Marketplace Lending, Information Aggregation, and Liquidity

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Abstract

"Fintech" innovations are redefining the boundaries between financial intermediaries and markets. In this paper, we study the recent experience of Funding Circle, a leading UK online marketplace that directly matches retail investors with small and medium size corporate borrowers. Recently, Funding Circle replaced its auction system, where both prices and loan allocations were determined by the market, with a posted price system, where only the allocation is determined by the market. An important focus of our analysis is the tradeoff between the information aggregation of auctions and their susceptibility to liquidity shortages. We show that auctions generate a price discovery process that reveals information that can improve the prediction of default events. At the same time, increasing difficulties in matching changes in the demand for loans to the supply of funds has led to a fall in the precision of that information over the sample period, and an increase in the volatility of interest rates. We believe this explains the eventual switch to posted prices.

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1 Introduction

Many insights of modern financial economics originate in the simple observation that information is a public good. Modern finance tries to rationalize the structure and organization of markets so as to amend potential market failures. In particular, financial markets need to facilitate two basic functions. First, providers of funds should *generate* information, along the lines of Townsend (1979) and Diamond (1984), bearing the cost of monitoring. Second, atomistic markets should *aggregate* dispersed information that traders obtain in the normal course of business; see Hayek (1945), Lucas (1972, 1973) and many who followed. An important insight of Grossman and Stiglitz (1980) is that, since the second function provides a disincentive for the first, the two functions need to be separated. Traditionally, banks have taken the role of monitoring while stock markets have taken the role of aggregating dispersed information; see Allen and Gale (1995) or Levine and Zevros (1998). Recently that division of labour has come under pressure from deregulation, globalization and, new technologies; c.f. Philippon (2016). It is the effect of new technologies that we investigate in this paper.

One might expect that the internet, which dramatically decreased the cost of acquiring, processing and communicating information, would expand the role of market-determined prices at the expense of intermediaries. Recent work by Einav et. al (2015) cast doubt on this seemingly straightforward hypothesis. First, they document a trend over time whereby relatively more eBay transactions are executed via posted prices rather than by flexible-price auctions. Second, in line with Hammond (2010), they show that item characteristics affect the mode of transaction: items with heterogeneous and uncertain values, for example, collectables, tend to be sold via auctions. Third, that controlling for changes in the composition of items traded cannot explain the trend away from auctions. They suggest that the result may be explained by some auction-aversion sentiment among buyers as in Arieli and Simonson (2003).

Funding Circle (FC) is a leading British Peer-to-Business (P2B) platform that can directly link retail investors to Small and Medium Size (SME) borrowers.[1] Starting up in 2010, the platform combined both information generation and information aggregation functions: FC's research department provided benchmark credit scores but the actual lending rate was determined by a continuous-time, multi-unit, discriminating auction. In spite of the platform's very high growth rate, in September 2015, FC announced that after "careful consideration" it found that the auction model had "significant drawbacks" and, hence, its decision to replace it with a posted price system, where lenders can determine the allocation of funds, at a price that is fixed by FC. Among the drawbacks of the auction

[1] The economics of P2B platforms is quite different from that of other types of crowdfunding platforms; see Belleflamme (2105) for a survey. For some broader implications of "Fintech" to the future of finance see Yermack (2016).

system, FC mentioned the complexity of the system and the price uncertainty faced by the borrowers. In contrast, under the new system, rates are to be set up "according to the risk of the loan, rather than the availability of investors funds". FC recognized that there was "a group of investors who actively use the auction model to earn above average returns" but expressed confidence that the change would benefit most investors.

We study the FC experiment in order to shed light on the advantages and disadvantages of flexible price auctions. Our sample, covering the period before the switch to posted prices, provides information of outstanding quantity and quality: it contains all the bids that were submitted to the platform, 34 millions, including bid price, bid size, the precise time (up to a split second) of placement and the identity number of the bidder. During the sample period the platform grew at an astonishing 1.9% *per week*.

While there is a vast literature of auctions of various types, treasury-bond auctions, IPOs, Ebay auctions or the micro structure of stock markets, we are not aware of any theoretical analysis that captures the exact design of FC auctions and which could guide our empirical studies. Since it is well known, theoretically, that small changes in auction design may have a dramatic effect on auction performance, we focus our analysis on reduced form properties that are likely to be relevant across structural models. We highlight a tension between two properties of price driven allocations. On the one hand, under the "Information Aggregation Hypothesis" (AGH), auctions generate at least *some* information that would be relevant to predicting default events.[2] On the other hand, we explore the hypothesis that shortages of liquidity have undermined the effectiveness of the auctions in aggregating information. In that we follow Shleifer and Vishny (1997) and Shleifer (2000) "Limits to Arbitrage". A similar idea is expressed in Duffie (2010) who provides an exhaustive survey of empirical results across many markets supporting a tentative theory of "Slow Moving Capital".[3]

We have four main findings. First, we provide a set of stylized facts about the auction's price discovery process. The process is, led by bigger, presumably more sophisticated lenders. The order flow picks up right from the opening of the auction and orders continue to flow in. Notional prices continuously adjust right up to the close. While almost forty thousand investors contributed funds to the platform, with a median of 665 investors per loan; however,83% of the funding for the average loan came from the highest decile of investors. Relative to small lenders, big lenders have a higher propensity to submit bids earlier on in the auction, revise their bids more frequently, but also withdraw from the

[2]We distinguish the AGH from the Famma's (1970) Efficient Markets Hypothesis (EMH), whereby *all* relevant information is priced in and *all* irrelevant information is priced out; see Fama (1970), among many others. EMH can be viewed as a limiting case of AGH. We consider EMH as a straw man, than can be easily rejected in our sample.

[3]See Shleifer (1986) for an early contribution. See also Duffie and Zhu (2015) for a theoretical model where large traders might prefer to "freeze" market prices so as to avoid adverse effects resulting from their own trades.

auction as the interest rate falls. They also have a higher propensity to submit individual supply curves that slope upwards.

Second, we discover evidence that the lack of market level synchronization between supply and demand correlates with the pricing of individual loans. Hence, a loan that is issued during a week of high demand would tend to close at a higher interest rate than one where demand was weak. Moreover, the effect may last for a week or two after the surge in demand. A surge in supply also matters and we proxy it via the magnitude of the order flow during the last hour that the auction is open. The null hypothesis is that a supply surge should lower the auction's closing rate. However identifying such supply shocks is more problematic, for we do not observe new potential lenders looking for trading opportunities, nor do we observe a greater readiness by existing users of the platform to deploy additional funds. We construct an instrumental variable that takes advantage of the fact that auctions have a randomly allocated closing hours. At the same time, the closing hour of an auction has a significant impact on the participation of retail investors, and therefore on the order flow accumulated during the last hour. On average, an auction closing between 3pm and 7pm, features a 10 percentage points higher order flow. This exogenous increase in the supply of liquidity reduces interest rates on average by 45 basis points. Consequently, there seems to be strong evidence that asynchronized flows of funds, on the demand side and on the supply side result in liquidity shortages (and slacks) that bias auction outcomes.

Third, in the spirit of the AGH, we estimate the likelihood of default events. As expected, public-information credit scores generated by FC's research department predicts default. However, controlling for these credit scores, the market price formed through the price discovery process, also has significant predictive power. This is consistent with the idea that both information generation and information aggregation play a role. Consistent with theories of slow moving capital, we also find that when we add variables that capture liquidity shortages, they increase significantly the power of the regression results. For example, high demand for funds in the week when the loan was priced has a negative sign in the default equation. Our interpretation is that when aggregate demand is high it biases the interest rate upwards.

Fourth, we use the slope of the supply curve at the close of the auction as a proxy for the precision of the price in predicting default: a flat supply curve indicates a relative uniformity in lenders' default expectations, and a resulting willingness to bid aggressively. We devise a formal test that confirms this interpretation of the slope of the supply curve, and then show that the average weekly slope of supply curves (across auctions) has increased over the sample period. This evidence suggests that the platform may have found it increasingly difficult to resolve the non-synchronization problem between inflows and outflows of funds and their adverse price effects. Finally, we test directly the hypothesis that prices became less predictive along the sample, demonstrating that it cannot be rejected.

Our paper relates to the emerging literature on online marketplace lending that is surveyed in Morse (2015). A large part of the current literature is based on the experience of Prosper, the leading American P2P lender. It is therefore interesting to briefly compare, and contrast, the design of FC to that of Prosper. FC intermediates corporate loans which are, on average, twenty times bigger than Prosper's consumer loans. Many more bidders participate in FC discriminating auctions than in Prosper's Walrasian auctions. The default rates on Prosper are an order of magnitude higher than those of FC. This is significant because Prosper's mispricing problems were particularly severe when it came to low quality loans.[4] Another important difference is in the institutional environment: England's Company House keeps a central register of all the country's companies, which are supposed to file annual reports at a level of detail that increases with the company's scale of operations. Corporate Bankruptcy law (called Insolvency Law in England and Wales) is much harsher than America's personal bankruptcy law. While Prosper's development was quite erratic, FC showed a stable growth trend, albeit with high short term volatility. Although both companies abandoned the auction system eventually, it seems that Prosper's experience was more negative than that of FC.

