FinTech Lending under Austerity

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Abstract

We document public welfare spending as an important growth driver of FinTech lending. Examining the massive austerity-led cuts to local welfare spending initiated by the UK government in 2010, we show that the gradual uneven rollback of the local welfare state since then is strongly associated with a rise in demand for peer-to-peer (P2P) consumer loans among affected areas, primarily in areas facing more banking and digital exclusion. P2P loans issued in austerity-affected areas are more expensive compared to those issued in unaffected areas, consistent with the P2P platform's risk pricing sensitivity to higher default rates in affected areas. Overall, our findings show that P2P lending, as an alternative means to household finance, can help smooth cuts in welfare transfers particularly among households in economically deprived areas.

JEL classification: D12, D14, G23

Keywords: Fintech; Financial Technology; Peer-to-Peer Lending; Austerity; Disintermediation; Reintermediation

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1 Introduction

Credit markets worldwide are experiencing the rapid proliferation of FinTech. A growing literature on this topic examines technological factors behind the rise of peer-to-peer (P2P) lending (Buchak, Matvos, Piskorski, and Seru, 2018; Fuster, Plosser, Schnabl, and Vickery, 2019), its impact on credit market frictions (Fuster, Plosser, Schnabl, and Vickery, 2019; Tang, 2019; Dobbie, Liberman, Paravisini, and Pathania, 2021; Fuster, Goldsmith-Pinkham, Ramadorai, and Walther, 2021), and the implications of competition between P2P and traditional lenders (de Roure, Pelizzon, and Thakor, 2021). However, factors governing the rising demand for P2P loans remain largely understudied. It is also unclear whether P2P lending improves financial inclusion as originally claimed by previous studies.[1]

Using data related to the ten-year *austerity* program launched by the UK central government (CG) in late 2008, this paper provides novel evidence that public welfare spending is an important growth driver of P2P lending activity. Public welfare spending mainly targets the poorer strata of society that depend on welfare assistance from the state (Van de Walle, Nead et al., 1995; Mackay and Williams, 2005), whose constituents face significant challenges in accessing formal finance due to low incomes and bad credit histories (Demirgüç-Kunt and Singer, 2017). Whether P2P lending, with its promise to provide small loans with simpler processing of applications and quicker disbursements, is able to cater to the financing needs of such economically deprived households remains an open question.

We focus on public welfare spending in England, and particularly on cuts in welfare spending introduced under the austerity program. These cuts were part of widespread efforts by the UK CG to reduce the massive budget deficit following the 2008 financial crisis, and were delivered mainly by reducing annual welfare grants made available by the CG to local authority districts (LADs) in England.[2] LADs depend heavily on these grants, which make up to three-fifths of their annual budget on average (Innes and Tetlow, 2015). As a result of cuts to their grants, LADs were forced to scale back on funding vital local public services including housing benefits, schools, hygiene, safety, and culture.[3]

The funding cuts were severe with LADs losing up to 37% of their grants in total between 2009 and 2019 (Institute for Government, 2022). However, our analysis interestingly reveals that the funding cuts have not been consistent or uniform across LADs, and even for a given

[1]See literature reviews by Thakor (2020), Allen, Gu, and Jagtiani (2021), and Berg, Fuster, and Puri (2021) for more information on these topics.

[2]LADs in Scotland, Wales and Northern Ireland receive grants from their national devolved governments instead of directly from the CG (Phillips, 2014). We do not consider these regions in our study since devolved governments follow their independent grant allocation schemes which are different from that of the CG.

[3]The austerity program ended officially in 2019, but it is unclear whether welfare grants to LADs have been increased since then. Details of the official announcement on ending austerity can be found here: `https://bit.ly/3tqQJFC`.

LAD over time. Funding changes measured over annual and multi-year rolling windows reveal that most LADs experienced both increases and decreases in CG grants during this period. Our analysis using data from the Bank of England's NMG Household Finance Survey furthermore reveals that households generally experienced greater financial constraints and reduced spending whenever their LAD experienced sustained funding cuts from the CG. These findings suggest that the variation in funding grants to LADs (determined exogenously by the CG) resulted in income shocks to households, particularly to those that are economically deprived and depend on welfare benefits and services from their LAD. Consistent with these facts, our main hypothesis is that greater financial stress among households following cuts in CG grants to LADs leads some among them to demand loans from P2P platforms.

Our analysis is organized in two parts. First, we build a theoretical model featuring welfare transfers to agents in an incomplete loan market, and use it to characterize the demand for P2P lending in response to income shocks to households subsisting at least partially on such transfers. Second, we test the model's predictions using publicly available data from a leading P2P consumer lending platform in the UK and quasi-exogenous variation in CG grants to LADs under austerity that generate income shocks among affected households.

We study the consequences of CG funding cuts to LADs on P2P lending using a regression discontinuity (RD) design. Specifically, we compare P2P lending outcomes in LADs that experienced negative changes in cumulative funding over the preceding three years (*treated* LADs) with P2P lending outcomes in a *control* group of LADs that experienced non-negative cumulative changes in funding over the same period. A three-year rolling window outweighs the prospect that LADs may adjust to funding cuts in the short-term by tapping into their existing financial reserves or other available means of income (such as raising council taxes or retaining a greater share of business rates).[4] Employing a three-year rolling window is also apt given the possibility that the CG may at times give political preference to certain LADs when allocating grants, or yield to the lobbying efforts of some LADs against lowering, or even increase, their grants. Such efforts may prove effective in the short-term but will most likely be noticed and cause political furore if they persist for longer periods such as three years. A three-year rolling window mitigates these possibilities and takes into account funding changes over longer periods that might affect an LADs ability to fund and provide

[4] Council taxes are the local taxes levied on domestic property collected by LADs. Residents may be eligible for a reduction in their council tax if they have low income or receive welfare benefits. Details on council taxes can be found at https://www.gov.uk/council-tax. Business rates are taxes on commercial properties that are also collected by LADs. Under the business rates retention scheme, LADs retain a portion of the business rates paid locally, whereas the rest is sent to the CG to be redistributed across all LADs. Details on council taxes can be found at https://www.gov.uk/introduction-to-business-rates. The money collected from council taxes and business rates is used to help partially pay for the social services and benefits provided by the LADs.

essential public services like housing, schooling, and security to the local population.

Using this design together with a rich set of controls, we avoid confounding the impact of funding cuts with unobserved shocks to the P2P platform, its investors, and prospective borrowers. We find that LADs just above and below the treatment cutoff (zero change in cumulative three-year funding) do not differ significantly in terms of observable socioeconomic characteristics, except in outcomes likely to be affected by the cumulative funding treatment, thus justifying our RD design. Our results are also robust to the exclusion of few LADs that experienced steady decline (increase) in CG grants during the sample period.

Following are our main findings. First, austerity led to greater demand for P2P loans, whereby *treated* LADs experiencing funding cuts witnessed 11% more P2P loan issuance per zipcode by the platform per year (17% in aggregate £) compared to P2P loans issued in zipcodes of comparable *control* LADs that did not face these cuts.[5] These results correspond to our model prediction that demand for debt is higher in aggregate states with low public transfers. Even among *treated* LADs, P2P loan origination is marginally higher in deprived areas that are either more financially excluded due to less bank branch coverage or digitally excluded due to poorer internet access.

Second, P2P loans issued in *treated* LADs are up to 40 basis points more expensive than similar loans issued in *control* LADs. This is consistent with the model prediction that the platform anticipates a higher default propensity among borrowers from LADs receiving fewer public transfers, and thus includes a higher default premium when pricing these loans.

Lastly, loans issued in *treated* LADs are on average about 39% more likely to default than comparable loans in *control* LADs, particularly in the case of new borrowers. This result fits well with the model prediction that income shocks resulting from prolonged funding cuts to LADs may affect local borrowers' ability to repay loans obtained previously from the P2P platform, leading to a higher incidence of loan defaults within affected LADs. These findings also demonstrate that higher default rates may be contributing contemporaneously to the platform's decision to charge higher interest rates on P2P loans issued to borrowers in LADs experiencing funding cuts.

Although our results are robust to the inclusion of various controls and robustness checks, one concern is that unobservable within-LAD heterogenity (say, among zipcodes within an LAD) may potentially bias our estimates. We address this concern by employing a more restrictive RD design wherein we compare P2P lending outcomes between contiguous *treated* and *control* LADs, specifically among zipcodes located within ten kilometers on either side of their common border. The key identifying assumption is that zipcodes falling within these

[5] Zipcodes in the UK are sub-administrative divisions within LADs. We use lookup data from the Office for National Statistics to map each borrower zipcode to its respective LAD.

narrow contiguous bands are likely to be characterized by similar socioeconomic conditions, with the only plausible difference being that people living on either side of the border are subject to different treatment status depending on their respective LAD. Results obtained from this restrictive empirical design are fully consistent with our main findings showing significant association between CG funding cuts under austerity and the rise in P2P consumer lending as well as their pricing and performance characteristics within affected LADs.

This paper contributes to several strands of literature. First, our paper is relevant to the fast growing literature on the impact of FinTech on credit markets. A large body of this literature is dedicated to understanding whether FinTech platforms lend more cheaply or provide better products compared to traditional lenders such as banks (Buchak et al., 2018; Tang, 2019; Balyuk et al., 2020; Erel and Liebersohn, 2020; Thakor, 2020; Berg et al., 2021; de Roure et al., 2021; Gopal and Schnabl, 2022). Several related studies explore the technological advantages that FinTech lenders have over traditional ones, and whether they can be effective in reducing search and intermediation frictions in the loan origination process (Bartlett et al., 2021; Fuster et al., 2019, 2021). While much of this prior research focuses on the role of technology in FinTech, there exists an outstanding question on "*who came first, the chicken or the egg?*" regarding FinTech's evolution and accessibility. In this context, to our best knowledge this is the first study to systematically show that income shocks to households, particularly the ones that are economically deprived, are an important driver of FinTech adoption. The UK is also home to the second largest market for alternative finance after the USA (Ziegler et al., 2021), and thus presents an important setting to study the demand dynamics underlying P2P lending. Our paper is most closely related to Erel and Liebersohn (2020), who study the role FinTech lenders played in facilitating credit access to small businesses under the USA Paycheck Protection Program in areas hard hit economically by the COVID-19 pandemic. Our paper is strongly complementary to theirs, and shows how income shocks due to welfare cuts under austerity affected the demand for consumer loans offered by P2P platforms, especially in areas deprived of banking and internet access, as well as their pricing and performance.

Second, our paper informs research on the role played by FinTech in fostering access to financial services. Very few papers have addressed this topic so far by focusing on how large, temporary macroeconomic shocks and natural disasters shape the adoption dynamics of digital payments systems in developing countries. For instance, Mas and Morawczynski (2009) show that political unrest in Kenya in 2008, which forced the temporary shutdown of traditional financial services for nearly two months, played a key role in the initial adoption wave of the mobile phone-based payment technology M-PESA. This initial wave led to persistent growth in M-PESA's adoption so much so that it was used by 97% of Kenyan households by 2014 (Suri and Jack, 2016). Similarly, the 2008 earthquake in the Lake Kivu region in Rwanda led to rapid growth in money transfers via mobile phones particularly to the affected region (Blumenstock et al., 2016). Relatedly, Mezzanotti et al. (2021) show that the adoption of mobile payment technology increased persistently following the large but temporary cash contraction induced by the 2016 Demonetization in India. Our paper instead focuses on how sustained reductions in public spending in a developed economy, and resulting drops in welfare payments, housing subsidies, schooling, and social services, can induce large increases in the demand for unsecured consumer loans offered by P2P platforms.

Finally, our paper relates to the longstanding debate on the economic fallout of austerity. At the macro level, some scholars argue that austerity reduced the UK's national debt and fostered better economic growth than the rest of Europe (Alesina et al., 2015, 2018). On the other hand, critics blame austerity for having lowered personal living standards, especially for the working classes (Blyth, 2013). Studies show that the most economically deprived LADs with the least revenue-generating capacity were the ones subjected to the largest funding cuts under austerity (Innes and Tetlow, 2015). These cuts exacerbated economic distress in areas that were already deprived in education, income, and employment, giving rise to populism that culminated in the 2016 Brexit vote in favour of the UK leaving the European Union (Becker et al., 2017; Fetzer, 2019). Other evidence suggests that austerity had a disproportionate impact on people living in poverty and at the same time put welfare and community services under increasing financial pressure due to reduced budgets (Maynard, 2017; Cummins, 2018; Fitzgerald, 2018). Our study contributes to this literature by showing that the austerity-led funding cuts had a systematic effect on individual borrowing behaviour, particularly among those living in LADs impacted by these cuts.

The remainder of the paper is organized as follows. Section 2 presents the theoretical model. Section 3 describes the institutional background and data. Section 4 discusses the empirical design and methodology. Section 5 reports the results. Lastly, Section 6 discusses the conclusions and key takeaways from our study.

2 Theoretical Model

The theoretical model used in this paper is adapted from LeGrand and Ragot (2021) to the context of individuals facing income risk. Building on their original work, the model developed in this paper is centered on partial equilibrium comparative statics. The purpose of the model is to provide a theoretical rationale to explain the demand for P2P loans from low-income households that rely on public welfare transfers. The model also offers predictions regarding the impact of welfare transfers on P2P loan interest rates and realized defaults.

2.1 Setup

We consider a two-period economy comprising a household whose income depends partly on public transfers. Specifically, the household's total income is made up of two components: a private income from labor and possibly a public welfare transfer complement. The private income y can either be high at y_h or low at y_l. When private income is low, it is complemented with a public welfare transfer T that is either high at T_G or low at T_B. The household's total revenues are thus characterized by an individual state $s \in \{h, l\}$ and an aggregate state $S \in \{G, B\}$. We focus on a two-period model with the probability to switch from state (s, S) today to (s', S') in the next period denoted by $\rho_{ss'}\pi_{SS'}$.[6] We make two assumptions. First, receiving a low private income is always worse than receiving a high one, independently of public transfers. In other words, states can be ranked in an increasing order of total revenues as follows: (l, B), (l, G), and h. Second, we assume that aggregate states are persistent: when the current state is B, it is more likely that the previous state was B rather than G, and the same applies if the current state in G.[7]

We restrict our attention to a household that would like to borrow to smooth out its consumption. For the sake of simplicity, we assume that the household has no access to traditional banking and borrows an unsecured and non-contingent loan from a P2P platform.[8] No perfect enforcement technology is available to the platform and the household can opt to strategically default on its debt repayment in the second period. However, if it defaults, the household suffers a private cost, equal to a share $\tau > 0$ of the total second-period endowment.[9]

The P2P lending platform is assumed to be a risk-neutral financial intermediary with access to a financial market paying a riskless interest rate r. The platform thus provides a risk-sharing arrangement that allows borrowers to pay a credit risk premium in accordance with their expected default probability.

