

Panel on Changing Market Structure and Implications for Monetary Policy

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Over the last decade, we have seen the start of a revolution in artificial intelligence (AI), big data and fintech that is changing many industries, including financial services. In my comments, I want to focus on two aspects of these emerging changes. First, how is fintech changing the competitive structure of the financial service industry? Second, what are the implications of fintech for pricing of financial services and monetary policy?

The increasing concentration of the U.S. banking industry has been widely documented. While the mergers and acquisitions wave of the 1980s and early 1990s was driven primarily by the interstate and intrastate bank branching deregulation, see Jayaratne and Strahan (1996), the mergers of the last decade seem to have been driven by market consolidation and technological leadership. The number of commercial banks fell from more than 2000 in 1995 to about 500 by 2016. And the average Herfindahl concentration index across local banking markets in the United States increased significantly.

Similar to many of the findings on the product market side presented by the authors in this conference, there is growing evidence that greater concentration of local banking markets leads to reduced access to financial services and higher prices for consumers. In a

recent paper using careful identification via quasi-random changes in the number of banks due to a regulatory cut off rule, Lieberman (2018) show that exogenous changes in local banking market competition lead to less lending to small business; loans sizes to small and medium-sized enterprises (SMEs) go down by more than 10 percent but without any improvement in nonperforming loans (NPLs) for banks. At the same time, the study finds that higher concentration leads to a worsening of deposit rates for savers (Chart 1).

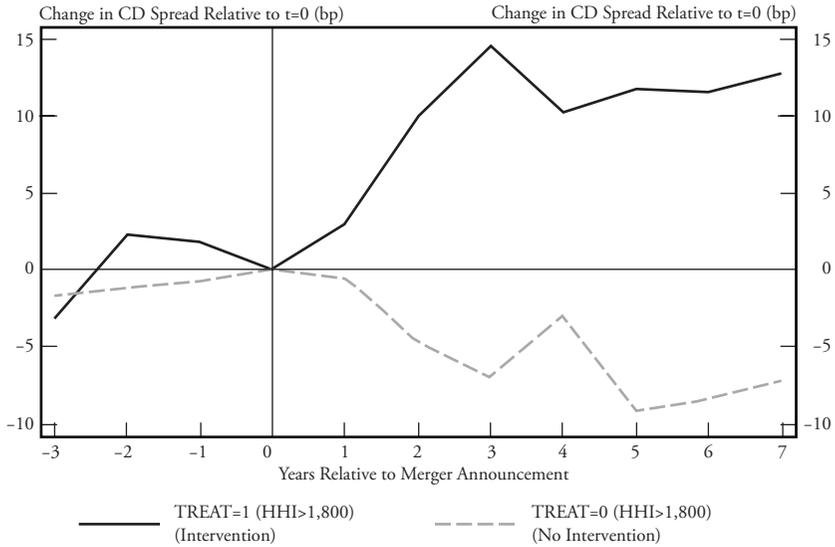
The Role of Fintech in Changing Market Structure

Against this backdrop, the emergence of new fintech firms might be greeted as a welcome new form of competition. In fact, investors have been pouring money into fintech companies at accelerating rate over the last decade. Using data from PitchBook, I show that deal volume in venture capital and private equity (VCPE) has increased significantly and peaked at about \$6 billion annually on average over the last three years. And some new players like PayPal, Square, Stripe and others have become important alternative services for many consumers, especially in the payments area (Chart 2).

But at the same time, data on exit statistics in venture capital suggest that the vast majority of exits from venture capital investments in fintech are not via initial public offerings (IPOs) and thus might not lead to new competitors. Instead the data in Chart 3 show that more than 95 percent of exits across all fields of fintech are via acquisitions to existing large companies. Many of these acquisitions are to commercial banks but also to other tech companies like Google, Apple and Facebook. In fact, this result is parallel to a more general trend over the last decade that a vast majority of venture-capital backed firms exit in acquisitions and do not attempt to go IPO.