The paper is organized as follows: Section 2 describes the data, section 3 describes the platform and Section 4 describes the price discovery process. Section 5 analyzes the implications of the asynchronization problem and Section 6 presents the AGH analysis. Section 7 analyzes the precision of prices in predicting default and Section 8 concludes.

2 Data

FC is an electronic platform providing intermediation services between SME borrowers, open to retail lenders. It is a hub, offering matching, communication, information, clearing and some legal services. Unlike a bank, it has no stake in the loans that it generates: the loans are sold directly to the lender who bear the entire risk of default. Hence, the traditional supply chain of the banking industry, where money is channeled into a retail deposit, then used to fund industrial loans, which later may be bundled up into marketable securities, and finally sold to other financial intermediaries, say life insurance or pension funds, is all vertically integrated into a single operation.

FC commenced business during the last quarter of 2010. In the years following the financial crisis, SMEs were affected by a reduction in bank lending and credit shortages while savers faced close to zero interest rates. An official investigation into the operation of "alternative credit" recognized the economic potential of this new model of financial

[4] See Figure 6 in Shleifer (2015), which is the source of the comparisons above.

intermediation and decided to leave the industry unregulated - for the time being.

Our sample covers the period from FC's creation up to the first quarter of 2015. Since early 2014, FC has increasingly attracted the attention of institutional investors (on the lending side). Since the main focus of this paper is the effectiveness of the auctions in aggregating dispersed information along the price discovery process, we discard from our sample $2,612$ loans totalling £154 million in value, where the entire loan was taken by a single lender, which we assume to be an institutional investor. We are aware of the existence of other FC auctions where institutional investors have participated alongside retail investors, but except for one case, discussed below, we cannot identify such investors with any confidence. Our sample, after discarding the above loans, is described in Table 1. It includes close to 8,000 loans, with a total value of £483 millions, a very modest amount relative to the loans outstanding of£95 billions for the UK SME sector[5], although Milne and Parboteeah (2016) and Zhang et. al. (2016) report that, as a group, peer to peer lenders account for 12%-13% of credit to very small SMEs. During the sample period, the platform has grown at a very high rate: from the first quarter to the last, the value of loans issued has increased some thirty times. As Figure 1 shows, growth was somewhat volatile with a standard deviation of 0.74%, challenging the platform's ability to match demand and supply flows.

Table 1 also reports the evolution of the "benchmark" interest rate, which applies to high quality loans with an A credit score, as calculated using the OLS regression (1), described below in section 3. On average, the benchmark rate is just above 8%, gross of a 1% annual service fee[6]. The Bank of England base rate during the period was 0.5%.

3 The Platform

In this section we describe the auction process, the lenders, the order flow and the bidding strategies.

3.1 The Auction

3.1.1 Multi unit auctions

Borrowers place a loan of specific size to be auctioned. Loan size varies from between £5k and £650k with a median of £50k; see Table 2. The median term of a loan is three years, with maturities up to five years. Lenders typically bid for fractions of loans. Only limit orders are accepted: they must specify both the size of the bid (at least £20) and the interest rate. At the close, the system accepts the most competitive bids and discards

[5]See Rhodes (2015).

[6]The service fee is calculated on the capital amount outstanding of each loan.

Table 1: Evolution of Platform during the Sample Period

Time	Number	Total Value	Benchmark Interest Rate
2010Q4	75	2.20	7.94
2011Q1	42	1.50	8.12
2011Q2	64	2.40	8.46
2011Q3	103	3.72	8.10
2011Q4	215	9.79	7.80
2012Q1	131	6.08	7.97
2012Q2	155	8.48	7.92
2012Q3	226	12.97	8.79
2012Q4	355	21.71	8.10
2013Q1	219	12.19	7.13
2013Q2	444	26.56	7.14
2013Q3	587	37.26	7.39
2013Q4	925	53.21	7.71
2014Q1	590	32.67	8.44
2014Q2	936	54.37	8.91
2014Q3	860	54.88	9.06
2014Q4	1,174	83.07	9.21
2015Q1	854	59.58	9.21
Total	7,955	482.62	8.41

The table reports, for each quarter, the total number of loans issued, the total value of loans issued. The Benchmark rate is calculated for an A credit score; see Table 3 below.

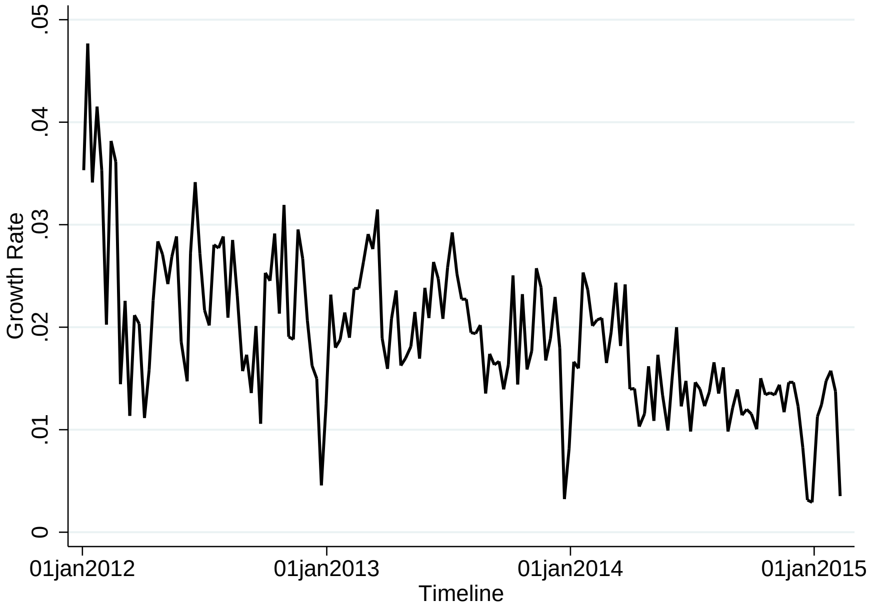
the rest. Accepted bids are called "loan parts". The number of loan parts per loan varies between 37 and 8.7k with a median of 665.

Table 2: Loan Characteristics

Variable	Mean	Median	Standard Deviation	Min	Max
Size	60,668	50,000	52,995	5,000	650,000
Maturity	44	36	15	6	60
Loan Parts	867	665	777	37	8,715
Range of Bids	2.07	1.90	1.64	0.00	10.80

Pooled loan-level data with monetary values expressed in GBP. *Size* is the granted amount of the issued loan. *Maturity* is defined as the duration of the scheduled repayments, expressed in number of months. *Loan Parts* is defined as the number of accepted bids that constitute the granted amount of the loan. *Range of Bids* is the difference between the minimum and maximum accepted interest rate within an auction.

Figure 1: Loans issued, weekly growth rate



3.1.2 "Hard" and "soft" information

Every loan placed on the system has a credit score. The score is based on the borrower's Experian credit score, its credit history and the analysis of FC's own credit department. The analysis is undertaken formally, but the credit department is allowed to add (or subtract) one tick from the score on the basis of soft information. In addition, the borrowing company provides a "prospectus". A typical prospectus would include the company's name, address, and some accounting information. Typically, during the bidding period an on-line Q&A log is opened, where potential lenders can ask the company for clarifying information. FC encourages borrowers to be as transparent as possible in providing full and detailed answers to questions placed on the log. These logs are active and detailed, covering questions like: "why did revenue fall in the second quarter of last year?"

It is noteworthy that the distinction between hard and soft information is blurred in such a system: a sophisticated investor may run a small-size informal survey among family and friends regarding, say, the quality of the borrower's product. Under the AGH, the market processes this survey, together with many other such mall surveys.

3.1.3 Discriminating auction

The FC platform is discriminating in prices: each loan part pays interest according to its submission rate. Hence, the loan rate, namely the interest rate paid by the borrowing SME, is a weighted average of the interest rates of the loan parts. The median difference between the minimum and maximum interest rate on the loan parts per auction, is $190bsp$.

Clearly, if we also consider bids that were not accepted by the platform, the difference would be even larger.