The timing of the market is as follows. In the first period, the initial aggregate and individual states are drawn. The household receives its endowment and then decides how much to consume and to borrow. In the second period, once aggregate and individual states have been determined, the household receives its second-period endowment and decides whether to repay its debt or default. The default decision is rational and based on comparison

[6] More precisely, the probability of private income to switch from y_s in the first period to $y_{s'}$ in the second period is $\rho_{ss'}$, while the probability for public welfare transfer to switch from T_S to $T_{S'}$ is $\pi_{SS'}$. Both processes are independent of each other.

[7] Formally this means that $\pi_{GG} + \pi_{BB} > 1$.

[8] Relaxing this assumption does not materially change the predictions of the model.

[9] To preserve simplicity in our two-period model, we assume a reduced-form exogenous private cost of default τ. It is possible to make this cost endogenous. For instance, this is the case in an infinite-horizon model, in which a defaulter would be prevented from borrowing further (see LeGrand and Ragot 2021).

of the household's relative utilities: it will default if the utility derived from defaulting is higher than the utility derived from repaying its debt. More formally, in state (s, S), with $s \in \{h, l\}$ and $S \in \{G, B\}$, repaying debt d corresponds to the second-period consumption $y_s + T_S \cdot 1_{s=l} - d$, while defaulting – to consumption $(1-\tau)(y_s + T_S \cdot 1_{s=l})$ because of the default cost τ. The household will default if $d > \tau(y_s + T_S \cdot 1_{s=l})$, or in words, if debt repayment is costlier than defaulting. In this case, default becomes the optimal strategic decision.

We will denote by:

$$\overline{d}_{l,S} = \tau(y_l + T_S), \text{ and } \overline{d}_h = \tau y_h, \tag{1}$$

the debt default thresholds. Any debt choice higher than $\overline{d}_{l,S}$ (respectively, $\overline{d}_h$) will yield a default in the second period when the state is (l, S) (respectively, h).

2.2 Equilibrium analysis

The economy features several possible types of equilibria, depending on whether default occurs or not, and on the state in which default occurs when it does. First, from equations (1) and the ranking of aggregate incomes, it can be readily deduced that default thresholds satisfy the following condition:

$$\overline{d}_h \geq \overline{d}_{l,G} \geq \overline{d}_{l,B} > 0. \tag{2}$$

This ranking implies that if the household defaults in state (l, G), it will also default when receiving a lower public transfer (state (l, B)). In loose terms, the default is "more likely" in the worst state (l, B) comprising a low private income and a low public transfer. Another implication of the ranking (2) is that choosing a debt level greater than $\overline{d}_h$ implies a default in all circumstances (no matter whatever the future state is). With default expected to be certain, the platform will refuse to lend (or in the model, offer a null price).

The household's default behavior is determined completely by its debt choice d and more precisely, where it fits in the ranking (2). Three outcomes are possible. First, $d \leq \overline{d}_{l,B}$ and the debt amount is sufficiently modest to be repaid no matter the household's future financial situation. There is consequently no default on the loan. Second, $\overline{d}_{l,B} < d \leq \overline{d}_{l,G}$ and the debt amount is too large to be repaid in some of the states. The household chooses to default in its poorest state (low private income y_l and low public transfers). However, the household does repay its debt in "better" situations, whenever the public transfer or private income is high. Third, $\overline{d}_{l,G} < d \leq d_h$ and debt is so high that it will only be repaid if the household earns a high private income (state h) but will default if its private income is low, independent of the amount of public transfers.[10] These three situations correspond to three

[10] We already ruled out the fourth situation when $d > d_h$ that would imply a default for sure and hence would be not served by the platform.

different types of equilibria, characterized by the states of default occurrences. Each of these equilibria differ along the debt interest rate, the outstanding debt amount, and the default probabilities.

We discuss the case of the equilibrium where the household defaults only in state (l, B). Formally, the household that is currently in state (s, S) will default on its debt repayment in the next period if it obtains a low private income and low public transfer. Default in this case occurs with a probability $\rho_{sl}\pi_{SB}$. The absence of arbitrage opportunities for the risk-neutral P2P platform implies that the household will be charged the (net) interest rate $\frac{1+r}{1-\rho_{sl}\pi_{SB}} - 1$, reflecting that the household will default in state (l, B) but repay its debt otherwise. Obviously, the more likely this bad state, the higher the interest rate that is charged to households. We can then show that the debt demand d must verify the following conditions:

$$\begin{aligned} \frac{1-\rho_{sl}(1-\pi_{SG})}{1+r} \leq \beta\rho_{sh} & \frac{u'(y_h - d)}{u'(y_s + T_S + \frac{1-\rho_{sl}(1-\pi_{SG})}{1+r}d)} \\ & + \beta\rho_{sl}\pi_{SG}\frac{u'(y_l + T_G - d)}{u'(y_s + T_S + \frac{1-\rho_{sl}(1-\pi_{SG})}{1+r}d)}, \end{aligned} \tag{3}$$

$$d \leq \tau(y_l + T_G), \tag{4}$$

$$d > \tau(y_l + T_B). \tag{5}$$

Equation (3) is the Euler equation for a household that will default in state (l, B). Therefore, there are only two terms corresponding to the two states h and (l, G), in which the debt will be repaid. The debt payoff in a given state is priced by the household through its intertemporal marginal rate of substitution between consumption in the current period and consumption in the same state during the next period. Equations (4) and (5) are the conditions guaranteeing that the borrower will only default in the state (l, B).[11] Overall, equations (3)–(5) characterize the household's debt demand in state (s, S) when default in state (l, B) is an equilibrium.

Two other equilibria are possible. The first one is the no-default equilibrium, in which the borrower repays her debt in all circumstances. The second one is the l-equilibrium in which the borrower defaults on her debt if she receives a low private income, independently of public transfers. Details can be found in Appendix C.

[11]For this situation to be an equilibrium, at least one equation between the Euler equation (3) and the default condition (4) has to hold with equality.

2.3 Model predictions

We now turn to comparative statics of the model parameters and state the following proposition.

Proposition 1 (Comparative statics) *We have the following results:*

1. *The household debt demand is larger when the public welfare transfer is low (state B) than when it is high (state G).*
2. *The interest rate is higher when the loan is contracted in a period with low public welfare transfers.*
3. *The share of defaulting loans is higher in periods where the public welfare transfer is low (state B) than when it is high (state G).*

Proposition 1 states the results regarding the comparative statics in the three possible equilibria. The first point of Proposition 1 states that households express a higher P2P debt demand when the public transfer is low. This result is less intuitive than it sounds. Indeed, household P2P debt demand is subject to two conflicting factors: consumption smoothing and interest rate. Consumption smoothing implies that the household demands a greater debt amount when its total revenues are low compared to when they are high. This factor therefore contributes to higher (lower) demand during periods of low (high) public transfers. However, as explained in the preceding paragraph, the household is likely to be charged a higher interest rate with low public transfers, which tends to diminish its debt demand. The overall effect is thus a horse race between the consumption-smoothing motive and interest rate. Overall, we can show that the consumption-smoothing effect dominates and the demand for P2P loans is higher when households receive a lower public transfer.

The second result is driven by the (l, B)-default equilibrium, in which the household will default if the next-period public transfers are low. Since aggregate states are persistent, default in the next period will be more likely when the current transfer is low than when it is high. The P2P platform is aware of this mechanism and therefore charges a higher interest rate when the current public transfers are low.

The final point is also driven by the (l, B)-default equilibrium and is the ex-post implication of default occuring when the household receives a low public transfer in the next period.

Overall, we acknowledge that our model is highly stylized and abstracts from much of the complexity and heterogeneity that characterize lending in the real world. One might therefore expect to see many more equilibria in the population than the three specified in our model (for example, due to heterogeneity in personal incomes). However, we strongly believe that the results of Proposition 1 will hold up in a more generic setup. In the following sections we empirically test the model's predictions using real data on public welfare transfers and P2P lending.

3 Background and data

We measure public welfare transfers to households, modelled in Section 2, using annual funding grants provided by the UK CG to LADs in England. We exploit the uneven, quasi-exogenous variation in these funding grants to represent welfare transfers to households in different aggregate states of the economy. We then investigate whether this funding variation has an effect on local P2P lending activity within LADs using relevant data from a leading P2P platform in the UK.

Accordingly, we first describe the administrative structure of LADs, the various social services and welfare assistance they provide to their respective local populations, and the extent of their dependence on CG funding for provision of these services and benefits. We then describe the P2P platform and its loan origination process.

3.1 Local governments and their funding in England

England is divided into multiple LADs which are essentially sub–national administrative regions that can be broadly classified into four types: boroughs, metropolitan boroughs, unitary authorities, and non-metropolitan districts. At the time of writing, there were a total of 309 LADs, comprising 32 London boroughs (12 of them are designated as Inner London boroughs, while the rest is designated as Outer London boroughs), 36 metropolitan boroughs, 58 unitary authorities, and 181 non-metropolitan (shire) districts.[12] While the majority of LADs have not undergone any major changes during our sample period, some LADs have been abolished and absorbed into other neighboring LADs, or have merged to form *Combined Authorities*.[13]

The local administration in each LAD is responsible for the provision of several essential public services to the local population, such as child and adult social care, public health services, school education (at all levels), housing services and allowances, public safety (policing), public transportation and parking, road construction, cultural and environment services, etc. To fund each of these services LADs depend on three primary sources: Revenue Support Grants from the CG, taxes levied on commercial properties known as *business rates*, and *council taxes* levied on residential property (Studdert, 2021). Unlike the CG, LADs cannot borrow to fund their services; they must therefore either run balanced budgets or draw on reserves accumulated in previous years (Commons Library Briefing, 2021; Institute for Government, 2022).

[12] The City of London and the Isles of Scilly do not fall under any of these categories.

[13] For example, East Dorset was abolished and incorporated into Dorset (unitary authority) on April 1, 2019. Similarly, the LADs of Bolton, Bury, Manchester, Oldham, Rochdale, Salford, Stockport, Tameside, Trafford, and Wigan merged to form the Greater Manchester Combined Authority on April 1, 2011.

Funding provided by the CG to LADs comes mainly in two forms. First, there is a *Revenue Support Grant* that LADs can use to finance expenditures and services. Second, a portion of business rates is returned by each LAD to the Central Government, which are subsequently redistributed among all LADs. Since 2013 this portion amounted to 50% of the business rates collected by LADs. Together, the Revenue Support Grant and the LAD's share of business rates constitute the *Settlement Funding Assessment* (SFA) which is the focus of this study.

The allocation of SFA is determined through a process known as *Local Government Finance Settlement* (LGFC). Each year LADs prepare revenue budgets which are then reviewed by the CG. Around December of each year, the CG announces the provisional LGFC, which after consultations with LADs is finalized around February for the upcoming fiscal year. The CG thus decides how much funds it will allocate to support the spending needs of LADs over the next fiscal period beginning from April 1 to March 31 of the following calendar year.

The funding of LADs by the CG has reduced substantially during the decade that followed the 2008 financial crisis. This severely impacted LADs' ability to provide social services. For example, Innes and Tetlow (2015) document that spending per capita at the LAD level declined rapidly in real terms by 23% between 2009 and 2015. Moreover, it appears that these funding cuts varied disproportionately across LADs: most deprived areas, especially in the north of England, experienced the sharpest drops in CG funding (Becker et al., 2017; Maynard, 2017).[14] According to more recent data from the Institute for Government (2022), and consistent with our own results, total CG funding of LADs declined by 37% in real terms between 2010–20 from "£41.0bn to £26.0bn (in 2019–20 prices)" (Institute for Government, 2022, p.1).

The importance of CG funding for LADs can be gauged from the fact that it represented nearly two-thirds of the average LAD's income in 2009–10, but has since declined to just 50% by the end of our sample period in 2019–20.

With no ability to borrow, LADs can potentially offset the CG funding cuts by tapping into their reserves and/or by increasing the council tax rates. Drawing upon reserves, however, can only be occasional. Reserves are intended to help LADs' finances in unexpected situations (like COVID pandemic). They are therefore not a substitute for a stream of budgeted yearly LADs revenues. They also have to be replenished to ensure that LADs can face unexpected situations in future (Studdert, 2021; Local Government Association, 2022). As such, reserves are usually not considered a sustainable source of funding (Innes and Tetlow,

[14] For example, Becker et al. (2017, p.616) suggest that due to funding cuts between 2010 and 2015, many LADs substantially reduced spendings on social services and housing benefits, resulting in an the "overall financial loss per working adult ... between £914 in Blackpool and £177 in the City of London".

2015).

The ability of LADs to increase the council tax rates is also limited. According to the 2011 Localism Act, increases in council tax rates cannot exceed 2% per annum without approval that can only be obtained through a local referendum (Institute for Government, 2022; Sandford, 2022). This 2% cap on the increase in council tax rate was effective for 2012–13, raised to 3% for 2018–19, and subsequently brought back to 2% for 2020–22.

Taken together, cuts in CG funding and pre-existing limitations to LADs' ability to raise funds from alternative sources have contributed to significant reduction in LADs' overall spending power since 2009. This in turn, has resulted in a worse quality of multiple public services and in lower amounts of social benefits, both of which are provided by LADs. For example, existing evidence indicates that cuts in the CG funding lead to the deterioration of the National Health and Social Care services across the country (Maynard, 2017). In turn, Cummins (2018) argues that funding cuts had disproportionate effects on people living in poverty, and in particular, on people suffering from mental health issues.

3.2 What are the treated and control LADs?

Our empirical analyses focus on changes in the SFA to each LAD in England over time and their effects on local P2P loan origination and performance. The SFA data is publicly available from the website of the Department for Levelling Up, Housing and Communities (DLUHC) of the UK government.[15] We use the annual revenue expense budget files from this portal to recover the SFAs for all LADs in England during the period 2007–20. Using this data we construct three-year cumulative rolling changes in SFA for each LAD–year in our sample. We refer to this measure as $\Delta Funding$. Formally, the cumulative change in SFA for LAD i over k periods is given as $\Delta Funding = \prod_{t=1}^{k}(1 + r_{i,t}) - 1$, where $r_{i,t}$ is the annual rate of change in SFA for LAD i between years t and $t-1$. We use $k = 3$ in this study and analyze the relationship between $\Delta Funding_{it}$ and P2P lending outcomes within the same LAD i during year t.[16]

The decision to estimate three-year cumulative changes in SFA funding is driven by two important considerations. First, it is plausible that annual changes in SFA may have a short-lived and inconsequential effect on P2P lending. For example, temporary funding cuts can be offset either by available LAD reserves, alternative sources of income, or through a

[15] https://bit.ly/3sHuCKM, accessed on December 18^{th}, 2020.

