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Regulatory constraint and small business lending: do innovative peer-to-peer lenders have an advantage?

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Abstract

This paper investigates whether innovative Peer-to-Peer lending by FinTechs' has a regulatory advantage over the big banks in respect of small business lending. We do this through the lens of the regulations imposed by the Dodd-Frank Act, using a difference-in-difference methodology. The Act tightened traditional bank credit standards on business loans, especially for small firms. However, the new FinTech lenders were not subject to the same regulatory burden. We find that traditional banks significantly reduced their lending to small businesses, as compared to their FinTech competitors. Our results suggest that while the Dodd-Frank Act constrained lending to small businesses, innovative new lending models gained a regulatory advantage and the Peer-to-Peer lenders capitalized on this.

Keywords: Small business, Dodd-Frank, FinTech, Innovative lending models

JEL Classification: G20, G21, G23, G28

Introduction

This paper investigates the regulatory advantage conferred on innovative Peer-to-Peer (P2P) lenders, in respect of lending to small businesses. It does this through the lens of the response to regulations imposed by the Frank-Dodd Act of both traditional banks and their online P2P competitors. The later are sometimes colloquially referred to as "FinTechs", in reference to their use of financial technology. In fact, P2P lenders are a subset of the FinTech sector. As P2P lenders are not deposit takers, they are subject to less regulation than traditional banks.

Small businesses[1] are the backbone of the U.S. economy and the provision of credit is central to their functioning[2] Since 1995, small businesses have created two—thirds of

[1] According to the U.S. Small Business Administration's (SBA) Office of Advocacy, a small business is defined as one with less than 500 employees and having $7.5 million or less in annual revenue.

[2] Small businesses represent 99.7 per cent of U.S. businesses and approximately 50 per cent of total private sector employment (Deloitte 2017).

every new job and have employed half of the private sector workforce (Mills and McCarthy 2014). The sourcing of credit is therefore of practical as well as scholarly importance. Innovation, in the form of FinTech, and P2P lending over the Internet, is changing lending dynamics (Broby 2021). Small firms are now getting access to credit from these non-traditional sources.

Small business loans[3] are also one of the primary sources of external financing for small firms. This type of funding is crucial to helping small enterprises maintain cash flow, purchase new inventory or equipment, hire new employees, and grow their business (Mills and McCarthy 2014). However, after the financial crisis bank loans declined and small business lending decreased by almost 18% over the period from 2008–2011 (Cole and Damm 2020). In contrast, the volume of loans exceeding $ 1 million in size grew by 80% in the same period (Bordo and Duca 2018). At around the same time, P2P lending grew to become a viable alternative source of credit for small businesses.[4]

We build on a growing body of literature. Gopal and Schnabl (2022) address a similar question to us but from the perspective of a shock (based on balance sheet impact of accounting rule FAS 166/167) and their definition of FinTech lender[5] is very different from ours. They highlight that the total small business loans held on the balance sheet of the 10 largest banks in 2016 was $10.28 billion. This contrasts with the significantly lower figure of $268.7 million for total small business, loans as at that date, for FinTech lender. This represents approximately a ratio of 3,826 to 1, which highlights the nascent level of the FinTech lenders.

It has been documented that the 2008 global financial crisis hit small businesses disproportionately. It was suggested that this was because they had less financing options than larger businesses (Wille et al. 2017). Although large firms have more varied sources of financing, such as direct credit, issuing and selling debt to investors, corporate bonds and commercial paper, small firms have limited or no access to equity capital markets and public institutional debt (Şahin et al. 2011). As such, they rely heavily on bank loans. The innovative nature of P2P lending changed that at around the same time as our study (Brill 2010). P2P lenders employ a process model that we argue widens access to smaller firms (Wang et al. 2015). It has not previously been investigated whether this model affords P2P lenders a regulatory advantage.

Dodd-Frank act

The Dodd–Frank Act[6] established new prudential standards including liquidity, enhanced risk–based and leverage capital, risk management and risk committee requirements; single–counterparty credit limits; stress test requirements (The Federal Reserve System 2018). Bordo and Duca (2018) suggest that small business lending from the

[3] The Community Reinvestment Act (CRA) provides a framework for financial institutions in the U.S., uses a definition for small business lending—business loans of $1 million or less (SBA Advocacy 2018).

[4] The first Peer to Peer lender, Zopa, was founded in 2005.

[5] Gopal and Schnabl (2022) use a sample of Merchant Cash Advance (MCA) lenders. These small business loan lenders make short-term loans repaid through deductions from credit card and debit card sales. Our focus is on the P2P lenders who make a more traditional unsecured lending decision.

[6] The act contains more than 2000 pages and 360,000 words (Hogan 2019).

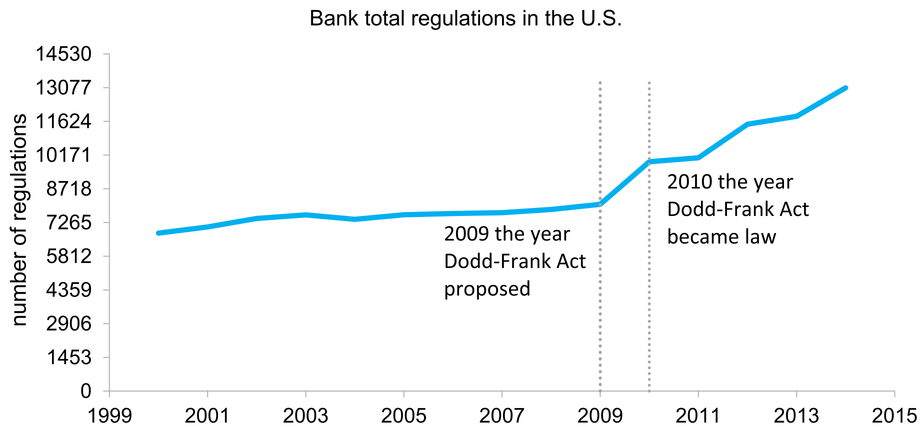

Fig. 1 Total cumulative regulations from the Federal Reserve Board (FED) from 1999 to 2015. The figure shows how the number of bank regulations have increased steadily over the period 1999–2015. The dotted line in the chart indicates the date when the Dodd-Frank Act passed in 2010 to regulate banks. The bank regulations accumulation accelerated between 2009 and 2010, and there was a more remarkable rise in total regulations in 2010 and after four years, as the FED added over 3,000 new regulations in response to Dodd-Frank Act. RegData can be downloaded from https://quantgov.org/regdata/. Source: Regdata

banks was hindered in the U.S. as a result of the Dodd–Frank Wall Street Reform[7] (commonly referred to as Dodd–Frank Act) and the Consumer Protection Act enactment on July 21, 2010.

According to academic studies (Bordo and Duca 2018; Acharya et al. 2018; Bouwman et al. 2018), the regulations of the Dodd–Frank Act[8] strained already high operational costs and increased capital constraints on banks, especially those with $10 billion or more in assets under the Federal Reserve's stress test requirements. The cumulative number of regulations are detailed in Fig. 1. Cortés et al. (2020) claim that such stress tests create a direct link from bank lending risk to capital and impose heavy capital requirements on small business loans. Therefore, the Dodd–Frank Act regulatory requirements cut down on the incentives for banks to make loans to serve businesses, especially small businesses, for which bank credit is one of the important sources of external financing (Mills and McCarthy 2014).

Under the Dodd-Frank Act, the average tier 1 risk-based ratio of U.S. banks increased by 22–27% between 2008 and 2015 (Buchak et al. 2018). In addition, banks with more than $10 billion in total consolidated assets are subject to an annual stress test which consists of dynamic capital requirements that impose risk-sensitive capital buffers on banks for expected deterioration in an adverse economic scenario (Bindal et al. 2020). In addition, Bindal et al. (2020) state that stress tests impose dramatically higher capital requirements on small business lending.

As mentioned, during the same period, the credit needs of small businesses started to be targeted by a new set of lenders that use innovative FinTech to disrupt the small business lending market (Mills 2018). These are collectively referred to as Peer–to–Peer

[7] Evanoff and Moeller (2012) claim that Dodd–Frank Act is the most significant regulatory reform since the Great Depression and the Banking Act of 1933.

[8] All federally regulated financial companies with $10 billion or more in total assets conduct annually their own internal stress tests and publicly disclose the results under the Dodd-Frank requirements (Fernandes et al., 2020).