In addition, even public fintech firms like OnDeck Capital, one of the largest online lenders providing unsecured loans to small businesses in the United States, are starting to work together with established banks like JPMorgan Chase to expand their outreach to customers and provide more competitive pricing of loans. The market share of even the largest fintech lenders such as OnDeck, Prosper Marketplace, LendingClub and others is still remarkably small

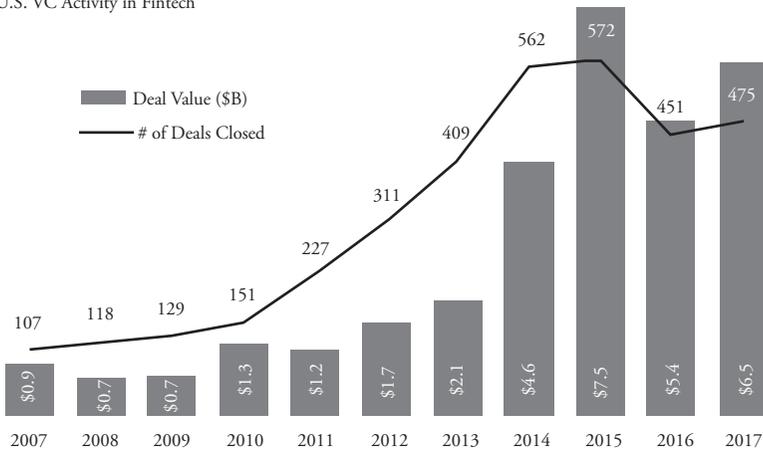
Chart 1
CD Rate Event Study



Notes: Event study graph of deposit rates. TREAT=1 are defined as mergers with a predicted HHI increase of at least 200 points and a predicted HHI level of 1,800-2,300. TREAT=0 are defined as mergers with a predicted HHI increase of at least 200 points and a predicted HHI level of 1,300-1,800.

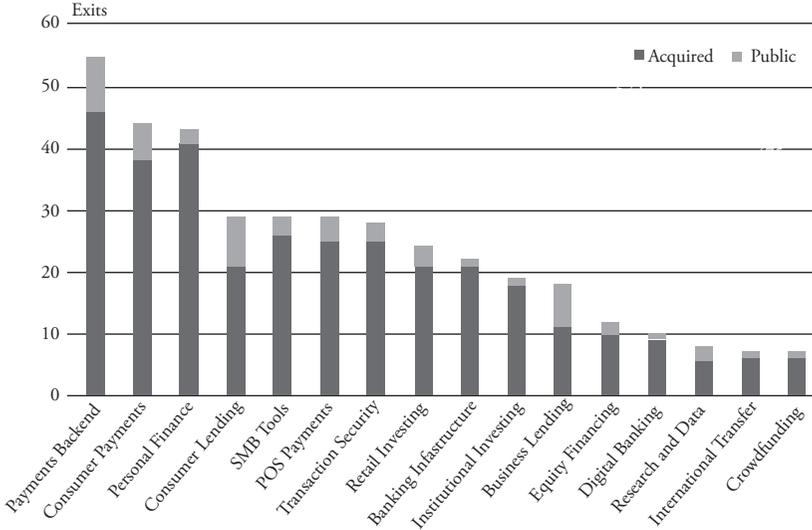
Chart 2
Venture Capital Funding of Fintech Startups in the U.S.

U.S. VC Activity in Fintech



Source: PitchBook-NVCA Venture Monitor.

Chart 3
Exits of Venture Capital Backed Startups
in the U.S. Between 2012-18



Note: Data cumulative through April 2018.

compared to large financial banks in the United States. These emerging trends might suggest that the large franchise value and existing client base of established large commercial banks might make it difficult for new entrants to successfully compete as standalone entities. As a result, in the United States, fintech firms seem to have been much less disruptive for existing financial institutions than originally envisioned. And their impact on market competition has so far still been limited. In fact, when looking at the investment behavior and acquisition activities of established banks, we see significant skewness in the budgets of incumbents. The investments of JPMorgan Chase, Citi, Goldman Sachs and Bank of America into AI, machine learning and big data are a multiple of all other banks. These emergent fintech technologies might in fact reinforce concentration in the industry given the enormous economies of scale from having larger datasets.