[16] The annual revenue expense budget files also contain budgetary details of each individual service area of an LAD. These service area budgets are the planned expenses for each category of services that LADs provide to their local population. As such, it might seem feasible to investigate how cuts in SFAs impact individual service area budgets, and how these in turn affect P2P lending outcomes. Identifying these patterns would require observing the exact annual allocations of SFAs, council taxes, and reserves to each service area budget of an LAD. Unfortunately, these allocations are neither revealed nor voluntarily disclosed to the public by the LADs, which prevents us from investigating this question.

short-term reallocation in the usage of funds. Moreover, the initial response of LADs to cuts in the SFA could be curtailing services that might not have much impact on the demand for P2P loans among local inhabitants at least in the short run. In contrast, funding cuts over longer periods would make it more difficult for LADs to adjust by tapping into their alternative funding sources, and force them to cut back the provision of many essential services like housing, education, or social care. For example, consider an individual who depends on periodic housing allowances from the LAD and has limited access to mainstream banking. If the SFA to her LAD diminishes for several years in a row, it is likely that this LAD depletes its reserves and may be forced to scale back the funding and provision of many essential public services including possibly housing allowances. If housing allowances are indeed reduced, then the resulting income shocks may force the individual to deplete her savings during such periods. To the extent that LAD reserves and the individual's personal savings and access to banking are limited, prolonged funding cuts will force the individual to seek alternative funds such as P2P loans. It is thus plausible that longer-term changes in SFA to a given LAD will likely lead to more systematic changes in the borrowing behavior of local inhabitants. Cumulative three-year changes in SFA thus serve as a good proxy for the aggregate net gain or loss of funds available to an LAD that can impact the demand for P2P loans among its inhabitants.

Second, a three-year time frame for estimating $\Delta Funding$ also makes sense given the characteristics of available data. Since the SFA data is reported from 2007 onwards, using three-year cumulative changes in SFA implies that the first P2P loan observations available for analysis begin in 2010. Alternatively, using five-year cumulative changes in SFA implies that the first available P2P loan observations begin in 2012. At the same time, Figure 3 clearly shows that P2P loan origination on the platform began to rise in 2010. There is thus a trade-off between the timeframe used for measuring $\Delta Funding$, and the sample period available for analysis. We therefore chose to go with three-year cumulative changes in SFA as it enables us to account for longer-term changes in LAD funding and yet provides us a sufficiently large sample of P2P loans to conduct empirical analyses.

We define *treated* LADs as those that experienced a negative change in cumulative SFA over the last three years with respect to the current year ($\Delta Funding < 0$). Accordingly, LADs in the *control* group are those that experienced a non-negative change in cumulative SFA over the past three years ($\Delta Funding \geq 0$). Figure 1a presents the time series of cumulative three-year changes in SFA per LAD. A majority of LADs experienced both positive and negative cumulative changes in SFA during the sample period. This variation is extremely useful for our setting as it allows for within-LAD comparison of P2P loan demand in response to funding changes that would place these LADs either above or below the zero threshold. The remaining LADs experienced consistently negative shocks in cumulative SFA until 2018, suggesting that these areas faced consistent declines in funding. The SFA was increased overall for all LADs in 2019.

In Figure 1b, we report the aggregate cumulative change in SFA for each LAD per year, starting from 2007 as the baseline year.[17] Some LADs fared consistently better than others until 2016, but most of them have experienced substantial declines in cumulative SFA ever since. Consequently, using cumulative changes in SFA from 2007 onwards does not provide sufficient treatment variation among LADs around the zero threshold, and is therefore not suitable for analyzing within-LAD variation in P2P lending outcomes in response to changes in SFA.

[Figure 1]

Figure 2 presents maps of England depicting cumulative changes in various characteristics within each LAD over the entire sample period. Panel 2a shows the overall change in SFA per LAD. By 2019, most LADs situated in the Midlands, Anglia, southern and north-west England, and Yorkshire and the Humber had witnessed drops of more than 50% in SFA, relative to 2008 levels. In contrast, very few LADs including Northumberland, Durham, Cornwall, Wiltshire, and Shropshire have seen an increase in SFA of between 25% to 50% since 2008. The remaining areas have generally experienced declines of up to −25% in SFA over the sample period. The other panels show the average unemployment rate (% LAD population), unemployment allowance claimant rate (% LAD population), and gross domestic household income per capita. There is no visible pattern between these socioeconomic characteristics and SFA changes across LADs, suggesting that central government funding to the LADs was not driven by local disparities in these characteristics.

[Figure 2]

3.3 The P2P lending platform

We obtain data on P2P loan origination and performance from the popular platform Zopa.[18] Zopa is one of the largest providers of non-bank consumer loans in the UK, with total loan issuance exceeding £4.8 billion since commencement of operations in March 2005. The platform offers loans between £1,000 and £35,000, with a repayment period ranging between one to five years from the date of loan issuance. To qualify for a loan, applicants should be aged 20 years or older, been a resident in the UK for at least three years, be either employed, self-employed, or retired with an annual income of at least £12,000, and have a

[17] For each LAD, funding for the year 2007 is normalized to one and cumulative funding changes thereafter are estimated with respect to this baseline as per the formula $\prod_{t=1}^{k}(1 + r_{i,t})$, where $t = 1$ denotes the year 2007 and $t = k$ denotes subsequent years.

[18] https://www.zopa.com/

good credit record with no history of insolvency.

To apply for a loan, prospective borrowers must visit the platform's website and specify how much they want to borrow and for how long.[19] The applicant must also furnish other information such as purpose for which the loan is being requested, age, employment status (and industry), annual income, home ownership (with or without mortgage), and geographical location. The platform uses these details to access the applicant's credit history and public record information from two credit reference agencies CallCredit and Equifax. This includes information on the applicant's previous and current credit agreements, financial assets and liabilities, and court records. The platform uses this information to ascertain the applicant's creditworthiness and decide whether to approve or decline the loan application.[20]

The platform makes a decision within two business days of submission of the loan application. If the application is approved, the platform will then quote an interest rate that will be charged on the loan conditional on the amount and duration requested by the applicant and her credit profile. Should the applicant accept the quoted rate, she will then be required to provide identity information such as a bank account and proof of income. The platform uses this information to conduct additional background checks, and upon further approval, deposits the loan money into the applicant's bank account within three business days.[21] The platform charges an origination fee and a servicing fee on approved loans.[22]

Money lent to borrowers by Zopa comes directly from a pool of investors, who can choose from several investment products offered by the platform based on their risk and return preferences. Funds deposited by investors are placed in a queue, split into smaller chunks, and matched automatically to borrowers by the platform's algorithms. This mechanism achieves sufficient risk diversification by ensuring that each borrower receives no more than 1% from any single investor. Investors receive monthly payments of interest and principal on their invested capital, which can be reinvested into the platform.

The platform publishes data on all approved loans on its website (updated monthly). This data contains information on loan characteristics like interest rates, maturities, loan

[19] Note that submitting a formal loan application to the platform will have some impact on the applicant's credit score and their ability to borrow in the future. To mitigate this problem, the platform allows applicants to perform a "soft" search to obtain an informal interest rate quote on the loan. Applicants can use these quotes to decide whether or not to submit an application. Soft searches do not impact the applicant's credit score.

[20] The platform can deny a loan for any one of the following reasons: (1) the applicant was denied a loan in the past six months, (2) application contained limited information, (3) credit check reveals applicant missed loan payments in the past six years, (4) applicant has high levels of outstanding unsecured debt (e.g. credit card loans), (5) applicant's financial circumstances raise questions on her ability to repay, and (6) applicant has a poor credit score.

[21] Applicants requiring funds more urgently can pay an additional £10 to receive the money within one business day of loan approval by the platform.

[22] The platform also levies a 1% commission on the capital committed by investors to be issued as loans.

amounts, and latest loan status (fully repaid/defaulted/prepaid). The data also contains anonymized borrower identifiers and their zipcode (only up to *postcode district* level for anonymity).

Figure 3 shows aggregate loan origination on the P2P platform, both in numbers and volumes (in millions of pounds sterling) of loans issued. Loan issuance increased steadily since 2009–10, picking up especially from 2014 onwards to reach over £703 million by 2018–19. Loan issuance to repeat borrowers also picked up during this period, reaching £243 million in 2018–19. These results show that the growth in P2P lending on the platform coincides strongly with the austerity program in the UK that led to substantial declines in funding to many LADs.

[Figure 3]

Connecting the model to the data. Proposition 1 is expected to have the following real-world implications. Cuts in funding to an LAD will: (i) increase the local demand for P2P loans; (ii) increase the interest rates on new P2P loans issued in the LAD; and, (iii) lead to higher default rates among P2P loans issued previously to borrowers in the LAD. We now present the empirical methodology to test these predictions on our sample.

4 Research design

Our empirical strategy is based on a regression discontinuity (RD) design that seeks to identify and exploit a discontinuity in cumulative LAD funding. We describe our approach and possible identification concerns in the following sections.

4.1 Is there a discontinuity in funding changes across LADs?

To motivate our empirical design, Figure 4a reports the distribution of the running variable $\Delta Funding$ for a sample comprising aggregate P2P loans issued per zipcode in a given year. Each zipcode is matched to its corresponding LAD.[23] The plot is truncated between −25% and +25% for clarity. We use the optimal bin size of 0.36%, which is determined by the *DCDensity* command in R and is proportional to the standard deviation of the running variable.[24] We observe a sharp discontinuous drop in loan origination at the *zero* threshold: there is a disproportionately large number of loans issued in LADs with negative $\Delta Funding$ in comparison to LADs where $\Delta Funding$ is non-negative.[25]

We analyse this discontinuity more formally using a probability density test developed by

[23] Some zipcodes may span more than one LAD. In such cases, we compare the populations of each corresponding LAD and assign the zipcode to the one that has the largest population.

[24] We use evenly-spaced bins that partition the running variable $\Delta Funding$ into non-overlapping intervals within either side (treatment status) of the zero threshold. Please see Cattaneo et al. (2019, p. 24) for more information on choosing bin size.

[25] In the context of our RD design, we use the terms "threshold" and "cutoff" interchangeably throughout the paper.

McCrary (2008). The null hypothesis of this test is that of a continuous distribution around the threshold while the alternate hypothesis suggests a discontinuous distribution. The test is implemented by fitting a density function on $\Delta Funding$ on either side of the threshold. Figure 4a shows that the fitted density function to the left of the zero cutoff lies above the density to the right, and their respective confidence intervals do not overlap with each other. This confirms a statistically significant discontinuity in P2P loan issuance per zipcode–year at the zero threshold. The McCrary (2008) t-test, reported on the upper-right of the plot, is –9.494 which rejects the null hypothesis of a continuous distribution at zero.

[Figure 4]

In some cases, the McCrary (2008) test is also indicative of possible manipulation of the running variable by participants in the sample. However, such manipulation is unlikely to be a concern in our setting as LADs do not have discretion over the allocation of SFA and thus lack the ability to self-select upward or downward around the zero threshold.

Another potential problem is that non-random sorting of LADs into treatment and control units may still occur if some LADs are consistently favored (or alternatively disfavored) for receiving SFA. The presence of such biased preferences may result in lack of discontinuity as some LADs will find themselves consistently on one side of the zero threshold (see Becker et al., 2017; Maynard, 2017; Fetzer, 2019; Institute for Government, 2022). To address the related concern that the null hypothesis of no discontinuity is rejected when we recognize the potential for such biases, we rerun the McCrary (2008) test after excluding LADs whose $\Delta Funding$ is consistently above or below zero throughout the sample period. We find that of the 352 LADs in our sample, 191 experienced negative $\Delta Funding$ and none saw a steadily positive change in $\Delta Funding$ throughout the sample period. Removing these LADs from the sample does not impact the baseline results as shown in Figure 4b. The distribution of $\Delta Funding$ continues to exhibit a sharp discontinuity at zero that is statistically significant at the 1% level.

We next examine whether the discontinuity is unique at the zero threshold by testing for discontinuity at other placebo cutoffs along the running variable $\Delta Funding$. We follow the method of Goncharov et al. (2021), under which the McCrary (2008) t-statistic is computed for 40 other thresholds to the left and right of the zero threshold (i.e. between -20%, -19%, -18%, ..., 18%, 19%, 20%). Presuming that the placebo thresholds are quasi-random, the magnitude of the McCrary (2008) t-statistic at zero relative to the t-statistics at these placebo thresholds should indicate whether the t-statistic at the zero threshold is not spurious or a mere artefact of chance. In other words, the t-statistics at the placebo thresholds should ideally not be as substantial as the t-statistic at the threshold of interest (Goncharov et al., 2021). Figure 4c shows that the zero threshold has the most prominent t-statistic value of -9.494 among all the thresholds, implying that the discontinuity at zero is unlikely to be spurious whereas any possible discontinuity at the placebo thresholds is most likely explained by chance.

Overall, these results indicate that the distribution of LADs into treatment and control groups is quasi-random in nature with a significant discontinuity at the zero threshold.

4.2 Empirical methodology

Our identification strategy compares LADs with negative $\Delta Funding$ (*treated* LADs) to those that experienced non-negative funding changes (*control* LADs). The baseline specification is as follows:

$$y = \beta_0 + \beta_1 \cdot NegFunding_{it} + \beta_2 \cdot f(\Delta Funding_{it}) + \beta_3 \cdot NegFunding_{it} \cdot f(\Delta Funding_{it}) + \\ + \beta X_{it} + \mu_i + \nu_t + \epsilon_{it}, \qquad \text{(I)}$$

where y represents various P2P loan-related outcomes as described in Table 1. Our primary analysis considers aggregate loan origination in volume (*Num loans*) and in value (*Sum loans*) at the zipcode level in response to changes in $\Delta Funding_{it}$ to the encompassing LAD i in year t. We focus on aggregate P2P loan origination within a zipcode since this is the level up to which the platform reveals borrower location.[26] We also investigate the impact of $\Delta Funding_{it}$ at the individual loan level, mainly by looking at interest rates charged in excess of prevailing UK gilt yields of closest maturity at the time of loan origination (*Interest Rate Spread*) and on the likelihood of default (*Default*).

The coefficient β_1 represents the mean effect of CG funding cuts to LADs ($NegFunding_{it}$) and is our main statistic of interest. $NegFunding_{it}$ is a dummy equal to one for treated LADs and zero for control LADs. X_{it} represents a vector of controls for socioeconomic characteristics at the LAD–year level that can influence P2P loan demand. This comprises total CG funding per capita (*Funding per capita*), annual gross domestic household income per capita (*GDHI per capita*), unemployment rate (*Unemployment*), percentage of unemployment claimants receiving an allowance from the CG relative to the local working population (*Unemp Claimants*), and LAD population (*LAD population*). Data on these variables were obtained from the Office for National Statistics (ONS). μ_i and ν_t denote LAD and year fixed effects, respectively.[27] Lastly, ϵ_{it} is the idiosyncratic error term assumed to be normally distributed and uncorrelated with the main regressors. We cluster the standard errors by year to account for correlated patterns in funding changes over time (as seen in Figure 1).

