Marketplace Lending, Information Aggregation, and Liquidity

September 14, 2018

Abstract

We analyze an electronic peer-to-business lending platform for small-and-medium-sized British companies, operated by Funding Circle. We examine a unique data set of 7,516 auctions involving 34 million orders, containing information on order size, price, time of submission and investors. We find an active price-discovery process that reveals valuable information about the loan's likelihood of default. Nevertheless, information efficiency was not reached. This pricing problem deteriorated over time, and was related to liquidity shocks, particularly when the demand for loans surged. Our findings shed light on the market design of Fintech platforms, and the future viability of auctions.

1 Introduction

It is often predicted that the rise of FinTech, understood as the application of internet tools for the rerouting of flows of funds, would cut out costly intermediaries. The result would be a substitution of traditional lending structures, that have dominated the finance industry for so many years, with more competitive market-based structures.[1]

Nevertheless, early experiments with electronic markets have generated mixed results. Einav, Farronato, Levin, and Sundaresan (2018) document an eBay trend away from flexible-price auctions towards posted (fixed) prices, a result that survives even after controlling for the properties of the traded items (for example, collectibles are more likely to be sold by auction). Wei and Lin, (2016) document the switch in December 2010 by Prosper, a leading American peer-to-peer (P2P) platform from auctions to posted prices. They provide a comprehensive before-after analysis showing that under posted prices borrowers are more likely to obtain credit but, also, more likely to default. Funding Circle (FC), a leading UK peer-to-business (P2B) electronic platform, which is the object of our study, abandoned auctions in favor of posted prices in September 2015. Subsequently, in September 2017, it took an additional step away from a market allocation mechanism, by offering only "posted portfolios", that is an algorithmic selection of loans to match the investor's preferences.

For both practical and analytical purposes, we believe that it is important to understand why market mechanisms have disappointed. Is it because these markets contain no information or is it because the FinTech industry is still in the learning stage, searching for effective designs through a process of trial and error? In an attempt to shed light on these questions we examine the inner workings of $7,516$ FC auctions (before the switch to posted prices) and, the subsequent performance of those loans. We have benefited greatly from private data made available to us by FC, including 34 million observations on each and every order that was placed on the platform, whether ultimately accepted or rejected.

[1] See Philippon (2016), Morse (2015) and Yermack (2015).

We conduct our investigation within the conceptual framework of information efficiency; see Fama (1970). We test whether auctions generate *any* information, over and above that contained in the publicly available credit scores, and whether that information is priced correctly. We also explore the factors that might explain any observed deviation from the benchmark of information efficiency. While we present no structural model of the FC auction, we find the Kyle models (1985, 1989) and Duffie's (2010) notion of "slow moving capital" particularly helpful in the interpretation of our findings. We also borrow freely from other strands of the finance literature.[2]

We have four main results. First, we provide a comprehensive description of the platform's design. We describe in some detail the dynamic bidding behavior of investors who participate in the auctions. That description points towards an active price discovery process. The description highlights the importance of the algorithmic allocation of funds by an "autobid" function administered by FC, for investors who lack the time, the skill or the motivation to engage in active bidding. We report that about half of the funding of the platform is intermediated by the autobid. Given the discriminatory nature of the auction (each accepted order pays the submitted interest rate), we report that the interest rate on funds allocated via the autobid is 0.6% lower than the interest rate on funds allocated directly by active investors in the auction.

Second, while we reject the hypothesis that the pricing of FC loans is information efficient, we find strong evidence that the interest rate, as determined by the auction, predicts default rates *over and above* the publicly observed loan's credit score. At the same time, there is a significant deviation of the auction price from the information-efficient price: loan interest rates exhibit excess sensitivity to credit default risk. Adjusting for the loss given default and systematic risk, we find that for a 1% increase in the loan rate, the default risk increases by only 0.4%. We also reject the hypothesis, consistent with learning, that information efficiency increases over time. In fact, it falls over time.

[2]For example, Cornelli and Goldreich (2001), Biais, Bossaerts and Rochet (2002), Shleifer (1986, 1997).

Third, we demonstrate that interest rates are affected by shortages of liquidity on the platform. In particular, we provide evidence that loans auctioned off at times of scarce liquidity tend to close at interest rates that are above the information-efficient level. This is related to FC's extraordinary growth rate of 2.4% weekly during the sample period. This growth rate made it difficult to synchronize flows of funds of borrowers and lenders. In these tests we use three proxies for scarce liquidity. The first is the platform's growth rate, so that an auction is likely to suffer from a liquidity shortage if it runs in parallel with many other competing auctions. The second is the auction's randomly assigned closing hour, so that auctions that close between 3pm and 7pm are likely to be more liquid relative to auctions that close outside of these peak hours. Both proxies point in the same direction, and suggest that scarce liquidity is related to mispricing. In a third test, we compute a measure of liquidity in the spirit of Amihud (2002), separating liquid from illiquid auctions. Using a measure of price sensitivity of bids we show that liquid auctions tend to suffer less from the mispricing problem.

Fourth, we provide a quantification of the information aggregated into the auction price. We show that the amount of information added by market signals, over and above the credit score, is significant. Adding the interest rate of the auction to the default equation improves the explanatory power of the regression. However, we estimate that no more than 24% to 28% of the variance in the closing price can be explained by default risk. Our results are not dissimilar to those of the corporate bond literature. Collin-Dufresne, Goldstein and Martin (2001) find that using numerous proxies for default probabilities and recovery rates "regression analysis can only explain about 25 percent of the observed credit spread [monthly] changes." In addition they find that "the dominant component of monthly credit spread changes in the corporate bond market is driven by local supply/demand shocks that are independent of both changes in credit-risk and typical measures of liquidity." Thus, the presence of a significant amount of noise in the price can account for the excess sensitivity result above. These results are consistent with ours, where we find that liquidity shocks are a significant determinant of pricing variability.[3]

Prior to its decision to move away from the auction mechanism, FC informed us of its concerns over the uneven flow of funds into the platform which they felt was increasing the volatility of interest rates, in a way that was largely unrelated to changes in default risk. Their concerns might have been reinforced by the increasing reliance on investors' funds allocated through the autobid, and the associated difference in interest rates with non-autobid, i.e., active investors. Notwithstanding the concerns of FC and some users about the success of the auction, our results suggest that the quality of the pricing of FC loans is similar in comparison with the pricing of bonds issued by much larger, typically listed companies. This raises the question whether the FC experiment should be deemed a failure. As the industry matures, two things might be expected to happen: first, growth would slow down, which would ease the problem of synchronizing the flow of funds in/out of the platform and the resulting liquidity problem; second, data would accumulate that would allow a better understanding of lenders' and borrowers' characteristics and behavior.

There are several recent papers in the emerging FinTech literature that are related to our work. Vallee and Zeng (2018) show, theoretically and empirically, the connection between the information provision of peer-to-peer platforms and rents extracted by sophisticated investors. Similar to our setting, the sophisticated lenders are able to outperform less sophisticated ones, especially when the platforms provide much information. D'Acunto, Prabhala, and Rossi (2018) study the implications of robo-advising for the portfolio choices and performance of investors in the Indian stock exchange. They document that the adoption of the delegated investment mechanism has heterogeneous effects across investors, with benefits decreasing in the amount of portfolio diversification. Grennan and Michaely (2017) study the operations of FinTechs that aggregate and synthesize public data. They find a reduction in the quality of information produced by online financial

[3] Similarly see Driessen (2005) and Houweling, Mentink and Vorst (2005)

analysis and, as a result, a deterioration in information efficiency. In an analysis of online lending markets Iyer, Khwaja, Luttmer, and Shue (2015) highlight that aggregating over the views of peers can enhance lending efficiency in peer to peer markets. Finally, several studies show how the design of peer-to-peer marketplaces affects the matching between borrowing households and contract terms (Hertzberg, Liberman, and Paravisini (2017); Cespedes (2017); Liskovich and Shaton, (2017)).

The paper is organized as follows: the data is described in Section 2 and the platform's operation is described in Section 3. Section 4 provides the detailed "anatomy" of FC auctions while Section 5 presents our methodology and predictions. Section 6 presents the results and Section 7 concludes.

2 The data

Our data cover the period from the last quarter of 2010, when FC started operations, to the first quarter of 2015, before the switch to posted prices. The data includes all the loans generated via the platform during that period. We have discarded loans that were granted to institutional investors without a public auction. The result is a data set with 7,516 loan auctions. Most of the results that we report below are based on slightly smaller samples due to data incompleteness. We believe that no material bias is introduced. The total value of the loan book is £0.46 billion. Although our sample closes in 2015, we track the performance of the loans to the end of 2016, so that even the most recent loans in the data set have a performance record of, at least, a year and a half. The data also exclude 875 loans where the auction was completed but were later rejected by the borrowers.[4]

The data are organized in three files. First, there is the loan book, which includes information about the loan size, interest rate, and maturity. In addition, there are details

[4]Borrowers always have the right to reject the loan resulting from the auction. The sample does not contain enough information to allow a detailed study of these rejected loans.

about the borrower, including type of business, location, and number of years in operation. All the borrowers are small to medium sized companies (SMEs). This file is very similar to the one that is publicly available on FC's website. Second, there is a file with the borrower's monthly payments of capital and interest: all the loans were amortized with equal monthly payments.[5] Our estimates of default probabilities are based on these data. Third, we have a file that contains the entire bidding information: a record of every order that was submitted to the platform, whether accepted or rejected, including the exact time of submission (up to a split second) and the investor's identification number, which allows us to track each investor's bidding activity in this and other auctions. This information does not exist in the public domain.

3 Institutional structure and descriptive statistics

Since early 2011 the loan book has grown at a mean weekly rate of 2.4% with a standard deviation of 1.2%. Such a volatile growth rate is the first indication of the difficulty that FC faced in matching investors-generated supply of funds with borrowers-generated demand for funds. In spite of its remarkable growth rate, FC was (and still is) a small operator relative to the British lending market, though it has become a significant source of funding to SMEs.[6]

The platform allows SMEs to auction loans directly to the retail market at a price determined by the auction. The platform also collects loan repayments and coordinates legal action in case of default. The platform charges a 1% service fee on the outstanding loan amount, and this charge is deducted from loan repayments made to the lender. These

[5] About a hundred interest-only loans were discarded; including them would complicate our formal analysis very considerably; see Section 5 below.

[6] Recently, for the first time, FC's net new lending to UK SMEs has surpassed major high-street banks; see the Financial Times, 2 November, 2017, based on Bank of England data. Among P2P/P2B operators, FC was the largest with a 30% market share; see Milne and Parboteeah (2016).

fees are the only exposure FC has to the loan's default risk.[7]

In our sample, loan size varies from £5 thousand to £0.52 million with a median of £50 thousand; see Table 1. Loan maturity is between 6 months and 5 years with a median of 3 years. According to the borrowers' own reports, the main use of the loans was to fund working capital, growth, or the purchase of assets. The vast majority of borrowers are organized as limited companies. Their median age is 9 years with a mean of 11 years. They come from all regions of the UK and from all sectors of the economy.

The borrowing process begins with FC's credit department. Some borrowers are rejected at that stage because of suspicions of fraud or an unacceptably high level of default risk. The rest are assigned with a credit score, set at A+ for the lowest default probability and D for the highest default probability. The analysis is based on hard information including the borrower's Experian (a credit research company) rating, its credit history, financial statements. The analysts of the credit department have the discretion to alter the credit score based on their appraisal of the loan's risk. The borrower provides a "prospectus", and in most cases, the platform opens an SME-investor Q&A line. Borrowers are encouraged to respond honestly and fully to questions. These exchanges are publicly available on FC's website.

In addition to active participation in loan auctions, investors could also delegate the allocation of funds to a platform's built-in algorithm called the autobid. An investor could specify an amount and a level of risk and the algorithm would submit, on his behalf, orders diversified over multiple auctions. On average, half of the funding comes from the autobid; see Table 1. As we shall see below, the autobid played a pivotal role in the operation of the FC platform.

More than 22 thousand investors actively (i.e., not via the autobid) contribute funding towards the loans. They do so in unequal measures: while the top decile funds 83% of the

[7]Unlike investment banks in securitization deals; see DeMarzo and Duffie (1999). See also Benmelech, Dlugosz and Ivashina (2012) for evidence on securitization of corporate loans.

