders can fund a portion (minimum of $25) or the entirety of the loan request. Any defaults are managed by collection agencies commissioned by the platform. The key dependent variable of interest is the loan funding outcome, which equals 1 if the loan is fully funded and 0 if it is not funded.[9]

The platform allows lenders to diversify across different loans. Paravisini et al. (2016), using both Lending Club data from its early days and private third-party data on lender identification, observe diversification decisions and estimate a risk-aversion parameter for different lenders on the platform. While we do not observe lender identification or lender's other investment vehicles and hence do not explicitly model the

[7]Details are available from http://www.lendingclub.com/public/how-we-set-interest-rates.action.

[8]See https://help.lendingclub.com/hc/en-us/articles/215437958-How-has-Lending-Club-s-investor-base-changed-.

[9]The majority (58.8%) of the loans were fully funded, 34.7% of the loans received no funding, and 6.5% received partial funding. For our empirical analysis, we have excluded the partially funded loans from our data set. Comparing estimates with these loans included and coding them as 1 if >.5 funded and 0 if <.5 funded yields the same substantive results. This results in 24,594 observations.

lenders' diversification decisions, our model does speak to the lenders' selection of loans to invest once a risk-balance allocation has been made and investors have decided how much to allocate to each loan asset class. As such, the lending decisions we model are in line with the modern portfolio theory prescription of selecting loans such that the expected return is maximized for a given level of risk. A loan that is fully funded implies that a sufficient number of lenders deemed it to have low probability of default and therefore worthy of funding (see the aforementioned discussion of loan selection).

As researchers, we observed exactly the same information that lenders did. In what follows, we classify the information available to the lenders as verifiable or nonverifiable.

Verifiable information. Lending Club collects information to verify borrowers' identity and assess creditworthiness. Using key indicators of creditworthiness, the lending platform classifies each potential borrower into seven grade categories, A–G, where A is the best and G the worst credit grade. These credit grades are determined by the lending platform as a function of the verifiable creditworthiness indicators. Interest rates are not set by the borrowers but instead are reflected by the credit grades; the relationship between the interest rate and risk is made salient by the lending platform. More specifically, much of the verifiable information (FICO score range, number of delinquencies in the past two years, number of credit inquiries in the past six months, revolving balance utilization, debt-to-income ratio, total credit lines, number of derogatory public records, number of public record bankruptcies, zip code, income, length of employment, employment title, etc.) is disclosed by the platform to potential lenders. As expected, the correlation between credit grade and interest rate in our data is .933, implying that credit grades are determined almost entirely by verifiable credit risks.

Nonverifiable information. While all borrowers are required to provide a "loan purpose" by selecting one of the categories offered by the platform, the thesis of our article focuses on the provision of the *optional*, open-ended loan description. We hypothesize that the presence and length of the description serve as a proxy for the effort a borrower uses to signal. Accordingly, we create a "no_description" indicator variable that is equal to 1 when borrowers provide no description and 0 otherwise, and a "description_length" variable that measures the number of words in the description. Of the 24,594 applications, 6,372 have zero words (no loan description).

We create several other variables to control for variations in the content of the descriptions. With the classification and linguistic processing algorithms provided by SPSS software,[10] we identify the top concepts that appear in loan descriptions. Automatic classification helps control for the content coding biases that might arise with a researcher-developed classification scheme. The top six categories account for more than 95% of the observations and account for both concreteness (e.g., budget) and attitudes of the description. Overall, the "budget" category represents the largest number of observations (65.7%). The most frequently used words in the descriptions in this category are "loan," "pay," "payment," "paying," "money," and "rate." Immediately following the budget category in magnitude are the "positive" category, with 36.4% of the observations (e.g., "excellent," "good," "timely"), and then the "negative" category (e.g., "problem," "bad," "difficult"). For each of the top six categories, we create a dummy variable that indicates whether an observation falls into that category. A single loan description can belong to multiple categories. We use these six dummy variables to control for variations across the content of loan descriptions.

Finally, the data include the date the application was posted on the platform. We create a time trend variable to account for potential changes in loan funding behavior over time due to macroeconomic environments.

TABLE 1
Model-Free Evidence

A: Percentage of Loans Funded with and Without Description

Credit Grade	Percentage of Loans with No Description	Overall Loan Funding Percentage	Funding Percentage for Loans with No Description
A	29%	66%	71%
B	27%	57%	62%
C	25%	54%	63%
D	25%	53%	58%
E	23%	50%	56%
F	21%	48%	52%
G	16%	45%	51%

B: Description Length (Words) for Funded and Nonfunded Loan Applications

	Funded			Nonfunded		
Credit Grade	M	Mdn	SD	M	Mdn	SD
A	65	43	68	46	28	56
B	72	49	75	55	35	66
C	73	48	77	54	34	64
D	76	51	80	62	36	75
E	78	53	78	63	38	78
F	90	59	102	78	40	94
G	76	47	74	73	38	84

Model-Free Evidence

We first present some model-free evidence consistent with our theory, highlighting the effects the optional description might have on the funding decision. Table 1, Panel A, shows, for each grade, the percentage of loans with no description, the overall loan funding percentage rate, and the funding percentage for those loans with no description. Table 1, Panel B, shows, for

[10]We use the software package SPSS Text Analytics for Surveys 3.0, which is designed to extract and categorize free-text responses using natural language processing capabilities. For more information, see the IBM Software Business Analytics white papers "Analyzing Survey Text: A Brief Overview" and "IBM SPSS Text Analytics for Surveys," available at http://www.ibm.com/software/analytics.

TABLE 2
Percentage of Loans Funded by Description Length

		Length Percentile			
	0 Words	**25th**	**50th**	**75th**	**90th**
Length of description (words)	0	6	28	72	139
Percentage of loans funded	62.2	53.2	55.1	55.4	58.3

those loans with descriptions, the mean, median, and standard deviations of description length for funded and nonfunded loans. Table 2 examines the overall funding percentages for loans with different description lengths.

The evidence shows that (1) loans with no descriptions are funded with higher probability than those with descriptions, and (2) if a description is provided, higher length improves the probability of funding, although the probability is still less than those for loans with no description. These nonparametric analyses point to a correlation between description length and loan funding. Finally, we see that borrowers with high credit grades are more likely to provide no description. This pattern is consistent with our analytical model, which states that unobservable loan quality drives the signaling effort and is also imperfectly yet positively correlated with the verifiable information.

Table 3 shows the summary statistics for our data set. The length of the description is relevant to the countersignaling account because it can serve as a proxy for signaling effort. For loans with descriptions, the average length is 54 words, and the 90th percentile is 139 words.

The Nonrandomness of Description Decisions

Before we present the empirical analysis, we address the matter that description provisions are nonrandom decisions and can be influenced by the factors that also influence the verifiable information. Recall that in our analytical model, borrowers first make description decisions based on their knowledge about their type, their belief about how their verifiable information will be presented to the potential lenders by the platform, and their expectation about how lenders will react to their description efforts. Borrowers who are confident about the later realization of their verifiable information (the high-quality types) will choose to countersignal, and those who are less confident will want to bolster their chances by providing a description, with the length varying depending on the cost and benefit of the description-writing effort for the borrower. Subsequently, lenders will observe the information provided by the borrowers and the platform and make their investment decisions.