The benchmark interest rate reported in Table 1 above is derived from an OLS regression:

$$r_i = \alpha + \beta \times Quarter_i + \gamma \times Score_i + \varepsilon_i, \tag{1}$$

where r_i is the loan rate for loan i (namely, the weighted average of the rates of the loan parts), $Quarter_i$ a vector of quarterly dummy variables for the period of issue (β is reported in Table 1) and $Score_i$ is a vector of dummy variables with the A score serving as a benchmark. The γ coefficients are reported in Table 3: they span the risk-adjusted interest rates against the benchmark. The coefficients are highly significant, indicating a strong relationship between the credit scores generated by FC's credit department and the interest rate as determined by the auction. At the same time, in many cases, the auction-determined interest rate deviates significantly from the rate implied by the FC score. The top line in Table 3 indicates that each credit score defines a band, about 1% wide, around the midpoint. The second line in the table reports the percentage of loans that are priced outside that band (namely $\pm 50bsp$ around the midpoint), 39% on average. The main question that we address in this paper is to what extent these deviations result from relevant information that the market has revealed during the price discovery process, and to what extent they reflect random "noise".

Table 3: Credit scores and pricing distribution

		Credit Score Benchmarks		
AA	A	B	C	D
-1.195***	Benchmark	.979***	2.012***	3.734***
(.045)		(0.024)	(0.025)	(0.035)
		% of loans deviating from FC scores (more than ±50bsp from midpoint)		
AA	A	B	C	D
42.7	37.4	40.3	40.2	29.5
		Distribution of Residuals		
Mean	Median	Standard Deviation	Min	Max
0.00	-0.09	0.79	-2.77	5.39

The top panel reports estimates of γ's from equation (1). The middle and bottom panels provides descriptive statistics on the predicted residuals from estimates of equation (1).

3.1.4 Continuous time

The typical duration of an auction is 168 hours (seven days), but some auctions are open for two weeks. Bids can be submitted at any time during the opening period. Once the auction is closed, supply and demand are crossed: the lowest-rate bids sufficient to "fill the tank" are executed and the rest are discarded.[7]

A bid that was submitted cannot be recalled back. It follows that although the bidding book is open, a bid cannot be revised according to information that is revealed later on: if the bid is accepted, it will be executed at the submitted rate. Otherwise, the funds tied up in the submission will not be released for re-bidding before the bid is rejected.

An auction may be terminated by the borrower, prior to the end of the auction period. It follows from the "no recall" property of the auction that an early termination has an unambiguous effect of (weakly) increasing the lending rate. (See Figure 3 below.) To the best of our knowledge, the most likely reason for an early termination is that the loan is intermediated by a loan broker who lacks the right incentive to minimize the interest rate.

3.1.5 Algorithmic trading

Lenders may delegate the allocation process to an FC algorithm, the so-called "autobid". Though bidders cannot distinguish an autobid from an ordinary bid, we can. FC considers the algorithm a trade secret, which it did not share with us. While, the algorithm represents on average 44% of accepted bids in an auction, the algorithm is programmed so as to diversify individual lenders over several loans.

3.1.6 Secondary markets

Lenders are allowed to offer loan parts for sale on the secondary market. The system would match a sale order with a buyer, but would not allow an interested buyer to solicit sell orders. Hence, lenders are motivated to split positions in loans to small parts so as to make the position more liquid. We postpone the analysis of the secondary market for future work.

3.1.7 Default

We have no information about borrower's secured bank debt, but the maintained assumption is that most borrowers have accumulated bank debt before raising money on the FC platform. The vast majority of FC loans are, therefore, junior to other outstanding loans. Some borrowers pledge personal guarantees, but their effective value in default is unknown. Hence, we take the conservative approach and treat all loans as junior and unsecured. Nevertheless, lenders do have legal remedies against strategic default. For example, they can threaten to file a winding-up order against the borrower. In case of

[7] Typically, the supply curve is a step function, flat at the closing rate (see Figure 3 below), so there is excess supply at the closing price, in which case bids are executed on a first come first go basis.

default, FC would try to recover as much as possible given the seniority of the lenders. All dealings between lenders and the defaulting borrower are intermediated by FC, acting as a "delegated monitor" on behalf of the lenders, as a group.

During the sample period, 3.4% (273 out of $7,955$) of loans have defaulted.[8] Given that our sample is highly non-stationary, with many loans not reaching maturity yet, this number cannot be regarded as a reliable statistic of the default rate. Hence, the approach adopted in Table 4 is to deflate the *flow* of loans that have defaulted during each quarter by the *stock* of loans outstanding, that is loans that have not yet matured and not previously defaulted. The result, a quarterly default rate, is then annualized. The calculation is executed in terms of the number of loans and in terms of the value of loans (measured at the point of issue). It yields a default rate of 2.9% PA per loan and 2.7% PA per £. The next step is to adjust these measures for the fact that since the loans are amortized at a constant monthly rate, the loss given default (LGD) is less than one. We measure LGD by deflating the number of monthly payments due at the point of default by loan maturity (at the point of issue).The downwards trend in this series is again to be interpreted with caution. For instance, in the third quarter no loan could have performed for more than nine months. Using the size weighted mean yields default rate of 1.9% PA per loan and 1.8% PA per £. The last column in Table 4 takes a direct approach to this compounding. We report a loss rate calculated as the amount to be paid at the point of default (i.e. issue value net of amortization and recovery rates) divided by the value of loans outstanding, as described above; it is 1.5% PA per £.[9]

Comparing the default rates as reported in Table 4 and loan prices as reported in Tables 1 and 3 (net of a 1% FC service fee), we draw two conclusions. First, there is no *prima facie* evidence any irrational exuberance in the pricing of loans.[10] Second, there is no way to asses whether the time-series macro risk was properly priced for the simple reason that the FC was never tested in a downturn.

Next, we provide evidence on the variation of default rates across credit score ratings by estimating the OLS regression:

$$Default_i = \alpha' + \beta' \times Quarter_i + \gamma' \times Score_i + \delta\text{'} \times Log\ Exposure_i + \omega_i. \qquad (2)$$

$Default_i$ is a dummy variable that receives the value of one if loan i has defaulted during the sample period and zero otherwise. $Quarter_i$ and $Score_i$ are defined as in equation (1). Throughout our analysis we correct for the non-stationarity of the sample in two ways. First, estimating equation (2) (and its extensions in Section 6 below) we limit the sample

[8] There are 153 delinquencies in our sample. Past experience implies that most are sorted out, eventually, so we do not count them as defaulted.

[9] Average recovery rates are 19 per cent of the loan outstanding.

[10] See, however, the discussion in Feldhutter and Schaefer (2015) regarding methodological difficulties.

to loans issued until the third quarter of 2014, implying that all loans have at least two quarters of repayment history. Second we we control for the length of time that the loan has been exposed to the sample, from issue to either the maturity, the termination of the sample, or default, a variable we denote as $Log\,Exposure_i$. We cluster standard errors at the issuance month level, and report estimates of γ's in Table 5. The estimates suggest that the probability of default increases by, roughly, 1% from one credit score to the next. As noted in Table 3 above, interest rates also increase by 1% from one credit score to the next, which given our findings about LGD, provids further support to the fair-pricing evidence.

Table 4: Default, By Event, Value and Performance

Time	Default (Events)	Default Rate (per loan) %-PA	Default Rate (per GBP) %-PA	LGD	Loss Rate (per GBP) %-PA
2010Q4	0	0	0	.	0
2011Q1	0	0	0	.	0
2011Q2	1	2.2	1.9	0.861	1.6
2011Q3	3	4.2	2.6	0.713	1.0
2011Q4	1	0.9	0.2	0.667	0.1
2012Q1	11	7.2	6.2	0.735	3.9
2012Q2	12	6.4	4.5	0.692	2.9
2012Q3	14	5.8	5.1	0.687	2.6
2012Q4	14	4.7	4.1	0.745	2.9
2013Q1	13	3.5	3.7	0.655	2.5
2013Q2	10	2.1	2.1	0.703	0.8
2013Q3	23	3.7	3.9	0.573	1.7
2013Q4	16	2.1	2.0	0.614	0.9
2014Q1	26	2.7	2.2	0.683	1.2
2014Q2	22	1.9	1.8	0.533	0.8
2014Q3	39	2.9	2.8	0.663	1.5
2014Q4	44	2.9	2.5	0.674	1.7
2015Q1	24	2.3	2.2	0.642	1.1
Total	273	2.9	2.7	0.656	1.5

Pooled loan-level data. Loan Default (event) is the flow of default events during the quarter. Default rate (per loan) is the former over the stock of loans (by number) outstanding, i.e. loans not yet matured and not previously defaulted, annualized. Default rate (per GBP) repeats the former calculation, accounting each loan by its GBP value at the point of issue, i.e. not accounting for amortization, annualized. Loss given default, LGD, is the loan maturity (in months) minus months of performance (before default) over loan maturity. Loss rate (per GBP) is the amount to be paid at the point of default (i.e. issue value net of amortization) over the stock of loans outstanding (i.e. loans not yet matured and not previously defaulted, accounted in GBPs at the point of issue), annualized. Except for the first column, Total is an average weighted by loans outstanding.