Table 1: Descriptive Statistics

	mean	med	SD	min	max
Loan Size (£000)	57	50	40	5	516
Maturity (months)	44	36	14	6	60
Age of SME (years)	12	9	10	0	107
Share of Autobid (%)	48	50	18	0	99
Number of Active Investors	200	176	127	2	985
Share of Top Lender (%)	8	10	7	0.2	83
Share of top 5 Lenders (%)	18	17	11	0.7	100
Share of top 20 Lenders (%)	29	27	14	0.7	100
Length of Auction (hours)	157	168	15	0.1	504.0
Average Closing Rate, A Rated (%)†	8.4	8.2	1.1	5.8	13.8
Marginal Closing Rate, A Rated (%)†	9.1	8.6	1.7	5.9	15.0
$\left.\frac{\text{payments to default}}{\text{payments due}}\right\vert_{\substack{\text{defaulted}\\ \text{A rated}}}^{\dagger\dagger}$	0.42	0.38	0.22	0.03	0.94
$\left.\frac{\text{recoveries post default}}{\text{balance remaining}}\right\vert_{\substack{\text{defaulted}\\ \text{A rated}}}^{\dagger\dagger}$	0.32	0.09	0.41	0	1.4

Descriptive statistics on a cross section of the 7,516 loans in our data set, except for the following cases where only a sub-sample was used: †, calculated for A rated loans only; ††, calculated for 169 A rated loans in default (out of 671 defaults).

total, the bottom 4 deciles jointly contribute less than 1%. Accordingly, on a loan level, the average contribution of the top lender is 8% of the loan while the largest 5 and 20 investors fund 18% and 29% of the loan, respectively; see Table 1. By value, the median contribution for the top lender is £3,000 and the mean is £5000. However, typically investors have multiple loans outstanding, for example for the year 2013 the top investor successfully placed £1.1 million across 600 different loans. It might be hypothesized that the big lenders were better informed, more sophisticated and better able to provide the market with liquidity.

Most auctions were scheduled to last 7 days (168 hours) but some lasted longer; see Table 1. Borrowers were allowed to discontinue the auction and accept the loan prior to the assigned termination time, which happened in 38% of cases. We believe that some of these early terminations were triggered by loan brokers who lacked a sufficient incentive to work towards a lower interest rate. In other cases termination was triggered by a borrower who needed cash so urgently that he was willing to give up the certain prospect of paying a lower interest rate. We will elaborate on this in section 4.2.

In order to prevent interest rates from falling to an "unreasonably" low level, FC imposed a floor on the lending rate. Once an auction hits that floor the auction would be effectively over. We distinguish such floor-hitting auctions from early terminations, since they may signal different loan characteristics.

Investors could access the system at any time during the day or the night. Orders that were placed on the system could not be subsequently withdrawn. The order book was open so that any investor could observe the activity of others, but investors were not informed whether orders were submitted directly or via the autobid function.

Every order had to specify both a quantity and a price. Upon closing, the orders were sorted by price, the best were accepted and the rest were discarded. In case of a tie, orders were prioritized on a first come first served basis. The auction was price discriminating, so that each accepted order earned the submitted interest rate. We refer to the highest of these as the loan's *marginal rate*, while the interest rate charged to the borrower, calculated by weighting each order according to its size, is called the *average rate* (gross of the service fee).

Our basic pricing equation is:

$$r_i = \alpha + \beta \times Dscore_i + \gamma \times Dquarter_i + \varepsilon_i, \tag{1}$$

where r is the closing interest rate (either marginal or average) charged on loan i, *Dscore* is a vector of credit score dummies and *Dquarter* is a vector of dummies for the quarter when the auction was executed. Results are reported in Table 1. The mean average (marginal) closing rate for A rated loans is 8.4% (9.1%) p.a. with a median of 8.2% (8.7%), respectively. Relative to the A credit rating, prices change by roughly 100 basis points per rating category; see Table 2. The quarterly dummies reflect changes in macroeconomic conditions but, also perhaps, market liquidity shortages (see below). During that period, the Bank of England's base rate was fixed at 0.5%.

We estimate the *quarterly* default probability using information in the repayment file to which we add the relevant SME characteristics:

$$Ddefault_{i,t} = \alpha' + \beta' \times Dscore_{i,t} + \gamma' \times Dquarter_{i,t} + \varepsilon'_{i,t}. \tag{2}$$

The dependent variable is a dummy that receives a value of 1 if loan i defaulted in the t^{th} quarter after inception (so that t is an index of loan time), and zero otherwise. Notice that loan i appears in the panel for as many quarters as it has performed plus the default period (if any). This procedure avoids potential biases that might result from the non-stationary nature of the data, due to the different maturities of the loans and the different exposure of the loans to the sampling window. For example, a 3-year loan issued in, say, 2011 was already resolved (either repaid or defaulted) by the close of the sample, while a 3 year loan issued in 2015 was still open. With $7,455$ loans and 671 defaults, this procedure yields a panel with $81,049$ lines; see Table 2. Since we estimate the equation by OLS, α' has the interpretation of a (stationary) quarterly transition probability from a state of "performance" to an (absorbing) state of "default".[8] At a quarterly default rate of 0.8% for A rated loans, the annualized default probability is thus 3.2%. Roughly, annualized default probabilities increase across ratings with the exception of C-rated loans that seem to have the same default probabilities as B-rated loans; see column 3 Table 2.

Default typically takes place around the mid point of a loan's life, so that conditional on default, column 4 of Table 2 reports that an A loan has already repaid 44% of the scheduled payments. There are no statistically significant differences across credit ratings.

Once default takes place, FC acts as a "delegated monitor" on behalf of the investors and is required to recover as much as possible from the lender; see Diamond (1984). As

[8]This approach yields results that are very close to those that one would obtain using duration analysis; see Soyeshi (1995).

the vast majority of loans in our data are unsecured,[9] and since we assume that, before approaching FC, borrowers have already used all the company's pledgeable assets in order to obtain bank credit, it follows that FC investors are junior creditors in any insolvency proceedings. In that respect, recovery rates post default are relatively high in comparison with unsecured creditors: column 5 of Table 2 estimates the recovery rate to be 25% of the remaining loan balance.[10]

It seems that the high recovery rates have to do with the the fact that virtually all loans are personally guaranteed by the SME's owners. Hence, FC, in its delegated capacity, can bankrupt the owners once their corporate entity has defaulted. In England, unlike in the US, personal bankruptcy has very serious consequences. First, protection for personal assets, including homes, is virtually non existent. Second, many restrictions apply to bankrupt individuals. For example, while in bankruptcy a person cannot "borrow more than £500 without informing the lender ... act as a director of a company without the court's permission ... create, manage or promote a company without the court's permission".[11] It is a common practice for British banks to freeze bank accounts of bankrupt individuals or to refuse to open new accounts. Indeed, Jackson (2016), Head of recovery at FC, argues that "for Funding Circle, 90-95% of recoveries come through the personal guarantor". Given FC's unsecured position, patience (effectively, loan rescheduling) may be the best option, a strategy Jackson (2016) calls "survival for revival". He argues that, currently, FC's "conservative estimate of recovery on defaults is 40p in the £ over a five-year period" (from the default date). Since our estimates are typically based on a time horizon that is significantly shorter than the five years post default, our recovery rates may not be inconsistent with FC's.

[9] Adding a security dummy to the recovery regressions in Table 2 does not produce statistically significant results.

[10] Several articles in the popular press have alleged that FC was not aggressive enough in pursuing borrowers in default. It is noteworthy, however, that junior creditors in England typically recover next to nothing, see Franks and Sussman (2005), although the junior creditors in their sample were mostly trade creditors without any security or personal guarantees.

[11] See www.gov.uk/bankruptcy/restrictions.

Crucially, considering the loss given default (LGD) figures within our sample, there is no prima facie evidence of any "exuberance" in the pricing of FC loans: the combined effect of default half way through an amortized loan plus the relatively high recoveries post default reduce the default rate per £1 lent to less than one half of the 3.2% default rate per loan; risk is quite conservatively priced. However, this statement should be treated with caution as FC, indeed the entire P2B/P2P industry, has yet to be tested by an economic downturn. The correct risk premium for such a macroeconomic risk is difficult to estimate on the basis of past performance (see Feldhütter and Schaefer (2018)).

4 The anatomy of FC auctions

4.1 A description of an auction

To better understand the price discovery process this section provides a detailed description of a single auction, i.d. number 2408, randomly selected, to fund an A-scored, three-year loan for £15 thousand, auctioned off in April 2013. The marginal closing interest rate was 6.6%, and the average closing interest rate was 6.49%.

Conceptually, at any point in auction time one may sort the orders submitted up to that point according to the interest rate, which yields a "supply curve". Over time, additional orders are submitted and the supply curve is dynamically updated. As noted above, orders that are submitted cannot be withdrawn, which implies that over time, the supply curve can move in one direction only, downwards. Figure 1 plots three such supply curves for the end of auction days $n = 1, 4, 7$, where the highest is day 1, and the lowest is day 7.[12] Amounts are normalized by the size of the loans, implying that the "demand curve" is fixed and vertical at one unit. Evidently, the loan was oversubscribed already on day 1. Crossing the day-7 supply curve with the demand curve we derive the marginal closing interest rate. To calculate the average closing rate integrate the day-7

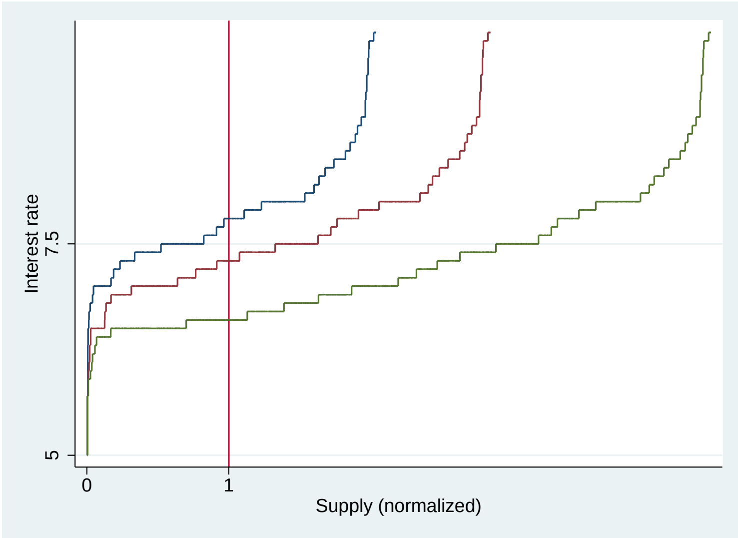
[12] End of day is defined as the opening hour plus $n \times 24$ hours. Notice, however, that since auction time is continuous, the concept of a day-end plays no role in the actual bidding process.

Table 2: loan interest rates, default rates, payments to default and recovery rates

	interest rates regressions		default regressions		
				conditional on default	
	(1)	(2)	(3)	(4)	(5)
	average close	marginal close	default dummy	$\frac{\text{payments to default}}{\text{payments due}}$	$\frac{\text{recoveries post default}}{\text{balance remaining}}$
Constant	8.472***	8.967***	0.008***	0.436***	0.247**
	(0.100)	(0.165)	(0.001)	(0.061)	(0.104)
Dummy: AA Rated	-1.164***	-1.096***	-0.004***	0.030	-0.085
	(0.032)	(0.053)	(0.001)	(0.043)	(0.072)
Dummy: B Rated	0.976***	1.002***	0.003***	0.023	0.001
	(0.024)	(0.040)	(0.001)	(0.023)	(0.038)
Dummy: C Rated	1.987***	1.986***	0.003***	-0.011	-0.038
	(0.025)	(0.042)	(0.001)	(0.024)	(0.041)
Dummy: D Rated	3.713***	3.423***	0.007***	-0.048	0.005
	(0.036)	(0.060)	(0.002)	(0.030)	(0.051)
Quarter FE	YES	YES	YES	YES	YES
R^2	78.7	61.8	0.2	12.4	13.1
N	7,455	7,455	81,049	671	671

The table presents OLS regressions about loan pricing and default characteristics. Across all columns the explanatory variables include credit scores and time dummies for the quarter when the loan was auctioned off. In columns 1 and 2, the dependent variable is the average and the marginal closing rates, respectively. In column 3, the cross section of loans is expanded to a quarterly panel, where each loan is sampled according to the number of quarters it is being serviced. The dependent variable is equal to 1 if the loan has defaulted in that quarter. Standard errors are adjusted for heteroskedasticity and clustering at the loan level. In columns 4 and 5, we consider the sub sample of defaulting loans and the dependent variables are the number of monthly payments received over number of monthly payments due and recovery rates (post default), respectively. ***, ** and * denote statistical significance at 1%, 5%, and 10%, respectively.

Figure 1: auction 2408, notional supply curves end of days 1, 4 and 7 (in descending order)



supply curve from zero up to the intersection point. Note that in this setting, the slope of the supply curve at the intersection point has an elasticity interpretation.