While the U.S. experience thus far seems to be very similar to what we see in many countries in Western Europe, the dynamic in particular in China is quite different. Established tech companies like Alibaba and Tencent have grown significant financing arms, especially

in the area of consumer lending and SME lending. While I do not want to speculate about the particular regulatory environment that allowed this expansion in China, it again reinforces the idea that access to superior customer information might lead to greater concentration rather than more competition through fintech.

Fintech and the Pricing of Financial Services?

While the implications of fintech for market structure are still emerging, I want to highlight that these new technologies already have had significant implications for the way—especially consumer financial products—are being priced. The availability of much more detailed data about individual customers combined with powerful new analytics tools, such as AI and big data, allows for much more individualized pricing of services. Financial service providers are able to model not only the credit risk of customers but also their latent demand and financial sophistication. This allows for highly individualized pricing, including the ability of target customers' behavioral biases and inattention to financial details. Many papers in behavioral economics have suggested that individuals find it difficult to understand the more complex features of a financial contract or display self-control problems to pay down credit balances in time, see Campbell et al. (2011). Recent papers suggest that in a competitive market, issuers might find it profit maximizing to target households that are myopic or prone to self-control issues with contract offers that are more complex and have more shrouded features in order to play to the behavioral biases of these customers, see Gabaix and Laibson (2006), Ru and Schoar (2016). The concern is that a greater ability of financial services companies to target these customer biases, might not only lead to higher rent extraction from parts of the customer base, which can have distributional implications on which customers pay higher cost of capital. But it might also affect the pass-through rate of monetary policy to customers.

In our paper, Ru and Schoar (2016), we use detailed offer data from the credit card market to test the validity of this hypothesis. We show that there are substantial differences in the offers that issuers extend to potential customers. To undertake this analysis, we draw upon a dataset gathered by Comperemedia, a company that tracks

entirety of the U.S. credit card lending market. This allows us to look at the structure of offers with which the same issuer targets different customers. We find that less-sophisticated borrowers receive offers with more back-loaded and hidden features. In contrast, more highly educated households were offered cards with front-loaded features such as stable regular purchasing annual percentage rates (APRs) and low late fees and over-limit fees (Chart 4).

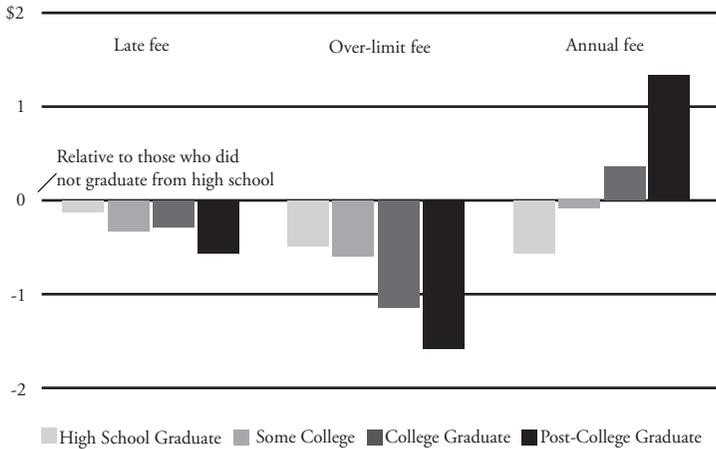
We interpret these findings as evidence that credit card issuers use the available data to segment customers by their likelihood of having behavioral biases.