Table 1 Alternative P2P lender data (loan volumes, county, and loan numbers). Source: Lending Club

Alternative P2P Lender	2007	2008	2009	2010	2011	2012
Loan origination volume (in million $)	5	21	52	132	262	718
County number	110	379	676	987	1359	1836
Loan application number	601	2392	5280	12,533	21,715	53,351

Table 1 demonstrates the number of a total loan application, total loan origination volume of Lending Club and give details the total number of counties where it served between 2007 and 2012

lenders. Although being small relative to incumbents, these alternative lenders provide rapid turnaround and online accessibility for borrowers and use new data-rich credit score algorithms (Palladino 2018). According to Jagtiani and Lemieux (2016), these lenders are enabled by technology and have little (or indeed, are not subject to any) regulation. It could be argued this makes alternative lenders attractive to small business lenders in a post-crisis environment, and thus emerging of alternative P2P lenders had begun to alter the game for how small businesses access financing in the U.S. (Mills and McCarthy 2014). Alternative P2P lender total loan origination volume, loan application number and county number are presented in Table 1.

In order to provide causal evidence that the Dodd Frank Act impacted the provision of loans to small businesses, we use a quasi-natural experiment. This allows us to investigate how the new requirements affected treated banks with $10 billion total assets or more small sized business loans supply relative to untreated banks with less than $10 billion assets. It allows us to evaluate how the lack of the regulatory requirements gave FinTech lenders an advantage.

Firstly, to address the impact on the banks, we used small business bank and county-level data. We replicate the method used by Tang (2019). After classifying treated and control banks (1), we investigate trends at the county level some counties have banks that were subject to the regulation, and others did not. It is suggested that those counties that had an impact from the Dodd-Frank Act saw less competition in banking, and therefore saw less of an impact. This follows the observations of Boot and Thakor (2000) regarding the development of relationship lending when there is less interbank competition.

We measure the banking competition intensity by (1) the concentration ratio of the "big three banks" (C3) and (2) the Herfindahl–Hirschman Index (HHI) using the banks' market share in terms of bank branches number in counties following Degryse and Ongena (2007) and Chong et al. (2013).

Treated counties are defined as counties if there is a bank with $10 billion assets or over which subject to the Dodd-Frank Act. We define treatment groups as counties with a high concentration of Dodd-Frank eligible banks. We further classify them as where there is a low banking competition at the 75th percentile of C3 and HHI. This means that where there is a bank asset that is below $10 billion, and there is a high competition at the 25th percentile of C3 and HHI, it is defined as a control county. In this way, our sample can be used to identify the impact of the Dodd-Frank Act impact on (1) aggregate county-level small business lending. Further, it can be used to identify (2) alternative P2P lender activity in treated and control counties.

In this regard, according to the results in Table 5, we conclude that treated banks saw a decrease in the amount of small business lending. In addition, we note that county-level aggregate small business loan volume declined after the enactment of the Dodd-Frank Act. At the same time, when bank small business loan supply declines, demand for alternative P2P lending increases. Supportive of our findings in the concentrated counties, Hodula (2022) found evidence that FinTechs may act as substitutes in highly concentrated markets.

To the best of our knowledge, ours is the first paper to investigate the activities of both traditional banks and innovative alternative lenders in the small business market using the Dodd-Frank Act as an exogenous shock at the county level. In addition, our paper adds alternative P2P lenders to the debate in the literature on small business lending (e.g. Buchak et al. 2018; Tang 2019; Fuster et al. 2019; Hughes et al. 2022; De Roure et al. 2022). We note that Bordo and Duca (2018) and Zou (2019) also focus on small business lending and the global financial crisis. We, however, utilize the Dodd-Frank Act's impact on small business lending to identify the regulatory advantage of the P2P lenders.

Despite a large volume of published studies on bank regulations, a small subset of them focuses on the Dodd-Frank Act (e.g. Krainer 2012; Acharya and Richardson, 2018; Balasubramnian and Cyree 2014; Dimitrov et al. 2015; Akhigbe et al. 2016; Lutz 2016; Li et al. 2016; Andriosopoulos et al. 2017; Allen et al. 2018; Bouwman et al. 2018; Calem et al. 2020; Bindal et al. 2020).

After the credit crisis, regulation was focused on both capital and liquidity requirements by regulators, particularly in view of the fact that reserve requirements for U.S. banks. According to Thakor (2018), higher capital requirements can make it more challenging for banks to attract capital, and so they decreased lending in response to an anticipated rise in regulatory capital requirements after the financial crisis. There are several reasons why small business owners might turn to business loan alternatives. These include lower credit requirements, easier qualification and faster approval thanks to innovative technology (Milne and Parboteeah 2016).

Akhigbe et al. (2016) present evidence that following the transition of the Dodd-Frank Act, banks discretionary risk-taking decreased due to the rising bank capital ratios and banks decreasing their non-performing loans levels. Andriosopoulos et al. (2017), meanwhile, investigate the impacts of key legislative events of the act and their conclusions support our view that there were changes to the competitive structure of the financial services industry.

Allen et al. (2018) further investigate the market's response to the elimination of too-big-to-fail for large banks against the passage of the Dodd-Frank Act and suggest that act do not eliminate Too-Big-to-Fail banks. In their recent study, Calem et al. (2020) investigate banks stress test exercises impact on the supply of mortgage credit which is implemented under the Dodd-Frank Act Stress Testing (DFAST) regulatory programs and according to the paper that stress tests only alter originations of credit in the jumbo mortgage market. Additionally, Bindal et al. (2020) investigate the Dodd-Frank Act's size based regulatory requirements impact on banks merger and acquisitions and small business lending. Their results indicate that the size-related regulatory thresholds created by the Dodd-Frank Act has significant real effects on loans to small businesses but have indirect treatment effects on bank acquisitiveness.

In summary, our use of the Dodd-Frank Act as a natural experiment ties together separate strands of the literature relating to small business lending and the growing role of innovative alternative lenders.

Small businesses lending and the role of innovative sources of lending

Our working hypothesis is that the innovative P2P lenders benefit from a regulatory advantage. We therefore use two testable hypotheses related to small business lending. This ties the Dodd-Frank Act and the increasing role of alternative lenders together.

The distinctive features that distinguish small businesses from medium and large sized enterprises have long been the subject of research. Ang (1991) claims that the source of the structural and managerial differences could be traced to several features peculiar to small businesses. Out of this set, small firms are shown to make financial decisions in a different way than large companies. In this line of enquiry, several papers investigate small business lending from different perspectives such as bank consolidation, mergers and acquisitions or banking market size structure effects on small business lending, relationship lending, opaque small businesses, and economies of small business finance. We suggest the nature of small businesses makes them more amenable to the use of FinTech.

Consolidation of the banking sector is ruled out as an exogenous factor. Weston and Strahan (1996) and Takáts (2004) claim that consolidation does not adversely affect the credit availability to small businesses contrast with those of Berger et al. (1998) and Sapienza (2002), who find that the effects of consolidation reduce the small business lending activity of banks. Peek and Rosengren (1998) also indicate that while acquirer banks have a higher degree of specialization in small business lending than non-acquirer banks, similar to the mergers increase the consolidated bank small business loans. In another study, results show an external impact of consolidation in which the bank lending to small businesses can be reduced by mergers and acquisitions (Berger et al. 2004).

The size of financial institutions does matter. DeYoung et al. (1999) reveal that there is a negative relation between the size of the bank and its small business lending activity, and Berger and Udell (1995) claim that as banks become larger and more complex, they can reduce to provide loans to small firms. Regarding the market size structure of local market participants, Craig and Hardee (2007) investigate whether banking consolidation has affected small business lending by using the Small Business Finances Survey. They find that access to bank credit for small businesses is lower in markets dominated by the largest banks.

Berger et al. (2007) also investigate market size structure affects the credit supply to small firms both in terms of prices and quantity and the point out that large banks compared to small banks tend to have lower loans to small businesses to assets, however, large banks take advantage of some transaction lending technologies to lend opaque small businesses.

Additionally, Mcnulty et al. (2013) indicate that the propensity to lend to small firms decreases as bank size rises. Further, that most loans to small businesses are made by small banks. In a recent study, Berger et al. (2015) show how local banks' market size structure impacts the loans received by small businesses and find that during normal times there is a greater market presence of small banks in more lending opaque and small firms, but this effect vanishes during the financial crisis.