[26] In unreported analyses, we find that aggregate P2P loan origination at the LAD level exhibits similar behavior in response to changes in $\Delta Funding_{it}$. These results are available on request

[27] The year fixed effects are assumed to account for any major updates implemented over time by the P2P platform to its algorithms for loan origination, investor-borrower matching, and loan pricing.

The estimation of β_1 requires strong assumptions about the unknown relationship between y and $\Delta Funding_{it}$ because estimating treatment effects near the cutoff might also require the use of data further away from the cutoff (Lee and Lemieux, 2010). We adopt two strategies to overcome the fact that the functional dependence of y on $\Delta Funding_{it}$ is unknown. First, we restrict the sample to a specific bandwidth h on either side of the cutoff. Focusing on LADs within this narrow bandwidth minimizes biases arising from unobservable factors that might be confounded with $\Delta Funding_{it}$ (Calonico et al., 2014). Second, we include up to the second-order polynomial in $f(\Delta Funding_{it})$ to control for any non-linear effects of $\Delta Funding_{it}$ on y. Our main analyses focus on LADs that are just above or below the zero threshold within a bandwidth $h = \pm 25\%$, which is is very close and below the optimal bandwidth of 27.9% determined using the *rdbwselect* command in R.[28] In subsequent analyses, we adopt tighter restrictions and compare P2P lending outcomes in contiguous treated and control LADs sharing a common border to eliminate any remaining identification concerns.

Table 1a presents descriptive statistics of the main sample used for our analysis.[29] On average, P2P loans have a principal amount of £7,385, are issued for a period of 42 months, and carry a relatively high interest rate of 9.52%. About 28% of these loans are issued to repeat borrowers, and about 4.78% of them default. The mean time to default is 14.66 months from the date of issue.[30] Finally, the mean recovery rate on a loan is 66.44%.[31] The average zipcode issues nearly 27 loans per year amounting to £198 thousands, of which 3.80% of them default.

[Table 1]

Funding changes in the SFA vary considerably across LADs. The year-on-year (three-year) percentage change in funding is on average −2.80% (−9.9%). LADs have a mean population of 191 thousand and mean unemployment rate of 6.63%. Importantly, one out of three unemployed individuals in an LAD claim related unemployment benefits from the CG's Department for Work and Pensions while they seek work, highlighting the extensive reliance of the local jobless population on welfare assistance to cover living expenses.

[28] *rdbwselect* identifies an optimal bandwidth with the least mean squared error for a given sample (Calonico et al., 2017, 2018). We use heteroskedasticity-robust standard errors and a triangular kernel, which weights observations by their distance to the zero cutoff within the selected bandwidth.

[29] Descriptive statistics of the unrestricted sample that includes observations from all LADs are reported in Table A1 of the Internet Appendix.

[30] Note that the maximum time to default is higher than the stated maximum maturity because the recognition of a defaulted loan is made at the discretion of the P2P platform. Some loans were thus recognized as defaulted long after their maturity date.

[31] Recovery rate is the percentage of the principal amount repaid by the time the loan is declared to have defaulted.

4.3 Addressing concerns about identification

We acknowledge and address several concerns related to the measurement of funding cuts, to the validity of our RD design, and to the comparability between the treatment and control LADs. These are discussed below.

4.3.1 The focus on Settlement Funding Assessment

As described in Section 3, we are interested in the causal effect of $\Delta Funding$ on P2P lending. We thus focus exclusively on the SFAs since these are exclusively determined and allocated by the CG. We also noted in Section 3.1 that LADs can rely on unspent reserves and council taxes to fund their budgeted expenses. To the extent that these alternative funding sources may be used by LADs to offset cuts in the SFA, our identification could be confounded. However, there are several reasons to believe that this is very unlikely.

First, unspent reserves are not considered a sustainable funding source in the long term (Innes and Tetlow, 2015). Second, under the Localism Act of 2011, LADs in England had very limited ability to change council tax rates in response to changes in SFA (Institute for Government, 2022; Sandford, 2022). Third, council taxes are collected from households based on the value of private real estate, which is generally inelastic over time. This, in turn, considerably limits the extent to which revenues from council taxes can be augmented. Therefore, council taxes are not informative about the effects of funding cuts on P2P lending. Taken together, these arguments suggest that the ability of LADs to offset cuts in the SFA using unspent reserves and council taxes is very limited. We therefore focus only on $\Delta Funding$ and do not include council taxes and reserves in our main analyses.[32]

4.3.2 Falsification tests

An important concern is that the running variable $\Delta Funding$, which assigns treatment status to LADs, is not by itself sufficient to guarantee the assumptions required for a credible RD analysis. For instance, systematic differences among LADs could influence the fund allocation process of the CG. If LADs that are just below the zero cutoff are systematically different in socioeconomic characteristics from LADs just above the cutoff, then such differences might be positively correlated with $\Delta Funding$ as well as the outcomes of interest pertaining to P2P lending, thereby invalidating our RD design. Below we present a series of tests that explicitly address this concern using the observable socioeconomic characteristics of local authority districts.

Individual LADs may also differ in an unknown way; for instance, they can actively lobby the CG for more grants in ways unobservable to the researcher such that they end up missing the treatment assignment. Unfortunately there is no publicly available data that allows us to

[32] As a robustness check, we rerun the analyses after including reserves and council taxes in $\Delta Funding$ and obtain consistent results. These results are available on request.

invalidate this concern directly. We revisit this point in Section 5.4.1 and present arguments, which we believe mitigate this concern.

We run several tests to verify our RD design and ensure that there are no systematic observable differences between treated and control LADs near the cutoff that are correlated with outcome differences. Figure A1 in the internet appendix presents a graphical illustration of the RD effects for several observable LAD characteristics that are not associated directly with $\Delta Funding$. These characteristics do not jump discretely at the zero cutoff. The intercepts of local polynomial regression fits to the left and right of the cutoff are very close to each other in all cases. More formal analysis using the *rdrobust* command in R shows that any visible jumps in these characteristics around the cutoff are not distinguishable from zero.

Table 1b compares P2P lending and socioeconomic characteristics of treated LADs that have $\Delta Funding$ in $[-25\%,\ 0\%)$ interval with control LADs having $\Delta Funding$ in $[0\%,\ 25\%]$ interval. While treated and control LADs have comparable population, unemployment rates, unemployment claimant rates, and per-capita household income (GDHI), there are significant differences in $\Delta Funding$ as well as individual and zipcode-level loan characteristics across both groups. These results provide further validation to our RD design by suggesting that LADs just above and below the zero cutoff do not differ significantly in terms of observable characteristics except the treatment by $\Delta Funding$, which likely affects P2P lending outcomes.

4.3.3 Are LADs with positive and negative funding changes comparable?

Another possible concern is that even though we control for observable socioeconomic conditions at the LAD level, unobserved heterogeneity in economic conditions among zipcodes within LADs could still confound our identification. We address this concern by focusing on zipcodes located within a narrow band on either side of the border along contiguous LADs that have different treatment assignment. Identification comes from the fact that zipcodes within these narrow bands around contiguous borders are likely to be characterized by similar socioeconomic trends, but will be subject to different funding shocks depending on the treatment status of the LAD they belong to. We re-run our analyses using these tighter restrictions and present the results in Section 5.4.

4.3.4 Did the funding cuts increase household financial distress?

Before turning to our main analyses, we perform one final check on whether funding cuts to LADs did indeed impact the financial stability of the local population. For this purpose, we use data from the annual NMG Household Finance Survey conducted by the

Bank of England (BoE) since 2004.[33] The NMG Survey is one of the best available sources to understand timely developments in the distribution of household balance sheets, and contains important questions devised to measure financial distress (Anderson et al., 2016). The survey is thus useful to understand how shocks such as austerity-led funding cuts impact the financial stability of households, and how they respond by adjusting spending. Over 6,000 households participate in this survey in September each year, which is nearly six months after the budgeted changes in SFAs start to go into effect within each LAD. Survey respondents are drawn randomly from a sample that is weighted to be representative of the UK population in terms of age, gender, region, housing tenure and employment status (Anderson et al., 2016).

We use zipcode details provided in the survey to match respondents to their respective LADs. We focus on two questions for our analysis: (i) whether the respondent is currently facing difficulties with loans repayment (survey item *qbe18*), and (ii) whether the respondent is putting off spending due to concerns over exceeding their credit limit and/or not being able to get further credit (survey item *be23*). We are unable to focus on other relevant questions in the survey due to missing data, and also restrict our analysis to the period 2013–19 due to this issue.

To understand the impact of funding cuts to LADs on individual financial stability, we run probit regressions on the two chosen questions from the survey against *NegFunding*, controlling for the respondents' age, gender, current employment status, education, number of children, and housing situation (owned, owned under mortgage, privately rented, or rented from the LAD) which are all available in the survey data. We also include up to the second-order polynomial in $f(\Delta Funding_{it})$ and its interaction with *NegFunding* as outlined in Equation I.

[Table 2]

The results are presented in Table 2. The coefficients of *NegFunding* are positive and statistically significant in all the models. Respondents that are younger, female, unemployed, have fewer educational qualifications, and more children tend to express financial difficulties. Interestingly, respondents living in housing rented out by their LAD seem more likely to face financial difficulties and delay spending compared to respondents living in other types of housing. Overall, these results clearly suggest that prolonged funding cuts to LADs increased financial stress on households and forced them to cut back spending.

[33] NMG Survey data are publicly available at https://www.bankofengland.co.uk/statistics/research-datasets

5 Results

Here we present our empirical results. In Section 5.1 we show the effects of CG funding cuts to LADs (*NegFunding*) on aggregate P2P loan origination in a given zipcode-year. In Sections 5.2 and 5.3 we investigate the effects of *NegFunding* on individual loan spreads and defaults, respectively. Finally, in Section 5.4, we conduct several robustness checks to validate our results and present additional findings.

5.1 P2P loan demand

Table 3 presents OLS estimates of the impact of funding cuts to LADs on aggregate P2P loan origination based on Equation (I). We measure P2P origination as the aggregate number of loans issued (*Num loans*) and total value of loans issued (*Sum loans*) per zipcode–year. These outcomes are expressed in logs to estimate proportional effects of the funding cuts on P2P loan origination. We also consider the annual growth rates in *Num loans* and *Sum loans* per zipcode-year. All specifications include the controls specified in Section 4.2. We also include one-year lags of the outcome variable, as well as LAD and year fixed effects, in all the specifications. Finally, we cluster standard errors by year to account for correlated shocks among zipcodes within an LAD.

The coefficients of *NegFunding* in models (1) and (2) suggest that there were nearly 11% more P2P loans issued per year among zipcodes belonging to treated LADs relative to zipcodes from control LADs. Similarly, models (4) and (5) suggest that aggregate P2P loan origination per treated zipcode-year was up to 17.8% more in value terms compared to control LADs, and are statistically significant at the 5% and 1% levels, respectively. Finally, models (3) and (6) indicate that the annual growth in *Num loans* and *Sum loans* is respectively 27% and 72% greater (both significant at the 1% level) in zipcodes belonging to treated LADs relative to those in control LADs.

[Table 3]

One might argue that the estimated increases in P2P loan origination are not influenced by funding cuts to LADs, but rather due to rising popularity and adoption of P2P lending at a macro level. To address this concern, we repeat the analysis by scaling *Num loans* and *Sum loans* in a given zipcode-year against the corresponding aggregate P2P loan origination at the national level during the same year. Table A2 in the Internet Appendix presents the results. Models (1) and (2) suggest that *scaled Num loans* in treated LAD zipcodes increase by nearly 14% relative to zipcodes in control LADs. Similarly, models (3) and (4) show that *scaled Sum loans* in treated LAD zipcodes increase by 27% (significant at the 1% level) compared to zipcodes in control LADs during the same year. These results highlight the robustness of our findings to secular trends in P2P lending, signifying that funding cuts to

LADs have contributed to a sharp increase in P2P loan demand.

Overall, the empirical evidence presented thus far is consistent with our theory section, and in particular part 1 of Proposition 1. Indeed, our empirical results suggest that cuts in funding to an LAD fosters greater demand for P2P loans from the local population. Using the mapping between theory and data that we explained at the end of Section 3, this corresponds to the model property that the demand for debt is higher in aggregate states in which the public transfer is low. Empirically, we find that despite the possibility of default, agents use P2P platform to smooth out consumption shocks implied by cuts in LAD funding.

We interpret the results as demand-driven for several reasons. First, under our RD framework, treated and control LADs are assumed to be comparable in all observable characteristics including credit supply, and differ only in the SFA allocated to them. Second, our sample period is not characterized by any major shocks to credit supply. Third, recent evidence suggests that P2P platforms adjust loan supply more elastically when loan demand increases (Fuster et al., 2019). This, together with the fact that the P2P platform breaks down each dollar invested such that each borrower receives at most 1% from any individual investor, implies that general shocks to P2P loan demand are unlikely to be correlated with loan supply. Given these reasons, we believe that the impact of *NegFunding* on P2P loan demand is ostensibly causal in nature.

We further investigate how variation in access to banking and internet might affect the impact of *NegFunding* on P2P loan origination. For this purpose, we source data on bank branch coverage from the ONS, and on mobile broadband download speeds measured in megabits per second (*mobile internet speed*) from ThinkBroadband Limited. The number of bank branches proxy for the degree of financial inclusion among residents in a given area, with prior studies such as Célerier and Matray (2019) showing the presence of more bank branches to be associated with better financial inclusion especially among low-income households.[34] Similarly, internet access proxies the extent of digital inclusion among households. This is an important metric as recent reports of the UK government suggest that digital exclusion due to poor and/or expensive internet access is inextricably linked to wider economic inequalities in British society.[35]

[34] Relatedly, Kerr and Nanda (2009) note that the number of bank branches in a given area reflects greater competition and increased consumer choice in local credit markets.

[35] A report presented by the Social Mobility Commission to the UK parliament in 2021 notes greater digital exclusion among low-income households, people over 65 and the disabled. The report also states that prior to the COVID-19 pandemic, only 51% of low-income households earning between £6,000–10,000 per year had some form of internet access compared to 99% among households with an annual income over £40,000. The full report can be found at `https://bit.ly/3OCgACG`. Relatedly, a report by Ofcom states that low-income households are less likely to have stable internet connection, and are forced to rely on expensive mobile data subscriptions to access basic digital services such as school education for their kids particularly during the COVID-19 pandemic. The full report can be accessed at `https://bit.ly/3AOJwAw`.

Both datasets are available only at the parliamentary constituency level, which are then mapped and aggregated to their corresponding LADs using relevant ONS identifiers. We develop scaled measures of the number of bank branches per LAD based on local population size (*bank branches per 1000 individuals*) and number of local businesses (*bank branches per 100 businesses*). We include these measures in our main specification I and interact each of them with *NegFunding*.