To model this two-step process and to control the nonrandomness of the description writing decisions, we use a two-stage regression approach. In the first stage, we use a zero-inflated Poisson (ZIP) regression to model borrowers' description decisions as a function of the creditworthiness information most salient to the borrower (i.e., FICO score). In the second stage, we use the residuals from the first-stage regression as a control for the lenders' funding decisions. This modeling approach not only provides us with empirical evidence of whether salient credit information would impact description decisions as we have hypothesized, but it also controls in the second stage for any potential biases arising from endogenous description decisions.

We model borrowers' description decisions (number of words) as ZIP (Böhning et al. 1999; Greene 1994; Lambert 1992), which we believe is appropriate because a large proportion of the loans lack descriptions. ZIP is a two-component mixture model combining a point mass at zero with a count distribution. It assumes that the excessive zeros (i.e., loans that lack descriptions) are generated by a separate process from the count values and that the excess zeros are modeled separately. Therefore, it has two parts: a Poisson count model and the logit model for predicting excess zeros.[11] Specifically, the first stage contains the following explanatory variables:

$$\text{description decision}_i = f(\text{FICO\_score}_i,\ \text{loan\_length}_i,\ \text{loan\_amount}_i).$$

We use FICO score in our data set because we believe it is the most salient to borrowers and therefore will have the most impact on their decisions to provide descriptions. We exclude FICO score in the second stage.[12] We include loan amount and loan length because large amounts or lengths might drive borrowers to offer explanations. We perform this analysis within each credit grade.

The results, shown in Table 4, suggest that for each of the credit grades, borrowers with higher FICO scores are less likely to offer a description, but for those who do write a description, a higher FICO score correlates with a longer description. The result is consistent with our theory for borrowers.

Model Specification for Loan Funding Outcome

In the second stage of our empirical analysis, we model the loan funding outcome and test for the existence of countersignaling from the lender's perspective. Specifically, we wish to answer the following question: Do lenders infer quality within a risk–reward class by considering the borrower's decision to exert effort to provide unverifiable loan descriptions? To answer this question, we include all information about the borrower that was

[11]For robustness check to assess dispersion, we also ran a zero-inflated negative binominal regression. The results are similar, but the fit is slightly worse, suggesting that overdispersion is not an issue.

[12]We choose FICO as an instrument for the following institutional reasons: (1) It is the most salient credit information that forms the borrower's belief of his/her quality, hence impacting his/her description decision. (2) The econometrist point of view needs to consider the lender's decision. The platform assigns credit grades largely according to FICO score, so credit grade already soaks up most of the effect of FICO score. The residual information should then be captured by other verifiable credit-related information, such as debt-to-income ratio, past delinquency, and so on. Thus, conditional on credit grades and other verifiable information, FICO score should have negligible residual effect.

TABLE 3
Descriptive Statistics for Loan Applications

A: Summary Statistics					
	M	SD	10th Percentile	Median	90th Percentile
Loan amount applied ($)	10,541	6,755	3,000	9,000	21,000
Loan description length (words)	54	73	6	28	139

B: Loan Proportions by Characteristic	Proportion of Loans
Percentage Funded	
0%	35.0%
100%	65.0%
Credit Grade	
A	16.8%
B	27.8%
C	23.9%
D	16.8%
E	9.1%
F	3.7%
G	2.0%
Loan Length	
36 months	88.7%
60 months	11.3%
Home Ownership	
None	1.2%
Mortgage	39.3%
Own	9.8%
Rent	49.7%
Description Content	
Contains “currency”	8.9%
Contains “buying”	12.1%
Contains negative words	18.4%
Contains positive words	36.4%
Contains date	4.4%
Contains “budget”	65.7%
Loan Purpose	
Car	3.5%
Credit card	11.1%
Debt consolidation	38.2%
Educational	3.1%
Home improvement	7.2%
House	1.5%
Major purchase	6.5%
Medical	2.0%
Moving	1.6%
Other	14.0%
Renewable energy	.2%
Small business	7.7%
Vacation	.8%
Wedding	2.5%

C: Borrower Characteristics	Mean Value
Number of delinquencies in past two years	.17
Number of credit inquiries in past six months	1.59
Revolving balance utilization	45.2%
Monthly income ($)	6,017
Debt-to-income ratio	12.1%
Total credit lines	9

TABLE 3
Continued

Notes: Total observations = 26,314.

available to the lender, to avoid omitted variable biases. We performed a variance inflation factor (VIF) analysis to address potential multicollinearity. The resulting model specification exhibited VIFs of less than 5 for all variables, so this model is unlikely to suffer from multicollinearity concerns. Interest rates correlated highly with credit grade (.933), so we could only include one of these two variables. After testing, the specification that provided the best model fit was the one that used credit grade instead of interest rates. Both models share the same qualitative results.

In summary, for the i^{th} loan request, the model we test is

$$\begin{aligned}\text{loan\_funding\_outcome}_i = f(&\text{loan\_amount}_i, \text{loan\_length}_i,\\ &\#\text{\_open\_credit\_lines}_i,\\ &\#\text{\_delinquencies\_past\_2\_years}_i,\\ &\#\text{\_total\_credit\_lines}_i,\\ &\text{revolving\_balance\_util}_i,\\ &\text{monthly\_income}_i,\\ &\text{debt-to-income\_ratio}_i,\\ &\text{home\_ownership\_status}_i,\\ &\text{state\_residence}_i, \#\text{\_credit\_inquiries}_i,\\ &\text{currency}_i, \text{buying}_i, \text{negative}_i,\\ &\text{positive}_i, \text{date}_i, \text{budget}_i, \text{credit\_grade}_i,\\ &\text{description\_length}_i, \text{description\_length}_i^2,\\ &\text{no\_description}_i, \text{time trend}_i, \text{residual}_i).\end{aligned}$$

Estimation and Model Comparison

We estimate the model for loan funding outcome using logistic regression on funding, and we compare our proposed model against two benchmark models that vary in their degrees of signaling. The first benchmark model assumes that the funding outcomes are based solely on verifiable information (controlling for loan amount, loan length, and date of the loan request, as captured in the “time trend” variable). Then, the second benchmark model accounts for the length of description but ignores the effect of countersignaling, so it excludes the “no_description” variable. For ease of presentation, we first run an aggregate model (using credit grades as dummies) for model comparison to assess model fit with and without countersignaling. We present the result in Web Appendix 3 (see Table W1). Then, because our model is within credit grade, we present the loan funding result for each individual credit grade in Table 5.