Furthermore, Petersen and Rajan (1994) investigate the effect of the relation between a small firm and their creditors (banks) on the availability and funding costs of credits and they find that the close relationship between the firm and the bank has little impact on credit pricing. Berger and Udell (1995) claim that small business pays lower interest rates and less collateral if there is a longer banking relationship.

Moreover, Cole (1998) shows that lenders are more likely to expand credit to firms with which they have a constituted relation. Berger et al. (2001) examine the bank relation with internationally opaque businesses and find that some foreign-owned and large banks that are generated by mergers and acquisitions and foreign institutions may have problem to provide loans to opaque small businesses. Berger and Black (2011) analyse the comparative advantages of large and small banks in specific lending technologies and show that small banks have a comparative advantage in relationship lending for small firms.

The relationship between the larger bank and small business lending has also been investigated. Begley and Srinivasan (2021) looked at the effects of new regulations that banks are exposed to after the global crisis on mortgage lending. They argue that the share of especially four big banks in mortgage loans has decreased, and some of this gap is provided by FinTech lenders in parallel with our study. But Gallo (2021) argues that these online FinTech platforms are not fully efficient, and these platforms may suffer from misrepresentation. This makes it difficult to know lenders' credit history and lead to problems with collections.

We argue that the new regulations applied to the banks negatively affected those banks with a particularly large and high market share. As a result, we observe that loans to small businesses have decreased in the counties where these banks are located and there is low competition. This yields our first hypothesis:

Hypothesis 1 Ceteris paribus, after the Dodd-Frank Act, aggregate small business lending declined in the counties where the banks affected by this legislation had a presence, and there was low competition to provide credit.

Apart from the small business lending studies, we further observe that small business loan origination occurs outside the traditional banking system with changing the regulatory structure of the banking system.

As mentioned, the FinTech phenomena began at the same time. There is now a growing literature on alternative P2P lenders (e.g., Cornaggia et al. 2018; Buchak et al. 2018; Tang 2019; Fuster et al. 2019; Allen et al. 2019; Hughes et al. 2022; De Roure et al. 2022). They all suggest P2P FinTechs' are becoming an alternative source of lending to traditional banks. This strand of the literature investigates these new type of lenders activities in the small business lending market. In this regard, Tang (2019) examines whether alternative P2P lending platforms act as substitutes for traditional financial intermediaries or instead as complements and find that alternative FinTech lending is a substitute for bank lending with regards to serving infra-marginal bank borrowers and complements for small loans.

Following a method similar to that used by Tang (2019), we observe that alternative P2P lenders can increase market share if the bank lending criteria are tightened and bank credit supply declines.

Philippon (2016) evaluates the potential impact of FinTech on the finance industry and claims that it provides efficiency-enhancing benefits. In this respect, Fuster et al. (2019) point out that the FinTech lenders provide a rapid origination process that is less susceptible to demand fluctuations than traditional lenders and so P2P lenders adjust supply in a more flexible way. In this regard, they are better positioned to deal with the external mortgage demand shocks. Wang et al. (2021) claim that online P2P lending services give consumers and small firms a convenient and affordable loan option. Similarly, Havrylchyk et al. (2020) examine the drivers of P2P earnings growth. They produce evidence on both the role of the Internet and weak banking competition being responsible for the growth.

In a recent study, Balyuk (2016) investigates how FinTech innovation in the form of alternative P2P lending affects the credit provided by traditional intermediaries, for example, banks demonstrate that alternative lending impacts the principles in the consumer credit market by developing the information environment. According to Balyuk (2016), financial innovation can play a significant role in lowering shortcomings in the consumer credit market and FinTech innovations mitigate these shortcomings by creating information spill overs to traditional financial intermediaries. In addition, Li et al. (2021) maintain that banks may benefit from financial innovations in the clustering of financial data for a number of financial applications such as fraud detection, reject inference, and credit evaluation. On the other hand, Kou et al. (2021a, b) contend investments in FinTech can assist banks in decreasing their operating expenses and payment and transactional data enhance SME bankruptcy prediction.

In addition, recent papers focused on P2P lending suggest that alternative lending platforms compete with incumbents at a certain level. Cornaggia et al. (2018) set up a causal relationship between alternative lending infringement and commercial bank lending. They did this by using the differences in regulatory barriers to P2P lending on the borrower, and investor. They conclude that small banks' lending volume decline due to the activities of alternative lenders.

Buchak et al. (2018) investigate the shadow banks' growth, particularly FinTech shadow banks, in the mortgage market. They show that both regulatory burdens and improved technology can explain the growth in FinTech shadow banking in the mortgage loan market. On the other hand, Jagtiani and Lemieux (2018) investigated whether alternative lenders' loans penetrated potentially underserved areas, where there are low-income borrowers, inadequate competition in banking services, and regions where bank branches have decreased more than others and regions with fewer bank branches per capita.

Finally, similar to Tang (2019), Havrylchyk et al. (2020) and De Roure et al. (2022) investigate whether alternative lending platforms are substitutes for traditional financial intermediaries or instead as complements (in the U.S. and Germany,

Table 2 Descriptive statistics of bank characteristics

Variable	Obs	Mean	Std. Dev	25th	Median	75th
SBLvol($k)	21,764	9.306	1.359	8.647764	9.382724	10.09371
SBLnmbr	21,324	4.887	1.468	4.143135	4.905275	5.645447
Size($bil)	22,504	12.071	1.283	11.21584	11.93074	12.74921
TRBCapital (%)	22,480	18.587	10.131	13.06045	15.64785	20.19954
Core Capital (%)	22,480	10.722	4.184	8.419788	9.667406	11.70716
CoreTier1 (%)	22,480	17.436	10.212	11.85806	14.46128	19.08427
Capital (%)	22,480	11.271	4.183	8.893805	10.2911	12.43739
Deposits (%)	22,504	82.665	8.264	79.74239	84.60511	88.10375
ROE (%)	22,480	4.598	12.538	2.229953	6.268635	10.62173
ROA (%)	22,480	.536	1.18	.2427241	.6774983	1.116585
NPL (%)	22,334	2.595	2.939	.6097619	1.667152	3.451154
SBLto TLoan (%)	22,334	9.361	7.081	4.401148	8.064407	12.76499
SBLto TA (%)	22,504	5.758	4.561	2.557525	4.825758	7.89244
C&I Loans($mil)	22,504	8.04	6.52	3.461009	6.612704	10.99003

This table presents the summary statistics of bank-level statistics. The main dependant variable *SBLvol* is the log amount of small business loan volume. *SBLnmbr* is the logarithm of small business loan number. *Size* is the logarithm of banks total asset. *TRBCapital* is a total risk-based capital ratio. *Core capital* is a leverage (core capital) ratio. *CoreTier1* is a Tier 1 risk-based capital ratio. *Capital* is the total bank capital to total assets. *Deposits* is the total deposits to total assets. *ROE* is the return on equity ratio. *ROA* is the return on assets ratio. *NPL* is the non-performing loans to total loans. *SBLtoTLoan* is the small business loan to total loans. *SBLtoTA* is the small business loan total assets. *C&I Loans* is the logarithm of commercial and industrial loans. Variables are winsorized at the 1st and 99th percentile

respectively). De Roure et al. (2022) show that alternative P2P lenders are bottom fishing when unexpected financial regulations generate a competitive disadvantage for some incumbents. This is supportive of our findings. Havrylchyk et al. (2020) contend that alternative lending platforms have partly absorbed banks in some U.S. counties that were more affected by the financial crisis. Moreover, Tang (2019) and De Roure (2022) claim that the banks affected by the decrease in loan supply are not fully substituted by other banks serving in the same region.

We also posit the view that while banks' small business lending activity is slowing down, thanks to digital solutions such as digital tools for loan processing and credit underwriting, information asymmetry and searching cost is reduced. Consequently, alternative small firms have an advantage in respect of accessing funds easily. This allows them to increase their lending market share in the county where the large and high market share banks were affected negatively by Dodd-Frank. This yields our second hypothesis:

Hypothesis 2 Ceteris paribus, after the Dodd-Frank Act, loans to small businesses are granted by P2P lenders increased in those counties where the banks that were affected by this legislation had a presence, and there was low credit competition.