[Table 4]

Table 4 presents the results of our analysis. *NegFunding* remains significantly positive in all the specifications. The interaction terms between scaled measures of bank branches and *NegFunding* in models 1–4 have negative coefficients, implying that P2P loan issuance in LADs experiencing funding cuts is marginally lower depending on the extent of local bank branch coverage. Models 5–6 show that LADs with better mobile internet access are associated with greater P2P loan issuance. However, the interaction terms suggest a significant negative relationship between mobile internet speeds and *NegFunding*. In other words, even among LADs that witness funding cuts, P2P loan origination is marginally higher in areas that are more digitally excluded due to weaker internet access. Overall, these findings suggest that funding cuts are an important driver of P2P lending growth particularly in areas that are more deprived of banking and internet access. This confirms the first item of Proposition 1 regarding the key role of public transfers on P2P loan demand.

5.2 P2P loan interest rate

Table 5 reports OLS estimates of the impact of *NegFunding* on the interest rates charged by the P2P platform on individual loans. The sample used for this analysis comprises observations at the individual loan level. The outcome variable is *Interest Rate Spread*, measured as the difference between the interest rate charged on the loan and the prevailing UK gilt yield of the closest maturity at the time of loan issue. The regressions are based on Equation (I), and include the same set of controls and fixed effects as in the previous section as well as loan size (*Loan Amount*), the loan maturity (*Loan Term*), and repeat borrower status (*Repeat Borrower*) as additional controls. Standard errors clustered by year are reported in parentheses.

Models (1) and (2) indicate that loans issued in treated LADs are 35–40 basis points (bps) more expensive compared to loans issued in control LADs. In both models, the effect of *NegFunding* on interest rates is significant at the 1% level. For better understanding, we split the sample into loans issued to new and repeat borrowers. Model (3) shows that new borrowers in treated LADs pay about 40bps higher interest rate on a loan relative to new borrowers from control LADs. In comparison, model (4) shows that repeat borrowers in treated LADs pay only 17bps higher interest rates than those from control LADs, and it is not statistically significant. The higher interest rates in treated LADs thus seem to be driven by loans issued to new borrowers in these areas. This implies that Zopa is likely using the repeat borrower status as a means to reduce information asymmetry: when the platform knows the borrower from prior interactions, then LAD funding cuts seem to have little effect on the interest rates of loans issued to them. Conversely, when the borrower is new to the platform and lives in a treated LAD, the interest rate charged on their loan in much higher.[36]

[Table 5]

Borrowers generally pay slightly higher spreads of up to 1.2bps on average per one log-month increase in loan maturity. Loan spreads are also lower by 2.2–2.4bps on average per one log-pound increase in loan size.[37]

Overall, the empirical results in this section are consistent with our theoretical model and especially with part 2 of Proposition 1. We indeed observe that borrowers pay a higher a interest rate in periods characterized by a cut in LAD funding. Taking advantage of the relationship between theory and empirics that we explicit at the end of Section 3, this empirical observation is akin to the model prediction that agents' debt interest rate is higher in states when the public transfer is low. This corroborates the theoretical prediction that the P2P platform expects a higher default probability when debt is raised in a period featuring a cut in LAD funding. This ex-ante expectation of a higher default rate translates into a higher default premium and higher borrowing cost.

5.3 P2P loan performance

We now turn to analyzing the effects of LAD funding cuts on P2P loan performance, measured in the form of defaults. This analysis holds significance for two key reasons. First, it allows us to determine whether current income shocks resulting from funding cuts to LADs affect local borrowers' ability to repay loans that were obtained previously from the P2P platform. Second, the analysis allows us to interpret whether the ex ante pricing of P2P loans by the platform, as outlined in Section 5.2, is influenced, at least partially, by the contemporaneous realization of default risk due to austerity-driven income shocks among

[36] We also analyze whether access to banking and internet services affects P2P loan interest rates in austerity-affected LADs. For this, we follow the approach outlined in Section 5.1 and estimate the effects of the interaction terms *NegFunding* × *Bank branches per 1000 individuals*, *NegFunding* × *Bank branches per 100 businesses*, and *NegFunding* × *Internet Speed* on the interest rates charged by the P2P platform on individual loans. The corresponding results in Table A3 in the Internet Appendix show that loans originated in LADs with funding cuts are not priced differently contingent of the quality of local banking coverage or internet access.

[37] One plausible explanation could be that Zopa limits loan amounts in relation to the borrowers' income. For instance, the amount borrowed could be such that the monthly payment does not exceed a certain fraction of the borrower's income. Larger loans are thus issued to higher-income borrowers who are also less likely to default, and therefore carry a lower spread.

incumbent borrowers.

As before, the specifications are based on Equation (I) and use the same set of controls and fixed effects. However, looking simply at the performance of individual loans presents a truncation problem: loans that did not default during the sample period may have defaulted thereafter. To resolve this problem, we use a stacked regression approach following Franks et al. (2020) to analyse the incidence of default.[38]

Under this method, rather than estimate the probability of default for a given loan, we estimate the per-period probability of default for each loan-year. We therefore construct a panel of 465,980 loan-years for 178,283 loans in our sample. A loan enters this sample during the origination year and drops out when it is either fully repaid or defaults. We estimate the transition probability of a P2P loan j issued in LAD i during year k from performance to nonperformance in some year t ($k \leq t$), with the $Default_{jit}$ dummy as the dependent variable. For this, we modify (I) into the following specification:

$$\begin{aligned} Default_{jit} = \beta_0 + \beta_1 \cdot NegFunding_{it} + \beta_2 \cdot f(\Delta Funding_{it}) + \beta_3 \cdot NegFunding_{it} \cdot f(\Delta Funding_{it}) \\ + \beta X_{jit} + \mu_i + \nu_t + \delta_k + \epsilon_{it}, \end{aligned} \tag{II}$$

Panel 6a reports GLM logit estimates of the stacked regression specification. Models (1) and (2) show that loans belonging to the treated LAD-year group have 1.41 ($= e^{0.342}$) times more odds of defaulting compared to similar loans in the control LAD-year group. These results are significant at the 5% level. Moreover, the estimated effect of *NegFunding* implies that for an average loan from control LAD the probability of default increases by about 39% when that LAD is subject to treatment.[39,40]

In models (3) and (4), we once again split the sample into loans issued to new and repeat borrowers. The coefficient of *NegFunding* in model (3) implies that new borrowers in the treated LAD-year group have 1.42 ($= e^{0.345}$) more odds of defaulting than similar borrowers

[38] See Sueyoshi (1995) and Cameron and Trivedi (2005) for a detailed explanation of the stacked regression methodology and its benefits.

[39] Given the sample average probability of default in control LADs of 0.0273, the associated odds of defaulting on a loan are $0.0281 \approx 0.0273/(1-0.0273)$. New odds of defaulting (after funding cuts) are then $0.0395 \approx 0.0281 \times 1.41$. Reverse computation of probability suggests that, further the treatment, the implied probability of default becomes $0.0380 \approx 0.0395/(1{+}0.0395)$, which is about 39% greater ($\approx 0.0380/0.0281-1$) than the unconditional default rate in the control LADs.

[40] We further investigate whether P2P loan performance in austerity-affected LADs varies according to the prevailing quality of banking and internet access in these areas. We use the methodology outlined in Section 5.1 and estimate the effects of interaction terms *NegFunding* × *Bank branches per 1000 individuals*, *NegFunding* × *Bank branches per 100 businesses*, and *NegFunding* × *Internet Speed* on the likelihood of loan defaults. Table A4 in the Internet Appendix presents the results. Coefficients of the interaction terms are negative implying that within austerity-affected LADs, loan default rates are marginally lower among LADs having better bank coverage or faster internet access. However, these coefficients are not statistically significant.

in the control LAD-year group. We find no such statistically significant difference among repeat borrowers across both groups.

The greater incidence of P2P loan defaults in treated LADs, relative to control LADs, indicates that the austerity-related cuts to LADs were largely unanticipated by the platform. Moreover, in Section 5.2, we documented that the platform charges higher interest rates on loans issued in treated LADs. These higher interest rates can be attributed, at least in part, to the fact that the platform perceives funding cuts as an exogenous risk and utilizes contemporaneous information in a given LAD when pricing new loans issued to borrowers from the same area. A possible mechanism to explain this behavior is the time persistence of funding cuts as postulated in the theoretical model of Section 2.

[Table 6]

For robustness, we compare the stacked regression results with estimates of the probability of loan default using the Cox proportional hazards model. Unlike stacked regressions that rely on a sample of completed loan performance periods (where the loan is eventually repaid or defaults), the Cox proportional hazards model requires only a measure of the time since origination at which the loan either defaults, is fully repaid, or remains outstanding at the end of the sample period. The corresponding estimates of the Cox model are presented in 6b. The coefficients of *NegFunding* in models (1) and (2) are positive and significant at the 1% level, and suggest that loans in treated LADs are 2.31–2.87 times more likely to default than similar loans in control LADs at any given time from origination. *Repeat Borrower* has negative coefficients significant at the 1% level, indicating that loans issued to repeat borrowers are up to 0.38 times less likely to default than loans issued on similar terms to new borrowers. In Models (3) and (4) we split the sample by repeat borrower status. The hazard coefficients suggest that new (repeat) borrowers in treated LADs are 2.97 (1.53) more likely to default on average than new (repeat) borrowers in control LADs, but are statistically significant only in the case of new borrowers. Overall, these results are consistent with the stacked regression estimates.

[Figure 5]

To get a better sense of the Cox hazard estimates, we plot Kaplan-Meier curves representing the fractions of un-defaulted loans from the origination date for treated and control LADs separately.[41] These are presented in in Figure 5, and clearly show that the fraction of loans that default at any given time in treated LADs is much greater than the fraction of defaulting loans in control LADs. In fact, approximately 10% (5%) of loans issued in treated (control) LADs tend to default within three years of origination.

Overall, this analysis shows that funding cuts to LADs increase the probability that bor-

[41]Figure A2 in the Internet Appendix presents Kaplan-Meier curves for loans with different maturities.

rowers from treated LADs will default on their P2P loans. These results are interesting on two counts. First, they show that the ex-post performance of loans is consistent with the ex-ante pricing by the platform, showing that Zopa is doing a good job in setting interest premium on borrowers. Indeed, borrowers from treated LADs default more often, consistently with the higher interest rate they pay. The same consistency in the ex-ante pricing and ex-post performance can be found for loan characteristics and repeat borrower. Second, these empirical results are also consistent with our theoretical model and especially with part 3 of Proposition 1. This simply comes from the fact that the model features rational expectation, implying that the pricing of the default risk is by construction consistent with the realized performance of loans.

5.4 Robustness checks and additional analyses

5.4.1 Unobservable differences across LADs

In Section 4.3.3, we noted the concern about unobservable differences between LADs that are correlated with funding cuts and which could be driving the observed differences in P2P loan origination, pricing, and performance across treated and control LADs. The presence of such factors unobservable to the researcher could weaken the causal interpretation of *NegFunding* on P2P lending. As a counter to this argument, we emphasize that our estimates of *NegFunding* are robust throughout the analyses. Specifically, the coefficients of *NegFunding* do not change much or flip sign and remain statistically significant even after the inclusion of various controls, higher-order polynomials of $\Delta Funding$ and their interactions with *NegFunding*, as well as LAD and year fixed effects.[42] We believe these strategies should mitigate any remaining concerns that our results are driven by unobservable factors.

5.4.2 Contiguous zipcodes

To verify the validity of our RD estimates, we run our specifications on a restricted sample of P2P loans that were issued in zipcodes located within d kilometers on either side of the border along contiguous LADs that differ in treatment status. Specifically, we first isolate all LADs that share common borders but have different funding treatment. We next subset the sample to zipcodes situated within a d kilometres band on either side of the common border. The identifying assumption here is that zipcodes falling within these narrow bands are likely to be characterized by very similar socioeconomic conditions. The only distinguishing factor then is the border separating zipcodes into their respective LADs, such that people living in zipcodes on opposite sides of the border will be subject to different funding treatment as they belong to different LADs.

[42] To the extent that unobserved LAD characteristics are correlated with the observed ones, controlling for the latter should have a sizable effect on the coefficient of *NegFunding*. Instead, $\hat{\beta}_1$ always remains stable.

[Table 7]

Table 7 reports results of the analyses on contiguous LADs using $d \leq$ 10km as the distance restriction from the common border. The estimated effects of *NegFunding* on P2P loan origination, interest rate spreads, and on defaults are very consistent with our main findings. As additional robustness checks, we rerun the analyses by expanding the distance bands to 20km and 30km on either side of contiguous LAD borders and obtain consistent results. These results are presented in Section B of the Internet Appendix.

5.4.3 Regional differences in P2P loan origination

Another interesting aspect related to this study is that changes in CG funding may be correlated within larger geographical and administrative areas such as the English regions. For example, it is quite possible that LADs in the London region experience similar trends in CG funding because commonality in their underlying socioeconomic characteristics give rise to similar funding needs to support the local population. As such, it is possible that funding changes among LADs located in a given region might give rise to common region-wide trends in P2P loan demand.

To investigate this possibility, we first look at the distribution of P2P loan origination across the various regions in England. Table A5 in the Internet Appendix shows that there are indeed some regional differences in the aggregate number and value of P2P loans issued. Interestingly, roughly 75% of loans issued in each region at any time are to new borrowers.

We next re-estimate loan origination regressions as specified by Equation (I), wherein we include interactions between Δ*Funding* and a categorical variable representing the region to which the LAD belongs. We keep everything consistent with our main analyses except for replacing LAD fixed effects with region fixed effects. The results are reported in Table A6 of the Internet Appendix. Coefficients of *NegFunding* are positive and statistically significant in all the specifications, once again confirming the robustness of our main findings. The interaction terms are not all significant with very few exceptions, suggesting limited geographical heterogeneity in the response of P2P loan demand to austerity-driven funding cuts.

6 Conclusions

This paper studies the importance of public welfare spending for FinTech adoption. Using data on the decade-long austerity program launched by the UK central government following the 2008 financial crisis, we study the relationship between public welfare spending and the demand for P2P consumer loans, their pricing, and performance.

The austerity program was characterized by gradual but uneven cuts in welfare grants that the CG allocates each year to LADs in England. These grants are crucial for LADs to fund the provision of various primary services such as education, housing benefits, social care, healthcare, culture, and safety to the local population. Prolonged cuts in CG grants to LADs under austerity have thus resulted in a progressive rollback of the local welfare state. In turn, these cuts have generated exogenous income shocks, in particular, to economically deprived households that rely extensively on welfare benefits and social services provided by their LAD.