Table W1 shows the estimated parameters for the lending decision across the proposed and benchmark models. According to the Bayesian information criterion, which compares nested models and penalizes model complexity, the best-fitting model is the proposed model, which accounts for both the

TABLE 4
Model for Description Decision

	Grade A		Grade B		Grade C		Grade D		Grade E		Grade F		Grade G	
	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD
Poisson Count Model														
Intercept	**5.409**	.032	**4.746**	.075	**4.395**	.032	**3.124**	.032	**2.567**	.042	**1.835**	.052	**1.707**	.092
FICO	**.002**	.001	**.001**	.001	.000	.001	**.002**	.001	**.003**	.001	**.004**	.001	**.004**	.001
Loan length	**.147**	.017	**.201**	.006	**.205**	.008	**.164**	.006	**.302**	.008	**.027**	.010	**.142**	.019
Loan amount	**–.018**	.001	**–.013**	.004	**–.010**	.000	**–.006**	.001	**–.004**	.001	**–.003**	.001	**–.009**	.001
Zero-Inflation Model (Binomial with Logit)[a]														
Intercept	**–2.503**	.924	**–1.622**	.743	**1.902**	.992	–1.431	1.153	**–3.223**	1.859	**–2.248**	3.095	–5.194	.527
FICO	**–.002**	.000	.000	.001	**–.006**	.001	**–.005**	.002	**–.004**	.002	**–.005**	.002	–.003	.001
Loan length	**.483**	.194	**.663**	.085	**.989**	.099	**.734**	.098	**1.050**	.111	**1.115**	.184	**1.416**	.303
Loan amount	–.003	.009	**–.017**	.005	**–.011**	.005	–.011	.006	–.001	.008	–.004	.011	.017	.017

[a]0 = no description.
Notes: Boldface indicates significance at the .05 level.

TABLE 5
Model of Lending Decisions by Credit Grade

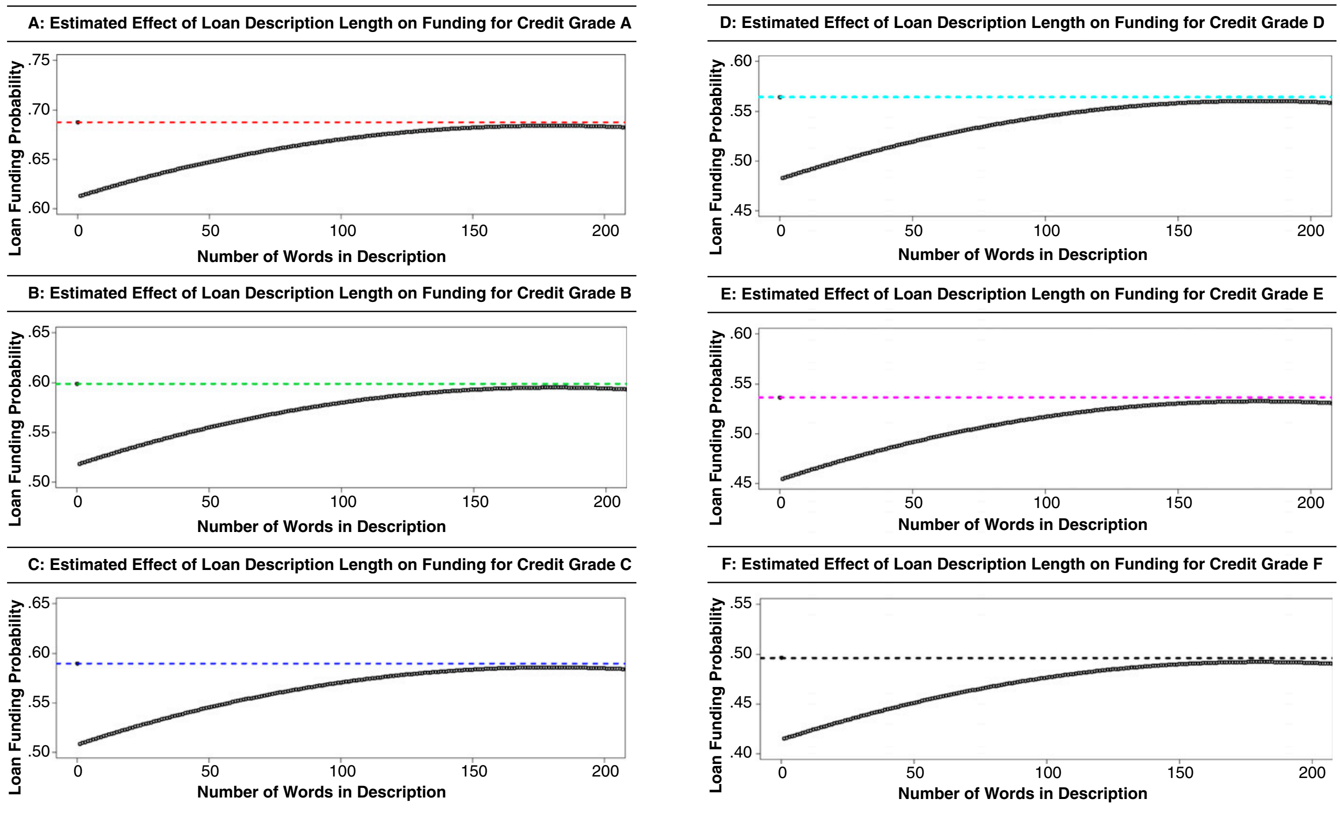
	Grade A		Grade B		Grade C		Grade D		Grade E		Grade F		Grade G	
	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD
Intercept	**2.856**	.759	**2.194**	.568	**2.265**	.647	**2.374**	.727	1.374	.827	−.285	.312	−.575	.311
Number of open credit lines	.007	.019	.006	.014	−.013	.014	.019	.016	**.056**	.022	−.025	.035	−.034	.034
Number of delinquencies in past two years	**−.199**	.234	−.018	.104	**−.180**	.031	.053	.082	.099	.113	**−.408**	.176	**−.286**	.060
Revolving balance utilization	−.337	.328	**−.908**	.183	**−1.185**	.178	**−.726**	.201	**−1.152**	.299	.205	.465	.472	.596
Monthly income	**.000**	.000	**.000**	.000	.000	.000	.000	.000	.000	.000	.000	.000	**.000**	.000
Debt-to-income ratio	−.380	.964	**−1.657**	.715	−1.129	.756	**−1.964**	.885	−1.239	1.250	**−4.736**	1.831	**−5.013**	2.547
Total credit lines	.010	.008	.006	.005	.009	.006	.012	.007	−.013	.010	.017	.015	.004	.019
Home Ownership (vs. None)														
Mortgage	.680	.357	**.820**	.249	**1.141**	.298	.399	.304	.440	.462	**1.850**	.585	.211	.776
Rent	−.275	.364	.271	.258	**.715**	.307	.027	.318	−.354	.484	.929	.836	.676	.859
Own	**.538**	.156	**.738**	.248	**1.069**	.296	.460	.300	.083	.457	.987	.783	−.238	.771
Inquiries in past six months	**−.138**	.045	−.022	.028	**−.043**	.022	−.021	.024	**−.059**	.021	−.068	.045	−.059	.050
Loan amount	**−.128**	.010	**−.042**	.004	**−.154**	.005	**−.046**	.006	**−.056**	.008	**−.059**	.013	−.037	.017
Term (60 months = 1)	**−.665**	.208	**−.558**	.092	**−1.302**	.110	**−.800**	.110	−.233	.147	**−.704**	.251	.417	.460
Time Trend														
Y2008	**−2.965**	.603	**−3.198**	.469	**−3.757**	.522	**−3.400**	.596	**−4.033**	.324	**−3.285**	.421	−1.769	.485
Y2009	**−2.603**	.599	**−3.039**	.466	**−3.740**	.519	**−3.544**	.592	**−4.120**	.324	**−3.332**	.485	−1.797	.422
Y2010	**−2.898**	.599	**−3.214**	.466	**−3.765**	.520	**−3.685**	.593	**−4.550**	.355	**−4.112**	.522	−1.837	.442
Loan Purpose														
Credit card	**.648**	.181	**.848**	.163	**.781**	.190	**.574**	.242	.113	.372	−.505	.719	2.036	1.283
Debt consolidation	**.740**	.158	**.848**	.148	**.720**	.172	**.943**	.223	.132	.337	.056	.665	2.014	1.236
Educational	−.282	.228	.014	.203	−.111	.224	−.155	.300	−.413	.429	−1.019	.870	1.387	1.344
Home improvement	**.748**	.185	**.824**	.166	**.528**	.197	**.707**	.262	−.345	.377	−.364	.729	.934	1.297
House	.104	.345	**.580**	.253	−.207	.283	−.320	.352	−.425	.520	.085	.874	2.578	1.547
Major purchase	.110	.167	.284	.169	.270	.199	.415	.255	−.365	.391	−.743	.766	.478	1.401
Medical	−.459	.242	−.010	.227	−.016	.259	.159	.325	−.286	.475	−.931	.966	−.205	1.512
Moving	.152	.272	.232	.246	−.126	.276	.316	.367	−.303	.498	−.237	.884	.982	1.635
Other	**.392**	.163	**.445**	.155	**.337**	.178	.408	.234	−.225	.352	−.184	.694	1.578	1.265
Renewable energy	**1.306**	.323	.337	.500	−.742	.576	**.588**	.425	−1.786	2.226	−1.572	3.956	−.163	.205
Small Business	−.133	.223	−.176	.177	−.337	.198	−.051	.241	**−.846**	.358	−.960	.679	1.255	1.245
Vacation	−.170	.307	.221	.333	.164	.381	.027	.469	−.778	.645	−1.988	1.175	1.041	1.645
Wedding	**.462**	.269	.287	.207	**.589**	.246	**.825**	.302	−.013	.460	−.655	.861	−.332	.398
Description Content														
Contains “currency”	−.105	.145	−.047	.106	−.071	.108	.204	.127	−.539	.485	−.359	.307	−.134	.361
Contains “buying”	**.240**	.119	−.066	.094	.039	.102	.176	.121	−.016	.167	−.249	.273	.068	.318
Contains negative words	−.015	.115	−.075	.078	−.089	.082	.017	.095	−.075	.135	−.288	.229	−.072	.266
Contains positive words	.048	.091	−.013	.065	.068	.069	−.025	.081	−.108	.116	.335	.190	.342	.536
Contains date	−.144	.205	−.053	.154	−.170	.160	.319	.181	−.209	.255	.012	.402	−.274	.305
Contains “budget”	**.325**	.104	**.192**	.078	**.242**	.085	**.240**	.101	**.363**	.143	.377	.236	.003	.008