Since the supply curve is bound to move downwards over auction time, the interest rate, both average and marginal, is bound to evolve in the same direction. Such a descending pattern bears only a superficial similarity to a Dutch auction, because the price of the "bond" is actually ascending in auction time. Functionally, the auction works more like an English auction, starting with a price that is attractive to many investors, but as the interest rate descends, some drop out. Notice, however, that unlike a textbook English auction, the signal regarding participation is noisy. An investor who submits an order at a certain price unambiguously reveals that he is participating - at that price. (Remember: orders cannot be withdrawn.) At the same time, if an investor fails to revise an order that has been pushed "out of the money" by a descending interest rate, that may indicate that the investor has dropped out of the auction, or it may indicate that he is delaying the revision to a later stage.

A more substantial deviation of FC auctions from a textbook English auction is the significant involvement of FC in the price discovery process. As already noted above, FC does not commit its own capital to fund any loan, but it does channel, via the autobid, very substantial amounts into the auction. Hence, in Table 3 we decompose the inflow by source: autobid and direct placement by active investors. Investors' inflows are further decomposed into new orders and revised orders. An order is considered a revision if it is submitted more than three hours after the placement of the earliest order by the same bidder.[13] For example: if a certain investor placed his first order on, say, the second day at 7pm, all bids submitted before 10pm of the second day would count as part of the initial order but the bids submitted after 10pm of the same day would be considered as revisions. We also identify "outflows" from the auction: the aggregate value of orders that were placed out of the money by the descending interest rate. For example, an order for 7.4% placed on day one, will be classified as an outflow on day 4, once the closing rate drops to 7.3%.

The most striking fact in Table 3 is the large injection of orders by the autobid right at the opening: almost 60% more than is required to fund the entire loan (see Day 1, column 3). About half of these orders are deemed out of the money by the end of day 1, (see Day 1 column 6). Autobid inflows virtually vanish on the following days while autobid outflows accelerate. Eventually, when the auction is closed, the accumulated value of in-the-money autobid orders is only $1.91 - 1.75 = 0.16$, i.e., 16% of the value of the loan.[14] In contrast, bidding by active investors is U-shaped: high on day 1 at $0.44 + 0.03 = 0.47$, falling later but accelerating towards the close at $0.49 + 0.37 = 0.86$ on day 7. Interestingly, most of the active bidding on the last day is new, by investors who bid only at the closing stage of the auction. We return to this issue below.

The second column of Table 3 reports, in the spirit of Amihud (2002), the depth of the

[13] It is common for FC investors to break up orders to smaller bids, either to create a price-sensitive supply curve or to be able to sell part of the order later on. Hence, it may take some time for an investor to place an order.

[14] Accumulating the totals, horizontally in Table 3, in the bottom line, yields a number greater than one. This is because at the end of day 7, there are many tied bids which are then resolved on a first come first served basis.

Table 3: Auction 2408, The Bidding Process

	Marginal Rate	Market Depth	Inflows			Outflows	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Day	Close (%)	Slope	Autobid	New	Revised	Autobid	Investor
1	7.8	1.004	1.58	0.44	0.03	0.77	0.20
2	7.6	0.817	0.07	0.10	0.00	0.18	0.02
3	7.5	0.306	0.11	0.10	0.08	0.08	0.01
4	7.3	0.578	0.06	0.13	0.17	0.42	0.13
5	7.1	0.672	0.03	0.16	0.09	0.06	0.25
6	7	0.31	0.03	0.21	0.16	0.03	0.09
7	6.6	0.252	0.02	0.49	0.37	0.2	0.87
Total			1.91	1.62	0.91	1.75	1.56

The table provides auction statistics across days by using bidding data of a single auction, i.d. number 2408, randomly selected to fund an A-scored, three-year loan for £15 thousand, auctioned off in April 2013. Column 1 provides marginal closing rates across days. Column 2 computes the slope of the supply curve across days. The slope is estimated locally by OLS, using bids that fall between 0.75 and 1.25 on the quantity axis. In columns 3 to 5, we decompose the inflow of funds by source: autobid and direct placement by active investors. Investors' inflows are further decomposed into new orders and revised orders in column 5. An order is considered a revision if it is submitted more than three hours after the placement of the earliest order by the same bidder. In columns 6 and 7, we measure outflows from the auction as the aggregate value of orders that were placed out of the money by the descending interest rate for autobid and non-autobid investors.

market as measured by the slope of the relevant supply curve around its intersection with the vertical demand curve.[15] More accurately, the slope is estimated by OLS, using bids that fall between 0.75 and 1.25 on the quantity axis. To better understand what the slope means, consider Table 3 estimates for the end of day 1. To the left of the intersection point, a unit slope implies that an investor who bids at the last minute and wants to secure a 10% allocation needs to undercut the closing marginal rate by at least 10bp. To the right of the intersection point, a unit slope implies that the best marginal bid 10% above the value of the loan was 10bp above the closing marginal rate. The former (latter) figure provides an indication of loan's risk assessment by relatively optimistic (pessimistic) investors who would (not) be willing to lend even if the closing marginal was lower (higher). Hence, the slope provides a proxy for the disagreement among investors

[15]Indeed, the effect is more accurately measured because the supply curve is directly observable, unlike in most applications of the Amihud measure.

regarding the fair value of the loan. Evidently, that disagreement has fallen over auction time, as the above figure dropped from 10bp at the end of day 1 to only 2.5bp at the close.[16]

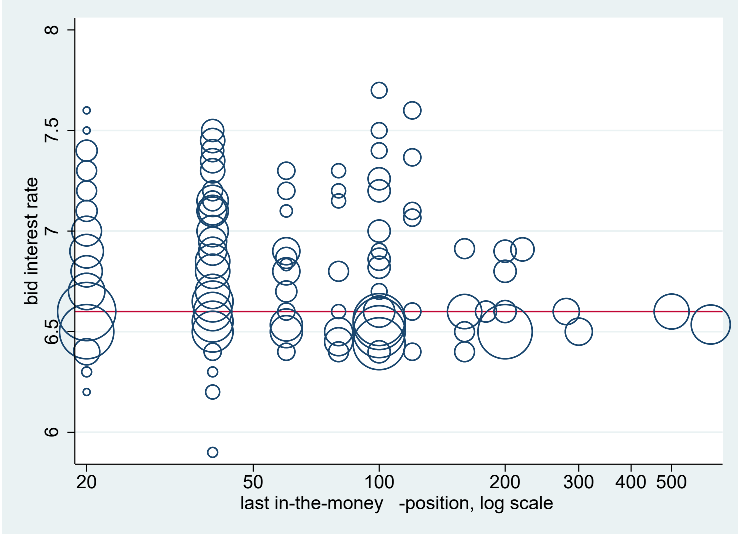
It is worth elaborating further on the dynamics of bidding in an open-book auction.[17] Arguably, while investors can profit from placing an order for a loan where the marginal rate is above their own valuation, they clearly have an incentive to slightly undercut the marginal rate, as it stands at the time of bidding. (Since there is no winner's curse in an English auction, investors need not "shade" their orders relative to their expectations.) But as the interest rate descends, existing orders are pushed out of the money. Suppose, for example, (still using auction 2408) that an investor placed on day 2 (when the closing marginal rate was 7.6%), an order of £100 at 7.5%. Clearly, the order is in the money. At the close of day 3, the marginal rate drops to 7.5%, placing the order just in the money. As it is highly likely that the marginal rate would drop further, the investor decided to place a new order at a lower rate of 7.2%. Since the price is less attractive, he also decreases his exposure to the loan from £100 to £50. Eventually, the price dropped further, closing at 6.6%, and the investor decided not to revise his order any further. It follows that 7.2% reflects the investor's estimate of the loan's risk. Investors' last in-the-money order is therefore a good indicator of the dispersion of expectations regarding the loan's risk of default.

Figure 2 plots these last in-the-money orders against the size of the order (the latter plotted on a logarithmic scale). The size of each "bubble" is proportional to the aggregate value of the orders placed by all investors, in that particular combination of order size and interest rate. For example, consider the "bubbles" at 6.9%, one for £20 and another for £200. That the two bubbles are of equal size implies that there are 10 times the amount of orders of £20 (at 6.9%) totaling the same value as the single order at £200 (also at

[16]Notice that the flattening of the slope, unlike the descent of the interest rate, is *not* a necessary consequence of the downwards shift of the supply curve over auction time.

[17]This paragraph is motivated by Haile and Tamer's (2003) analysis of English auctions.

Figure 2: Auction 2408, individual investors, last in-the-money orders

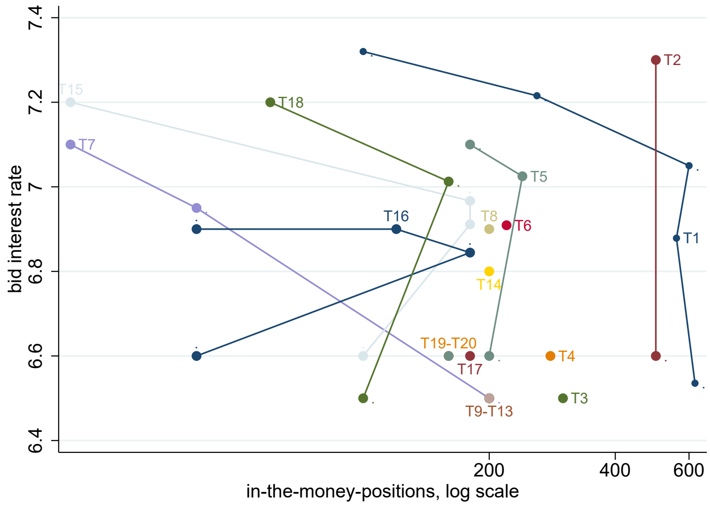


6.9%). Evidently, the distribution of bidding prices is highly skewed, with only a few bubbles (of a small size) below the marginal close of 6.6% and many bubbles above. It seems safe to infer that investors understand the logic of the previous paragraph, and that they bid at the marginal rate or just below it. An additional implication is that the price-discrimination property of the auction has little effect on active investors. In contrast, passive investors that delegate their decision to the autobid are likely to have their order placed well below the marginal closing rate. Indeed, we calculate that averaging over the entire sample, active investors' interest rate exceeds the autobid interest rate by 0.6%.[18]

In Figure 3 we identify the top-20 investors who participate in the auction and rank them, (from T1 to T20) according to their largest in-the-money order over the entire duration of the auction. It turns out that while some investors (namely: T3, T4, T6, T8-T14, T17, T19-T20) prefer to wait until they get a fair assessment of the closing rate and only then place a single order, others prefer early bidding with eventual revisions. Among the seven investors who chose the second strategy, one would expect that due to

[18]The statistic is calculated as follows: at the auction level, we take the weighted-average interest rate across accepted orders submitted by active investors from which we subtract the weighted-average interest rate across accepted orders submitted via the autobid. The difference is then averaged across all the loans in the data set.

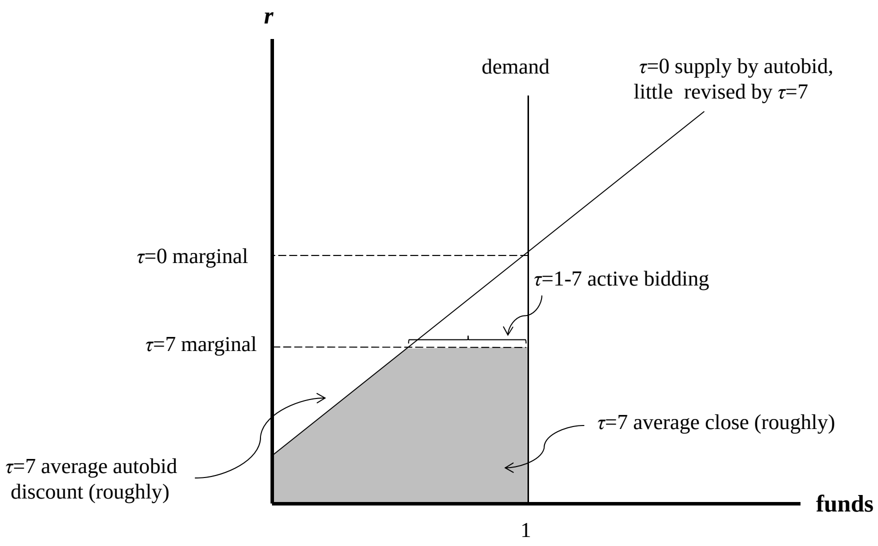
Figure 3: Auction 2408, top twenty investors, over time in the money positions



risk aversion, the exposure to the loan would decrease as the interest rate falls so that the individual supply curve is upwards sloping. Surprisingly, this is not always the case. Take, for example T18 who placed his first order of £60 when the marginal rate was 7.2%. As the marginal rate dropped to 7% T18 *increased* his exposure to £180. Eventually, as the closing marginal rate dropped to 6.6%, T18 decided that even at this lower rate the loan is still worth investing in, albeit with decreased exposure. It seems, however, that T18 has delayed his decision for too long and could no longer receive an allocation at a rate of 6.6%; remember that in case of a tie, allocations are granted on a first come first served basis. As a result, T18 was forced to bid below the closing rate at 6.5%, at which price his £100 order is serviced. Evidently, the backward bending segment is not unique to T18. It is hard to say whether this pattern resulted from observing other investors (possibly herding) or because of additional research into the borrower. In both cases, Figures 2 and 3 indicate a substantial diversity of bidding strategies among investors.