In this context, the central hypothesis of this paper is that greater financial stress imposed on individuals and households due to negative shocks to their income under austerity has led some of them to seek loans from P2P platforms. To understand the relationship between austerity-driven income shocks and the demand for P2P consumer loans, we build a theoretical model that features government transfers to low income agents that have access to an incomplete loan market and can strategically default. Using a regression discontinuity design, we then test and confirm the three model predictions regarding the impact of austerity-driven cuts to LADs on the local demand for P2P loans, their pricing (interest rates) and performance (defaults).

Our main empirical findings are as follows. First, we find that P2P loan issuance was significantly greater in LADs suffering from austerity cuts relative to other LADs that did not face these cuts at any time during the sample period. Moreover, the increase in P2P loan issuance is more pronounced in austerity-affected areas that also have a lower density of bank branches or poorer internet access. Second, P2P loans issued in austerity-affected LADs are significantly more expensive, particularly for new borrowers, in comparison to P2P loans issued in similar areas that experienced no such cuts in CG funding. Lastly, the performance of P2P loans, measured by way of incidence of defaults, deteriorates in areas that faced funding cuts in comparison to areas that were relatively unaffected by austerity.

Our findings offer many interesting avenues for future research and stem in large part from the limitations in the sample used for this study. One limitation is that we do not have information on loan applications made to the P2P platform, which would have enabled us to better understand how individuals respond to exogenous income shocks, especially if their subsistence depends on the welfare state. We are also unable to observe individual borrower characteristics such as gender, age, race, education, profession, marital and parenting status, income level, savings, investments, etc. Future studies on this topic could incorporate these characteristics, where available, to better understand how income shocks might affect the demand for P2P loans, the pricing strategy of the platform, and eventual loan performance. Another interesting research question concerns the exact service areas through which cuts in CG funding under austerity affected P2P lending outcomes. Finally, even though our paper focuses on the second largest P2P consumer lending market in the world, it would nevertheless be interesting to study the relationship between public welfare spending and alternative credit markets, especially in developing economies where income constraints are much more severe and public reliance on welfare spending is high.

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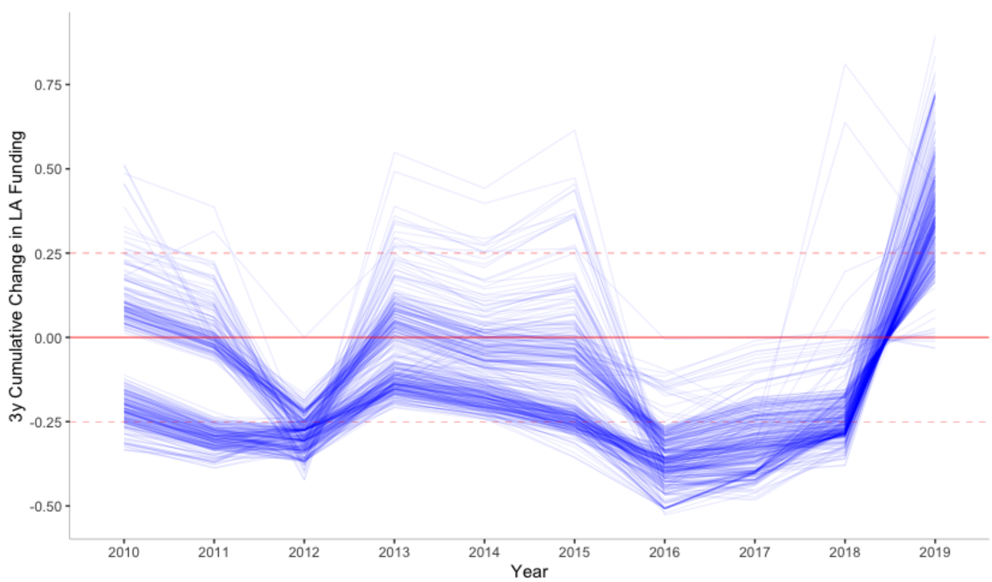
Figure 1: Changes in funding per local authority

Figures plot the cumulative changes in central government funding per local authority district (LAD). Each blue line corresponds to the evolution in funding for a given LAD over the period 2007–19. Panel (a) shows the three-year cumulative change in funding per LAD measured as $\Delta Funding = \prod_{t=1}^{k}(1 + r_{i,t}) - 1$, where $r_{i,t}$ is the annual rate of change in settlement funding assessment for LAD i between years t and $t-1$, and $k = 3$. Panel (b) shows the cumulative change in funding per LAD starting from 2007. For each LAD, funding for the year 2007 is normalized to one and cumulative funding changes thereafter are estimated with respect to this baseline as per the formula $\prod_{t=1}^{k}(1 + r_{i,t})$, where $t = 1$ denotes the year 2007 and $t = k$ denotes subsequent years.

(a) Three-year rolling changes in funding per LAD



(b) Cumulative changes in funding per LAD (since 2007)

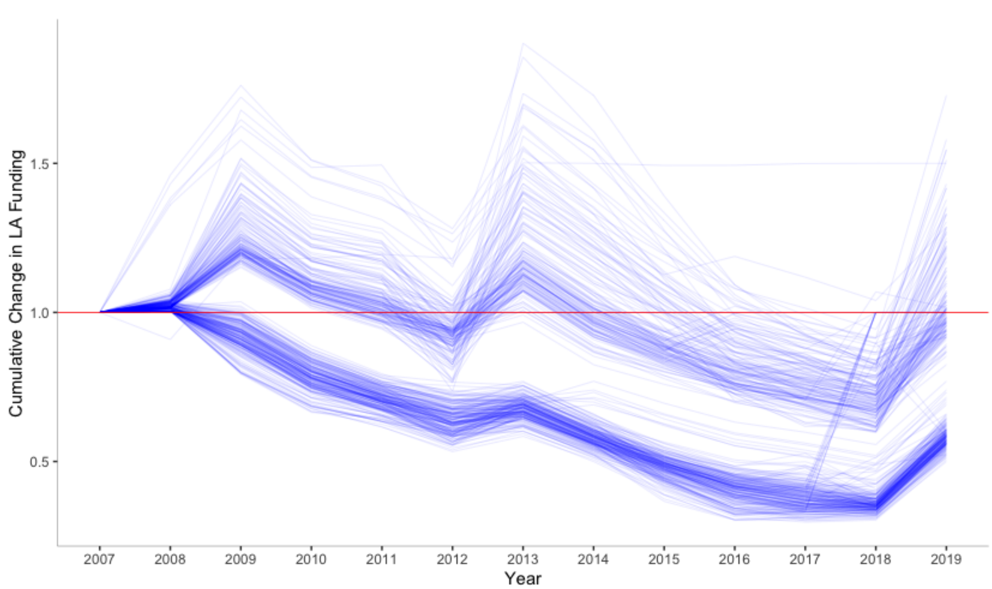
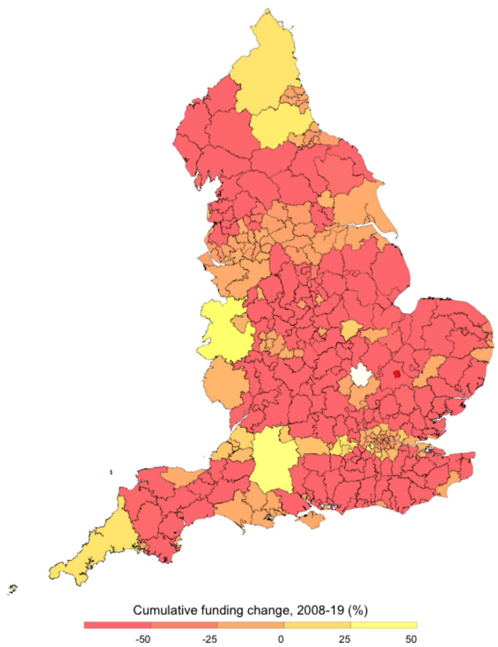


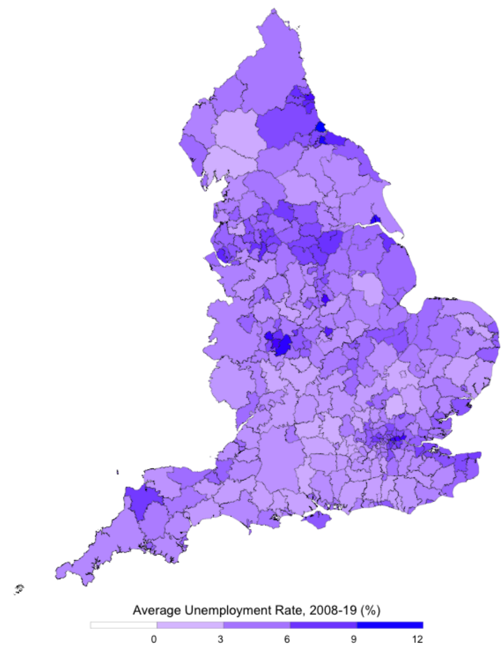
Figure 2: Distribution of select LAD characteristics.

Plots show cumulative change in LAD characteristics over the period 2007–19. Data on settlement funding assessments (SFAs) are obtained from the Department for Levelling Up, Housing and Communities of the UK government. Data on unemployment rates, number of claimants of jobseekers' allowance (as percentage of the working population in the LAD), and gross disposable household income (GDHI) per LAD are obtained from the Office for National Statistics.

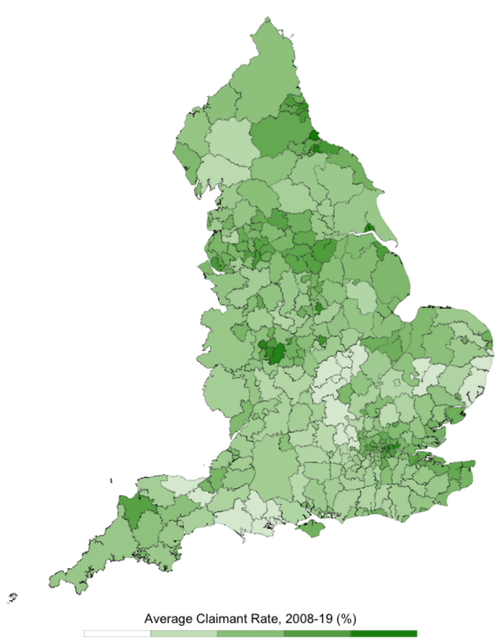
(a) Cumulative change in LAD funding (SFA)



(b) Unemployment rate



(c) Jobseekers' allowance claimants



(d) Log(GDHI)

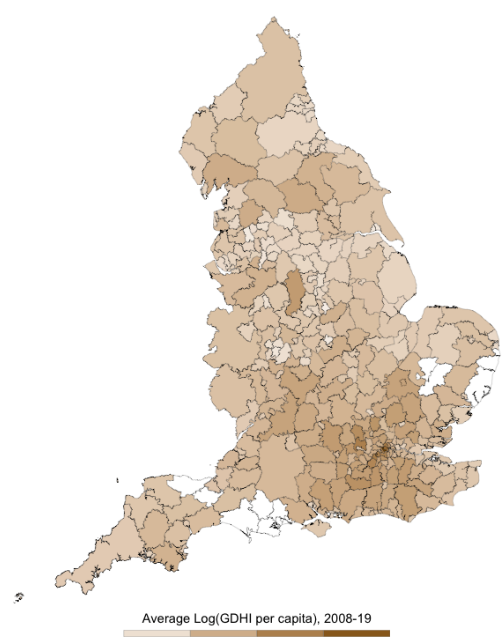


Figure 3: P2P loan origination by year

Figure shows the time series of P2P loan origination over the sample period 2009–19. Solid lines represent the aggregate value of loans originated by the P2P platform (left vertical axis), while the bars correspond to the number of loans issued by the platform (right vertical axis).

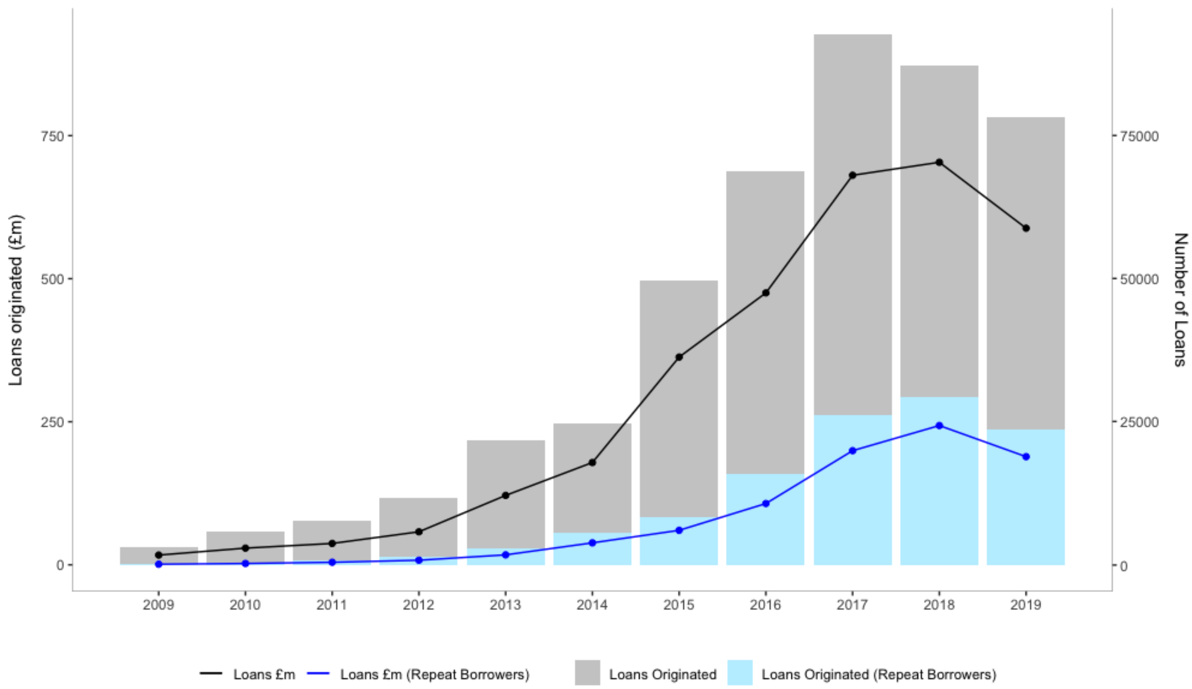
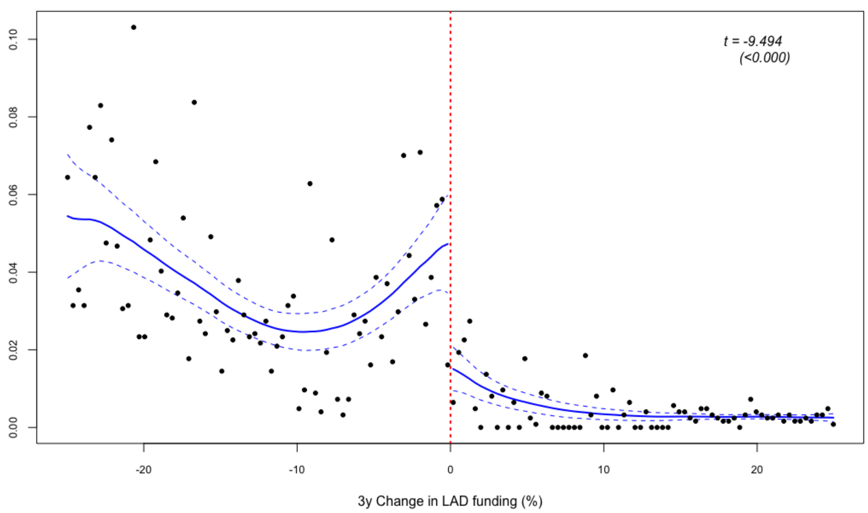