Data

The main source of data is the Federal Financial Institutions Examination Council's (FFIEC) Consolidated Reports of Condition and Income (Call Reports) that are filed by U.S. banks. To address regulatory deficiencies identified during the last financial crisis,

Table 3 Descriptive statistics of county characteristics

Variable	Obs	Mean	Std. Dev	25th	Median	75th
SBLoan (%)	12,952	8.664	1.73	7.599	8.735	9.857
SBLoan1 (%)	12,866	8.16	1.978	6.894	8.215	9.504
SBLoan2 (%)	12,897	8.317	2.07	7.005	8.284	9.700
Population	12,572	10.266	1.439	9.313	10.159	11.111
DebtoIncome (%)	12,553	1.815	.982	1.190	1.580	2.630
Income	12,568	10.656	.23	10.500	10.641	10.794
Unemployment (%)	12,550	8.743	3.026	6.620	8.540	10.610
BRNUM	12,651	7.438	3.194	5.081	8.211	9.694
C3 (%)	12,556	71.838	19.186	54.010	68.390	89.250
HHI (%)	12,522	7.737	.625	7.218	7.606	8.191
Domdep($k)	12,826	18.87	3.496	15.975	19.693	21.451

This table shows the descriptive statistics of county-level variables. There are three main dependant variables. *SBLoan* is the log amount of loans to small businesses in each county. *SBLoan1* is the log amount of loans to small businesses for businesses with gross revenues less than $1 million in each county. *SBLoan2* is the log amount of loans to small businesses for businesses with gross revenues more than $1 million in each county. The sample also covers county level variables. *Population* is the county level population. *DebtoIncome* is the median household debt-to-income ratio by county. *Income* is the dollar amount of income per person by county. *Unemployment* is the ratio of jobless people by county. *BRNUM* is the number of branches per capita in the county. *C3* is the share of deposits of the three largest banks in the county. *HHI* is the Herfindahl–Hirschman index and HHI ratio accounts for the market share of banks in the county. *Domdep* is the sum of the dollar amount of banks' branch domestic deposits by county. Except for *DebtoIncome*, *Unemployment* and *C3*, all variables are logarithmic and is taken logarithm before they are applied. Variables are winsorized at the 1st and 99th percentile

banking regulators were directed to begin collecting annual data on lending to small businesses by the Federal Deposit Insurance Corporation's (FDIC) Improvement Act of 1991. Regulators provide information on loans to small businesses in the Call Report of June each year as required by this act. The Call Report data covers 2009–2012. Table 2 presents the summary statistics of bank-level data.

The second primary source of county small business data is the FFIEC's Community Reinvestment Act (CRA) database. In 1977, CRA was enacted by Congress and had been carried out by bank regulators. In regard to CRA, Congress aimed to stimulate each financial institution to meet the needs of each firm that doing business.

In part, regulations of CRA require that financial institutions report annual information on their lending to small businesses. Especially, it is necessary to report the amounts and numbers of business loans originated in amounts less than $100,000, more than $100,000 through $250,000 and more than $250,000 through $1 million. In addition, they must report the number and amount of loans originated to firms with less than $1 million in revenues. This paper is on a similar tack as ours, albeit looking at it the other way around from a size perspective. It covers annual CRA data covering the total amount and number of loans to small businesses between 2009 and 2012.

In addition to county small business loan data, county level macro variables are collected from the U.S. Census Bureau, St. Louis and New York FED database, Bureau of Economic Analysis (BEA) and FDIC, which displayed with county level data in Table 3.

Lastly, the P2P lender data is sourced with comprehensive information on funded loans and loan volume from Lending Club's website. We justify our use of lending club data following the extensive analysis of the publicly available databases by Teply and Polena (2020). As a U.S. based alternative lender, only Lending Club makes its data publicly. We note this as a limitation of our study but find comfort in the dominant market share position the company enjoyed at this time. This data covers the credit score of

Table 4 Descriptive statistics for alternative P2P lender at county-level

Variable	Obs	Mean	Std. dev	25th	Median	75th
Panel A. alternative peer-to-peer lender loan characteristics						
P2PSBL	3584	9.307	.815	8.764	9.210	9.903
Term(months)	3584	3.737	.234	3.584	3.584	4.094
Int_rate (%)	3584	.13	.047	0.098	0.121	0.165
Loan_status	3584	1.738	.44	1	1	2
Annual_inc($)	3584	11.095	.533	10.779	11.156	11.462
Dti(%)	3584	13.022	7.471	6.970	13.060	18.510
Fico	3584	6.576	.051	6.532	6.561	6.616
Panel B. County control variables						
Population	3584	10.176	1.555	9.098	10.042	11.150
Income	3584	10.682	.24	10.524	10.668	10.821
Unemployment (%)	3580	8.034	2.7	6.09	7.78	9.60
C3 (%)	3576	71.21	19.174	53.96	68.2	88.45
HHI (%)	3568	7.709	.604	7.21	7.568	8.168
BRNUM	3576	3.048	1.689	1.609	2.708	4.673
DebtoIncome (%)	3584	1.675	.975	1.01	1.58	2.16
Domdep($k)	3575	18.607	3.857	14.764	19.654	21.551

This table presents the summary statistics of alternative small business lender Lending Club. According to the Lending Club dictionary, the main dependant variable *P2PSBL is* the logarithm of amount of small business loan volume. *Term* is the payment numbers on loan. *Int_rate* is the interest rate on loan. *Loan_status* is a dummy variable and set to 1 if charged off, set to 2 for a fully paid loan. *Annual_inc* is the annual income provided by the borrower. *Dti* is the "ratio calculated using the borrower's total monthly debt payments on the total debt obligations, excluding mortgage and the requested Lending Club loan, divided by the borrower's self-reported monthly income". *Fico* is the credit score of borrowers. *Term,Fico* and *Annual_inc* are logarithmic. The county control variables are described in Table 3. Variables are winsorized at the 1st and 99th percentile

borrowers, payment information of funded loans, status of loan and all loan application details from 2009 to 2012 is displayed in Table 4.

After data is collected for the bank, county and alternative P2P lending variables, we merged the three datasets into one. To find treated bank and county and control bank and county unique 5-digit zip code is used. However, although bank and county small business data is provided with a 5-digit zip code level, the alternative P2P lender data is identified at the 3-digit zip code level. In order to evaluate alternative P2P lender activity in treated and control counties, county-level and alternative P2P lender data are merged according to this unique 3-digit zip code.

Method

We use a method that allows us to look at the impact of the regulation at a county level, following the approach taken by Tang (2019). We then apply a difference-in-differences (DiD) approach to obtain our empirical results.

We limited the research period so that the 2008 global financial crisis does not affect the data set exogenously. Our sample period starts after this date and due to using policy change in 2010 as an exogenous shock in our research method, we kept sample period limited to 4 years between 2009 and 2012 in order to mutually coincide the pre and post

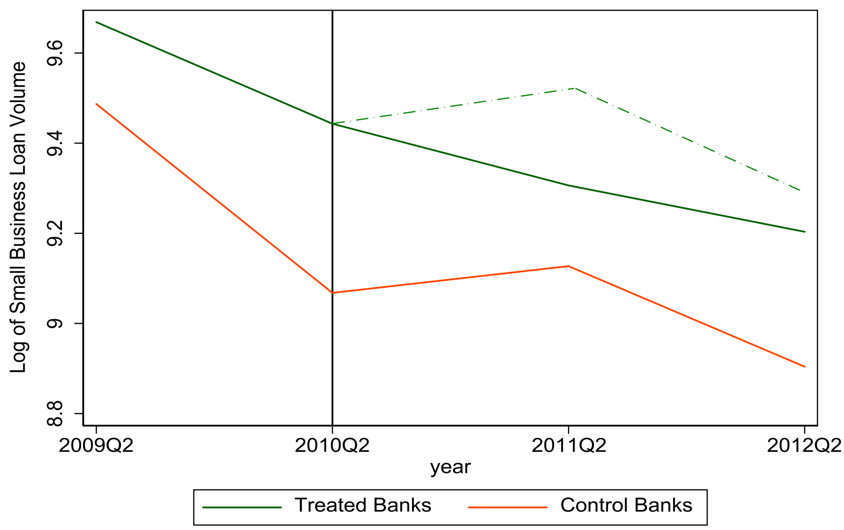

Fig. 2 Bank level small business loan -Parallel-Trends. Figure 2 shows the trend of the annual mean values of small business loan volume of treated and control banks before and after the introduction of the Dodd-Frank Act. Data Source: FFIEC

periods.[9] This sample was analysed in with a similar empirical method in Tang's (2019) article where the period is 2009Q1–2012Q2. After the research period was limited to this period, we performed parallel trend analyses to test the robustness of the analyses results, and the results were confirmed.