Table 5: Probabilities of Default Relative to the Benchmark

AA	A	B	C	D
-.02***	Benchmark	.01***	.01**	.035***
(0.005)		(0.003)	(0.004)	(0.008)

OLS estimates of the γ's, as defined in equation (2). ***, **, and * denote significance at 1%, 5% and 10%, respectively.

3.1.8 "Shut Down" Auction

971 auctions were "shut down" because, in FC's judgment, excess supply of funds had pushed down the lending rate below a reasonable level. FC has no fixed definition of the "floor" that is implied, implicitly, by this process: it moves over time and across credit scores. We can imperfectly identify such auctions by the fact that they have a multitude of lenders, but no price heterogeneity across bids within the auction. Though these auctions convey less information about the price discovery process we chose to leave them in the sample. (Unlike the auctions wholly allocated to a single institutional investor, already deleted from the sample.) In those cases where the shut-down auctions are excluded from the analysis a specific notification is posted.

3.2 The lenders

During the sample period, $39,596$ lenders provided funds via the FC platform. Like in any other market, some were more sophisticated than others, and some better informed. Table 6 provides the distribution, by decile, of lenders contribution to the platform. While the bottom decile of lenders has contributed less than 0.1 of the total amount lent, the top decile has contributed 82% of the total. While the bottom decile typically took positions in (i.e. provided funding to) only 4 auctions, the top decile typically participated in over 500. While across all auctions, the typical lender in the bottom decile has contributed a total of only £100, the respective amount for a typical lender in the top decile is almost £70k. In the bottom decile, the largest position per lender is typically £20, whereas in the top decile the largest position per lender is £860, or 1.1% relative to the size of the loan.

The mirror image of this observation is the stake of the top lenders within auctions, reported in Table 7. On average the top lender holds, 9.3% of the loan, with the top 10 and 20 lenders holding 31.7% and 42.2%, respectively. The corresponding medians are 10%, 29.9%, and 40.4%.

It is thus tempting to think of the largest lenders as the wealthier and more sophisticated relative to the smaller lenders. As such, they can perform the essential task of providing the market with liquidity. We are told by FC (and provide a formal evidence

Table 6: Lender's Exposure Across Wealth Deciles

Decile of Wealth	Share of Funds (%)	Positions per Lender (#)	Positions per Lender (GBP)	Largest Position per lender (GBP)	Position/Loan
1	0.0	4	100	20	0.0
2	0.1	13	380	40	0.0
3	0.3	36	940	53	0.1
4	0.5	68	1,640	60	0.1
5	0.8	110	2,780	60	0.1
6	1.4	166	4,640	80	0.1
7	2.4	227	7,700	100	0.2
8	4.0	287	13,020	140	0.3
9	7.7	370	24,480	260	0.4
10	82.8	529	69,144	860	1.1
Total	100.0				

Loan-level data. Lenders are sorted to deciles. Adding up loan parts, owned by a single lender, within a loan, is a "position". Adding up positions, in all loans, by all lenders is the total value of funds lent through the platform. First column reports the share of each decile. All other columns report medians within deciles. Last column reports the largest position by lender divided by the size of the respective loan.

Table 7: Position / Loan: Accumulated %

Top positions	Mean	Median	Standard Deviation	Min	Max
1	9.3	10.0	7.0	1.1	84.0
2	14.3	13.3	8.8	2.1	93.2
3	17.9	16.5	9.8	3.1	97.2
10	31.7	29.9	12.5	8.3	98.7
20	42.2	40.4	13.7	13.9	100.0

Loan level data. Within loan, positions (see Table 5 for definition) are sorted by size (number 1 is the top position), divided by the size of the loan,. Then the shares are accumulated over normalized by accumulated, and then divided For each auction, we sort lenders by share of funds provided, and report characteristics for the group of n top lenders.

below) that the growth in demand for loans did not always match the growth in the supply of funds. Wealthy and sophisticated lenders can smooth out these gaps, by identifying periods of excess demand (supply) for loans and by increasing (decreasing) lending accordingly. They can perform this role informally and competitively, as in the Kyle (1989) model, without holding any formal office of a market maker. At the same time (and unlike in the Kyle model), they can also be better informed, either because they are well connected or because their larger positions provide them with a stronger incentive to collect and process information. Either ways, they can smooth out the "noise" created by the small lenders, thereby contributing towards a more precise price-discovery process.

The above classification of small, uninformed and generating noise trading versus big, uninformed and noise smoothing requires a cautionary disclaimer. As noted above, over the sample period, institutional investors have shown a growing interest in FC. Even after discarding auctions with only one lender (assumed to be an institutional investor), we suspect that there are some unidentified institutional investors who take partial positions in loans. FC helped us identify (by ID number only) one lender who invested £18m over the sample period. The rest are likely to be large, but may not be well informed and may not even be sophisticated in the sense of having the incentive to identify mis-valued auctions. In short, these institutional investors may be big, but resemble noise traders in their behavior.

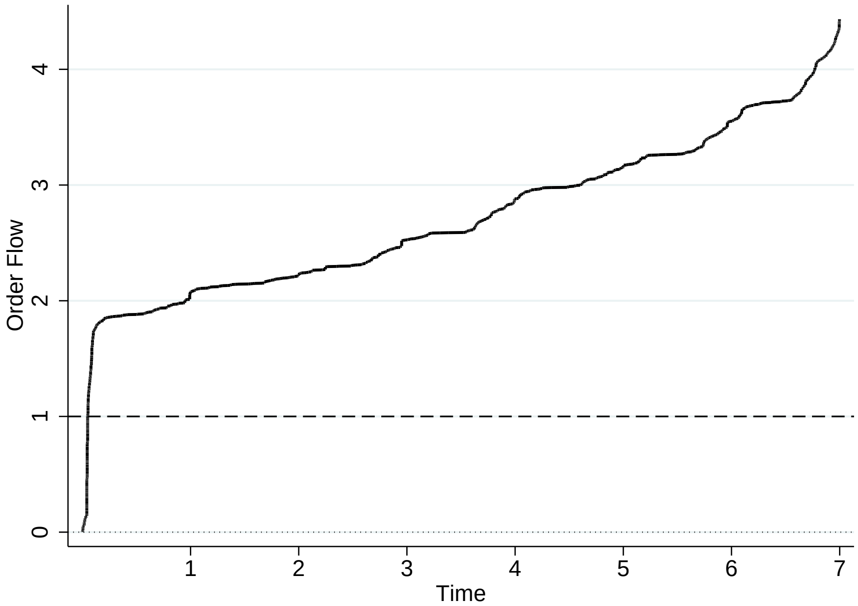
4 Price discovery

FC auctions demonstrate an active price discovery process. By that we mean that the order flow picks up early on during the auction, that the accuracy of pricing seems to improve during the auction, that lenders bid several times in the same auction, and many bidders submit an upwards sloping supply curves. There seems to be no prima facie evidence for herding.

4.1 Order flow

One might hypothesize an equilibrium where lenders prefer to wait for the last minute so as to benefit from the information supplied by other lenders without revealing their own information, in which case the entire process collapses to a sealed-bid batch auction. In fact, this hypothesis is rejected by the evidence. A typical example is described in Figure 2. Auction, 2408, for £15k, with an A credit score, was executed in April 2013 and was open for the full 168 designated hours (seven days). The book was opened at 7pm. The graph plots the total value of bids submitted (both accepted and rejected at the eventual close), at any point in time during the auction, normalized by the size of the loan. By the no-recall property of the auction, the graph must be increasing, monotonically (weakly), as it evidently is. In this case, a strong supply of bids has "filled the tank" (namely, the order flow reached one) within one hour and 10 minutes. The order flow slowed after a few hours, but kept on accumulating at a roughly stable rate. A certain acceleration can be observed towards the close, when the auction was more than four times oversubscribed. Table 8 provides data on the distribution over time, based on those auctions that were opened for the full 168 designated hours (i.e. not terminated prematurely). With some exceptions, about 46 of the orders, by value, are placed in the first day, and about 30% are placed on days 2-6, and about 24% on day 7.

Figure 2: A Typical Order Flow



The order flow is the total value of bids submitted at each point of time, normalized by loan size. Auction 2408, April 2013.