We summarize our observations regarding the functioning of the auction and the nature of the price discovery process with the aid of Figure 4. At the open, auction time $\tau = 0$, the autobid places an upward-sloping supply curve. By and large, the autobid supply

Figure 4: A summary of the auction process



curve does not change till closing time at $\tau = 7$ (days). The intersection of that supply curve with the demand curve marks the $\tau = 0$ marginal close and puts an upper bound on the marginal closing rate throughout the auction. Then, active (i.e. non autobid) investors buy into the loan by undercutting that initial closing rate. As a result, the closing marginal rate *falls* along autobid's supply curve. The movement down the autobid supply curve will end when the time allocated to the auction expires, at $\tau = 7$. At that point, the effective supply is made of two segments: the horizontal part at the marginal closing rate and the autobid supply curve, below. The active and passive investors are lined up along these two segments, respectively. The average closing rate is calculated by integrating the shaded area below the effective supply curve. The passive investor's discount is represented by the non-shaded triangle to the left.

4.2 Early bidding and early terminations

Two aspects of the decision making process raise questions about rationality of lenders and borrowers and hence, are worth further investigation. The first is the substantial participation of investors at the start of the auction, against the strategy of bidding at the very last minute, free riding on the information that is revealed by other investors but without revealing any information of their own. The second is the early termination of auctions by borrowers when interest rates can only decline in auction time. Early termination therefore implies a strictly higher interest rate to the borrower.

We first examine early bidding behavior. Table 4 generalizes and extends previous observations. We report order flows, normalized by loan size, by active (non autobid) investors on a sub sample of 3,355 auctions that lasted for seven days. As we have done in Table 3, auction time is divided into twenty four hours intervals, each interval is defined as an auction day. Investors are defined as large if the total amount of their daily orders exceed £100. Within an auction, the total amount of orders submitted by a certain investor on the first day that he was active in that particular auction is classified as new, the rest are treated as a revision. We then report in columns 6 and 7, the value for each day of bids that were executed at the close of the auction. We also report the average closing interest rate at the end of each auction day.

Two observations are important. First, there is substantial participation of investors, including large ones, in the early stages of the auction. Large investors' active orders amounted to 2.71 over the entire auction period, of which 0.42 participated for the first time on the last day of the auction. A large amount of the participation, 1.27, takes place on day one. The second observation is that the vast majority of that initial bidding is not executed, i.e., of the total amount of 1.27 submitted by large investors only 0.02 is executed. The amount executed of small investors' bids is only 0.1 and, again, the vast majority is submitted on day seven.[19]

[19]The amounts do not add up to one because the rest of the execution comes comes from the autobid.

Table 4: Mean order flows, by active investors, by investor size, eventual execution and timing of submission; daily changes average interest rates

	daily flows			new flows		executed flows		interest rate change
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	small	large	total	small	large	small	large	
Day 1	0.05	1.27	1.31	0.05	1.26	0.01	0.02	.
Day 2	0.02	0.17	0.19	0.01	0.04	0.00	0.01	-0.32
Day 3	0.02	0.16	0.18	0.01	0.04	0.00	0.01	-0.25
Day 4	0.03	0.14	0.16	0.01	0.03	0.00	0.01	-0.23
Day 5	0.03	0.13	0.16	0.02	0.03	0.01	0.01	-0.23
Day 6	0.04	0.16	0.20	0.03	0.05	0.01	0.01	-0.25
Day 7	0.13	0.68	0.81	0.10	0.42	0.07	0.36	-0.55
Total	032	2.71	3.01	0.23	1.87	0.1	0.43	-1.83

The table is based on a sub sample of 3355 loans that were scheduled to last for seven days and were not terminated early. Means are calculated over auction days. Lenders are classified as large if, within an auction day, their overall orders exceeded £100. Within an auction, first day orders are classified as new. Execution is determined on the last day by interest rate and,in case of a tie, on a first come first served basis. Changes in the average interest rate are calculated relative to the (notional) close of the previous day.

The phenomenon of not-for-execution orders is widespread. Biais, Hillion and Spatt (1999) analyze pre opening bidding on the Paris stock exchange. In their case pre market orders can be canceled before the market opens. A similar outcome is achieved in FC auctions as investors' initial bids are are unlikely to be executed. At the same time, non-executed order contribute to the price discovery process that takes place above the closing interest rate. Indeed, analysis by Biais, Hillion and Spatt (1999) indicates that early pre market bidding assists the price discovery process and improves the quality of the price, see also Bellia, Pelizzon, Subrahmanyam, Uno and Yuferova (2016).[20] Interestingly, even in single unit auctions such as eBay auctions, Bajari and Hortacsu (2003) document that a significant proportion (68%) of orders are made prior to the final hours of the auction.

As for early terminations, Table 5 presents estimates of probabilities of termination given several loan characteristics. The first point to note is that the quantitative effect

[20]Several theoretical papers (Medrano and Vives, 2001; Admati and Pfleiderer, 1991) have provided a rationale for early bidding by investors.

Table 5: Early termination rates conditional on loan characteristics, %

By credit scores		By maturity		By region	
A+	25.7	6 months	76.5	London	27.6
A	29.7	12 months	34.5	other	30.6
B	30.0	24 months	42.3		
C	31.7	36 months	30.1	By loan purpose	
D	37.3	48 months	30.0	tax payment	47.2
				other	30.2

Based on a sub sample of 2,032 early terminations.

of early termination is relatively small. According to the evidence in the last column of Table 4 the opportunity cost of terminating on days 3 or 4, the average termination day, is about 100bps. For six month maturity loans of £50k the cost would amount to £250. 76.5% of such loans are terminated early. Offsetting the cost of early termination one has to consider the potential benefits for timely transactions where delays may carry significant penalties. For example loans where the declared purpose is tax payments have an early termination rate of 47% against 30.2% for other purposes. Similarly, the share of early terminations is significantly larger for loans used for working capital, where firms can earn the suppliers' discounts for early cash payment. Consistent with evidence to be presented below, the incidence of early terminations is larger for borrowers with lower credit ratings.

5 Methodology and simulations

To guide our empirical analysis, we develop a simple conceptual framework that helps us to formulate testable hypotheses from a stylized model of price formation and information aggregation. The hypotheses are intended to test whether the auction's price adds information about default probabilities over and above the credit scores, as well as identify the factors that drive the price away from the information-efficient one. We use a Monte-Carlo simulated population of auctions to illustrate the empirical implications of the framework outlined in this section.

5.1 Setup and benchmark pricing

Consider an electronic platform where SME borrowers can auction off debt to a population of investors. In the spirit of Kyle (1985), we assume that this platform is managed by a single liquidity provider – a market maker. Evidently, in the FC case there are several liquidity providers, more akin to Kyle (1989): some deep-pockets sophisticated investors and the autobid. Nevertheless, we assume, for the time being, that these liquidity providers can be represented by a reduced form entity. That representative market maker is risk neutral, proficient in statistical inference and has unlimited liquidity at his disposal. Since it represents a multitude of liquidity providers, we assume that competition drives profits down to zero.

For simplicity, we assume that borrowers are of two types, with high and low default probabilities, $\pi^h > \pi^l$, respectively. The incidence of the h type in the borrower population is η. At this stage we assume that the loans have a one-period maturity with LGD of 100%. Subsequently we relax this assumption.

The market maker sets the loan's interest rate on the basis of two signals. The first is the borrower's credit score, a *public* signal $s \in \left\{s^l, s^h\right\}$, with precision λ^s:

$$prob\left(s = s^h \left|type = h\right.\right) = prob\left(s = s^l \left|type = l\right.\right) = \lambda^s > \frac{1}{2}.$$

A second, $p \in \left\{p^l, p^h\right\}$ is derived from the order book and has precision of λ^p:

$$prob\left(p = p^h \left|type = h\right.\right) = prob\left(p = p^l \left|type = l\right.\right) = \lambda^p > \frac{1}{2}.$$

The market maker extracts the p signal from the order book, but the information originates in private signals that some investors receive. Since we do not know how the market processes that information, we treat p as a *private* signal. Namely, the credit score is observable by both the market maker and the econometrician while the private signal is observed by the market maker alone.

Given the realization of the pair (s,p), the market maker applies Bayes Law, computes the posterior probability of default type[21], and derives an expected probability of default, π^*,

$$\pi^* = \pi^h \times prob\left(type = h\,|s,p\right) + \pi^l \times prob\left(type = l\,|s,p\right). \tag{3}$$

Due to the zero profit assumption, the expected gross return on the loan, $(1-\pi^*)(1+r)$, must equal $1+\rho$, where r is the loan's interest rate and ρ is the riskless rate. Hence, the efficient market hypothesis (EMH) implies:

$$r = \frac{1+\rho}{1-\pi^*} - 1 \approx \rho + \pi^*. \tag{4}$$

To illustrate, consider our first numerical example:

$$NE1: \quad \pi^h = 0.1, \quad \pi^l = 0.05, \quad \eta = 0.5, \quad \lambda^s = \lambda^p = 0.7, \quad \rho = 0.$$

Table 6 reports, for each combination of signals, the inferred probability of the borrower's type and, hence, the interest rate. For example, the first column shows that, when the private and the public signals both indicate a high-risk loan, the market maker uses equation (3) to set the updated probability of default at 9.22% and, hence, using equation (4), to set the interest rate at $\frac{0.092}{1-0.092}$, namely 10.16%. Using the same logic, when the private and public signals both indicate a low-risk loan, the expected probability of default is 5.78% and the interest rate is 6.13%. That the two middle columns yield the same price is due to the assumptions that s and p have the same precision.[22] Table 6 also reports,

[21]For example, $prob\left(type = h\left|s^h, p^h\right.\right) = \frac{\eta\lambda^s\lambda^p}{\eta\lambda^s\lambda^p + (1-\eta)(1-\lambda^s)(1-\lambda^p)}$.

[22]When one signal indicates an h type and the other indicates an l type, the posterior probability of

Table 6: Signals, probabilities and prices under $NE1$

	(1)	(2)	(3)	(4)
Signals	(s^h, p^h)	(s^h, p^l)	(s^l, p^h)	(s^l, p^l)
$prob\,(type = h\,\|s, p)$	0.845	0.5	0.5	0.156
π^*	9.22%	7.5%	7.5%	5.78%
r	10.16%	8.11%	8.11%	6.13%
Incidence	0.29	0.21	0.21	0.29

The table is based on parameter value of NE1 and reports, for each combination of signals, the inferred probability of the borrower's type, the inferred default probability, and the associated interest rate. The bottom row reports the incidence of types and signals for a sample of 1000 auctions.

in the bottom row, the incidence of each pair of signals and, therefore, the entire price distribution. For example, in a sample of 1000 auctions, we would expect to observe 290 closing at an interest rate of 10.16%,[23] 420 closing at an interest rate of 8.11%, and 290 auctions closing at an interest rate of 6.13%.

5.2 Simulations and hypotheses

This setting allows us to formulate the null hypothesis of EMH, in which the price contains all relevant signals, public and private. To see then how prices aggregate information about the default probabilities, we simulate a Monte-Carlo sample of 5000 auctions and estimate the benchmark default equation below, augmented with the interest rate. This provides us with a useful benchmark for establishing the extent to which the data and the empirical results depart from the EMH. It also allows us to model alternative assumptions about how the signals are aggregated into prices. For example, how the relationship between prices and default predictions change in the presence of liquidity constrained investors.

$$Ddefault_i = \alpha + \beta r_i + \gamma Dscore_i + \varepsilon_i, \tag{5}$$

default equals the prior probability of default, namely 7.5%, so that the interest rate is 8.11%.

[23] The incidence of a (s^h, p^h) signal in the population is $0.5 \times 0.7 \times 0.7 + 0.5 \times 0.3 \times 0.3 = 0.29$.