In a second step, we test how these differential pricing strategies interact with changes in monetary policy. We find that when the federal funds rate (FFR)—the bank's cost of funding—rose, the late and over-limit fees in unsophisticated customers' offers also rose, suggesting that banks were using these back-loaded and shrouded features to pass funding costs to these customers. In offers to sophisticated customers, FFR increases were associated with increases in regular APRs and annual fees, and with decreases in late fees and over-limit fees. Table 1 shows there is an asymmetry in the sensitivity of payment terms to changes in the FFR.

These results suggest that the pass-through rate of monetary policy might be very different for parts of the population. Educated and financially sophisticated customers receive more transparent and front-loaded contracts and, as a result, can adjust their borrowing and spending behavior accordingly. However, for less-sophisticated customers our analysis suggests that an increase in FFR in particular is passed through via increased late fees and other back-loaded fees. However, the upfront fees such as APR are much less sensitive to changes in the FFR. Therefore, if these customers indeed are targeted for their myopia they might only adjust very slowly to the changes in the cost of capital, since they will mainly experience the higher cost of capital with a delay, when late fees or other charges come due. In fact, one might conjecture that there can even be an asymmetry between monetary policy tightening and loosening. Looser monetary policy allows issuers to engage more aggressively in this back-loading and shrouding of features than after a tightening of monetary policy.

Chart 4 Credit Card Offers and Education

Less-Educated More Likely to be Offered Cards with Higher Late and Over-Limit Fees



Source: Authors' calculations using Compemedia data.

Furthermore, this type of pricing strategy exposes banks to more credit risk when lending to customers with behavioral biases, since payments are backloaded. Credit card companies realize that there is an inherent trade-off in the use of back-loaded features in credit card offers: They might induce customers to take on more credit, but at the same time, they expose the lender to greater risk if those consumers do not anticipate the true cost of credit. Our research suggests that banks consider the likelihood that an unsophisticated customer might default on their debts, and incorporates these probabilities into their card offers. However, from the perspective of the central bank it is important to realize this interaction between pricing responses of financial institutions and their exposure to credit risk.

Final Consideration

Historically we often believed that central banks had the most comprehensive and accurate view of the state of the economy. But the rapid growth of these new digital technologies has created a market dynamic, where many institutions outside the central bank system might soon have much more comprehensive, more accurate and also more timely information than the regulators. Companies like

Table 1
Relationships Between APRs/Fees and Education

	1	2	3	4	5	6	7	8
	APR	APR	Annual Fee	Annual Fee	Late Fee	Late Fee	Over-Limit Fee	Over-Limit Fee
FFR	0.813*** (0.005)	0.755*** (0.005)	0.498*** (0.025)	0.671*** (0.033)	0.047*** (0.008)	0.007 (0.011)	-0.356*** (0.008)	-0.424*** (0.011)
Low Edu	0.133*** (0.021)	0.163*** (0.032)	-0.213** (0.089)	1.148*** (0.158)	0.320*** (0.027)	0.007 (0.043)	0.490*** (0.029)	-0.042 (0.047)
Low Edu FFR		-0.050*** (0.008)		-0.440*** (0.048)		0.101*** (0.014)		0.173*** (0.016)
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	785,950	785,950	800,546	800,546	798,936	798,936	749,306	749,306
R-Squared	0.103	0.318	0.251	0.252	0.208	0.208	0.198	0.199

Notes: LS regressions to estimate relationship between education and credit card features. All regressions control for household demographic cell fixed effects based on states, age, income, and household composition and bank fixed effects. LowEdu is a dummy for household head's education level below college (highest degree is high school). Standard errors in parentheses are clustered by cell.

Google or Amazon can use their data to predict regional sales growth or job losses. Google Trends is just one example of the power of aggregation from individual search information. This poses a challenge going forward that is structural and intellectual. On the one hand we need to think about how central banks can get visibility into the types of data that private sector institutions are collecting as part of their core business. On the intellectual side the availability of this hypergranular data asks for a new way of building economic models based on individual purchase or borrowing decisions. This of course is a challenge to whole field of (macro)economics.

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