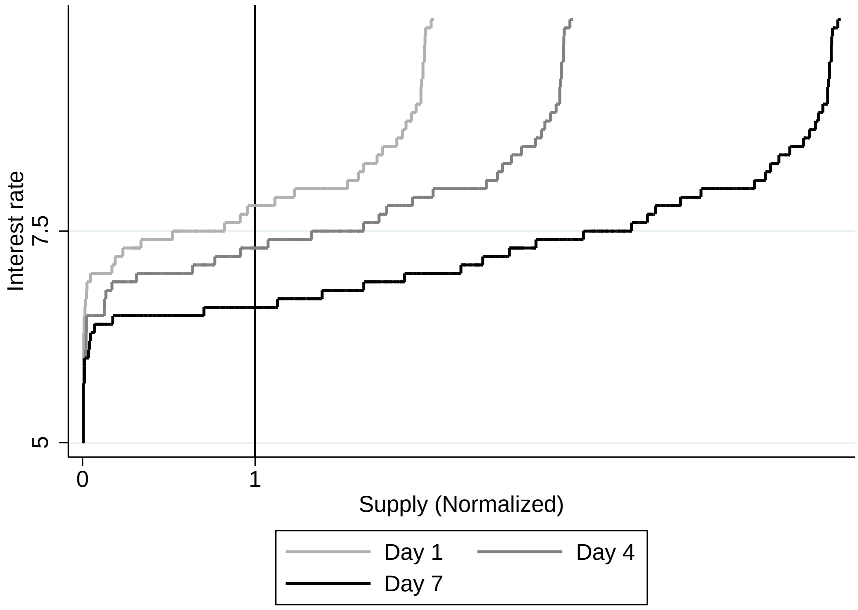
Table 8: Order Flow, over Time, as % of Total Value of Bids Placed

Daily Flow	Mean	Median	Standard Deviation	Min	Max
1	45.8	48.7	23.5	2.4	98.5
2	52.2	55.9	22.9	4.9	98.3
3	58.1	62.2	21.6	5.9	98.1
4	63.6	68.4	20.4	7.6	98.3
5	69.1	73.8	18.7	10.4	98.5
6	75.7	80.5	16.3	11.8	99.6
7	100.0	100.0	0.0	100.0	100.0

The table uses auctions that were opened for the full 168 designated hours (seven days). The order flow accumulates the value of bids submitted up to each point in time and is normalized by the size of the loan.

This pattern of early bidding differs from the one observed in, say, eBay auctions; see Roth and Ockenfels (2002). It is more in line with the findings by Biais et. al. (1999) who study pre-market bidding on the Paris stock exchange (bids can be canceled once the market is opened for trade), possibly to communicate and exchange information prior to trading. Due to the no recall property of FC auctions, bidders may be communicating by placing bids above the conceivable closing price, not to be executed eventually. An alternative interpretation may be in the spirit of Admati and Perry (1991) whereby funding for a public good emerges as an equilibrium outcome of a non cooperative dynamic game

Figure 3: Supply Curves Dynamics, Auction 2408, days 1, 4 and 7



The order flows at the end-of-auction day n of Auction 2408 are sorted by interest rates to derive notional, dynamic, supply curves. An end of auction day n is defined the time of open plus $n \times 24$, $n = 1, 3, 7$ (7 being the close). Supply is normalized by the size of the loan. By construction, demand is a vertical line at the one unit.

with no commitment. One way or another, sophisticated bidders may have found ways to exchange information (a public good!) to their mutual benefit and cooperate in making the price discovery process more effective.

At any point of time, the bids that constitute the order flow can be sorted by the interest rate to derive a notional supply curve. This curve updates dynamically as the platform receives additional bids. Figure 3 plots end of day n supply curves for $n = 1, 4, 7$ (in auction time, namely opening plus $n \times 24$ hours) for auction 2408. At any time during the auction, supply and demand can be "crossed" to generate a hypothetical closing rate had the auction been terminated at that point. The $n = 7$ close is the auction actual close. We refer to the highest accepted bid as the marginal interest rate, while the loan rate (i.e. the interest rate charged to the borrower) is the weighted average of all interest rates of the accepted bids (the loan parts). By the no-recall property, the supply curves can move only rightwards and the closing rate, both marginal and weighted average, only downwards.

Table 9 reports the dynamics of end-of-day marginal rates. It turns out that from the close of day one to the close of the auction, the marginal rate dropped, on average, by 284*bsp*. It is interesting to note that although, on average, only a quarter of the order flow is submitted on day 7 (see Table 8), about half of the price adjustment takes place on that day. Table 9 also reports the dynamics of the slope of the supply curve around the crossing point (i.e. between 0.75 and 1.25) estimated by an OLS procedure. Notice that since the supply curve is normalized by the loan size, that slope has an elasticity interpretation. In addition, while the mechanics of FC auctions drives the closing rate down over the duration of the auction, no such implication exist for the slope, which can move either upwards or downwards.

We interpret the slope as a proxy for the precision of the price discovery process (see formal test below). Intuitively, as lenders become more confident that the loan is correctly priced they become more inclined to bid aggressively so as to undercut other bidders. As a result, a mass of bids accumulates around the closing price and the supply curve becomes flatter; c.f. Kyle (1985, 1989) where low price sensitivity is associated with a more elastic supply of liquidity by market makers. Based on that insight, Amihud (2002) suggests his "price impact" measure as a "rough measure" of market liquidity. Notice that while the Amihud measure is rough in the sense that does instrument demand shocks so as to identify the supply curve, in our setting demand is not price sensitive so that the supply curve is directly observable. Another intepretation of the informativeness of the slope of the supply curve is suggested by Plott and Pogorelskiy (2015). They use a laboratory experiment to argue that slopes of supply and demand curves determine the dynamics of the price discovery process across multiple iterations (albeit in a market with no private information), which can be modeled as an application of Newton's Algorithm.

To conclude, provided that we accept the slope as a measure of precision of pricing, the evidence in Table 9 is consistent with an active price discovery process whereby information accumulated over the duration of the auction, results not just in a revision of the the default risk (priced into the loan rate) but also in a more precise estimate of that risk.

4.2 Bidding behavior

Next, we turn our attention from bids to individual supply curves. In our data, a supply curve presents as a cluster of bids, by the same lender in the same auction, submitted within a short while. There are two reasons why a lender might want to split up bids within an order: first, to gain liquidity by having the option to sell, later on, loan parts on the secondary market. Second, to submit an upwards sloping individual supply curve. The latter interpretation is interesting because an upwards sloping individual supply curve indicates an awareness of the lender to the functioning of the platform and a more active participation in the price discovery process. Similar points have been made in different contexts: see Cornelli and Goldreich (2001) in relation to the Initial Private Offering market.

To be more specific, we use a three hour interval between bids in order to separate one supply curve from another. We measure the size of a supply curve by adding up the value of all the bids that constitute the curve, regardless of price. We measure the

Table 9: Interest rate Dynamics Over Auction Days

Day	Mean	Median	Standard Deviation	Min	Max
			Marginal Closing Rates		
1	.	.	.	.	.
2	-0.37	-0.20	0.59	-5.80	0.00
3	-0.29	-0.10	0.50	-6.50	0.00
4	-0.26	-0.10	0.41	-5.30	0.00
5	-0.27	-0.20	0.35	-4.30	0.00
6	-0.35	-0.20	0.39	-4.20	0.00
7	-1.30	-1.20	1.02	-5.70	0.00
			Slope of the Supply Curve		
1	.	.	.	.	.
2	-0.60	-0.05	5.03	-140.86	7.20
3	-0.30	-0.02	3.84	-130.45	19.65
4	-0.11	0.00	2.12	-59.80	14.21
5	-0.25	0.02	4.02	-108.60	5.78
6	0.01	0.04	2.23	-51.72	13.08
7	-0.88	-0.42	1.54	-21.46	4.22

All auctions with 7 day duration. Marginal Closing Rates is the highest bid that would have been accepted had the auction been terminated on the respective day relative to the closing rate of the previous closing day. Slope of the Supply Curve is estimated by OLS, around the “crossing point”, namely on the (.75,1.25) range.

lender’s size by the largest supply curve that she has placed in a given auction.[11] Table 10 then sorts lenders into size groups, reports the number of supply curves submitted and the timing of the submission. Clearly, big lenders submit more supply curves. Perhaps more surprisingly, they also tend to bid earlier on in the auction.

Next, we analyze the factors affecting the decision to submit an upwards sloping supply curve. Table 11 presents OLS estimates of the probability of submitting an upwards-sloping individual supply curve conditional on participating in the auction. The dependent variable is a dummy that gets the value of one if the supply curve is upwards sloping and zero otherwise. The specification is estimated separately over auction days so as to give a better idea of market dynamics. Unsurprisingly, the bigger is the individual supply curve, the more likely it is to be upwards sloping. Regression intercepts indicates that the probability of submitting an upwards sloping individual supply curve falls sharply from day one to day two and increases, less sharply, from day six to day seven. Consistent with previous observations, the price discovery process seems to be most active at the open and at the close of the auction. We also include in the regression the slope of the *market* supply curve as measured and reported in Table 9 above. It turns out that the

[11] Unlike in Table 6 where we measured a lender’s size by his contribution to the platform: due to the non-stationary nature of the sample, the former measure would bias against late joiners.