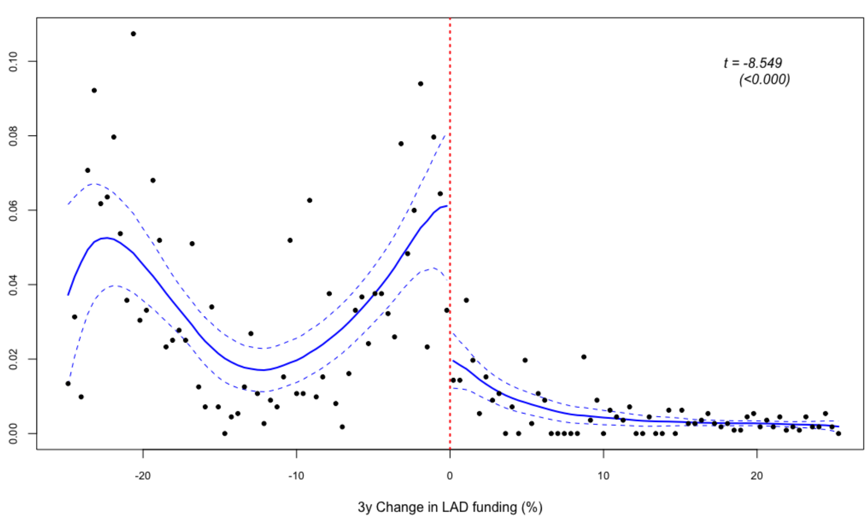
Figure 4: Distribution of UK central government funding to LADs

Panels (a) and (b) plot the density of P2P loans issued in an LAD in a given year as a function of the cumulative change in central government funding to that LAD over the preceding three years ($\Delta Funding$). The distribution of $\Delta Funding$ is trimmed at [-25%, 25%]. For both plots, each dot represents the fraction of P2P loans within each bin. The dashed red vertical line indicates the cutoff point at which $\Delta Funding$ for an LAD is 0%. The solid blue line is the locally weighted polynomial fit applied to each side of the cutoff while the dotted black lines represent its 95% confidence intervals. The McCrary (2008) t-test examining whether the discontinuity at the zero cutoff is statistically significant is reported on the upper right-hand corner of each plot. Panel (c) shows the McCrary (2008) t-statistics at the zero cutoff and 40 other placebo thresholds.

(a) All LADs



(b) Excluding LADs with persistent +ve or -ve three-year cumulative changes in funding



(c) McCrary t-statistics for different cutoffs

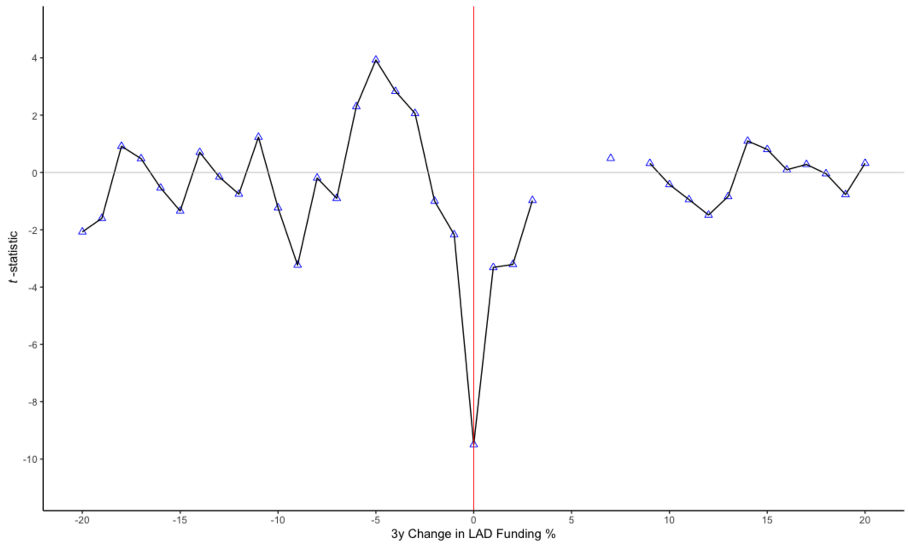


Figure 5: Kaplan-Meier curves of loan performance

Figure shows Kaplan-Meier curves of loan performance for a sample of P2P loans issued in treated and control LADs. An LAD is considered *treated* if it experienced a negative change in cumulative funding from the central government over the preceding three years ($\Delta Funding < 0$), and is considered *control* if the corresponding change was non-negative ($\Delta Funding \geq 0$). To minimize the effect of confounding factors, the analysis is restricted to loans from LADs whose $\Delta Funding$ is within a bandwidth $h = \pm 25\%$ around the zero cutoff. Loans issued in LADs with $\Delta Funding$ outside these intervals are not considered. For loans belonging to either treatment status, the plot shows the fraction of loans that did not default (i.e, were either fully repaid or outstanding at the end of the sample period) together with 95% confidence intervals as a function of time since their origination.

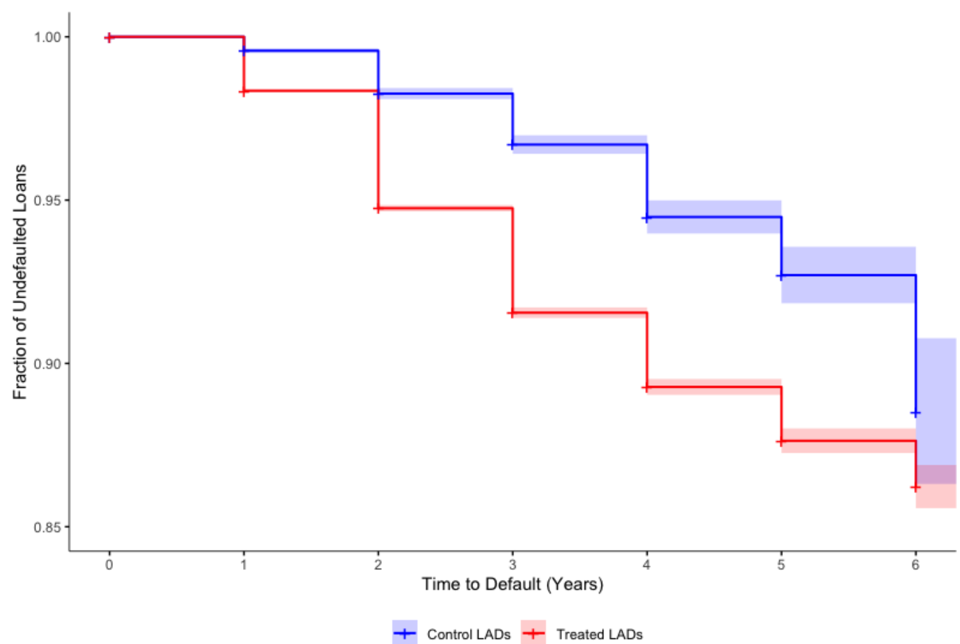


Table 1: Summary statistics

Table reports summary statistics of the sample used for our regression discontinuity analysis comprising treated and control LADs. An LAD is considered as *treated* if the cumulative change in funding it received from the central government over the preceding three years $\Delta Funding \in [-25\%, 0)$, and *control* if $\Delta Funding \in [0, 25\%]$. See Section 4.2 for definitions of the variables. Panel (a) reports summary statistics for the whole sample. Panel (b) presents means, standard deviations, and *t*-tests of difference in means of several variables between treated and control LADs.

(a) Main sample

	Mean	SD	Minimum	25 pct	Median	75 pct	Maximum
Individual Loan Characteristics							
Loan Amount (£)	7385	5774.36	260	3060	5500	10170	35000
Term (m)	41.71	16.25	10	24	36	60	60
Interest (%)	9.52	6.40	2	4.30	7.50	13.10	33.65
Repeat Borrower (%)	27.63	44.72	0	0	0	100	100
Defaulted (%)	4.78	21.33	0	0	0	0	100
Time to Default (m)	14.66	9.35	1	8	13	19	89
Loan Recovery (%)	66.44	35.63	0	30.57	80.71	100	100
Zip-level Loan Characteristics							
Num Loans per year	26.74	34.85	1	2	10	42	415
Sum Loans per year (1000'£)	197.51	269.29	1.02	12.94	54.27	318.21	2742.10
Defaults per year (%)	3.79	10.11	0	0	0	4.55	100
LAD Characteristics							
ΔFunding (1y)	-2.80	12.18	-33.03	-8.93	-6.16	1.72	101.88
ΔFunding (3y)	-9.86	13.56	-24.99	-20.75	-15.07	-1.11	24.95
LAD Population (1000s)	190.65	136.19	37.10	103.83	146.38	252.21	1141.82
Unemployment (%)	6.63	2.72	1.42	4.58	6.17	8.36	16.55
ΔUnemployment (1y) (%)	0.68	11.97	-44.35	-5.44	-0.36	5.96	68.14
Unemp Claimants (% Unemployed)	34.59	16.58	1.50	21.52	34.06	45.78	90.86
GDHI per capita (1000'£)	18.72	5.09	10.70	15.28	17.58	20.95	54.85
ΔGDHI per capita (1y) (%)	3.09	1.88	-3.60	1.90	3.10	4.30	12.30

(b) Treated versus Control LADs

	Treated LADs		Control LADs		Difference in means	
	Mean	SD	Mean	SD	t-stat	p-val
Individual Loan Characteristics						
Loan Amount (£)	7320.22	5770.78	7774.60	5780.48	-11.09	***
Term (m)	41.54	16.30	42.73	15.85	-10.52	***
Interest (%)	9.71	6.47	8.42	5.86	30.45	***
Repeat Borrower (%)	27.46	44.63	28.69	45.23	-3.85	***
Defaulted (%)	5.12	22.04	2.73	16.28	19.59	***
Time to Default (m)	14.58	9.22	15.60	10.67	-2.34	**
Loan Recovery (%)	66.71	35.33	64.78	37.32	7.37	***
Zip-level Loan Characteristics						
Num Loans per year	27.53	36.28	17.21	24.61	14.09	***
Sum Loans per year (1000'£)	201.52	277.82	133.82	204.73	11.54	***
Defaults per year (%)	3.92	9.86	2.77	11.89	2.36	**
LAD Characteristics						
ΔFunding (1y)	-5.67	8.28	6.39	17.00	-19.34	***
ΔFunding (3y)	-16.31	6.70	11.14	7.45	-93.18	***
LAD Population (1000s)	190.44	136.75	194.72	138.37	-0.74	
Unemployment (%)	6.39	2.56	6.42	2.83	-0.13	
ΔUnemployment (1y) (%)	-0.13	12.71	1.39	12.13	-1.32	
Unemp Claimants (% Unemployed)	36.58	16.06	34.86	16.87	1.14	
GDHI per capita (1000'£)	18.89	4.65	19.22	4.93	-0.82	
ΔGDHI per capita (1y) (%)	2.77	1.91	3.03	2.10	-1.41	

Table 2: LAD funding and household financial distress

Table presents probit estimates of the impact of central government funding cuts to LADs on individual financial stability. Data for this analysis are drawn from the NMG Household Finance Survey conducted every year in September by the Bank of England (BoE). The dependent variable in models 1–2 is a dummy indicating whether the survey respondent is currently facing difficulties with loans repayment (survey item *qbe*18). The dependent variable in models 3–4 is a dummy indicating whether the survey respondent is putting off spending due to concerns over exceeding their credit limit and/or not being able to get further credit (survey item *be*23). *NegFunding* is a dummy equal to one for *treated* LADs that experienced a negative change in cumulative funding from the central government over the preceding three years ($\Delta Funding < 0$), and zero for *control* LADs that experienced a non-negative change in cumulative funding over the past three years ($\Delta Funding \geq 0$). The regressions control for the respondents' age, gender, current employment status, education, number of children, and housing situation (owned, owned under mortgage, privately rented, or rented from the LAD) which are all available in the survey data. All regressions include up to the second-order polynomial terms of $\Delta Funding$ and their interactions with *NegFunding*, as well as LAD and year fixed effects. Standard errors are clustered by year and reported in parentheses. ***, **, * indicate 1%, 5%, and 10% significance levels respectively.

Dependent Variables:	Facing Difficulties Repaying Credit		Put Off Spending	
	(1)	(2)	(3)	(4)
NegFunding	0.28**	0.31**	0.55**	0.58***
	(0.083)	(0.091)	(0.112)	(0.154)
Age Group	-0.137***	-0.094***	-0.149***	-0.084***
	(0.019)	(0.022)	(0.014)	(0.018)
Male Respondent	-0.126***	-0.094***	-0.061	-0.028
	(0.020)	(0.013)	(0.050)	(0.035)
Unemployed	0.069*	0.036	0.129**	0.097***
	(0.037)	(0.038)	(0.051)	(0.028)
Education Level	-0.077***	-0.045***	-0.061***	-0.029***
	(0.006)	(0.004)	(0.006)	(0.006)
Has Children	0.278***	0.290***	0.291***	0.313***
	(0.033)	(0.043)	(0.048)	(0.061)
Housing - Owned under Mortgage		0.383**		0.119
		(0.169)		(0.135)
Housing - Owned		-0.035		-0.339*
		(0.126)		(0.183)
Housing - Rented from LAD		0.756***		0.519***
		(0.136)		(0.134)
Housing - Rented Privately		0.623***		0.486***
		(0.142)		(0.141)
Polynomials	Yes	Yes	Yes	Yes
Local Authority FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	11,929	11,929	19,552	19,552
Pseudo R^2	0.073	0.099	0.081	0.118

Table 3: LAD funding and aggregate P2P loan origination

Table presents regression discontinuity OLS estimates of the effect of LAD funding cuts on aggregate P2P loan origination. All models follow the specification outlined in Equation I. The dependent variables represent P2P loan origination at the zipcode level, and are measured as the log number of loans (models 1 and 2), one-year growth in the number of loans (model 3), log amount of loans (models 4 and 5), and one-year growth in the amount of loans (model 6). *NegFunding* is a dummy equal to one for *treated* LADs that experienced a negative change in cumulative funding from the central government over the preceding three years ($\Delta Funding < 0$), and zero for *control* LADs that experienced a non-negative change in cumulative funding over the past three years ($\Delta Funding \geq 0$). To minimize the effect of confounding factors, the analysis is restricted to loans from LADs whose $\Delta Funding$ is within a bandwidth h = ±25% around the zero cutoff. See Section 4.2 for definitions of the other variables. All regressions include up to the second-order polynomial terms of $\Delta Funding$ and their interactions with *NegFunding*, as well as LAD and year fixed effects. Standard errors are clustered by year and reported in parentheses. ***, **, * indicate 1%, 5%, and 10% significance levels respectively.