TABLE 5
Continued

	Grade A		Grade B		Grade C		Grade D		Grade E		Grade F		Grade G	
	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD
Description Length														
Description length	**.010**	.003	**.011**	.002	**.009**	.002	**.008**	.002	**.018**	.003	**.009**	.005	**.006**	1.44E-04
Description length^2	**−1.34E-05**	.000	**−1.41E-05**	.000	**−1.48E-05**	.000	**−1.17E-05**	.000	**−2.07E-05**	.000	**−9.30E-05**	.000	**−9.14E-04**	4.35E-01
Countersignaling														
No description	**1.378**	.290	**1.415**	.213	**1.275**	.254	**.832**	.300	**.651**	.214	**.426**	.120	**.522**	3.82E-03
Interaction Terms:														
Description Length × …														
Number of open credit lines	**3.00E-04**	2.15E-05	**2.18E-04**	3.40E-05	**1.75E-04**	3.44E-05	**1.77E-04**	4.50E-05	**7.62E-04**	2.27E-04	**4.84E-04**	2.60E-04	1.82E-04	3.82E-04
Number of delinquencies in past two years	−1.22E-03	3.54E-03	−1.35E-03	8.32E-04	2.80E-05	8.88E-04	**−1.08E-03**	1.01E-04	**−2.01E-03**	3.69E-04	**−2.22E-03**	5.41E-04	**−2.52E-03**	2.05E-04
Revolving balance utilization	−1.62E-03	3.90E-03	7.99E-05	1.74E-03	**−3.79E-03**	1.73E-03	−1.83E-03	1.76E-03	**−5.75E-03**	2.65E-03	−1.50E-03	3.40E-03	1.96E-03	5.72E-03
Monthly income	5.68E-08	1.31E-07	4.23E-08	5.20E-08	−1.10E-07	8.33E-08	3.60E-08	7.56E-08	−6.03E-08	1.63E-07	−8.98E-08	1.90E-07	**5.42E-06**	3.14E-07
Debt-to-income ratio	−5.47E-03	1.18E-02	4.41E-04	7.25E-03	−5.92E-03	7.63E-03	−8.30E-03	8.02E-03	−7.30E-03	1.16E-02	**−2.19E-02**	3.69E-03	−1.42E-02	2.87E-02
Total credit lines	1.34E-04	9.69E-05	4.82E-05	5.38E-05	8.61E-05	5.71E-05	4.01E-05	6.40E-05	2.84E-04	2.04E-04	−2.24E-04	1.22E-04	4.93E-05	1.89E-04
Inquiries in past six months	−5.92E-04	5.38E-04	−2.48E-05	2.73E-04	8.53E-05	2.47E-04	1.72E-04	2.54E-04	**−6.46E-04**	3.06E-04	5.69E-04	3.88E-04	−3.55E-05	5.76E-04
Residual from first stage	**.066**	.016	**.090**	.030	.022	.025	**.071**	.018	**.065**	.022	.045	.027	**.075**	.022

Notes: Bold estimates indicate significance at the .05 level.

FIGURE 2
Effect of Countersignaling on Loan Funding Probability



Notes: To create the graphs, we run separate models for each credit grade and use the credit grade–specific parameters. The graphs show description lengths ranging from 0 to 180 words, which account for 95% of the cases in our data. Dashed lines denote the level of funding predicted with no description.

effect of nonverifiable information and countersignaling. All the parameters from the proposed model, as well as those of the two benchmark models, are in the expected direction and support our theory. For instance, borrowers with lower credit grades are less likely to be funded, and we find a residual impact of verifiable information after controlling for credit grade (e.g., borrowers with higher debt-to-income ratios, more past delinquencies, and more inquiries in the past six months are less likely to be funded). These results provide face validity for our analyses and show that lenders base their decisions on multiple pieces of information in addition to the summary credit grade. Loans of larger amounts and longer terms also are less likely to be funded, but we find no impact of the borrower's state of residence on funding decisions. For time trend, we use the year indicator[13] and find that compared with 2007, all subsequent years result in lower funding likelihood, which reflects increasing lender caution as the economy proceeded deeper into recession after the bankruptcy of Lehman Brothers.