Table 7: Monte-Carlo experiments, default regressions

	(1)	(2)	(3)	(4)	(5)
r		1.014**	0.574**	0.177	0.450
		(0.446)	(0.253)	(0.250)	(0.336)
Dscore	0.02**	−0.000	0.000	0.016*	0.011
	(0.007)	(0.11)	(0.011)	(0.009)	(0.010)
Liquidity					−0.046
					(0.038)
Constant	0.07***	−0.000	0.033	0.054***	0.037
	(0.005)	(0.095)	(0.016)	(0.017)	(0.023)
R^2	0.14	0.25	0.25	0.15	0.18
N	5,000	5,000	5,000	5,000	5,000

OLS regressions on a simulated sample of 5000 auctions. The dependent variable: $Ddefault$ dummy is a dummy that equals one if the loan defaults and zero otherwise. The default data and the interest rates are generated in columns 1 and 2 using the parametrization of NE1. Column 3 is parametrized according to $NE2$. Column 4 is parametrized according to $NE3$. Column 5 is parametrized according to $NE4$.

The dependent variable, $Ddefault$, is a dummy defined as in equation (3) above, namely it equals one if the loan defaults and zero otherwise. The default data are generated by using, for each of the four prices in Table 6, equation (5) to "predict" the number of defaults. The test of the EMH hypothesis is therefore simple: the β estimator should be equal to one, i.e., a 1% increase in the interest rate should reveal a 1% higher default probability. Note that the estimators for all other coefficients, α and γ in this particular case, should be equal to zero. The results of the estimation are reported in Table 7, column 2. Clearly, given the underlying data generating process, the EMH of $\hat{\beta} = 1$ hypothesis cannot be rejected.[24]

That column 2 reports an insignificant credit score coefficient, γ, *does not* imply that the credit score is uninformative. In fact, under the $NE1$ assumption that the p and s signals have equal precision, about half of r's information content comes from the credit score. To see why, notice that the credit score is a signal, while the interest rate is an

[24] In the experiment, we use the approximated value for the interest rate, namely π^* rather than $\frac{\pi^*}{1-\pi^*}$, see equation (4), the latter being a non-linear transformation of the default probability yields a slightly lower estimator for β but, otherwise, the same implications.

information aggregate, which therefore subsumes *all* the relevant information available in both signals. As such, it "robs" the *Dscore* variable of all its explanatory power. Notice, however, that while the information content of the credit score is not captured by the γ coefficient, it is detected by the regression's R^2. Augmenting the regression with the r variable in column 2 of Table 7, we almost double the regression's R^2, relative to that in column 1, which includes only the credit score, consistent with the $NE1$ assumption that r "owes" half of its information content to the credit score.

The regression's R^2 is extremely low, which *does not* indicate that the market price is deprived of information. In fact, the opposite claim would be correct: in almost 60% of auctions, 2×0.29, when the signal is either $\left(s^h, p^h\right)$ or $\left(s^l, p^l\right)$, the interest rate provides a strong indication of the loan's type, which is correct 84.5% of the time. The unit coefficient of β reflects, *precisely*, the information that is available during the time of the auction regarding the borrower's type and, therefore, the loan's default probability. The reason for this (apparently deceptive) discrepancy between the quality of the regression and the quality of the price is simple: the R^2 reflects a low predictability of the *event* of default, which is clearly distinct from the ex-ante heterogeneity of borrowers in terms of their *probability* of default.[25]

We now consider two possible mechanisms which may generate a departure from the benchmark estimates in the EMH. First, in addition to competence in Bayesian updating, the EMH assumes that the market maker commands much prior knowledge about the properties of the borrowing population. To see the point, we extend $NE1$ so that $\widetilde{\pi}^h$ is the market maker's beliefs, prior to initiating the platform, regarding the default probability of the h type (and similarly for type l), while the true probabilities of default are still

[25] Even with perfect information, namely with signals that could separate the h type from the l type a 100% of the time, an h signal would "fail to predict" the event of default 90% of the time. By a similar argument, if the signals carried no information at all (i.e. $\lambda^s = \lambda^p = 0.5$), the price distribution would collapse to a single number, namely an interest rate of 8.11%, corresponding to a posterior default probability of 7.5% (same as the prior default probability). In such a case, the EMH still holds because the market price reflects *perfectly* the absence of any ex ante information that would allow us to differentiate default probabilities across auctions.

given by $NE1$. Hence,

$$NE2: \quad NE1, \quad plus \quad \widetilde{\pi}^h = 0.12, \quad \widetilde{\pi}^l = 0.03.$$

In such a case, loans are priced on the $NE2$ priors while the stochastic process that generates the default data is still the same as in $NE1$. The coefficient of 0.574 in column 3 of Table 7 confirms that there is no longer a one-to-one relationship between the interest rate and the default probability. This wedge reflects the fact that the market maker underestimates (overestimate) the default probability of the low (high) type borrowers. Obviously, we expect that as the platform expands operations, the market maker builds up a sample of default *events*, which would allow him to update his priors and correct his pricing policies. An econometrician should be able to test this "learning hypothesis" through a time trend of the β estimator – towards one.

Second, the reality of FC auctions differs from the one discussed so far in two important respects: liquidity is provided by several market makers; and, neither individually, nor jointly do they have unlimited liquidity. It is therefore possible that by the time that the price discovery process ends, a shortage of liquidity prevents the market maker from bidding the interest rate down towards its efficient level; see the discussion of Figure 4 above. Conversely, it is also possible that a surge of uninformed funding, to which the market makers are too slow to respond to, can drive the closing interest rate below the information-efficient price. Let μ be the probability that the auction is hit by a liquidity *shock*, which is negative or positive with equal probabilities, independently of the signal. If so, assume that the shock drives the closing interest rate 20% away from the information-efficient price. With a probability of $(1 - \mu)$, the market makers have enough liquidity to implement the efficient price. Let:

$$NE3: \quad NE1, \quad plus \quad \mu = \frac{2}{3}, \quad r = (\rho + \pi^*) \times [1 + 0.2 \times sign\,(shock)]\,.$$

In column 4 of Table 7 we report the estimation of equation (5) based on the $NE3$ data generating process. As expected, $\hat{\beta}$ loses statistical significance and falls sharply below 1, to 0.18. This is because the variation in the interest rate contains so much noise so as to introduce a downwards bias into the estimator and generate excess sensitivity with respect to default risk. For a similar reason, the *Dscore* coefficient, γ, gains both economic and statistical significance. Due to the "error" in r, the interest rate no longer conveys the entire information contained in the credit score, so that the *Dscore* variable makes a larger contribution to the prediction of the default events.

Next, suppose the econometrician has an opportunity to observe the liquidity event (either negative, positive, or zero) with a probability of ν, so that:

$$NE4: \quad NE3 \quad plus \quad \nu = 0.75.$$

The inclusion of the liquidity variable in the regression in column 5 does not imply any causal relationship between the liquidity event and the default event. Rather, it allows the econometrician to correct some of the bias in the estimator, as well as to test the hypothesis that the noise in the price results from a liquidity shock. Although, in this particular setting, the coefficient of the liquidity variable is not significant, its negative sign is consistent with the hypothesis. To see why, suppose that the auction is affected by a positive shock that drives the closing rate above the information efficient price. Compared with another auction with the same closing price but without a liquidity shock, the estimator tracks a low probability of default and corrects the estimation by assigning a negative sign to the coefficient of the liquidity variable. Since part of the measurement error is corrected, the estimate on the interest rate gains economic and statistical significance.

While the inclusion of the liquidity variable in column 5 allows the econometrician to remove some noise from the estimation of the default probability, it makes no difference to the borrowers. A borrower who is unlucky to auction off his loan at a time of short liquidity would be stuck with a high interest rate for the entire duration of the loan. It is less of a problem for investors who hold a diversified portfolio of loans and are therefore more likely to average out discounts and premia. The efficiency of the capital allocation process would be undermined as a result. As already hinted above, the critical question is not whether the price carries information but, rather, the extent to which price variability reflects information: a market with no information and flat prices would be considered information efficient, while a market with some information but with significantly larger noise in the price would be considered information inefficient.

5.3 Adjustments for loss given default and systematic risk

Two additional adjustments are required before we can apply the results of this section to our data. In our sample, LGD is much lower than 100%, closer to 50%. Denoting LGD by γ, and still within the risk-neutral framework, the zero profit condition can be written as.

$$1 + \rho = (1 - \pi)(1 + r) + \pi (1 - \gamma)(1 + r),$$

linearly approximated by:

$$\rho \approx r - \gamma\pi. \tag{6}$$

It follows that there is still a one-to-one relationship between the LGD-adjusted interest rate, $\frac{r}{\gamma}$ and the default probability:

$$\pi \approx -\frac{\rho}{\gamma} + \frac{r}{\gamma},$$

so that estimating the default equation (5) using the LGD-adjusted interest rate, EMH still implies $\beta = 1$. To illustrate, consider a loan with LGD of 50% whose default probability increased by 1%. The pricing equation (6) implies that the lending rate has increased by only 0.5%. So once we adjust $r = 0.5$ by $\gamma = 0.5$ we are back to the one to one relationship.

In estimating γ we account for two factors. First, our loans are amortized in monthly payments. If they default, they do so after performing, on average, for 42% of the monthly payments due; see Table 1. Second, as noted above, FC has high recovery rates on the balance left, 29% on average; see Table 1. Let m_i be loan $i's$ maturity (in months), m_i^{prf} the number of months that it performed before defaulting, and μ_i the recovery rate, post default, on the balance left at the point of default. Then, loan i's LGD is given by:

$$1 - \gamma_i = \frac{m_i^{prf} + (m_i - m_i^{prf}) \times \mu_i}{m_i}.$$

Taking the mean over the loans that have defaulted we obtain the adjustment factor, γ, that we use in order to adjust the interest rates of all the loans that participate in the estimation of equation (5), whether they have defaulted or not.

The second important adjustment is related to the effect of systematic risk. While it is generally agreed that "fundamental" factors cannot explain all, not even most of the variability in bond prices, they do have some explanatory power. For example, Schaefer and Strebulaev (2008) consider a decomposition of the price of a bond into a fundamental credit component, namely that part that can be explained by a structural model such as Merton (1974), and a noncredit part. They demonstrate that the fundamental part is related to the value of the firm. In the absence of our SME loans being listed, we augment the default equation (5) with an industry level asset beta for companies, in the expectation that they will capture the systematic component of the loan price.[26] In theory, this variable should have a negative coefficient. Consider two loans, A and B, the former has an asset beta of zero and the latter has a positive asset beta. It follows that loan A should be priced on a risk-neutral basis, while loan B should include a risk premium component. It follows that, conditional on the same price, loan B should have

[26] The data source is: $http://pages.stern.nyu.edu/\ adamodar/New_{H}ome_{P}age/datafile/Betas.html$.

a smaller idiosyncratic default probability. [27]

6 Results

The main object of this section is to test the hypotheses that were developed in Section 5. In section 6.1, we test the benchmark hypothesis that loans are efficiently priced. In section 6.2, we explore whether liquidity shocks explain deviations from efficient pricing. Section 6.3 assesses information aggregation, and section 6.4 provides a robustness check.

6.1 Default probabilities and prices

Table 8 presents our baseline default equation (5) with $Ddefault$ as the dependent variable. Since we estimate the quarterly default probability (as we have done in Table 2 above) we use quarterly interest rates and adjust them for our empirical estimates of LGD as described in Section 5 above. As before, the specification is estimated using OLS with heteroskedasticity robust standard errors, clustered at the loan level.[28]

Columns 1 and 2 show that estimates for the average interest rate are significantly greater than 0 and significantly smaller than 1 at the 1% significance level. That is, a 1% increase in the lending rate is associated with an increase of just 0.40% in the probability of default. This result is consistent with interest rates having a predictive power over and above the credit scores and, therefore, with the idea that the market can generate/aggregate information on top of institutionalized providers of information.

[27] Feldhütter and Schaefer (2018) point out an additional problem related to the clustering of defaults around downturns of the business cycle, resulting in statistical biases in the estimation of default probabilities in long time series. Hopefully, our sample with relatively short maturity loans and no downturn in the business cycle avoids this problem.

[28] Estimates of marginal effects using non-linear probability models, such as logit and probit models, yield very similar results.

However, the coefficients are also significantly below one (excess sensitivity), and therefore indicate that information efficiency in the pricing of loans was not reached.