In order to isolate the regulatory impact, we apply a negative shock at county level to supply of bank loans that leads banks to tighten their lending criteria. In this regard, we consider an arguably exogenous shock to bank small business credit supply that was due to the implementation of the Dodd-Frank Act in June 2010 which is described as the beginning point of the post-shock term. Using small business loan data at bank and county level in regard to the Dodd-Frank Act, we follow Tang[10] (2019) and De Roure (2022) analyses who find that treated banks reduced lending.

In order to provide causal evidence, the Dodd-Frank Act is used as an exogenous shock. The DiD model compares the volume of small business lending one year before and two years after July 21, 2010 (the implementation date of the Dodd-Frank Act). The treatment group are banks that are affected by this regulation and control group are banks that are not affected.

We cannot completely exclude the possibility that time-varying, unobserved market variables, even with the "DiD" technique, simultaneously affect the development of Fintech loans and the position of traded banks before the shock. To alleviate this problem, we present in Fig. 2 findings that show a parallel trend of FinTech lending in both traded and non-traded markets before 2010Q2. We also show that the benefits of treatment began to take effect in the second quarter of 2010. Given the date of the Dodd-Frank,

[9] After the research period was limited to this period, we performed parallel trend analyses to test the robustness of the analyses results, and the results were proven to be correct.

[10] According to Tang (2019), the impact of adverse shock affecting small business credit supply was greater for businesses with annual revenue below $ 1 million.

we also examine the impact of other additional regulations in the robustness section, it seems unlikely that other variables are responsible for this trend.

There are two cut-offs for financial institutions according to the Dodd-Frank regulations. The first one is for banks which are exceeding $10 billion in assets that subject to annual stress test and higher disclosure requirements. And the other is one for bank holding companies that are exceeding $50 billion in assets (called "systemically important banks") that subject to semi-annual stress tests and a far-reaching list of disclosure requirements. However, due to having limited data about bank holding companies, we could not include systemically important banks in the DiD model, which are exceeding $50 billion in assets; therefore, we only use $10 billion as a cut-off and therefore could not apply alternative method Regression Discontinuity.

Firstly, by using equation one, we test and analyse the qualification of existing research related to the Dodd-Frank Act impact on bank level small business lending activity.

$$\log(SBLoan)_{i,t} = \beta_{i,t}(Treated_i * DFA_t) + \lambda DFA_t + \rho Treated_i + C_{i,t} + \theta_t + \Pi_i + \epsilon_{i,t} \tag{1}$$

where $log(SBLoan)_{i,t}$ is originated small business loans (origination volume $1 million or less) by bank i in year t. $Treated_i$ is a dummy variable that identifies the treatment group, one if the banks with assets over $10 billion threshold which are subject to the Dodd-Frank Act and zero for the banks with assets right below $10 billion threshold and exempted from Dodd-Frank Act. DFA_t is the treatment dummy that takes the value one from Dodd-Frank Act enactment date (21$^{\text{th}}$ July 2010), and zero prior for this date. $C_{i,t}$ is a vector of bank-level control variables are defined in Table 2. θ_t is a variable for the county-year fixed effects and Π_i is a variable for bank fixed effects, and both are used to help remove unobserved heterogeneity such as variation in local loan demand due to (county-specific) business conditions and for unobservable bank characteristics. $\epsilon_{i,t}$ is an error term.

The four columns of Table 5 report the Dodd-Frank Act impact on bank small business loan volume. According to results, the coefficient of interaction term, $Treated_i$ *x* $DFA_{t,}$ is negative and highly in all estimations with bank, county and year fixed effects. The results show that small business lending volume in treated banks decreases.

In order to check traditional banks' responses to Dodd-Frank Act in the counties for evaluating small business loan applications, we use the following equation:

$$\log(SBLoan)_{t,c} = \beta_t(Treated_c * DFA_t) + \lambda DFA_t + \rho Treated_c + C_{t,c} + \delta_c + \gamma_t + \epsilon_{t,c} \tag{2}$$

where $SBLoan_{t,c}$ is originated loans to small businesses(loans origination volume $1 million or less) in county c in year t. $Treated_c$ is a dummy variable that identifies the treated counties and takes the value of 1, if there is a bank with $10 billion assets or over affected by the Dodd-Frank Act and there is low competition according to the C3 and HHI, which are in the top 75th.

If the county has a bank asset below $10 billion, and there is high competition in the bottom 25th, it is defined as a control county and takes 0. Counties other than the 75th and 25th percentile are not included in the model. DFA_t is the treatment dummy that takes the value one from Dodd-Frank Act enactment date (21th July 2010), and zero prior for this date. $C_{t,c}$ is a vector of county-level control variables. δ_c variable for the

Table 5 Impact of Dodd-Frank Act on bank small business credit supply

	Bank small business lending			
	(1)	**(2)**	**(3)**	**(4)**
	SBLoan	**SBLoan**	**SBLoan**	**SBLoan**
Treated*DFA	− 0.628**	− 0.346**	− 0.333**	− 0.116***
	(− 4.607)	(− 4.843)	(− 5.368)	(− 8.123)
Size	0.554***	0.692***	0.713***	0.947***
	(7.956)	(14.933)	(16.550)	(27.115)
TRBCapital	0.354***	− 0.015	− 0.006	0.030
	(12.225)	(− 0.695)	(− 0.229)	(1.556)
CoreCapital	0.029	0.089**	0.086*	0.045***
	(2.035)	(3.732)	(3.093)	(4.266)
CoreTier1	− 0.432***	− 0.040	− 0.048	− 0.067***
	(− 13.811)	(− 2.143)	(− 1.865)	(− 3.453)
Deposits	0.023***	− 0.008	− 0.009	0.005**
	(6.921)	(− 1.632)	(− 2.296)	(2.221)
NPL	− 0.024**	− 0.009	− 0.008	− 0.010***
	(− 4.715)	(− 1.937)	(− 1.538)	(− 3.836)
ROE	0.005**	− 0.001	− 0.000	− 0.002*
	(3.501)	(− 0.508)	(− 0.226)	(− 1.769)
ROA	− 0.019	− 0.005	− 0.013	0.029*
	(− 0.611)	(− 0.222)	(− 0.582)	(1.823)
Capital	0.084***	− 0.023	− 0.021	0.010
	(6.494)	(− 1.356)	(− 1.015)	(1.057)
Bank FE		Yes	Yes	Yes
County FE			Yes	Yes
Year FE				Yes
Obs	21,676	21,584	21,576	21,576
Adj. R^2	0.430	0.878	0.885	0.898

Table 5 shows the difference-in-differences estimation results in Eq. (1). The dependant variable *SBLoan* is the bank level total loan volume. The variable *Treated* takes on the value 1 for the banks with assets over $10 billion and zero for the banks with assets right below $10 billion. *DFA* is the treatment dummy that takes the one from July 2010 onwards and zero prior to that date. Standard errors are clustered at the bank level and shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *,** and ***, respectively.t-statistics are presented in parentheses

county fixed effect, and γ_t is a variable for time fixed effect. $\epsilon_{t,c}$ is an error term. The county level variables are defined in Table 3.

Table 6 reports the Dodd-Frank Act's effect on county small business lending activity. The first column shows the result for the aggregated small business loan activities county and columns 6 and 9 show the small business loan for businesses with gross revenues less than $1 million and for businesses with gross revenues of at least $1 million, respectively.

According to results, the coefficient of the interaction term, $Treated_c\ x\ DFA_t$ is both negative and high in all predictions with county and time fixed effects. The results show that small business lending in treated counties decrease relative to control group counties after the Dodd-Frank Act in terms of aggregate small business loan and for businesses with gross revenues less than $1 million, respectively. There is no significant impact on for businesses with gross revenues of at least $1 million.