Several interesting insights stem from these model comparisons. First, the two models that account for the effects of nonverifiable information (proposed model and benchmark model 2) fit the data better than the model that accounts only for verifiable information (benchmark model 1), Therefore, nonverifiable information influences loan funding decisions and is not viewed by lenders as uninformative cheap talk (Crawford and Sobel 1982). For instance, mentions of "budget" in the description might signal concreteness of financial planning and thus increase funding likelihood. Second, in our proposed model, the parameter estimate for no_description is positive and statistically significant. In Table 5, we show this effect to hold across all credit grades, showing that within each credit grade and conditional on verifiable information, borrowers who do not provide a loan description are more likely to have their loans funded than those who provide a loan description, in support of H_1.

We also find a positive, statistically significant parameter value for "description_length" and a negative, statistically significant parameter value for "description_length." Once borrowers decide to provide a reason for the loan request, their chances of getting funded increase with the number of reasons, in a concave manner (i.e., decreasing returns to the number of words), in support of H_3.

We then run separate models for each credit grade, and the same patterns emerge. We present these results graphically in Figure 2, using the parameter estimates from the separate regressions. The patterns in Figure 2 are consistent with the prediction in our analytical model. Specifically, not providing a loan description is a countersignal of high quality and is rewarded by lenders with greater funding likelihood. When borrowers provide

[13]We also ran models using month/year and quarter/year indicators. Both models give insignificant results for these indicators.

TABLE 6
Loan Delinquency by Credit Grade

	Grade A	Grade B	Grade C	Grade D	Grade E	Grade F	Grade G
Number of delinquencies	187	275	229	174	87	35	29
Delinquency percentage for all loans	6.0%	6.4%	6.5%	6.9%	7.8%	8.3%	12.0%
Delinquency percentage for loans with no description	2.9%	2.6%	3.6%	3.9%	3.9%	5.8%	7.5%
Delinquency percentage for loans with descriptions of below-median length	11.2%	13.9%	12.2%	15.7%	14.0%	14.1%	20.8%
Delinquency percentage for loans with descriptions of below-median length	4.7%	5.5%	4.8%	5.4%	5.3%	6.3%	8.8%

descriptions, however, longer descriptions are perceived more favorably than shorter ones. Together, these results are consistent with the proposed countersignaling theory. The statistical significance in several interactions between description length and verifiable borrower creditworthiness information is in line with our theory that some consumers naively use the combination of description length and verifiable creditworthiness information to assess the quality of the loan requests in the platform.

A critical element of our theory is that lenders correctly infer loan descriptions as a mechanism for strategic information transmission. We next consider ex post loan performance to test H_2 and H_4.

Loan Description and Borrower Performance

The relationship between lending decisions and the optional borrower-provided nonverifiable information empirically supports countersignaling theory. In this section, we provide further support for countersignaling as an explanation of loan funding outcomes in P2P lending. An integral part of countersignaling theory is that the interpretation of the signal should be consistent with the strategy and the type of sender. Otherwise, lenders would learn not to trust the signal, and the descriptions would become uninformative. We therefore turn our attention to testing the observed ex post performance of the loans (i.e., long-term performance, as measured by payment delinquency). With this analysis, we can determine whether, within a given credit grade, borrowers who countersignal are of higher quality, as indicated by a lower likelihood of delinquency.

Because high-quality borrowers should countersignal and refrain from providing a description, loans with no description should be less likely to be delinquent than loans with descriptions. Countersignaling theory also suggests that once a description is provided, a longer description should be negatively correlated with loan delinquency. We describe the loan performance measurement and specify the model to test our loan performance prediction based on countersignaling theory. We perform the analysis using the funded applications from our data set.

Of the funded loans in our data set, 6% are noncurrent, exhibiting one of the following four statuses: "late (16–30 days)," "late (31–120 days)," "charged off," or "default," which represent various stages of delinquency. We pool these four categories, due to the sparseness of these data points, and create a binary "delinquency" variable that is equal to 1 if the loan is delinquent and 0 otherwise. We present in Table 6 model-free evidence showing delinquency percentage by credit grade and compare the percentages across various description lengths. Preliminary evidence suggests that having no description results in the lowest delinquency rate, followed by long descriptions, with short descriptions having the highest rate.

To examine the effect of countersignaling on the probability of delinquency, we model the delinquency of loan i with the same two-step approach, with ZIP as the first stage. The second stage is a logistic regression with delinquency as the dependent variable:

$$\begin{aligned}\text{delinquency}_i = f(&\text{loan\_amount}_i, \text{loan\_length}_i, \text{\#\_open\_credit\_lines}_i,\\ &\text{\#\_delinquencies\_past\_2\_years}_i,\\ &\text{\#\_total\_credit\_lines}_i,\\ &\text{revolving\_balance\_util}_i,\ \text{monthly\_income}_i,\\ &\text{debt-to-income\_ratio}_i,\ \text{home\_ownership\_status}_i,\\ &\text{state\_residence}_i, \text{\#\_credit\_inquiries}_i,\ \text{currency}_i,\\ &\text{buying}_i,\ \text{negative}_i,\ \text{positive}_i,\ \text{date}_i,\ \text{budget}_i,\\ &\text{credit\_grade}_i,\ \text{description\_length}_i,\\ &\text{description\_length}_i^2, \text{no\_description}_i,\\ &\text{time\_trend}_i).\end{aligned}$$

Similar to the loan funding results, we present in Web Appendix 3 (Table W2) the model comparisons results based on aggregate analysis using credit grade as dummies. In Table 7, we present our full results, broken down by credit grade.

Table W2 shows the estimated parameters for the likelihood of the loan being delinquent. We compare the proposed model with the same benchmark models used in the funding outcome analysis in Table W1 to examine the extent of the impact of countersignaling on loan performance. Overall, the results confirm the convergence between the funding decisions and delinquency rates. The proposed model provides the best fit for the data, according to the Bayesian information criterion, in support of the predicted, nonmonotonic relationship between the number of words in the loan description and the borrower's quality (in terms of delinquency).

As Table 7 shows, within each credit grade, the coefficient for the "no_description" variable is negative and statistically significant, providing evidence that borrowers who provide no description in their loan requests are less likely to be delinquent in their payment than those who provide short descriptions, in support of H_2. The coefficient for "description_length" is negative and statistically significant, which demonstrates that borrowers who provide longer descriptions are less likely to be delinquent than borrowers who provide shorter descriptions, in support of H_4.