Table 10: Supply Curves Per Lender Per Auction

Size Group(GBP)	Mean	Median	Standard Deviation	Min	Max
		Number of supply curves			
0-50	1.9	1.0	1.6	1.0	17.0
50-100	2.8	2.0	2.5	1.0	21.0
100-500	4.0	3.0	3.3	1.0	26.0
500+	5.6	5.0	3.8	1.0	24.0
		Timing of submission (earliest supply curve)			
0-50	80.2	76.0	62.2	0.0	168.0
50-100	68.9	50.0	62.3	0.0	168.0
100-500	55.1	22.5	60.2	0.0	168.0
500+	33.2	5.2	50.0	0.0	168.0

A Supply curve is defined as a cluster of bids by the same lender in the same auction, submitted within a short while. A 3 hour interval is sufficient to separate one cluster from another. We measure the size of a supply curve by adding up the value of all the bids that constitute a supply curve, regardless of price. We measure the size of a lender by the largest supply curve that he places on a given auction. Lenders are sorted to classes, by size. For each lender, we count the number of supply curves, per auction, that the lender has placed. Timing of first placement reports the time, in hours, from auction open, when the first supply curve was placed.

submission of an upwards sloping *individual* supply curve is more likely when the market supply curve is steeper, consistent with the notion that the individual bidders respond to market uncertainty about pricing by contributing more intensively to the price discovery process.[12]

Another important aspect of lenders' behavior is the way they revise their supply as auctions reveal more information about the loan and its price. We focus here on active bidders, who submitted more than one supply curve, so that each supply curve (except for the first one) is a revision of the previous one. If the last supply curve was rejected by the platform (eventually, at the close) we can conclude that this active lender has pulled out from an auction in which she participated. Table 12 reports the results for the same size groups as in Table 10 above. There are two interesting findings. First, consistent with the hypothesis already formulated above and due to the no-recall property of FC auctions the price discovery process takes place above the close. Even in the smaller size group, only 2% of the revision are upwards. (Less than 0.5% in the largest size group). Second, 76% (45%) of active bidders in top (bottom) size group are being priced out at the close of the auction.

[12]Admittedly, causality goes both ways here, but market supply is also affected by other factors, particularly the interest rates dispersion, across lenders, around the closing price.

Table 11: Probability of Submitting Upward Sloping Supply Curves

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
Lender Size	1.074***	5.113***	5.298***	5.506***	7.073***	6.701***	5.220***
	(0.026)	(0.288)	(0.216)	(0.413)	(0.335)	(0.657)	(0.243)
Market Slope	-0.000	0.002***	0.002***	0.002***	0.005***	0.013***	0.008***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)	(0.003)
Constant	0.264***	0.146***	0.147***	0.134***	0.116***	0.103***	0.186***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
R-squared	0.035	0.042	0.047	0.038	0.038	0.033	0.016
N	586,310	222,397	209,751	216,195	246,876	321,119	876,871

The table reports OLS estimates of the probability of submitting an upwards sloping supply curve. The specifications are estimated separately over auction days. Lender size is the total amount of bids submitted by lenders within the same session. Market slope is an OLS estimator of the slope of the market supply schedule at the end of the trading day. The estimate is obtained from the (.75,1.25) range of the normalized supply curve. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

Table 12: Dynamics Per Lender Per Auction

Dynamics	Down	Unchanged	Up	Total
		Size Group: 0-50		
Revise Bid	101,471	6,058	4,316	111,845
Stop Bidding		92,919		92,919
Total	101,471	98,977	4,316	204,764
		Size Group: 50-100		
Revise Bid	44,408	4,422	2,277	51,107
Stop Bidding		53,471		53,471
Total	44,408	57,893	2,277	104,578
		Size Group: 100-500		
Revise Bid	37,664	4,339	1,871	43,874
Stop Bidding		64,824		64,824
Total	37,664	69,163	1,871	108,698
		Size Group: 500+		
Revise Bid	10,436	1,562	538	12,536
Stop Bidding		39,663		39,663
Total	10,436	41,225	538	52,199

The analysis focuses on active bidders, for whom the last submission is not the first. Stop Bidding refers to a lender whose last supply schedule was rejected (partial rejection is classified as accepted). Revise Bid refers to a lender whose last submission was (at least) accepted. Up, Down, Un- changed, refer to the direction adjustment of the last supply schedule (relative to the penultimate).

5 Asynchronization and liquidity shortages

As already documented by Figure 1 above, the growth of the FC platform was outstanding in both long term magnitude and in short term volatility. There is no reason to think that flows of funds, on the supply side and on the demand side were synchronized. At the same time, given the small size of the platform relative to the British capital market, and given the active role that big lenders have played in the price discovery process, it is theoretically conceivable that the system was highly liquid. Namely, that the big lenders were holding sufficiently large cash inventories, and and had a sufficiently large risk tolerance so as to accommodate any mismatch between supply and demand. This hypothesis is not supported by the evidence.

Table 13 reports OLS regression results of various auction outcomes on distributed lags of the platform's weekly growth rate (as defined in Figure 1). We interpret a high growth rate as a surge in the demand for funds, increasing the platform-wide scarcity of funds. We find that, controlling for loan characteristics, including quarterly time dummies to capture changes in macroeconomic conditions, a loan that is issued on a week when platform-wide funds are scarce would tend to close at a higher interest rate. Even stronger evidence for liquidity shortages is that the first and second weekly lags are significant at the 1% level. The share of the top-10 lenders would increase, consistent with the idea that the big lenders provide liquidity to the system, evidently, not enough to fully smooth out the the asynchronization between supply and demand. Following the interpretation of the slope variable suggested above, platform-wide scarcity of funding decreases the precision of the loan pricing. Less surprisingly, over subscription falls at the time of platform-wide scarcity of funding.

While demand shocks are relatively easy to identify, supply shocks are more problematic, for we do not observe new potential lenders looking for trading opportunities, nor do we observe a greater readiness by existing users of the platform to deploy additional funds. We therefore proxy a surge in supply via the magnitude of the order flow during the last hour that the auction is open. The null hypothesis is that a supply surge would impact negatively on the auction's closing rate. Columns (1) and (3) in Table 14 report OLS results, whereby the relevant coefficient is positive and statistically significant, inconsistent with the null. Yet, columns (2) and (4) show that, once properly instrumented a surge in the supply has the correct, negative, sign. To construct the instrumental variable we take advantage of the fact that auctions have a randomly allocated closing hours. At the same time, the closing hour of an auction has a significant impact on the participation of retail investors, and therefore on the order flow accumulated during the last hour. On average, an auction closing between 3pm and 7pm, features a 10 percentage points higher order flow. This exogenous increase in the supply of liquidity reduces interest rates on average

Table 13: Distributed lags, weekly frequency

	Rate	Top 10	Slope	Over subscription
FC growth rate	2.662	61.110***	4.582	-12.590*
	(2.067)	(20.107)	(2.852)	(6.397)
L1 FC growth rate	9.157***	32.467	5.431*	-9.774**
	(3.116)	(21.702)	(2.936)	(4.802)
L2 FC growth rate	6.539***	-2.348	0.220	-6.705
	(2.406)	(16.569)	(2.991)	(4.377)
L3 Issuance Rate	0.962	9.207	-1.051	0.939
	(1.944)	(16.311)	(3.701)	(3.377)
lsize	0.471***	-3.830***	-0.098**	-0.633***
	(0.032)	(0.398)	(0.037)	(0.083)
Credit score	Yes	Yes	Yes	Yes
Year*Quarter FE	Yes	Yes	Yes	Yes
Other Controls: SIC, Purpose, Legal Status, Region				
R-squared	0.839	0.301	0.122	0.313
N	7936	7590	6920	7117

The table reports OLS regressions of several auction outcomes on distributed lags of the platform's weekly growth rate. The dependent variables are: *Rate* is the loan rate, namely, the weighted average interest rate of the loan parts. *Top 10 Share* is the total share of the loan parts of the top-10 lenders on that auction. *Slope* is the slope of the supply curve in the neighborhood of the crossing point as in Table 8. *Oversubscription* is the total amount of bids submitted, divided by the size of the loan. *FC growth rate* is the growth rate in the size of the FC platform during the week that the auction was closed. The size of the FC platform is measured by the total value auctions closed during the week. $L1 - L3$ are lag operators. *lsize* is the log of the size of the loan. *Credit score* is a vector of dummy variables for credit scores. *Year*Quarter* is a vector of dummy variables for the auction quarter between August 2010 and January 2014. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

by 45 basis points.[13]

To sum up, there seems to be strong evidence that asynchronized flows of funds, on the demand side and on the supply side result in liquidity shortages (and slacks) that bias the results away from informational efficiency.