Table 6 Impact of Dodd-Frank Act on aggregate county-level small business lending

	Total small business loan volume			Small business loan for businesses with gross revenues less than $1 million			Small business loan for businesses with gross revenues more than $1 million		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	SBLoan	SBLoan	SBLoan	SBLoan1	SBLoan1	SBLoan1	SBLoan2	SBLoan2	SBLoan2
Treated*DFA	− 0.941***	− 0.928***	− 0.586***	− 0.235***	− 0.234***	− 0.033*	− 0.195***	− 0.196***	0.007
	(− 51.388)	(− 51.543)	(− 32.475)	(− 18.138)	(− 19.054)	(− 1.862)	(− 16.862)	(− 17.862)	(0.425)
Population	0.890***	0.893***	0.895***	0.881***	0.892***	0.892***	0.972***	0.978***	0.978***
	(56.357)	(54.393)	(53.690)	(53.577)	(50.847)	(50.861)	(66.149)	(64.003)	(63.756)
DebtoIncome	0.005	0.002	− 0.020	0.059***	0.058***	0.050***	− 0.075***	− 0.074***	− 0.082***
	(0.335)	(0.130)	(− 1.284)	(3.944)	(3.823)	(3.244)	(− 5.973)	(− 5.562)	(− 6.017)
Income	0.613***	0.569***	0.551***	0.430***	0.380***	0.376***	1.110***	1.088***	1.081***
	(8.181)	(7.389)	(7.015)	(5.305)	(4.569)	(4.498)	(15.434)	(14.688)	(14.511)
Unemployment	0.012*	0.012*	− 0.004	− 0.013**	− 0.014**	− 0.018***	− 0.007	− 0.009	− 0.014**
	(1.932)	(1.884)	(− 0.672)	(− 2.189)	(− 2.259)	(− 2.944)	(− 1.347)	(− 1.592)	(− 2.376)
BRNUM	0.034***	0.030***	0.021**	0.183***	0.176***	0.169***	0.156***	0.150***	0.144***
	(4.025)	(3.274)	(2.276)	(20.949)	(18.520)	(17.930)	(19.719)	(18.066)	(17.283)
C3	0.001	0.001	0.001	0.003	0.003	0.003*	0.003*	0.003*	0.004*
	(0.539)	(0.549)	(0.567)	(1.416)	(1.599)	(1.664)	(1.764)	(1.751)	(1.824)
HHI	− 0.028	− 0.057	− 0.045	− 0.053	− 0.095	− 0.094	− 0.098*	− 0.119**	− 0.118**
	(− 0.472)	(− 0.953)	(− 0.755)	(− 0.866)	(− 1.520)	(− 1.505)	(− 1.676)	(− 2.037)	(− 2.027)
Domdep	− 0.003	− 0.006*	− 0.003	0.000	− 0.002	− 0.001	0.003	0.001	0.002
	(− 0.843)	(− 1.856)	(− 0.800)	(0.065)	(− 0.523)	(− 0.285)	(1.084)	(0.287)	(0.542)
County FE		Yes	Yes		Yes	Yes		Yes	Yes
Year FE			Yes			Yes			Yes
Obs	12,183	12,183	12,183	12,173	12,173	12,173	12,183	12,183	12,183
Adj. R^2	0.670	0.663	0.681	0.824	0.824	0.827	0.857	0.856	0.859

Table 6 shows the difference-in-differences estimation results in Eq. (1). The variable *Treated* takes on the value 1 for the counties where there is a bank with $10 billion assets or over affected by the Dodd-Frank Act and there is low competition according to the concentration of the three largest banks (C3) and Herfindahl–Hirschman Index (HHI), which are in the top 75th. If the county has a bank asset below $10 billion, and there is high competition in the bottom 25th, it is defined as a control county and takes 0. Counties other than the 75th and 25th percentile are not included in the model. *DFA* is the treatment dummy that takes the one from July 2010 onwards and zero prior to that date. There are three dependant variables. *SBLoan* is the county level total small business loan volume. *SBLoan1* is a total small business loan for businesses with gross revenues less than $1 million and *SBLoan2* is a total small business loan for businesses with gross revenues of more than $1 million. Standard errors are clustered at the county level and shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *,** and ***, respectively.t-statistics are presented in parentheses

In order to check if alternative lenders increased their lending in counties where small business lending decreased due to the credit supply shock's effect on small business loan applications, we use the following equation:

$$\log\left(SBLoan_{t,c}^{P2P}\right) = a_{t,c}(Treated_c * DFA_t) + \lambda DFA_t + \rho treated_c + C_{t,c} + \delta_c + \gamma_t + \epsilon_{t,c} \tag{3}$$

where $SBLoan_{t,c}^{P2P}$ is small business loan origination volume of alternative lenders loan in county c in year t. $Treated_c$ is a dummy variable that identifies the treated counties and takes the value of 1 if there is a bank with $10 billion assets or over and affected by Dodd-Frank Act and there is low competition according to the C3 and HHI, which are in the top 75th. If the county has a bank asset below $10 billion exempts from the Dodd-Frank Act and there is high competition in the bottom 25th, it is defined as a control county and takes the value of 0. Counties other than the 75th and 25th percentile are

Table 7 Impact of Dodd-Frank Act on aggregate alternative P2P lending

	(1) P2PSBL	(2) P2PSBL	(3) P2PSBL
Treated*DFA	0.674***	0.678***	0.863***
	(30.179)	(29.373)	(24.741)
Population	0.016	0.027*	0.027*
	(1.379)	(1.901)	(1.961)
Income	− 0.385***	− 0.470***	− 0.456***
	(− 5.265)	(− 5.660)	(− 5.515)
Unemployment	0.028***	0.043***	0.043***
	(5.068)	(6.743)	(6.770)
C3	− 0.003	− 0.004	− 0.004
	(− 1.324)	(− 1.454)	(− 1.225)
HHI	0.160**	0.166**	0.151*
	(2.316)	(2.044)	(1.849)
BRNUM	0.006	0.005	0.007
	(0.423)	(0.278)	(0.381)
DebtoIncome	0.046**	0.067***	0.070***
	(2.591)	(3.051)	(3.218)
Domdep	0.011***	0.013***	0.013***
	(2.996)	(3.089)	(3.105)
County FE		Yes	Yes
Year FE			Yes
Obs	3555	3555	3555
Adj. R^2	0.189	0.175	0.191

Table 7 shows the difference-in-differences estimation results in Eq. (3). The dependant variable *P2PSBL* is the small business loan origination volume of alternative lenders in counties. The variable *Treated* takes on the value 1 for the treated counties where there is a bank with $10 billion assets or over and affected by Dodd-Frank Act and there is low competition according to the C3 and HHI, which are in the top 75th. If the county has a bank asset below $10 billion exempts from the Dodd-Frank Act and there is high competition in the bottom 25th, it is defined as a control county and takes the value of 0. Counties other than the 75th and 25th percentile are not included in the model. *DFA* is the treatment dummy that takes the one from July 2010 onwards and zero prior to that date. Standard errors are clustered at the county level and shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by*,** and ***, respectively.t-statistics are presented in parentheses

not included in the model. DFA_t is the treatment dummy that other takes the value one from Dodd-Frank Act enactment date (21th July 2010), and zero prior for this date. $C_{t,c}$ is a vector of county-level control variables. δ_c variable for the county fixed effect, and γ_t is a variable for time fixed effect. $\epsilon_{c,t}$ is an error term. All variables are defined in Table 4 with loan-level variables. We acknowledge that it is not clear whether the DiD coefficient of this regression reports the effect of Dodd-Frank exposure (the main point of our paper) or the effect of bank concentration (unrelated to the paper). That said, we emphasize that the high concentrated counties with low competition are exposed to more regulatory impact and that this in turn should result in an advantage to P2P lenders in the less concentrated counties.