Column 3 provides estimates of the information content of prices across time by interacting the interest rate with annual time dummies. The results in column 3 are striking. They indicate that the interest rate coefficient for auctions in 2011 does not differ significantly from one, suggesting that we cannot reject the EMH for that year. However, subsequent years tell a very different story. The coefficients are negative and significant suggesting an increasing wedge with respect to our benchmark. Indeed by 2015, the year before the move to posted prices, the coefficient on the interest rate was virtually indistinguishable from 0, suggesting that there was little additional information provided by prices over and above the credit scores. The results are clearly inconsistent with the learning hypothesis discussed in Section 5.[29]

Another result, emerging from a comparison of columns 1 to 3 with columns 4 to 6, is that the coefficient of the average closing rate is closer to one relative to the coefficient of the marginal closing rate. As noted above, on average, the interest rate for autobid orders is 0.6% below that of active orders. One interpretation, is that the autobid moderates the over sensitivity tendency in FC auctions, driving the interest rate closer to the information-efficient price; see further discussion below.

The estimates in Table 8 also provide preliminary evidence on the importance of liquidity constraints in the pricing of loans. During the sample period, FC's growth rates were exceptionally high and quite volatile. In a perfect EMH world, the liquidity providers would be able to bridge funding gaps and price the loans on information alone. In practice, it might take them time to adjust their supply of liquidity. On the FC platform, given the volatility of loan demand and slow moving capital, the timing of an auction can therefore affect the borrower's cost of capital. To test this idea we aggregate, for any loan i in

[29]We also test the learning hypothesis through a linear time trend, and by splitting the sample into batches of 1,500 auctions.

Table 8: Baseline Regression

	(1)	(2)	(3)	(4)	(5)	(6)
Average Interest Rate	0.409***	0.447***	1.006***			
	(0.079)	(0.081)	(0.257)			
Marginal Rate				0.225***	0.250***	0.577**
				(0.046)	(0.047)	(0.224)
Rate 2012			-0.535**			-0.314
			(0.231)			(0.213)
Rate 2013			-0.530**			-0.327
			(0.242)			(0.220)
Rate 2014			-0.688***			-0.424*
			(0.244)			(0.221)
Rate 2015			-0.811***			-0.525**
			(0.252)			(0.228)
Aggregate Growth Rate		-0.003**	-0.003**		-0.003**	-0.003**
		(0.001)	(0.001)		(0.001)	(0.001)
Industry Asset Beta	0.007**	0.007**	0.007**	0.007**	0.007**	0.007**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Early Closure			0.003***			0.003***
			(0.001)			(0.001)
Floor Auction			-0.001			-0.000
			(0.001)			(0.001)
Constant	-0.018***	-0.016***	-0.019***	-0.010***	-0.008*	-0.010**
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.2	0.2	0.3	0.2	0.2	0.3
N	80,529	80,529	80,529	80,529	80,529	80,529

OLS regressions over loan quarters to either default, maturity, or currently being serviced of $7,455$ auctions. Dependent variable: a dummy, equals 1 if default took place during the quarter and 0 otherwise. "Average Interest Rate": weighted average across accepted orders. "Marginal Interest rate: highest accepted rate. Both rates were adjusted to mimic 100% loss-given-default loans. "FC Growth Rate": aggregate value of loans open in the 7 days prior to the close of loan i deflated by the balance of all loans issued by FC up to 8 days prior to the close of auction i, deviations from a logistic trend. "Early Closure": dummy, equals 1 if the auction was terminated prematurely and 0 otherwise. "Floor Auction": dummy, equals 1 if the auction hit an FC-set floor and 0 otherwise. "FE": fixed effects. Standard errors are adjusted for heteroskedasticity and clustering at the loan level. ***, ** and * denote statistical significance at 1%, 5%, and 10%, respectively.

the sample, the value of all the other loans whose auctions were open during the seven days prior to the close of the auction. That number is normalized by the total value of FC's outstanding loan book on the eighth day prior to the close. The ratio measures the growth rate of FC's loanbook in the seven days that the auction was open.[30]

The coefficient on the aggregate growth rate is negative, significant at the 5% or 10% level.This provides additional evidence against the null of the EMH hypothesis, and is consistent with our discussion of liquidity in the Monte Carlo experiments (see column 5 of Table 7). Consider, for example, two auctions, one closing when there is a high demand for loans and a liquidity shortage, and the other when the demand for new loans is normal. They both close at an interest rate of 8%, say, but the loan in the high-demand auction has a lower probability of default, *given* the interest rate. It follows that the "right" interest rate of the high-demand loan should be lower, or, that loans funded during periods of high demand are priced *above* the information efficient interest rate. The Monte Carlo experiment also predicted that including a proxy for the shock would drive the coefficient of the interest rate closer to one, which is indeed the case between columns 1 and 2, providing further support for the hypothesis that the deviations from EMH are at least partly the result of liquidity shortages.

Columns 3 and 6 also include the variable "Early Closure", a dummy that receives a value of 1 if the auction is terminated by the borrower, before it runs its full course of (typically) seven days. The variable is positive and highly significant, statistically and economically. The implication is that an early termination auction has a higher probability of default relative to auctions with the same closing rate that did not close early. Annualized, the 30bp per quarter coefficient implies an annual default probability that is 1.2% higher relative to a loan that closed at the same rate and was not terminated early by the borrower. A plausible interpretation, consistent with our evidence on the characteristics of early terminators in subsection 4.2, is that they have a high opportunity

[30] Given the high growth in FC's loanbook, this expression is decreasing monotonically. We filter out the very strong downward trend in the series through a logistic fitted line.

cost of waiting and are therefore willing to sacrifice the downward trend in rates over auction time. Clearly, they have no incentive to inform the market of their intention to terminate the auction prematurely, thereby preventing any adjustment in prices.

The last variables included in the specifications are the industry-beta and the indicator for a floor auction. Contrary to the EMH prediction, the industry-beta variable has a positive rather than a negative sign. That is, high-beta industries have high default rates that were *not* priced in. Remember that the EMH prediction of a negative beta is based on the assumption that the default probability is priced in correctly. The "Floor Auction", is a dummy variable that receives a value of one if the auction hits the floor imposed by FC, and zero otherwise. It tests the hypothesis that such interference has reduced information efficiency. Evidently, the hypothesis is rejected in the data and suggests that FC operated the floor in a way that did not distort the interest rates.

6.2 Information efficiency and liquidity

The evidence so far not only suggests that information efficiency was not achieved, but that the excess sensitivity increased over time. Initial results, consistent with the methodological framework, suggest that the wedge is correlated with surges in demand for loans proxied by the growth rate of the platform. We provide two more refined tests.

The first test is based on Amihud (2002), and measures the depth of the market by the slope of the investors' supply curve around its intersection with the demand curve. The slope is estimated locally by OLS on the $[0.75, 1.25]$ interval of the supply schedule. We take auctions that closed with steep supply curves to be illiquid, thereby more prone to mispricing. A steep supply curve indicates that the price discovery process was less effective in narrowing investors' expectations regarding default risk and, therefore, the pricing of the loan was set further away from the efficient market benchmark.

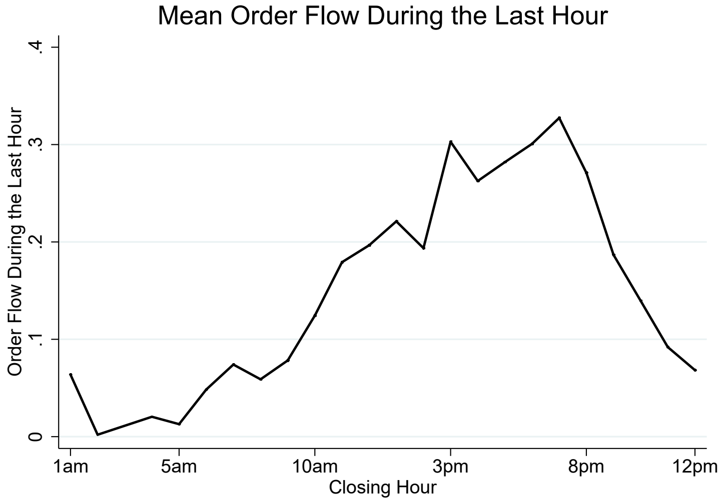
Table 9: Liquid and Illiquid Auctions According to Supply Curve Slope

	(1)	(2)	(3)	(4)
Average Interest Rate	0.340***	0.596***		
	(0.081)	(0.149)		
Marginal Rate			0.174***	0.513***
			(0.048)	(0.123)
Above Median Slope		0.010**		0.013***
		(0.004)		(0.004)
Above Median Slope*Rate		-0.167**		-0.213***
		(0.078)		(0.066)
Industry Asset Beta	0.008***	0.006**	0.008***	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)
Early Closure	0.004***	0.003***	0.004***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Aggregate Growth Rate	-0.074*	-0.075*	-0.071	-0.074*
	(0.044)	(0.045)	(0.044)	(0.045)
Constant	-0.015***	-0.028***	-0.008**	-0.026***
	(0.005)	(0.008)	(0.004)	(0.007)
R-squared	0.3	0.3	0.2	0.3
N	80,529	76,860	80,529	76,860

Baseline regressions as in Table 8, separated by the slope of the supply curve at the close. Dependent variable: a dummy, equals 1 if default took place during the quarter and 0 otherwise. "Average Interest Rate": weighted average across accepted orders. The slope is estimated by OLS on the $[0.75, 1.25]$ interval of the quantity axis. "High Slope" is dummy variable that receives a value of 1 if the slope is above median and zero otherwise. Standard errors are adjusted for heteroskedasticity and clustering at the loan level. ***, ** and * denote statistical significance at 1%, 5%, and 10%, respectively.

Column 1 in Table 9 reports the base level regression. In Column 2 we add the "High Slope" dummy that receives a value of one if the auction's supply curve (at the close) is steeper than the median slope of our sample of auctions. More importantly, we also add an interaction term between the slope dummy and the interest rate. Column 2 shows that for liquid auctions, namely auctions with a flat supply curve, the over reaction problem is significantly smaller. The coefficient of the average interest rate for liquid auctions is 0.596, while the price coefficient on illiquid auctions is almost 30% smaller.

Figure 5: Mean Inflow of Funds, According to Closing Hour



The second test examines the effect of liquidity changes and exploits the quasi-random allocation of an auction's closing hour as a "pure liquidity event". Figure 5 plots the average inflow of active orders[31] (by value, normalized by loan size) during the last hour that the auction is open against the closing hour. Clearly, there is much more active bidding in auctions that close between 3pm and 7pm compared with auctions that close in "off peak" hours such as 10am. Using this distinction, we provide a comparison of borrower characteristics across peak and off peak closing hours in Table 10. The results confirm that the allocation of the closing hour is, in all likelihood, random. Indeed the closing hour of the auction is not correlated with any borrower characteristics, including credit rating, industry, purpose of loan and geographic location. The table also confirms that peak order flows differ significantly from off peak order flows: 29.3% of the value of the loan in the former case against only 17.3% in the latter case.[32]

Under the EMH hypothesis, such a pure liquidity event should not affect the price, as the liquidity providers should be able to compensate for the shortage of liquidity and avoid mispricing. Columns 2 and 5 in Table 11 include the peak time dummy as a control

[31] There is no autobid activity during that time.

[32] Floor-hitting auctions, which might be more likely to close off peak (at a low interest rate) are excluded from the tests in Table 10.

Table 10: Balancing Tests According to Closing Hour

Variable	(1) Off Peak	(2) Peak	(3) Difference	(4) Standard Error	(5) N	(6) P-Value
Rating: A+	0.123	0.130	0.00723	0.00811	6,715	0.373
Rating: A	0.309	0.306	-0.00304	0.0113	6,715	0.787
Rating: B	0.273	0.267	-0.00644	0.0108	6,715	0.552
Rating: C	0.234	0.229	-0.00536	0.0103	6,715	0.603
Rating: D	0.0608	0.0684	0.00761	0.00600	6,715	0.205
Activity: IT	0.0695	0.0713	0.00183	0.00625	6,715	0.770
Activity: Manufacturing	0.138	0.126	-0.0122	0.00825	6,715	0.138
Purpose: Expansion	0.466	0.466	0.000848	0.0122	6,715	0.944
Purpose: Working Capital	0.404	0.391	-0.0126	0.0119	6715	0.290
Geography: London	0.126	0.133	0.00717	0.00819	6,715	0.382
Geography: South East	0.214	0.229	0.0151	0.0101	6,715	0.137
Last Hour Order Flow	0.173	0.293	0.120	0.00632	6,567	0
Auction-Aggregate Autobid share	0.0426	-0.00869	-0.0513	0.00392	6,715	0

The table reports the mean of borrowers according to the closing hour of the auction. "Peak" refers to auctions closing between 3pm and 7pm, "Off Peak" refers to all other auctions. "Auction-Aggregate Autobid Share": the difference between auction-i autobid funding and "Aggregate Autobid Funding" in the seven days before the close of auction i. ***, ** and * denote statistical significance at 1%, 5%, and 10%, respectively.

variable. The positive sign, significant at a 10% level, is consistent with a liquidity shortage off peak. The argument is similar to the one already used above: consider two auctions, one closing at peak hours and the other closing at off peak. Conditional on the interest rate at off peak and peak being the same, the implication of the coefficient of .001 is that loans at off peak have about a 20% lower probability of default and therefore are mispriced relative to loans closing at the peak.[33] It follows that the off peak auction closed above the information-efficient interest rate, and the augmented OLS estimator adjusts the probability of default downwards.