Table 14: Last hour order flow

	Marginal rate		Loan rate	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Last Hour Order Flow	0.361***	-4.405***	0.452***	-2.144***
	(0.070)	(0.427)	(0.049)	(0.243)
Loan Size	0.693***	1.027***	0.434***	0.616***
	(0.023)	(0.043)	(0.014)	(0.025)
Constant	1.447***	2.548***	3.201***	3.801***
	(0.351)	(0.502)	(0.206)	(0.285)
Credit score	Yes	Yes	Yes	Yes
Year*Quarter FE	Yes	Yes	Yes	Yes
Other Controls: SIC, Purpose, Legal Status, Region				
R-squared	0.709	0.431	0.840	0.710
N	6569	6569	6569	6569

The table reports OLS and IV estimation of auction outcomes. *Marginal rate* is the highest interest rate across loan parts. *Loan rate* is the weighted average of interest rates across loan parts. The supply of liquidity is measure by *Last hour order flow*, is the order flow on the last hour that the auction is open. The instrument in the IV regressions is a dummy variable equal to one if the closing hour falls between 3pm and 7pm, 0 otherwise. *Credit score* is a vector of dummy variables for credit scores.*Year*Quarter* is a vector of dummy variables for the auction quarter between August 2010 and January 2014. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

6 The tradeoff: information aggregation vs. liquidity

The evidence presented so far is consistent with both an active price discovery process and with "noisy" liquidity mismatches that divert the interest rate away from the information-efficient price. It follows that the FC auction system has both advantages and disadvantages. On the positive side, it allows the price discovery process to aggregate dispersed information that the lenders have. On the negative side, an auction is vulnerable to bi-

[13] In Table 18 of the appendix, we provide balancing tests on the basis of the proposed instrumental variable. We find no economically or statistically significant differences in loan quality, activity, or location of firms in terms of the closing hour of their auctions.

ases, away from the informationaly efficient price, due to asyncronization between supply and demand for funds.

To explore these conflicting effects further, we augment equation (2) with two types of variables: the interest rate as determined by the auction, and the liquidity effects. We interpret the auction rate along the lines of a standard AGH: the auction price adds information on top of FC's credit scores, resulting in a better prediction of default events. As for the liquidity effects, since we expect them to bias away from the AGH price, and including them should improve the prediction of default events even further. Finally, to account for the full information set available to investors, we also include the information provided by the prospectus.

OLS results are reported in Table 15, using both marginal and average interest rates. As in equation (2), the dependent variable is a dummy that equals to one if the loan defaults and zero otherwise. The loan rate has the right sign and is highly significant: high interest rates predict a higher default rate over and above the credit scores. A one standard deviation increase in the interest rate predicts a 50% increase in the likelihood of default. At the same time, the various liquidity variables that capture deviations from the informationally efficient price are also highly significant with signs consistent with our hypothesis. For example, FC growth measures platform-wide shortage of liquidity at the time that the auction was open. As argued above, it would divert the interest rate upwards. The negative coefficient corrects for that upwards bias. Over subscription operates in a similar way. Share of bot accepted captures surges in supply and operates in the opposite direction. As noted above, some auctions are terminated half way, probably by brokers that lack a sufficient incentive to minimize the loan rate, which has an unambiguous effect of increasing the loan rate. The negative coefficient corrects for this effect.

Consistent with our conjecture that price precision has declined over time, we document, in Figure 6, an increase in the the average slope of the supply curves (as defined and reported in Table 9 above.) We suggest that the diminishing precision might explain FC's decision to replace the auction system with a posted price system.

Since the point is central to our conclusions, we suggest a formal test along the following lines. Consider a population with high and low risk of default. Suppose, further, that the population is sorted to these groups by an indicator of high or low precision. Consider, first, the high risk group. Among the members of the high precision subgroup we should expect to find a high incidence of default (in absolute terms). As for the low precision subgroup, we should observe a lower incidence of default because some members of this subgroup are actually low risk individuals, erroneously classified into the high risk group by a low precision indicator. The same effect should operate in the opposite direction in the low risk group. Among the members of the high precision subgroup we should expect

Table 15: AGH regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Marginal Rate	0.004*	0.005**	0.004*			
	(0.002)	(0.002)	(0.002)			
Average Rate				0.010**	0.013***	0.010**
				(0.004)	(0.004)	(0.005)
Loan Size	-0.002	-0.002	0.003	-0.003	-0.003	0.002
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Share of Bot Accepted	0.052**	0.049**	0.036*	0.056**	0.053**	0.041*
	(0.022)	(0.022)	(0.021)	(0.022)	(0.022)	(0.022)
Oversubscription	-0.028***	-0.027***	-0.021***	-0.026***	-0.026***	-0.021***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Oversubscription Sq.	0.004***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log Exposure	0.040*	0.043**	0.042*	0.043**	0.046**	0.044**
	(0.020)	(0.020)	(0.021)	(0.021)	(0.020)	(0.021)
Issuance Rate		-1.023***	-0.874**		-1.035***	-0.894***
		(0.312)	(0.331)		(0.310)	(0.330)
L1 Issuance Rate		-0.806	-0.653		-0.812	-0.670
		(0.571)	(0.559)		(0.567)	(0.556)
L2 Issuance Rate		0.160	0.195		0.153	0.186
		(0.287)	(0.307)		(0.287)	(0.305)
Days Open			-0.005**			-0.005**
			(0.002)			(0.002)
Credit score	Yes	Yes	Yes	Yes	Yes	Yes
Year*Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls: Maturity, Purpose, SIC, Region						
R-squared	0.076	0.079	0.081	0.076	0.080	0.081
N	6201	6189	6189	6201	6189	6189

AGH, auction level OLS regressions. Dependent variable: a dummy variable equals to 1 if the loan defaulted and zero otherwise. *Marginal rate* is the highest interest rate across loan parts. *Loan rate* is the weighted average of interest rates across loan parts. *Share of bot accepted* is the share of loan parts placed by the autobid as a percentage of loan size. *FC growth rate* is the growth rate in the size of the FC platform during the week that the auction was closed. *L.* is the lag operator. *Over subscription* is the total value of bids placed over the size of the loan. *Exposure* is the duration of loan exposure to the sample, from the point that the loan started to perform to the point where it either matured, or defaulted or the sample has terminated. The size of the FC platform is measured by the total value auctions closed during the week. *Credit score* is a vector of dummy variables for credit scores. *Year*Quarter* is a vector of dummy variables for the auction quarter between August 2010 and October 2014. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

to find a low incidence of default. As for the low precision subgroup, we should observe a high incidence of default because some members of this subgroup are actually low high risk individuals, erroneously classified into the low risk group by a low precision indicator.

We execute the analysis in Table 16. We partition the sample to high and low risk, above and below the median predicted by the AGH regression of Table 15. We then

Figure 4: Average weekly supply-curve slope, evolution over time

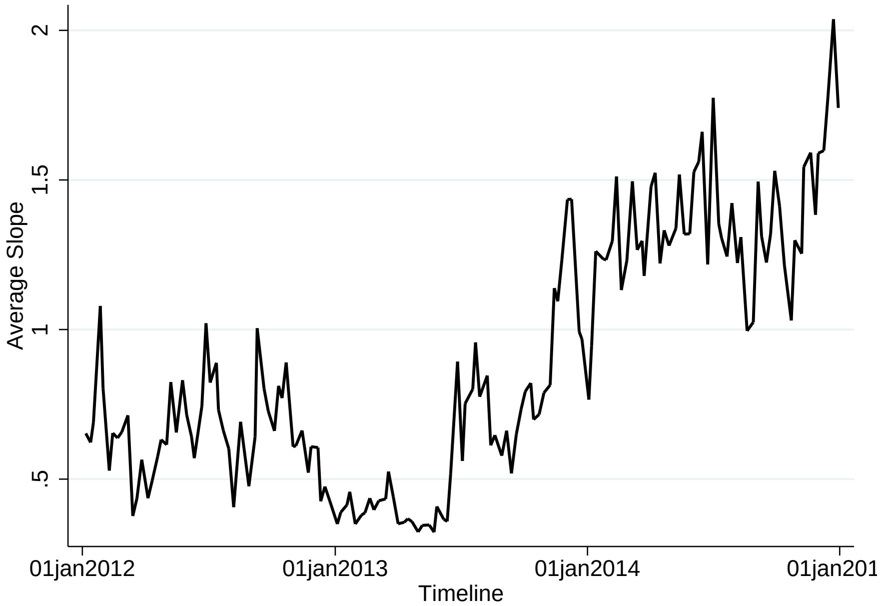


Table 16: Signal Precision and Default Rates

	Noisy Signal	Precise Signal
High Risk Group	7.82%	9.36%
	(107/1368)	(128/1368)
Low Risk Group	0.44%	0.58%
	(6/1369)	(8/1369)

The table presents default rates across groups of high/low predicted default risk, and across groups of high/low signal precision. Predicted default rates are computed according to estimates from column 4 in Table 15, and excludes shut down auctions. High/Low risk groups are defined on the basis of the median predicted default rate. Within each group Noisy/Precise signals are defined on the basis of the median of the slope of the supply curves.

partition each group to high and low precision subgroups, above and below the median slope of the individual supply curve. The predicted effect is clearly observed among the members of the high risk group, across the high and low precision subgroups. The effect is not observed among the members of the low risk group, but the total number of defaults is so small that it is hard to draw definitive conclusions.