The main dependant variable measures lending volume of the alternative P2P lender data that we used the dollar amount of alternative P2P lender origination volumes from the loan book that is specified at the county level. Due to having limited county-level

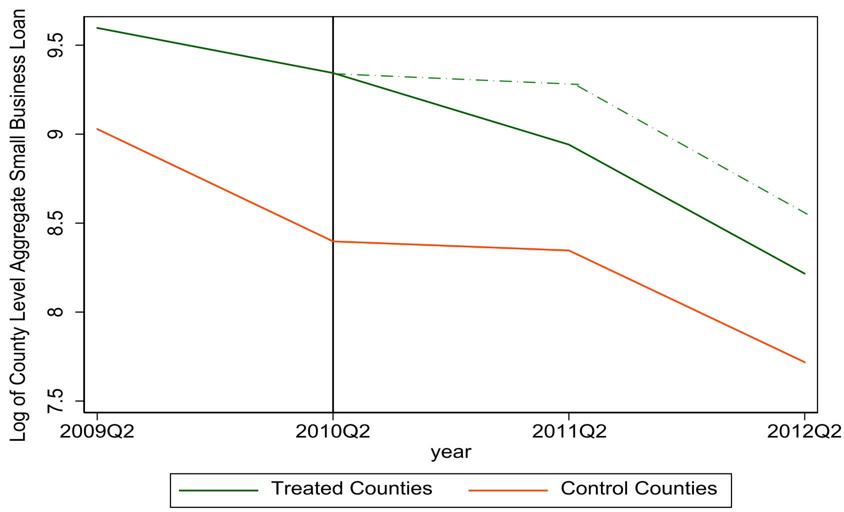

Fig. 3 County level small business loan -Parallel-Trends. Shows the trend of the annual mean values of small business loan volume of treated and control counties before and after the introduction of the Dodd-Frank Act. Data Source: CRA

data, instead of using normalized[11] variables similar as in Tang (2019) paper, the logarithm value of the small business loan origination is used in the analysis.

The results of Eq. (3) are presented in Table 7. It is proved that in regard of control counties, loan origination volume of alternative P2P lender enhanced remarkably in treated counties after the Dodd-Frank Act became law in July 2010, in terms of the total loan amount. According to our results, there was a notable difference, between control and treated counties, in alternative P2P lender loan volume after the enactment of Dodd-Frank. The trend after the Dodd-Frank Act proves that the growth in demand for alternative credit between control and treated markets is unlikely to be urged by observable differences.

In accordance with Table 4, we find that treated counties experienced an increase in alternative P2P lender mall business loan applications compared to control counties.

This result is coherent with FinTechs' and banks being substitutes or complements with the findings of Tang (2019). However, this analysis is necessary for validating the Dodd-Frank Act as a negative shock to incumbents' small business loan supply. We emphasise the limitation to our approach is the restricted data available on alternative lenders. To sum up, the results on the volume of alternative P2P lender loans reveal that, when incumbents cut lending in the small business credit market, some borrowers tend to move from incumbents to alternative P2P lenders.

To check the parallel-trends assumption, we present Fig. 2, which shows lending by banks overtime for the treated and control group.

The Fig. 2 shows that in treated states, new small business loan volume is similar to that in control states before the Dodd-Frank Act. This indicates that the parallel-trends assumption is valid. After the Dodd-Frank Act, the new small business loan volume decreased both

[11] Tang (2019) notes that there is no quantitative difference between the results of using the normalized or logarithmic dependant variable.

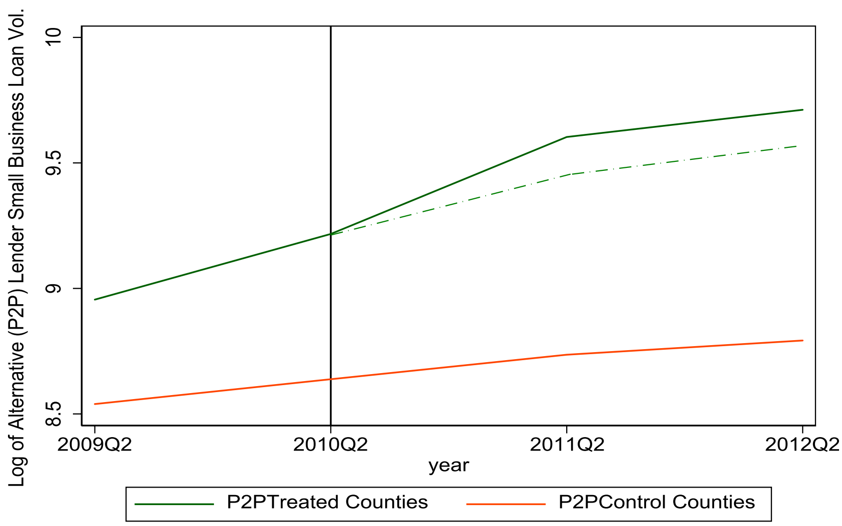

Fig. 4 Alternative P2P lender small business loan -Parallel-Trends. Figure 4 shows the trend of the annual mean values of small business loan volume of Alternative P2P lenders in treated and control counties before and after the introduction of the Dodd-Frank Act. Data Source: Lending Club

for treated and control banks, but it decreased more and faster in treated counties than in control counties which are presented in Fig. 3.

Similarly, we check the parallel-trends assumption with an alternative P2P lender. Figure 4 shows an alternative P2P lender credit provision in treated and control counties. It shows that the volumes of new alternative P2P lender loans to small businesses in control and treated counties displayed parallel trends prior to the Dodd-Frank Act. After the Dodd-Frank Act, P2P small business lending increased in treated counties.

Robustness and additional tests

As a robustness check, we also conducted the difference-in-differences analysis for a restricted 2009–2010 period. By reducing the research period, we compare the predicted treatment and whether the parallel trend assumption is violated. The results are even more significant. At both the county bank lending level and the individual bank level, we have an even bigger negative coefficient for the interaction term: treatedb _ EBAt, and this coefficient is always significant at the 1% level except county level analysis results for the small business loan for businesses with gross revenues more than $1 million. Detailed results are reported in Tables 8, 9 and 10.

We also conduct the main analysis conditioned on the bank- and county-year- fixed effects and various bank characteristics, with concurrent shocks that impose disparate effects on small business lending and the control banks. As part of this, two major potential coincident changes are examined. Collectively, these tests mitigate concerns regarding omitted concurrent shocks that drive the primary result.

Next, the Troubled Asset Relief Program (TARP)[12] was evaluated. TARP introduced by the U.S. government through the Emergency Stabilization Act (2008) to respond to the global financial crisis (Cornett et al. 2013). The TARP was planned to stabilize the

[12] A $700 billion fund was approved by the U.S. Congress to aid the financial institutions (Choi 2012).

Table 8 Robustness results for bank level data

	Bank small business lending			
	(1)	**(2)**	**(3)**	**(4)**
	SBLvol	**SBLvol**	**SBLvol**	**SBLvol**
Treated*DFA	− 0.453***	− 0.272***	− 0.275***	− 0.336***
	(− 23.314)	(− 25.128)	(− 24.707)	(− 16.285)
Size	0.498***	0.677***	1.127***	1.056***
	(30.373)	(12.388)	(12.021)	(10.885)
TRBCapital	0.389***	− 0.002	0.030	0.026
	(6.389)	(− 0.067)	(0.855)	(0.753)
CoreCapital	− 0.001	0.028	− 0.010	− 0.003
	(− 0.062)	(1.368)	(− 0.401)	(− 0.117)
CoreTier1	− 0.467***	− 0.034	− 0.069*	− 0.069*
	(− 7.753)	(− 0.991)	(− 1.870)	(− 1.887)
Deposits	0.025***	0.006*	0.004	0.002
	(8.696)	(1.709)	(1.199)	(0.573)
NPL	− 0.018***	− 0.009*	− 0.008	− 0.007
	(− 3.345)	(− 1.729)	(− 1.519)	(− 1.347)
ROE	0.002	− 0.006**	− 0.005*	− 0.005*
	(0.507)	(− 1.985)	(− 1.792)	(− 1.655)
ROA	0.024	0.074**	0.061*	0.054
	(0.707)	(2.208)	(1.779)	(1.579)
Capital	0.108***	0.022	0.062***	0.060***
	(8.085)	(1.241)	(2.800)	(2.691)
Bank FE		Yes	Yes	Yes
County FE			Yes	Yes
Year FE				Yes
Obs	11,039	10,922	10,906	10,906
Adj. R^2	0.414	0.881	0.878	0.879

Table 8 shows that by limiting the research period to one year before and after treatment, there is no change in banks' small lending activity and the effect of the Dodd-Frank Regulation is still significant. Standard errors are clustered at the county level and shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *,** and ***, respectively.t-statistics are presented in parentheses

financial system by purchasing troubled assets from banks to inject liquidity into the financial system, and reactivate the credit markets (Harris et al. 2013).