TABLE 7
Model of Delinquency by Credit Grade

	Grade A		Grade B		Grade C		Grade D		Grade E		Grade F		Grade G	
	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD	Estimate	SD
Intercept	−.264	1.615	.270	.920	.269	1.172	1.396	1.378	−.168	.102	−.149	.192	−.160	.220
Number of open credit lines	**.100**	.037	**.078**	.030	.007	.029	−.044	.038	**.075**	.023	**.126**	.009	**.073**	.010
Number of delinquencies in past two years	.434	.431	−.329	.282	−.119	.203	−.242	.171	.061	.129	.143	.537	.501	.513
Revolving balance utilization	−.719	.603	−.052	.387	.321	.397	**.448**	.048	−1.003	.724	−.141	1.321	2.458	2.025
Monthly income	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Debt-to-income ratio	−.739	2.051	1.097	1.578	−1.935	1.694	−1.565	2.081	−2.175	2.741	−2.931	4.688	−5.837	7.318
Total credit lines	.027	.014	−.001	.012	.016	.011	.021	.015	.031	.025	.028	.042	−.012	.053
Home Ownership (vs. None)														
Mortgage	.549	1.045	−.554	.523	−.274	.778	.194	.779	.152	.122	−.158	.592	−.190	.420
Rent	.877	1.062	−.110	.550	−.045	.804	−.406	.847	.163	.113	.140	.392	−.180	.412
Own	.599	1.046	−.385	.517	−.163	.775	.110	.774	.153	.132	.154	.142	.189	.420
Inquiries in past six months	.000	.066	.014	.038	.024	.030	−.030	.031	−.007	.035	−.058	.078	.052	.062
Loan amount	.024	.023	−.009	.012	**.036**	.014	−.027	.017	.004	.025	−.047	.039	**.120**	.058
Term (60 months = 1)	−.619	1.072	−.231	.444	−.866	.612	−.585	.640	−.224	.848	−.522	1.176	−1.582	2.125
Time Trend														
Y2008	**−1.020**	.315	**−.975**	.245	**−.499**	.242	**−.851**	.265	−.416	.323	**−.878**	.579	.968	.739
Y2009	**−1.716**	.300	**−1.653**	.241	**−.597**	.232	**−1.625**	.269	**−1.415**	.382	**−2.091**	.685	**−2.365**	.586
Y2010	**−2.570**	.328	**−2.673**	.268	**−.844**	.275	**−1.875**	.349	**−1.972**	.667	**−2.674**	.944	−1.213	1.799
Loan Purpose														
Credit card	.439	.428	.701	.519	−.414	.507	.643	.800	.295	1.195	.201	1.458	−.883	1.895
Debt consolidation	.074	.407	.513	.501	−.315	.473	.430	.774	1.023	1.120	.388	1.353	−2.733	1.795
Educational	.164	.617	.901	.579	−.502	.615	.744	.898	.286	1.281	1.540	1.614	.981	2.246
Home improvement	.034	.461	.265	.555	−.111	.524	.109	.865	.430	1.279	1.067	1.666	−1.443	1.989
House	.377	.852	1.026	.660	.250	.729	−.402	1.315	2.031	1.379	3.532	2.081	−.204	.202
Major purchase	.483	.451	.774	.537	−1.039	.643	.097	.869	1.340	1.280	2.344	1.902	−.182	.359
Medical	.105	.672	.829	.652	−.138	.687	.569	.945	−.047	1.534	.131	.185	−.184	.300
Moving	−.085	.725	1.207	.665	−.774	.872	.078	1.094	−.138	.807	−.135	.152	−.187	.449
Other	.255	.414	.536	.511	−.117	.484	−.175	.808	.737	1.146	−.971	1.679	**4.542**	1.850
Renewable energy	2.382	1.244	1.221	1.182	−.135	.103	−.124	.213	1.307	1.182	2.206	1.445	1.221	1.182
Small business	−.143	.659	−.204	.631	−.748	.592	.153	.842	−2.540	1.605	−2.955	2.620	**3.912**	1.186
Vacation	1.170	.650	.035	1.153	−.141	.468	−.142	1.100	1.454	1.373	1.990	1.865	.035	1.153
Wedding	−.045	.654	.380	.643	.317	.591	−.142	.432	.380	.643	.555	.461	−.197	.432
Description Content														
Contains “currency”	.282	.279	−.133	.270	.136	.277	.040	.308	.194	.473	−.587	1.116	2.401	1.518
Contains “buying”	.363	.275	.355	.218	−.179	.278	.044	.311	−.561	.504	−.029	.824	1.996	1.343
Contains negative words	.123	.248	.051	.189	−.126	.207	.264	.224	.396	.329	−1.026	.702	.239	.938
Contains positive words	−.182	.192	−.118	.156	.068	.170	−.141	.203	−.139	.309	−.255	.525	−.332	.752
Contains date	.300	.437	−.532	.426	.444	.383	−1.048	.753	−.093	.790	.138	1.057	1.695	1.772
Contains “budget”	−.212	.213	**−.386**	.175	−.223	.202	−.359	.238	.078	.357	−.306	.690	−.561	.707
Description Length														
Description length	**−1.00E-02**	5.06E-03	**−1.34E-02**	4.29E-03	**−7.66E-03**	2.58E-03	**−1.98E-02**	6.75E-03	**−9.84E-03**	8.77E-03	**−1.17E-02**	1.56E-03	**−1.23E-02**	4.70E-03
Description length^2	**2.50E-05**	9.47E-06	**3.31E-05**	6.46E-06	**2.93E-05**	7.38E-06	**3.48E-05**	2.16E-06	**2.15E-05**	3.78E-06	**2.50E-05**	5.49E-06	**2.89E-05**	6.66E-06
Countersignaling														
No description	**−1.96E+00**	6.99E-01	**−1.51E+00**	6.10E-01	**−7.35E-01**	2.81E-01	**−1.98E+00**	4.44E-01	**−8.86E-01**	3.56E-01	**−8.26E-01**	2.48E-01	**−1.99E+00**	4.87E-01
Residual from first stage	**.022**	.003	**.019**	.004	**−.030**	.020	.032	.005	.004	.002	**.072**	.009	.035	.019

Notes: Boldface indicates significance at the .05 level.

The depiction of the results in Figure 3 uses the parameter estimates from Table 6. Combined with the loan funding results, these findings support the four hypotheses predicted by countersignaling theory with respect to how lenders correctly discriminate borrowers' types using the signal associated with the length of their loan descriptions.

Recall that our theoretical model assumes there is some proportion of naive lenders, and the analytical results hold even for a very small proportion of such lenders. Our empirical evidence supports our theory for the existence of some naive lenders. In reality, even in the world of institutional lending, the fact that some funds perform better than others indicates that there are variations in the processing of financial and creditworthiness information.

Robustness Checks

To provide further evidence for the theory, we performed the following robustness checks:

1. Tested various specifications of no_description and description_length.
2. Checked whether the effect of no_description is unique to zero words.
3. Tested for the influence of repeat borrowers.
4. Tested whether there exists evidence of other signal mechanisms (e.g., loan terms, loan amounts).
5. Checked the potential effect of description content and quality.