Table 17 provides a more precise statistical testing. It duplicates the predictive regressions of Table 15 with the following additions. First, in columns (1) and (4) we directly add an interaction term between the rate and the slope of the supply curve($slope * rate$). In line with the argument above, auction rates should provide a stronger prediction of default where the slope of the supply curve is low. Indeed the coefficient is negative, albeit statistically significant only for the marginal closing rate. In columns (2) and (3) we weight our AGH specification by the slope of the supply curve of each auction. In other words, this specification attaches higher weight to auctions with a low slope of the supply curve, in which the established market price should be more informative about future default events. As expected, the resulting estimates are significantly larger in magnitude with respect to the equally-weighted pool of auctions.[14] Finally, we directly test our conjecture that the predictive power of the auction rates has declined over time. To do so, we add an interaction term between the rate and a linear time trend ($rate * time\,trend$). The coefficient is negative and and highly significant for both the marginal and the loan rate.

7 Discussion and Conclusion

Upon a first inspection, FC has managed to resolve the Grossman-Stiglitz (1980) problem. Its research department was generating monitoring information while its trading platform was aggregating dispersed information that, according to evidence that we present, could contribute towards a better prediction of default events. At the same time, monopolizing the trade on the platform and collecting a service fee on the volume could cover the cost of monitoring, therby resolving the free riding problem inherent in the public good naturre of monitoring.

We hypothesize that the Achilles heal of the platform was that the quality of that information was falling through the sample period. What determines price precision in an auction system? Probably two factors: the number of sophisticated and informed traders relative to uninformed traders, and the relative levels of wealth across the two groups. The richer are the informed traders, the more capable they are to provide liquidity so as to smooth out random deviations from the informationally-efficient price caused by asynchronized flow of funds in and out of the platform. Neither of these factors was under FC's control. Eventually, the auction system was replaced by a posted price system.

The ongoing "Fintech" revolution is now enabling the innovation of entirely original institutions. Trying to understand the operation of organizational forms never observed before, it is important to remember the old lesson taught by Merton (1995): original, innovative and unprecedented as innovations may be, they are, ultimately, just a reconfiguration of functions that were performed by financial markets for hundreds of years: generating information, aggregating information and providing market liquidirty.

[14] Note that in this specification, we need to exclude outliers in terms of the slope (e.g. auctions with 0 slope cannot be included in the weighting).

Table 17: Tests of Price Precision

	(1)	(2)	(3)	(4)	(5)	(6)
Marginal Rate	0.009**	0.015**	0.032***			
	(0.003)	(0.006)	(0.011)			
Loan Rate				0.012**	0.022***	0.056***
				(0.005)	(0.007)	(0.013)
Rate*Slope	-0.002**			-0.002		
	(0.001)			(0.002)		
Rate*Time Trend			-0.001***			-0.001***
			(0.000)			(0.000)
Slope	0.026**			0.021		
	(0.013)			(0.017)		
Time Trend			0.005			0.008**
			(0.004)			(0.004)
Credit score	Yes	Yes	Yes	Yes	Yes	Yes
Year*Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls: all control variables from column (3) Table 15						
R-squared	0.082	0.102	0.083	0.082 column 3	0.103	0.085
N	6189	5160	6189	6189	5160	6189

AGH, auction level regressions, OLS, OLS weighted. Dependent variable: a dummy variable equals to 1 if the loan defaulted and zero otherwise. *Marginal rate* is the highest interest rate across loan parts. *Loan rate* is the weighted average of interest rates across loan parts. *Slope* is the slope of the supply curve in the neighborhood of the crossing point. *Time Trend* is the number of months since the platform started operating. Other control variables are defined in Table 15, and consist of: *Maturity, Purpose, SIC, Region, Loan Size, Share of Bot Accepted, Oversubscription, Oversubscription Sq., Log Exposure, Issuance Rate, L1/L2 Issuance Rate*. *Credit score* is a vector of dummy variables for credit scores. *Year*Quarter* is a vector of dummy variables for the auction quarter between August 2010 and October 2014. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively. Equations (1)-(3) and (4)-(6): OLS. Equation (2) and (5): OLS weighted by slope.

References

[1] Admati, Anat R. and Motty Perry, (1991). "Joint Projects without Commitment." *Review of Economic Studies*, 58 (2), pp. 259-276.

[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] Ariely, Dan, and Itamar Simonson (2003). "Buying, Bidding, Playing, or Competing? Value Assessment and Decision Dynamics in Online Auctions." *Journal of Consumer*

Psychology 13 (1&2), pp. 113-123.

[5] Baruch, Shmuel, (2005). "Who Benefits from an Open Limit-Order Book." *Journal of Business*, 2005, 78 (4), pp. 1267-1306.

[6] Belleflamme, Paul,Nessrine Omrani and Martin Peitz (2015). "The Economics of Crowdfunding Platforms." *Information Economics and Policy*, 33, pp. 11–28

[7] 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.

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

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

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

[11] Duffie, Darrell and Haoxiang Zhu (2015). "Size Discovery." mimeo.

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

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

[14] Feldhutter, Peter and Stephen M. Schaefer (2015). "The Credit Spread Puzzle - Myth or Reality?" mimeo.

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

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

[17] Hammond, Robert G. (2010). "Comparing Revenue from Auctions and Posted Prices." *International Journal of Industrial Organization*, 28(1), pp. 1-9.

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

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

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

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

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

[23] Merton, Robert C., (1995). "A Functional Perspective of Financial Intermediation." Financial Management, 24 (2), pp. 23-41.

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

[25] Morse, Adair (2015). "Peer-to-peer crowdfunding: Information and the potential for disruption in consumer lending." NBER, 20899.

[26] Townsend, Robert M. (1979). "Optimal Contracts and Competitive Markets with Costly State Verification." *Journal of Economic Theory*, 21, pp. 265-293.

[27] Philippon, Thomas (2016). "The Fintech Opportunity." NBER, 22476.

[28] Plott, Charles R. and Kirill Pogorelskiy (2015). "Call Market Experiments: Efficiency and Price Discovery Through Multiple Calls and Emergent Newton Adjustments." mimeo.

[29] Rhodes, Chris (2015). *Business Statistics*, House of Commons Library, Briefing Paper, 06152.

[30] Roth, Alvin E., and Axel Ockenfels (2002). "Last-Minute Bidding and the Rules for Ending Second-Price Auctions: Evidence from eBay and Amazon Auctions on the Internet". *American Economic Review*, 92 (4), pp. 1093-1103.

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

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

[33] Shleifer, Samuel (2015). "The Folly of the Crowd: Market Inefficiencies in Peer-to-Peer Lending." mimeo.

[34] Yermack, David (2015). “Corporate Governance and Blockchains.” NBER Working Paper, 21802.

[35] Zhang, B., Baeck, P., Ziegler, T., Bone, J., & Garvey, K. (2016). *Pushing Boundaries: The 2015 UK Alternative Finance Industry Report.*

Appendix

Table 18: Balancing Tests According to Closing Hour of Auction

Variable	Mean Instrument 0	Mean Instrument 1	Difference	Standard Error	N	P-Value
Rating: A	0.434	0.434	4.43e-06	0.0119	6984	1.000
Rating: B	0.273	0.268	-0.00585	0.0106	6984	0.582
Rating: C	0.292	0.298	0.00583	0.0109	6984	0.593
Acitvity: IT	0.0724	0.0713	-0.00108	0.00618	6984	0.861
Activity: Manufacturing	0.136	0.126	-0.0101	0.00807	6984	0.212
Purpose: Expansion	0.473	0.466	-0.00715	0.0120	6984	0.550
Purpose: Working Capital	0.398	0.391	-0.00710	0.0117	6984	0.544
Geography: London	0.128	0.133	0.00538	0.00806	6984	0.504
Geography: South East	0.215	0.229	0.0143	0.00995	6984	0.150

The table reports the mean of borrowers according to the closing hour of the auction. "Instrument 1" refers to auctions closing between 3pm and 7pm, while "Instrument 0" refers to all other auctions.