According to Black et al. (2013), it was expected from the TARP to increase the lending of participating banks in the initial funding program. In this regard, Li (2013) finds evidence that TARP banks significantly increased bank loan supply. In addition, Berger et al. (2019) and Chu et al. (2019) document that banks increased credit supply to businesses by way of TARP capital injections. However, Cole and Damm (2020) find no evidence that the TARP program increased lending and claim that non-TARP banks reduced lending less than TARP recipient banks.

During the research period, we note that it is possible that control banks received more government aid from TARP after the financial crisis. They would therefore extend more credit to small businesses relative to treatment banks. To test the impact of this we used the period 2009–2012 (TARP $participation_{it}$). This variable is equal to one and zero otherwise is created as a new one and interact this variable with

Table 9 Robustness results for county level data

	Total small business loan volume	Small business loan for businesses with gross revenues less than $1 million	Small business loan for businesses with gross revenues more than $1 million
Treated*DFA	− 0.591***	− 0.068***	0.001
	(− 17.942)	(− 2.867)	(0.054)
Population	0.879***	0.891***	0.973***
	(34.882)	(46.980)	(58.192)
DebtoIncome	− 0.027	0.057***	− 0.081***
	(− 1.084)	(3.460)	(− 5.242)
Income	0.657***	0.296***	1.104***
	(4.945)	(3.270)	(12.696)
Unemployment	0.002	− 0.023***	− 0.013*
	(0.193)	(− 3.182)	(− 1.830)
BRNUM	0.014	0.175***	0.146***
	(1.140)	(16.431)	(16.599)
C3	− 0.001	0.002	0.003
	(− 0.342)	(0.969)	(1.501)
HHI	0.000	− 0.039	− 0.097
	(0.001)	(− 0.583)	(− 1.485)
Domdep	− 0.006	− 0.001	0.001
	(− 1.306)	(− 0.264)	(0.234)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs	5589	5584	5589
Adj. R^2	0.739	0.842	0.867

Table 9 shows that by limiting the research period to one year before and after treatment, there is no change on county-level small business lending and the effect of Dodd-Frank Regulation is still significant except for small business loans businesses with gross revenues of more than $1 million. Standard errors are clustered at the county level and shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by*,** and ***, respectively.t-statistics are presented in parentheses

Year2010+, and then added to the regression. The results are shown in Table 11. *small business lending* continues to load (two-tailed p-value < 0.01).

We also reviewed a non-TARP program, the Small Business Lending Fund (SBLF), which was passed by U.S. Congress and signed into law in 2010 (Wilson 2013). The SBLF was created as part of the Small Business Jobs Act to encourage liquidity in the interbank lending market and intended to provide low-cost funding since, therefore, banks could lend to small businesses (Berger et al. 2020).

Balla et al. (2017) claim that participants in the SBLF program were well-capitalized and healthier financially so that after two-quarters of the start of the SBLF program, SBLF participated banks experienced stronger aggregate growth in lending to small firms. In contrast, Basset et al. (2020) find evidence that there was not any difference between the loan growth of participated and non-participating banks in government financial aid program.

To test the impact of SBLF, we create an indicator equal to one if a bank is participated ($SBLF\ participation_{it}$), and zero otherwise, and interact this variable with *Year2010+*. After adding this interaction to the regression, unlike TARP, we find a significant coefficient on *small business lending* continues to load (two-tailed p-value < 0.01) in the second column of Table 11.

Table 10 Robustness results for alternative P2P lending

	(1) P2PSBL	(2) P2PSBL	(3) P2PSBL
Treated*DFA	0.559***	0.515***	0.612***
	(8.664)	(5.952)	(4.737)
Population	0.023	− 6.220	− 5.910
	(0.841)	(− 1.157)	(− 1.094)
Income	− 0.473**	− 1.351	− 1.279
	(− 2.491)	(− 1.033)	(− 0.971)
Unemployment	0.047***	0.102	0.099
	(3.430)	(1.263)	(1.221)
C3	− 0.000	0.102**	0.112**
	(− 0.104)	(2.226)	(2.245)
HHI	0.445***	− 0.800	− 0.905
	(3.193)	(− 0.448)	(− 0.497)
BRNUM	0.123**	− 3.612	− 3.958
	(2.437)	(− 0.923)	(− 0.985)
DebtoIncome	0.046	0.251	0.240
	(1.326)	(1.303)	(1.235)
Domdep	− 0.003	0.027	0.025
	(− 0.321)	(0.260)	(0.226)
County FE		Yes	Yes
Year FE			Yes
Obs	732	594	594
Adj. R^2	0.165	0.328	0.324

Table 10 shows that by limiting the research period to one year before and after treatment, there is no change on alternative (P2P FinTech) lending for small businesses and the effect of Dodd-Frank Regulation is still significant. Standard errors are clustered at the county level and shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by*,** and ***, respectively.t-statistics are presented in parentheses

A limitation of our approach is the limited-time sample. Parallel trends cannot be strongly verified if there is only one time period in the pre-period. Without strong evidence of parallel trends, it is difficult to assume that the treatment and control counties would have seen a similar credit growth after the regulation. Treatment counties had larger banks and a more concentrated banking environment. Such counties were also disproportionately exposed to the housing crisis since larger banks had higher MBS exposure. It is plausible that lower credit growth is an artifact of the damage caused by the crisis. A larger time sample would help address such concerns, but this was simply not available.

We observe that our results are consistent with Cortés et al. (2020) analysis of the way in which the Dodd-Frank Act acted on banks at the local level. They suggest that affected locals raise interest rates to compensate for the capital burden imposed by the stress test element. This gives an advantage to P2P lenders because banks reduce small business loans that are more like commodities as that leads borrowers to switch.

Table 11 Tests for successive shock

Additional controls			
Small business lending			
	Control of banks receiving TARP aid	**Control of banks receiving SBLF funding**	**Control of TARP and SBLF**
	(1)	(2)	(1)− (2) (3)
Dodd− Frank	− 0.346***	− 0.335***	− 0.116***
	(− 36.557)	(− 35.446)	(− 8.111)
TARP	0.041		− 0.011
	(1.160)		(− 0.372)
SBLF		0.107**	− 0.043
		(2.013)	(− 0.837)
Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs	21,584	21,576	21,576
Adj. R^2	0.876	0.885	0.898

Table 11 shows the result of additional tests for bank small business lending volume. In column 1, *TARP* is an indicator equal to one if a bank or its affiliated holding company participates in the TARP program and zero otherwise for years 2009–2012. In column 2, *SBLF* is an indicator equal to one if a bank or its affiliated holding company participates in the SBLF program and zero otherwise between 2009 and 2012. In column 3, all two potential successive shocks are controlled for. Standard errors are clustered at the bank level and shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by*,** and ***, respectively.t-statistics are presented in parentheses

Conclusion

This paper investigated how innovative lending models gained a regulatory advantage over traditional banks, particularly in respect of loans to small businesses. We developed an empirical model for bank, county, and innovative P2P lending. We separately tested the impact of a negative regulatory shock on small business lending.

We examined two main hypotheses. First, we investigated new regulations' impact on county-level small business loan origination at traditional banks. We found that in treated counties where there was a bank with $10 billion assets or over and affected by Dodd-Frank Act, and where there was low competition according to the C3 and HHI, there was a decrease in the small business loan volume according to control counties. We conclude that unexpected regulatory reform like the Dodd-Frank Act has led regulators to make changes that impact financial institutions, especially banks, and may cause them to reduce their lending to small businesses.

Second, we examined whether innovative P2P lenders increase their lending in counties where small business lending decrease due to the credit supply shock's effect on small business lending. The analysis shows that alternative P2P lender volume of loan origination rose considerably in treated counties after the Dodd-Frank Act became law. This shows that there was a regulatory advantage.

We conclude that policy makers should consider whether the regulatory advantage is equitable and/or desirable. Clearly, FinTech lenders can be regulated like traditional banks, but they would then lose this regulatory competitive advantage. Our contribution is in showing how the lack of regulation gives FinTech lenders a comparative advantage over traditional banks.

The important implication of our paper's findings is that higher capital requirements and regulatory enforcement on banks may lead regulated banks to reduce their loans to small firms and thereby providing an opportunity for P2P lenders to grow market share.

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Authors' contributions
Both authors read and approved the final manuscript.

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The authors are happy to provide open access availability of data and materials.

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The authors declare they have no competing interests.

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