So far, we did not distinguish between the role of active investors and autobid in providing liquidity. The distinction may be of importance given the amounts channeled through autobid, and the extent to which it was used to mitigate the adverse consequences of liquidity shortages to borrowers. Under the EMH, a carefully optimized autobid should only remove the effect of random liquidity shocks but correctly price in all the information contained in the order flow. To further investigate the role played by the platform algorithm, we augment the baseline regression with the variable "Auction-Aggregate Autobid Share", defined as the share of the autobid in auction i funding, minus the overall aggregate autobid share during the week that auction i was open. The idea is to capture auctions in which the autobid activity was above (or below) the average share across all auctions.

In columns 1 and 4 the variable "Auction-Aggregate Autobid Share" is positive, between 0.006 and 0.005, and statistically significant. All else equal, a one standard deviation increase in loan level autobid activity, resulting from a low level of active bidding (see Figure 4), predicts a 10% higher default probability, over and above what is already priced into the lending rate. This suggests that the low level of active bidding was not related to liquidity shocks but rather to information of investors about the quality of the loan. A possible refinement in autobid design would have allowed a stronger reaction of

[33] The unconditional quarterly probability of default is .5%.

interest rates to information in the order flow through, say, a steeper supply curve at the start of the auction.

We further disentangle the impact of the autobid by focusing on pure liquidity shocks arising from closing hours. In columns (3) and (6) we instrument the loan-level autobid funding with the off peak dummy. Strikingly, the coefficient on the autobid variable becomes negative, -.088, and is statistically significant at the 10% level. The result suggests that, when the surge in autobid activity results from pure shortages of liquidity, the increase in the interest rate was unrelated to a higher default probability. Therefore the estimate on the autobid adjusts the probability of default downwards. Given that the information on closing hours is common knowledge a possible refinement in autobid design would have shifted the supply schedule to the right in off peak hours.

The dual role of the autobid was subject to discussion amongst investors. For example, one blogger wrote on February 2014: "The autobidder will now be chucking every penny it can into that loan. ... If I were an Autobid user, I'd want it to buy me a random sample, like a sort of index tracker - not something programmed to soak up the [loans] that manual bidders don't want.[34]" Our results suggest that such a criticism does not fully reflect the trade offs faced by FC in balancing the two sides of the market. Notwithstanding, FC offers today something close to what the blogger suggested for investors, i.e., a diversified portfolio of loans at a pre-specified interest rate.

6.3 Assessing information aggregation

As noted in the discussion of Section 5 above, incremental changes in the R^2 in response to the inclusion of additional regressors in the default equation can help us identify the various sources of information, in particular credit scores versus market signals.

Panel A of Table 12 repeats earlier results and shows that adding the average interest rate to the default equation we improve the explanatory power of the regression by 23%

[34] Post by blogger who identifies himself as "aloanatlast" on Feb 21, 2014 at 1:28pm.

Table 11: Off/On Peak Closing Hours and Auction Level Autobid Activity

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	IV	OLS	OLS	IV
Average Interest Rate	0.351***	0.355***	0.206			
	(0.084)	(0.084)	(0.128)			
Marginal Rate				0.177***	0.180***	0.204***
				(0.051)	(0.051)	(0.061)
Aggregate Bot Funding	-0.011	-0.010	-0.026**	-0.012*	-0.011*	-0.026**
	(0.007)	(0.007)	(0.012)	(0.007)	(0.007)	(0.011)
Auction-Aggregate Autobid Share	0.006**	0.006**	-0.088*	0.005*	0.005**	-0.093*
	(0.002)	(0.002)	(0.054)	(0.002)	(0.002)	(0.056)
Peak (3pm-7pm) closure		0.001*			0.001*	
		(0.001)			(0.001)	
Industry Asset Beta	0.008***	0.008***		0.008***	0.008***	
	(0.003)	(0.003)		(0.003)	(0.003)	
Aggregate Growth Rate	-0.002*	-0.002*	-0.002	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Early Closure	0.003***	0.003***	0.017**	0.003***	0.003***	0.017**
	(0.001)	(0.001)	(0.008)	(0.001)	(0.001)	(0.008)
Floor Auction	0.001	0.001	-0.010	0.001	0.001	-0.010
	(0.001)	(0.001)	(0.006)	(0.001)	(0.001)	(0.006)
Constant	-0.010*	-0.011*	0.011	-0.002	-0.003	0.012**
	(0.006)	(0.006)	(0.009)	(0.005)	(0.005)	(0.006)
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.3	0.3	.	0.3	0.3	.
N	80,529	80,529	80529	80,529	80,529	80,529

Baseline regressions as in Table 8, augmented with "peak" dummy variable equal to one if the auction closes at peak hours (3pm to 7pm) and zero otherwise. Dependent variable: a dummy, equals 1 if default took place during the quarter and 0 otherwise. "Average Interest Rate": weighted average across accepted orders. In columns 2, and 5 the closing hour dummy is used as an explanatory variable, in columns 3 and 6 it is used to instrument auction level autobid activity. The variable "Auction-Aggregate Autobid Share" is defined as the difference between auction-i autobid funding and "Aggregate Autobid Funding" in the seven days before the close of auction i. Standard errors are adjusted for heteroskedasticity and clustering at the loan level. ***, ** and * denote statistical significance at 1%, 5%, and 10%, respectively.

Table 12: Information content of prices

	credit scores	plus average interest rate	plus other market indicators
	Panel A, dependent variable: default dummy		
R^2	0.17	0.21	0.25
N	80,529	80,529	80,529
	Panel B, dependent variable: average interest rate (on fitted values from Panel A)		
R^2	13	28	24
N	7,455	7,455	7,455

In Panel A, column 1 includes, on the right hand side, only the credit scores and quarterly dummies. Column 2 adds the loan's average interest rate. Column 3 adds "FC Growth Rate" "Floor Auctions" "Early Closure" "Marginal Closing Rate" and "Auction Autobid Share" as defined in Table 8 In Panel B we compresses the sample back to loan book file, same as in columns 1 and 2 of Table 2 and run regressions of the average interest rate on the fitted values from Panel A.

$(0.21/0.17-1)$. Clearly, the amount of information added by market signals, over and above the credit score, is not trivial. In the third column we augment the regression with those variables that the previous section has identified as having power in predicting default: "FC Growth Rate", "Floor Auctions", "Early Closure", "Marginal Closing Rate" and "Auction Autobid Share". We interpret the substantial increase in the R^2 as evidence that during the time of the auction, some additional information was present in the market, but that information was not fully incorporated into the closing price. Had the entirety of that information been priced in, through certain refinements in the design of the autobid, it would have improved the information efficiency of the price by 19% $(0.25/0.21-1)$ over and above the credit scores. Unfortunately, we cannot account for changes in the bidding behavior of investors in response to changes in the design. We therefore interpret the 19% figure as an upper bound to the potential improvement in price efficiency.

As noted in Section 5, the test of market efficiency is not in the amount of information that an econometrician can extract from the market price, but the extent to which information that exists at the time that the market is open is incorporated into the market price: a market with little information and little price variability may be considered more information efficient relative to a market with some information but much *unrelated* price volatility. The appendix provides Monte Carlo simulations showing that the fitted value from the default regressions of Panel A, can be used as a proxy for the best estimate of the loan-level default probability, given the information available at the time of the auction.[35] Panel B of Table 12 relates the variation in interest rates to the predicted value of the loan default probability. The striking result is, that no more than 28% of the price variability is related to information in the credit score and the market prices. Clearly such a large amount of noise in the price decreases the coefficient of the interest rate in the default regression thereby accounting for the excess sensitivity result.

6.4 Robustness check

Iyer et. al. (2015) question whether significant interest-rate coefficients in EMH regressions as in Table 8 actually imply that markets aggregate useful *private* information, dispersed across platform participants. Their argument is based on the observation that the entire process starts with *continuous* credit scores, derived by the analysis of credit data from largely *public* sources, which are then converted into discrete credit scores, A+ to D, by the platform. Possibly, investors may reverse engineer the discrete scores back to the continuous scores, thereby improving the predictability of default events "over and above" the platform's credit scores, but without actually adding much new information. Such a null hypothesis has quite a negative implication for an auction design of P2B platforms, since although it recognizes that markets aggregate information, it also implies that there is a much simpler way to price that information: the platform should reveal the continuous score instead (perhaps on top) of the discrete scores.

Like Iyer et. al. (2015), we reject this hypothesis albeit using our own framework. As

[35] See Appendix. We demonstrate, there, that $1 - R^2$ is a lower bound to the actual amount of noise. We also show that the bias is small when the other signals are relatively precise. Hence, we treat the numbers in Table 12 as a "good approximation" to the information content of the price. We also have an analytical characterization of the estimator (available on demand).

demonstrated in columns 1 and 2 of Table 2, credit scores define interest rates bands, about 1% wide. At the same time, pricing outside of the band is quite a common occurrence. Consequently, if lenders just reconstitute the finer rating information, pricing outside of the band should be relatively less informative about the likelihood of credit events. In other words, under the null of our test, the auctions generate information only within the interest rate band, $\pm 50bp$ around the midpoint of each interest rate band.

The results are presented in Table 13. “High Deviation” (“Low Deviation”) is a dummy variable that receives a value of 1 if the loan is priced more (less) than $50bp$ away from the midpoint and zero otherwise. The interaction between the “High Deviation” dummy and the “Rate” yields a positive coefficient significant at the 5% level. This implies that, when a loan is priced above the usual benchmark, a 1% increase in the average lending rate predicts a 0.446+0.284=0.730% higher default rate. Instead, inside the band, a 1% increase in the average lending rate predicts only a 0.446% higher default probability. In other words the information content of prices is even higher for loans priced above the band.

7 Conclusions: why did FC abandon auctions?

In September 2015 FC announced that it was abandoning auctions in favor of posted fixed prices. Their justification for this change was threefold: “(i) Businesses are put off by a lack of certainty around the cost of their loan, which is important to them; (ii) The price of each loan will now be based on the risk (and term) of the loan, rather than the availability of investor funds; and, (iii) Borrowers will know how much their loan will cost before the funding process, attracting more businesses to Funding Circle, which will create more lending opportunities for you.”[36] It is important to note that FC appreciated that the uneven flow of funds into the platform was increasing the volatility of interest rates that was largely unrelated to changes in default risk. In our early discussions with FC they brought this issue to our attention. Thus our results in Section 6.2 confirm a strong relation between changes in liquidity and pricing efficiency.

[36]https://www.fundingcircle.com/uk/fixedrate/.

Table 13: Pricing In And Out Of The Credit Rating Band

	(1)	(2)	(3)	(4)
Average Interest Rate	0.336***	0.255**		
	(0.128)	(0.111)		
Marginal Rate			0.260***	0.160**
			(0.086)	(0.067)
High Deviation	-0.017***		-0.004	
	(0.005)		(0.005)	
Rate*High Deviation	0.259***		0.028	
	(0.092)		(0.073)	
Low Deviation		0.007*		0.006
		(0.004)		(0.004)
Rate*Low Deviation		-0.179**		-0.123*
		(0.080)		(0.072)
Industry Asset Beta	0.008**	0.008***	0.008***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)
Early Closure	0.003***	0.004***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Floor Auction	0.000	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Aggregate Growth Rate	-0.002*	-0.003**	-0.002*	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-0.013**	-0.010*	-0.010**	-0.006
	(0.006)	(0.006)	(0.005)	(0.005)
Rating FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
R-squared	0.3	0.3	0.2	0.2
N	80,529	80,529	80,529	80,529

Baseline regressions as in Table 8, augmented with High-Low, $\pm 0.5\%$, deviation from the benchmark interest rate as defined by the credit-rating dummies in Table 2, interacted with "Rate". Dependent variable: a dummy, equals 1 if default took place during the quarter and 0 otherwise. "Average Interest Rate": weighted average across accepted orders. Standard errors are adjusted for heteroskedasticity and clustering at the loan level. ***, ** and * denote statistical significance at 1%, 5%, and 10%, respectively.