First, in test 1, we tested various combinations of no_description and description_length in the model. The best-fitting model is one that includes "no_description," "description_length," and "description_length^2." Because all three variables are significant, excluding one would result in a worse fit. The cubed term "description_length^3" is not significant, which indicates that the probability will not invert and increase after certain number of words. Interaction terms of "no_description" and "description_length" with credit grades are not significant, suggesting that although no_description is important within each credit grade, its effects do not differ significantly across credit grades. We also discretized "description_length" in three to five groups and reran the model using these indicator variables (e.g., short, medium, long). We also tested an empirical model in which description lengths were classified as high-quality (H), medium-quality (M), or low-quality (L) type instead of using a continuous classification. More specifically, we lumped descriptions shorter than the median length as L type, descriptions longer than the median length as M type, and absent descriptions as H type. The substantive results hold with these discretization efforts (that is, M type results in higher likelihood of funding than L type), albeit with a slightly worse fit compared with using a continuous variable for number of words, as in the proposed model. This result is expected because we do not a priori know the cutoffs for the discretization, and the continuous type offers more flexibility. Finally, we included interaction between credit grades and the description variables, as well as interaction terms between description variables and other credit information of borrowers, both as continuous length in words and as discretized buckets. We find no effect of the interaction.

Next, in test 2, we investigated whether the proposed model correctly captured a unique zero-word effect of no_description rather than an alternative effect caused by a length below some other threshold. We compared the proposed model with models including dummy variables that reflected whether the descriptions contained fewer than X number of words, where X = 3, 5, or 10 words, while holding everything else the same. We find that as X increases from 0, the effect size of the dummy variables "X_words_or_less" decreases and the model fit worsens. Therefore, providing no loan description is a unique signal. This phenomenon holds for both the loan funding decision and the ex post likelihood of loan delinquency. The result of this check is available in Web Appendix 4.

As mentioned earlier, Lending Club keeps lenders and borrowers anonymous to each other, and the platform does not provide information about repeat borrowers or past performance indicators on the platform. Nevertheless, in test 3, we empirically investigated the presence of repeat borrowers by performing exact matches on time-invariant demographic and behavioral information such as income, credit grade, state of residence, earliest credit line opened, and home ownership. We found 120 borrowers who met the criteria, suggesting they may have applied twice. This group represented less than .5% of applications, and there were no matches to indicate any borrowers applied three times or more. When we exclude these 120 observations from the data, the same results hold.

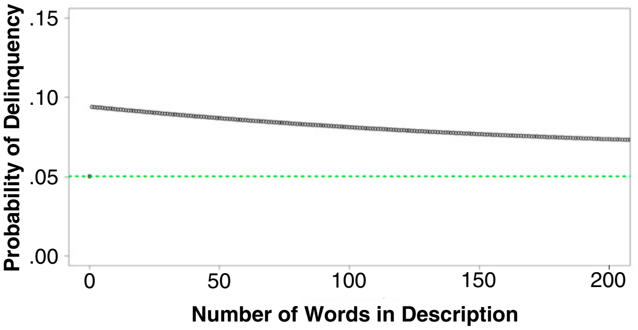
In test 4, we considered two situations. First, we investigated whether borrowers signal through loan amount or loan terms (durations) and whether certain lenders might treat loans of varying magnitudes differently (e.g., larger loans might signal a more responsible borrower, with strong repayment ability and consequently easy access to outside lending markets). To do so, we divided the loan amounts into quintiles and created a dummy variable for each of the following quintiles: amount ≤ \$500; \$500 < amount ≤ \$5,000; \$5,000 < amount ≤ \$9,000; \$9,000 < amount ≤ \$15,000; and \$15,000 < amount ≤ \$25,000. We included these indicator variables in addition to the amount and found that, relative to the baseline of the first quintile (amount ≤ \$500), the other four quintile dummy variables are nonsignificant. This indicates that, aside from the fact that larger loan amounts tend to decrease funding probability, there is no significant signaling value from loan amounts that would lead to lenders to behave differently. The same nonsignificant result also holds on the loan performance side, confirming that loan magnitude has no significant effect on borrowing and lending behavior in the platform we study.[14]

In addition, to rule out potential signaling via loan length, we run the model on a subset of the data from the period when Lending Club did not allow borrowers to request 60-month loans (thus, all loans were 36 months in duration). All the substantive results are similar between the subset of the data and the full data set.

Finally, test 5 assessed whether shorter or longer descriptions contain specific words that drive decisions. We modeled description length as a dependent variable on content dummies and found no significant differences between the effects of different content dummies. Correlations between description lengths and various content dummies ranged from

[14]It is worth mentioning that even if some degree of signaling by amount was operating in the platform, undetected by our empirical analysis, such signaling effort would not invalidate our countersignaling results. As discussed in the literature (Feltovich, Harbaugh, and To 2002), signaling and countersignaling can coexist in the same strategic interaction of economic agents.

FIGURE 3
Effect of Countersignaling on Delinquency Probability



Notes: To create this graph, we varied the number of words in the description from 0 to 200, and the remaining independent variables were fixed at their mean levels. Credit grade has no significant effect on delinquency probability, and thus the graph is pooled across all credit grades. Dashed lines denote the level of delinquency predicted for loans with no description.

.16 to .22; we observed no particular content variable that had a systematically higher impact on description_length.

To assess whether different description lengths exhibit different qualities of writing, we randomly selected 40 descriptions from each of the following groups: less than 33rd percentile, or 12 words (short group); between 33rd and 66th percentile, or 13–39 words (medium group); and greater than 66th percentile, or 40+ words (long group). We conducted a survey of quality with 153 Amazon Mechanical Turk respondents, who were asked to rate the quality of the descriptions and the effort exhibited in them. The correlations are .7 between description_length and quality, .88 between description_length and perceived effort, and .92 between effort and quality. Regressing perceived effort on description_length yields an R^2 of .7, and regressing quality on description_length yields an R^2 of .5. This shows that longer descriptions are seen as both more effortful and of higher quality, and that people perceive that it takes more effort to write high-quality descriptions.[15]

In summary, the robustness analyses lend support for H_1–H_4. We now discuss how our countersignaling theory and results compare with other prior theories.

General Discussion

Alternative Explanations

Following our theoretical and empirical analysis of countersignaling in P2P lending, we discuss candidate explanations for the observed phenomena. We describe how these theories do not explain the totality of our results.

Persuasion. According to persuasion theory, the provision of descriptions might be interpreted as a compliance issue. Individuals and companies acting as persuaders often attempt to increase compliance with their requests by offering reasons why others should behave accordingly (Langer et al. 1978; Petty and Cacioppo 1984). These predictions could accommodate the behavior of naive consumers in the analytical model, but they cannot accommodate the effect of no_description. These predictions also cannot account for the observed relationship between loan description and ex post loan delinquency.

Preemptive behavior. In mortgage applications, if there is something negative in a borrower's verifiable information, the lender often asks the borrower to write an explanation for this potential blemish in the credit record. Borrowers in this setting might act preemptively and, without being asked, write a description to explain any negative verifiable information. However, if such preemptive behavior were successful in attracting lenders, it could explain the positive relationship between ex post loan defaults and the presence of a description, but it would not explain the negative relationship between funding and the presence of a description. Moreover, this explanation cannot address the nonmonotonicity of both borrower and lender behavior.

Sufficiency of verifiable information. A final alternative explanation is that some borrowers do not provide descriptions because their applications get funded without any further information. That is, similar to the countersignaling explanation, only borrowers who are truly confident that positive information about their profile would be revealed by the platform can afford not to send a description, so they forgo the opportunity to persuade some naive lenders. However, in this explanation, the empirical model accounting for all other information would reveal no effect of description length because it has no signaling effect. Such an explanation is not consistent with the empirical findings.