Rather than moving to posted prices FC could have engaged in refining the auction design so as to make the price more efficient. We have already mentioned the fact that, on average, active (non autobid) investors gain a 0.6% premium on their accepted orders relative to autobid investors. That premium could have been raised so as to increase the reward to active, informed investors; see Cornelli and Goldreich (2001) for a similar measure used in IPOs. For a similar reason, the minimum size of an active order could have also been increased above £20, as small stakes are a disincentive to monitoring and screening by investors. Another change to the design could have involved decreasing the sensitivity of the closing price to liquidity shocks by having loans placed in a queue, to be auctioned off only when there was sufficient supply of liquidity in the market. Such measures have also been used in IPO markets.[37]

Another factor that could explain the transition to posted prices is that P2B is an industry with extremely strong network externalities, so that the first to accumulate a critical market share is likely to be the industry's winner. These considerations might have motivated FC to abandon the quest for a refined auction design in favor of a mechanism allowing for the greater growth of lending. At the same time, the growth in lending volumes was increasingly financed by autobid investors, which came to dominate the allocation of funds on the platform. In the words of one investor on the thread of the FC forum in November 2013: "I'm left wondering whether FC's model is now becoming reliant on attracting ever increasing numbers of auto-bidders as the funds required increase, and the effort of even basic due diligence becomes too great for manual bidders."[38] As noted above, the posted price regime did not survive for long. Our analysis helps explains why: if anything, the new design of the market exacerbated the informational advantages of sophisticated investors, as they no longer revealed their valuations through the bidding process.

[37]To solve the problem of the mispricing in early termination, borrowers could also get the option of jumping the queue. However, such a request might be made public, providing investors an additional indication that the borrower is more financially constrained.

[38]http://p2pindependentforum.com/thread/85/dramatic-increase-loan-requests-good

Going forward, what is the future of auctions in Fintech? Our analysis confirms that auctions can reveal some valuable information about default probabilities, even in relatively small and illiquid SME markets. Indeed, the information content of the price seems to be comparable to that in developed corporate bond markets. The analysis also suggests, at least qualitatively, ways to improve the design of the auction. Perhaps, once the market matures, so that demand and supply becomes less volatile and more data is accumulated, auctions could could be used in on line debt markets. Perhaps the most important lesson of the analysis is that advanced technology, while capable of dramatic decreases in transaction costs, cannot eliminate the information and liquidity frictions that are familiar to classical financial analysis.

Appendix: the noise content of prices

How much of the interest rate variance is due to noise? In a Monte Carlo setting, that magnitude can be identified with the R^2 in a regression of the closing price on the *true* probability of default, π^*. For example, since all price variability in column 2 of Table 7 is due to information, a regression of that sort would yield an R^2 of one, but that would not be the case in column 4 because some of the price variability is due to liquidity shocks. Clearly, this observation is irrelevant in practice because π^* is not observable to the econometrician. It does, however, suggest an alternative: instead of π^* use the "best guess" that the econometrician has regarding the probability of default, namely the fitted value, $\widehat{\pi}$, from the regression in column 4.

We test the effectiveness of this intuitive solution with the same Monte Carlo experiments as in Section 5. We start by regressing the unobservable "true" probability of default, π^* on the fitted value $\widehat{\pi}$. As the top line in Table 14 show, $\widehat{\pi}$ predicts almost 70% of the variance in π^*. (The slope coefficient in that regression is 1.038.) Then, in the

Table 14: Monte Carlo experiments, information content of prices

regression	R^2
π^* on $\widehat{\pi}$	69
r on π^*	52
r on $\widehat{\pi}$	55
r on $\widehat{\pi}$ and liquidity	75

Information content under $NE4$. $\widehat{\pi}$ is the fitted value from Table 7 Column 4 while π^* is the "true" ex ante probability of default, same as under $NE1$.

second and third rows of Table 14, we move on to compare the R^2s in regressions of r on the true and on the fitted value of the probability of default. The results are strikingly similar: a partial R^2 of 55% when using the fitted value compared with a partial R^2 of 52% when using the fitted value. Analytical results with algebraic derivations of the R^2 are available on request. They confirm that the method gives slightly biased results that under (over) state the noise (information) content of the price (consistent with the simulation results above). The analysis also confirms that the bias is decreasing in the precision of the non-price variable that is used in the estimation of $\widehat{\pi}$, in our case the credit score.

Lastly, we try to identify the source of the noise through the signal ν. The result is presented in the bottom row of the Table 14. An econometrician would suggest the following interpretation: could liquidity shock be removed, the information content of the price would be improved to 75%, equal to the precision of ν in capturing the liquidity shock. The market maker would suggest a slightly different interpretation: if he had an unlimited amount of liquidity, he could restore information efficiency 100% of the time, provided that liquidity is the only factor that drives the closing price away from information efficiency. As noted in the discussion of Section 5 above, the low R^2 in the default regressions is irrelevant to the analysis of market efficiency. At the same time, incremental changes in the R^2 in response to the inclusion of additional regressors in the default equation can help us identify the various sources of information, in particular credit scores versus market signals.

References

[1] Admati, Anat and Paul Pfleiderer, (1991). "Sunshine Trading and Financial Markets Equilibrium." *The Review of Financial Studies,* 4 (3), pp. 443-481.

[2] Allen, Franklin and Douglas Gale, (1995). "A Welfare Comparison of Intermediaries and Financial Markets in Germany and the US." *The European Economic Review*, 39, pp. 179-209.

[3] Amihud, Yakov, (2002). "Illiquidity and stock returns: Cross-section and time series effects," *Journal of Financial Markets* 5, pp. 31–56.

[4] Biais, Bruno, Peter Bossaerts and Jean-Charles Rochet (2002). "An Optimal IPO Mechanism," *Review of Economic Studies*, 69 (1), pp. 117-146.

[5] Biais, Bruno, Pierre Hillion, and Chester Spatt, (1999). "Price Discovery and Learning during the Preopening Period in the Paris Bourse." *Journal of Political Economy*, 107 (6), pp. 1218-1248.

[6] Cespedes, Jacelly. (2018). "Heterogeneous Sensitivities to Interest Rate Changes: Evidence from Consumer Loans," Working Paper.

[7] Collin-Dufresne, Pierre, Robert S. Goldstein and J. Spencer Martin, (2001). "The Determinants of Credit Spread Changes," *The Journal of Finance*, 56 (6) pp. 2177-2207.

[8] Cornelli, Francesca and David Goldreich, (2001). "Bookbuilding and Strategic Allocation." *The Journal of Finance*, 56 (6), pp. 2337–2369.

[9] D'Acunto, Francesco, Nagpurnanand Prabhala, and Alberto Rossi, (2018). "The promises and pitfalls of robo-advising." Forthcoming. Review of Financial Studies.

[10] DeMarzo Peter and Darrell Duffie, (1999). "A Liquidity-Based Model of Security Design." Econometrica. 67 (1), pp. 55-99.

[11] Diamond, Douglas W., (1984). "Financial Intermediation and Delegated Monitoring." The Review of Economic Studies, 51 (3), 393-414.

[12] Driessen, Joost, (2004). "Is Default Event Risk Priced in Corporate Bonds?" The Review of Financial Studies, 18 (1), 165-195.

[13] Duffie, Darrell, (2010). "Asset Price Dynamics with Slow-Moving Capital." *The Journal of Finance*, 65 (4), pp. 1237-1267.

[14] Duffie, Darrell and Mathew O. Jackson, (1989). "Optimal Innovation of Futures Contracts." *Review of Financial Studies*, 2, pp. 275-296.

[15] Einav, Liran, Chiara Farronato, Jonathan D. Levin and Neel Sundaresan (2013). "Sales Mechanisms In Online Markets: What Happened to Internet Auctions?" NBER, 19021.

[16] Fama, Eugene F., (1970). "Efficient Capital Markets: A Review of Theory and Empirical." *The Journal of Finance*, 25 (2), pp. 28-30.

[17] Feldhütter, Peter and Stephen M. Schaefer, (2018). "The Myth of the Credit Spread Puzzle," *The Review of Financial Studies,* Forthcoming.

[18] Franks, Julian and Oren Sussman, (2005). "Financial Distress and Bank Restructuring of Small to Medium Size UK Companies." Review of Finance, 9, pp. 65-96.

[19] Grennan, Jullian and Roni Michaely, (2017), "FinTechs and the Market for Financial Analysis", working paper.

[20] Grossman, Sanford J. and Josrph E. Stiglitz (1980). "On the Impossibility of Informationally Efficient Markets." *The American Economic Review*, 70 (3), pp 393-408.

[21] Hayek, F. A. (1945). "The Use of Knowledge in Society." *The American Economic Review*, 35 (4), pp. 519-530.

[22] Haile, Philip A. and Elie Tamer (2003). "Inference with an Incomplete Model of English Auctions." *Journal of Political Economy*, 111 (1), pp. 1-51.

[23] Hertzberg, Andrew, Andres Liberman and Daniel Paravisini, (2018) "Screening on Loan Terms: Evidence from Maturity Choice in Consumer Credit Credit," Forthcoming. Review of Financial Studies.

[24] Houweling, Patrick, Albert Mentink, and Ton Vorst, (2005). "Comparing Possible Proxies of Corporate Bond Liquidity," The Journal of Banking and Finance, 29 (6), pp. 1331-1358.

[25] Iyer, Rajkamal, Asim Ijaz, Khwaja, Erzo F. P. Luttmer and Kelly Shue, (2015). "Screening Peers Softly: Inferring the Quality of Small Borrowers," Management Science, 62 (6), pp. 1554-1577.

[26] Jackson, Andrew (2016). "Marketplace lending: a new strategy for dealing with distressed businesses." *Corporate Rescue and Insolvency,* June, pp. 125-127.

[27] Kyle, Albert S. (1985). "Continuous Auctions and Insider Trading." *Econometrica*, 53 (6), pp. 1315-1335.

[28] Kyle, Albert (1989). "Informed Speculation with Imperfect Competition." *Review of Economic Studies*, 56 (3), pp. 317-355.

[29] Liskovich, Inessa and Maya Shaton. (2018). "Borrowers in Search of Feedback: Evidence from Consumer Credit Markets." Working Paper.

[30] Lucas, Robert E. Jr., (1973)"Expectations and the Neutrality of Money." *Journal of Economic Theory*, 4, pp. 103-124.

[31] Levine, Ross and Sara Zervos, (1998). “Stock Markets, Banks, and Economic Growth.” *The American Economic Review*, 88 (3), pp. 537-558.

[32] Lucas, Robert E. Jr., (1973). “Some international evidence on output-inflation trade-offs.” *The American Economic Review*, 63 (3), pp. 326-334.

[33] Medrano, Luis Angel and Xavier Vive, (2001). “Strategic behavior and price discovery.” RAND Journal of Economics, 32 (2), pp. 221-248.

[34] Merton, Robert C., (1974). “On the pricing of corporate debt: The risk structure of interest rates.” *Journal of Finance*, 29, pp. 449-470.

[35] Milne, Alistair and Paul Parboteeah, (2016). “The Business Models and Economics of Peer-to-Peer Lending.” European Credit Research Institute, No. 17.

[36] Morse, Adair, (2015). “Peer-to-peer crowdfunding: Information and the potential for disruption in consumer lending.” NBER Working Paper, 20899.

[37] Philippon, Thomas, (2016). “The Fintech Opportunity." NBER Working Paper, 22476.

[38] Schaefer, Stephen M. and Ilya Strebulaev, (2008). “Structural models of credit risk are useful: Evidence from hedge ratios on corporate bonds,” *Journal of Financial Economics*, 90 (1), pp. 1, 1-19.

[39] Shleifer, Andrei (1986). “Do demand curves for stocks slope down?” *Journal of Finance*, 41 (3), pp. 579-590.

[40] Shleifer, Andrei (2000). *Inefficient Markets.* Oxford, Oxford University Press.

[41] Shleifer, Andrei and Robert W. Vishny (1997). “The Limits of Arbitrage.” *The Journal of Finance*, 52 (1), pp. 35-55.

[42] Soyeshi, Glenn, (1995). "A Class of Binary Response Models for Grouped Duration Data." *Journal of Applied Econometrics*, 10 (4), pp. 411-431.

[43] Vallee, Boris and Yao Zeng, (2018) "Marketplace Lending: A New Banking Paradigm?" Forthcoming. Review of Financial Studies.

[44] Wei, Zaiyan and Mingfeng Lin (2016). "Market Mechanisms in Online Crowdfunding." Forthcoming, *Management Science.*

[45] Yermack, David (2015). "Corporate Governance and Blockchains." NBER Working Paper, 21802.