In summary, none of these explanations can explain the totality of the nonmonotonic pattern of behavior we observe and the ex post efficiency of borrowers' and lenders' decisions.

Theoretical Contributions

In this research, we find that the strategic transmission of nonverifiable information by borrowers is an important influence on P2P lending platforms. Lenders make decisions on loan investments on the basis of both verifiable information and the optional nonverifiable information provided by borrowers, and such decisions are validated by subsequent loan performance.

We show that the presence of an optional loan description and its length both influence loan funding, so the provision of such information is not viewed as uninformative cheap talk. Borrowers and lenders use nonverifiable information in a way that is consistent with the properties of a countersignaling equilibrium. Specifically, our empirical evidence suggests that lenders view those who provide no loan description as high-quality borrowers. Moreover, medium-quality borrowers can distinguish themselves from low-quality borrowers by exerting greater effort to provide more nonverifiable information (i.e., longer descriptions) than low-quality borrowers do. It is important to note that we are not suggesting the act of writing requires so much effort that someone might not undertake it. Rather, the marginal benefit of writing a description (or not) is the probabilistic improvement of obtaining

[15]We also note that the respondents are all likely to have limited lending experience, so in absence of other cues, they make take the length of description as a proxy for effort and quality of writing, thus behaving in the way we theorize naive lenders would do.

funding, and this improvement depends on the quality of the borrower. Thus, the marginal effort cost of writing need not be so great as to offset the value of the loan completely; rather, borrowers weigh the effort costs, however small, relative to the associated marginal improvement in funding probability.

The evidence from loan funding and ex post loan performance suggest that countersignaling is a robust explanation of lending behavior in a P2P environment. Even after we control for all the information that lenders encounter when making funding decisions, loan applications with no loan description turn out ex post to be higher-quality loans within a given credit grade, as measured by their lower delinquency rates. Applications that provide longer descriptions are less likely to be of low quality than applications with short descriptions. Thus, lenders are correct in interpreting the signaling effect of nonverifiable information when making loan funding decisions, because their funding decisions correspond with ex post loan quality.

The convergence between lenders' view of nonverifiable information and ex post loan performance suggests that nonverifiable information serves as a mechanism to attenuate information asymmetry regarding unobserved borrower quality. Borrowers who shrewdly recognize the signal/countersignal properties of nonverifiable information are rewarded, on average, by lenders. Lenders who correctly identify the signals will be rewarded with better-performing loans. An essential characteristic of marketing is understanding the marketplace and the factors that encourage consumers to engage in it (Bradford 2015). We identify a robust factor that affects both consumer exchange behaviors and the makeup of the marketplace. As P2P lending becomes a big part of the current financial landscape, our work contributes to a growing body of research that provides empirical insights into the intricacies of consumer lending decisions as the result of availability of large-scale data sets (Galak, Small, and Stephen 2011; Stephen and Galak 2012), something that was difficult to do a few years ago.

Managerial Implications

Substantively, we provide several insights that can be broadly contextualized to the parties involved in P2P transaction platforms such as Lending Club, eBay, Upwork, and Airbnb. First and foremost, designers of the platforms should realize that verifiable information is not enough to eliminate asymmetric information and reveal the true nature of a seller. Although offline communication between buyer and seller could reduce the information asymmetry, the platform runs the risks of prolonging the transaction time and the risks of the two parties transacting outside of the platform, which would reduce platform revenue. Thus, platforms always need to balance the benefits of allowing parties to transmit information with the risks of potentially losing platform revenue (e.g., Amazon and eBay both block email addresses in communication and cancel accounts that try to do business outside the platforms). Because countersignaling behavior has quality content, platforms that disallow communication (such as Lending Club) should improve their proprietary seller-quality metrics by incorporating countersignaling behavior in their computations (e.g., those who countersignal by not providing a description could get a score of 3, long descriptions a 2, short descriptions a 1). This scoring algorithm should remain proprietary so participants cannot game the system (akin to the review filtering algorithm on Yelp or the "portfolio health meter" by Lending Robot). As P2P platforms become more important, platforms that can fine-tune their rating systems to better reflect true risks and to resolve information asymmetry more effectively without communicating with each other offline would (1) ensure the revenue stays on the platform and (2) instill more confidence among participants.

For sellers who are reading this article, those who are confident in the quality of their profile as a provider should abstain from providing unsolicited information about their superior capabilities (e.g., repayment ability, reliability in terms of packaging quality and speed of delivery, quality of their freelance work) when verifiable information about their quality as a provider is available. For these sellers, volunteering nonverifiable information can lower their probability of making a deal (e.g., getting a loan funded, renting their apartment, making a sale). To illustrate, high-quality sellers on eBay should refrain from providing superfluous information and instead let their "power-seller" status do the talking; similarly, professionals who market their services in freelancing marketplaces (e.g., Upwork) should let their references, performance records, and professional portfolios speak for themselves, instead of providing nonverifiable descriptions of their skills or the quality of their services.

Limitations and Future Research

We note some limitations and suggest avenues for future investigation. During the time frame in our analysis, the platform was open only to individual, as opposed to institutional, investors. Starting in 2012, the platform was opened to institutional investors, which by December 2015 made up 33% of the funding. One can examine how asymmetric information is resolved differently in P2P versus peer-to-business (P2B). As the percentage of sophisticated investors is likely to be higher for institutional than for individual investors, our model suggests that the impact of countersignaling would be even stronger for institutional investors. Further, in light of the recent Lending Club scandal in the P2B domain,[16] we performed an analysis in which we excluded data from the month of December 2009, and we observed that the results do not change (which is to be expected, given the small proportion of loan transactions relative to all the transactions in the platform). Nevertheless, one can examine how the lender decision model and the weights they place on various pieces of information evolve. We suspect that now that the scandal has revealed that certain variables within the loan can be manipulated, lenders may deemphasize these variables and shift weight to other variables to form their decisions. Even so, we believe that as long as the public company and the industry as a whole conduct business in a legitimate fashion, they can provide value to both lenders and borrowers. During the time frame of our analysis, buyers and sellers could not communicate offline, and the platform's

[16]In April 2016, an investigation indicated that the now-ousted CEO Renaud Laplanche and three of his family members had taken 32 inside loans (totaling $720,000) to inflate growth, a practice Silicon Valley insiders call "growth hacking." Lending Club shares plunged 51% the week after the reporting of the scandal as institutional investors suspended debt purchases and the U.S. Justice Department announced a probe. For more information, see http://www.bloomberg.com/news/features/2016-08-18/how-lending-club-s-biggest-fanboy-uncovered-shady-loans.

disclosure rules have not changed. Further research could examine a period when there is change in the platform's communication rules (e.g., change of sequence, opening or closing avenues of disclosure), which could shed light on how signaling mechanisms shift to alleviate asymmetric information. Finally, further research could examine whether characteristics specific to other P2P contexts moderate or replicate the signaling/countersignaling dynamics present in P2P lending.

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