Dependent Variables:	Log(Num loans)		Num loans (1yr growth)	Log(Sum loans)		Sum loans (1yr growth)
	(1)	(2)	(3)	(4)	(5)	(6)
NegFunding	0.109*	0.106**	0.270***	0.178**	0.172***	0.715***
	(0.048)	(0.044)	(0.051)	(0.053)	(0.050)	(0.210)
Log(Funding per capita$_{t-1}$)	-0.150	-0.109	-0.203	-0.067	0.009	-0.482
	(0.121)	(0.098)	(0.229)	(0.105)	(0.102)	(0.462)
Log(GDHI per capita)	1.49**	1.27**	1.11	3.16***	2.75***	-1.74
	(0.623)	(0.489)	(0.756)	(0.531)	(0.398)	(1.36)
Unemployment (%)	-1.16	-0.841	0.106	-3.93***	-3.34***	0.170
	(1.07)	(0.895)	(1.06)	(0.995)	(0.779)	(3.09)
Unemp Claimants (%)	0.064	0.084	0.240	-0.293	-0.256	0.016
	(0.124)	(0.116)	(0.213)	(0.193)	(0.174)	(0.387)
Log(LAD population$_{t-1}$)		1.22	0.366		2.24***	-3.59
		(0.749)	(1.41)		(0.660)	(2.62)
Log(Num loans$_{t-1}$)	0.950***	0.949***				
	(0.049)	(0.049)				
Log(Sum loans$_{t-1}$)				0.305***	0.305***	
				(0.039)	(0.039)	
Polynomials	Yes	Yes	Yes	Yes	Yes	Yes
Local authority FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,874	4,874	4,874	4,874	4,874	4,874
Adjusted R^2	0.884	0.884	0.164	0.795	0.795	0.070
Control zipcodes mean	1.645	1.645		3.483	3.483	
Control zipcodes SD	1.664	1.664		1.878	1.878	

Table 4: LAD funding, aggregate P2P loan origination rates, and the role of banking and internet access

Table presents regression discontinuity OLS estimates of the effect of LAD funding cuts and banking/internet access across LADs on aggregate P2P loan origination rates. All models follow the specification outlined in Equation I. The dependent variables represent P2P loan origination at the zipcode level, and are measured as the log number of loans and log amount of loans issued. *NegFunding* is a dummy equal to one for *treated* LADs that experienced a negative change in cumulative funding from the central government over the preceding three years ($\Delta Funding < 0$), and zero for *control* LADs that experienced a non-negative change in cumulative funding over the past three years ($\Delta Funding \geq 0$). To minimize the effect of confounding factors, the analysis is restricted to loans from LADs whose $\Delta Funding$ is within a bandwidth $h = \pm 25\%$ around the zero cutoff. For a given year, the number of bank branches per LAD is scaled separately by local population size (*bank branches per 1000 individuals*) and number of local businesses (*bank branches per 100 businesses*). Data on bank branch coverage are from the Office for National Statistics. Similarly, for a given year, *mobile internet speed* is the average mobile broadband download speed measured in megabits per second per LAD. Data on internet access are from ThinkBroadband Limited. All regressions include the control variables described in Section 4.2, up to the second-order polynomial terms of $\Delta Funding$ and their interactions with *NegFunding*, as well as LAD and year fixed effects. Standard errors are clustered by year and reported in parentheses. ***, **, * indicate 1%, 5%, and 10% significance levels respectively.

	Banking Access				Internet Access	
Dependent Variables:	Log(Num loans) (1)	Log(Sum loans) (2)	Log(Num loans) (3)	Log(Sum loans) (4)	Log(Num loans) (5)	Log(Sum loans) (6)
NegFunding	0.170***	0.280***	0.230***	0.373***	0.095*	0.131*
	(0.030)	(0.052)	(0.055)	(0.088)	(0.044)	(0.059)
Bank branches (per 1000 individuals)	0.115	0.253				
	(0.113)	(0.203)				
NegFunding × Bank branches (per 1000 individuals)	-0.346***	-0.675**				
	(0.103)	(0.246)				
Bank branches (per 100 businesses)			0.016	0.013		
			(0.050)	(0.149)		
NegFunding × Bank branches (per 100 businesses)			-0.212***	-0.372**		
			(0.057)	(0.155)		
Mobile internet speed					0.010***	0.022**
					(0.002)	(0.008)
NegFunding × Mobile internet speed					-0.014***	-0.028***
					(0.002)	(0.007)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Polynomials	Yes	Yes	Yes	Yes	Yes	Yes
Local authority FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,796	4,796	4,796	4,796	4,796	4,796
Adjusted R^2	0.879	0.798	0.879	0.798	0.878	0.796

Table 5: LAD funding and P2P loan interest rate

Table presents regression discontinuity OLS estimates of the effect of LAD funding cuts on the interest rates charged on individual P2P loans. All models follow the specification outlined in Equation I. The dependent variable *interest rate spread* is measured as the difference between the actual P2P loan interest rate and the UK gilt yield of the closest maturity prevailing at the time of origination. *NegFunding* is a dummy equal to one for *treated* LADs that experienced a negative change in cumulative funding from the central government over the preceding three years ($\Delta Funding < 0$), and zero for *control* LADs that experienced a non-negative change in cumulative funding over the past three years ($\Delta Funding \geq 0$). To minimize the effect of confounding factors, the analysis is restricted to loans from LADs whose $\Delta Funding$ is within a bandwidth $h = \pm 25\%$ around the zero cutoff. All regressions include the control variables described in Section 4.2, up to the second-order polynomial terms of $\Delta Funding$ and their interactions with *NegFunding*, as well as LAD and year fixed effects. Standard errors are clustered by year and reported in parentheses. ***, **, * indicate 1%, 5%, and 10% significance levels respectively.

Dependent Variable:	Interest Rate Spread			
	All Loans		New Borrowers	Repeat Borrowers
	(1)	(2)	(3)	(4)
NegFunding	0.394***	0.347***	0.404***	0.174
	(0.108)	(0.102)	(0.120)	(0.159)
Log(Loan Amount)	-0.024***	-0.023***	-0.024***	-0.022***
	(0.0004)	(0.0004)	(0.0004)	(0.0005)
Log(Loan Term)	0.007***	0.007***	0.006***	0.012***
	(0.0007)	(0.0007)	(0.0009)	(0.0008)
Repeat Borrower	-0.039***	-0.008***		
	(0.003)	(0.0003)		
Other controls	No	Yes	Yes	Yes
Polynomials	Yes	Yes	Yes	Yes
Local authority FE	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	178,283	170,230	130,573	39,657
Adjusted R^2	0.215	0.215	0.224	0.191

Table 6: LAD funding and P2P loan performance

Table presents regression discontinuity logit estimates (panel (a)) and Cox proportional hazard estimates (panel (b)) of the effect of LAD funding cuts on the performance of individual P2P loans. All models follow the specification outlined in Equation II. The dependent variable is a dummy equal to one if, after origination, the loan went into default and zero if it was fully repaid or outstanding at the end of the sample period. *NegFunding* is a dummy equal to one for *treated* LADs that experienced a negative change in cumulative funding from the central government over the preceding three years ($\Delta Funding < 0$), and zero for *control* LADs that experienced a non-negative change in cumulative funding over the past three years ($\Delta Funding \geq 0$). To minimize the effect of confounding factors, the analysis is restricted to loans from LADs whose $\Delta Funding$ is within a bandwidth $h = \pm 25\%$ around the zero cutoff. All regressions include the control variables described in Section 4.2, up to the second-order polynomial terms of $\Delta Funding$ and their interactions with *NegFunding*, as well as LAD, issue year, and loan performance year fixed effects. Standard errors are clustered by year and reported in parentheses. ***, **, * indicate 1%, 5%, and 10% significance levels respectively.

(a) GLM

Dependent Variable:	Default			
	All Loans		New Borrowers	Repeat Borrowers
	(1)	(2)	(3)	(4)
NegFunding	0.330**	0.342**	0.345**	0.471
	(0.159)	(0.166)	(0.160)	(0.465)
Log(Loan Amount)	-0.244***	-0.262***	-0.285***	-0.181***
	(0.018)	(0.018)	(0.019)	(0.040)
Log(Loan Term)	1.11***	1.18***	1.17***	1.34***
	(0.036)	(0.038)	(0.043)	(0.077)
Repeat Borrower		-0.618***		
		(0.024)		
Other controls	No	Yes	Yes	Yes
Polynomials	Yes	Yes	Yes	Yes
Local authority FE	Yes	Yes	Yes	Yes
Issue Year FE	Yes	Yes	Yes	Yes
Loan Performance Year FE	Yes	Yes	Yes	Yes
Observations	465,980	437,023	341,397	91,836
Adjusted R^2	0.049	0.052	0.053	0.053

(b) Cox proportional hazards model

Dependent Variable:	Default probability			
	All Loans		New Borrowers	Repeat Borrowers
	(1)	(2)	(3)	(4)
NegFunding	0.839***	1.055***	1.089***	0.426*
	(0.078)	(0.079)	(0.084)	(0.228)
Log(Loan Amount)	-0.16***	-0.198***	-0.21***	-0.141***
	(0.013)	(0.013)	(0.014)	(0.029)
Log(Loan Term)	1.082***	1.176***	1.139***	1.267***
	(0.029)	(0.028)	(0.031)	(0.072)
Repeat Borrower	-0.349***	-0.482***		
	(0.023)	(0.023)		
Other controls	No	Yes	Yes	Yes
Local authority FE	Yes	Yes	Yes	Yes
Loan Performance Year FE	No	Yes	Yes	Yes
Observations	180,618	180,618	180,618	180,618
Log Likelihood	-162298.69	-160460.908	-131817.668	-22411.149
LR Test (χ^2)	6742.154***	10417.718***	8559.971***	1497.72***

Table 7: LAD funding and P2P lending outcomes across contiguous zipcodes

Table presents regression discontinuity estimates of the effect of LAD funding cuts on P2P loan outcomes. The analysis is performed on a restricted sample of P2P loans issued in zipcodes located within 10 kilometers on either side of the border along contiguous LADs that differ in treatment status. Panels (a) and (b) show OLS regression estimates based on the specification outlined in Equation I. The dependent variables are measures of P2P loan origination at the zipcode level in panel (a), and loan interest rate spreads in panel (b). Panels (c) shows regression estimates based on the specification outlined in Equation II. Panel (c) shows Cox proportional hazard estimates of loan default rates, where the dependent variable is a dummy equal to one if, after origination, the loan went into default and zero if it was fully repaid or outstanding at the end of the sample period. *NegFunding* is a dummy equal to one for *treated* LADs that experienced a negative change in cumulative funding from the central government over the preceding three years ($\Delta Funding < 0$), and zero for *control* LADs that experienced a non-negative change in cumulative funding over the past three years ($\Delta Funding \geq 0$). To minimize the effect of confounding factors, the analysis is restricted to loans from LADs whose $\Delta Funding$ is within a bandwidth h = ±25% around the zero cutoff. See Section 4.2 for definitions of the other variables. All regressions include up to the second-order polynomial terms of $\Delta Funding$ and their interactions with *NegFunding*, as well as LAD and year fixed effects. Standard errors are clustered by year and reported in parentheses. ***, **, * indicate 1%, 5%, and 10% significance levels respectively.

(a) Loan origination

Dependent Variables:	log(Num loans)		$\log \frac{\text{Num loans}_{lad}}{\text{Num loans}_{national}}$		log(Sum loans)		$\log \frac{\text{Sum loans}_{lad}}{\text{Sum loans}_{national}}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NegFunding	0.060**	0.064**	0.089**	0.093**	0.089**	0.081**	0.117**	0.107**
	(0.024)	(0.021)	(0.030)	(0.028)	(0.032)	(0.020)	(0.036)	(0.031)
Other controls	No	Yes	No	Yes	No	Yes	No	Yes
Local authority FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,230	11,685	11,868	11,335	12,230	11,685	11,868	11,335
Adjusted R^2	0.836	0.832	0.605	0.604	0.733	0.725	0.491	0.491

(b) Interest rate spread

	All Loans			New Borrowers	Repeat Borrowers
	(1)	(2)	(3)	(4)	(5)
NegFunding	0.304***	0.238**	0.290***	0.249**	0.141
	(0.101)	(0.093)	(0.095)	(0.100)	(0.178)
Repeat Borrower	-0.864***	-0.838***	-0.675***		
	(0.060)	(0.062)	(0.079)		
ΔCum funding (-ve) × Repeat Borrower			-0.316**		
			(0.137)		
Other controls	No	Yes	Yes	Yes	Yes
Local authority FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	37,807	36,622	36,622	30,696	5,926
Adjusted R^2	0.195	0.199	0.199	0.201	0.182

(c) Loan defaults

	Default probability		
	(1)	(2)	(3)
NegFunding	0.439***	0.469***	0.432***
	(0.112)	(0.116)	(0.115)
Interest Rate	0.155***	0.161***	0.16***
	(0.003)	(0.003)	(0.003)
Repeat Borrower	-0.361***	-0.298***	-0.321***
	(0.074)	(0.074)	(0.074)
Other controls	No	Yes	Yes
Local authority FE	Yes	Yes	Yes
Loan Performance Year FE	No	No	Yes
Observations	37,855	37,855	37,855
Log Likelihood	-21504.766	-21298.828	-21244.523
LR Test (χ^2)	2813.797***	3225.674***	3334.283***

Internet Appendix

for

FinTech Lending under Austerity

A Additional figures and tables

Figure A1: Distribution of observable LAD characteristics around the RD cutoff

Figure shows evidence of smoothness of various observable LAD characteristics as a function of the cumulative change in central government funding per LAD over the preceding three years ($\Delta Funding$). The black vertical line represents the zero treatment threshold ($\Delta Funding = 0\%$). Red lines represent the local polynomial fit of order two with observations weighted using a triangular kernel function, and are fitted separately on either side of the threshold. Discontinuities in the fitted prediction lines around the zero threshold imply that the concerned LAD characteristic is imbalanced at the threshold. *GDHI* is the gross domestic household income, *FT* denotes Full-time, and *PT* denotes Part-time. See Section 4.2 for definitions of the other variables.

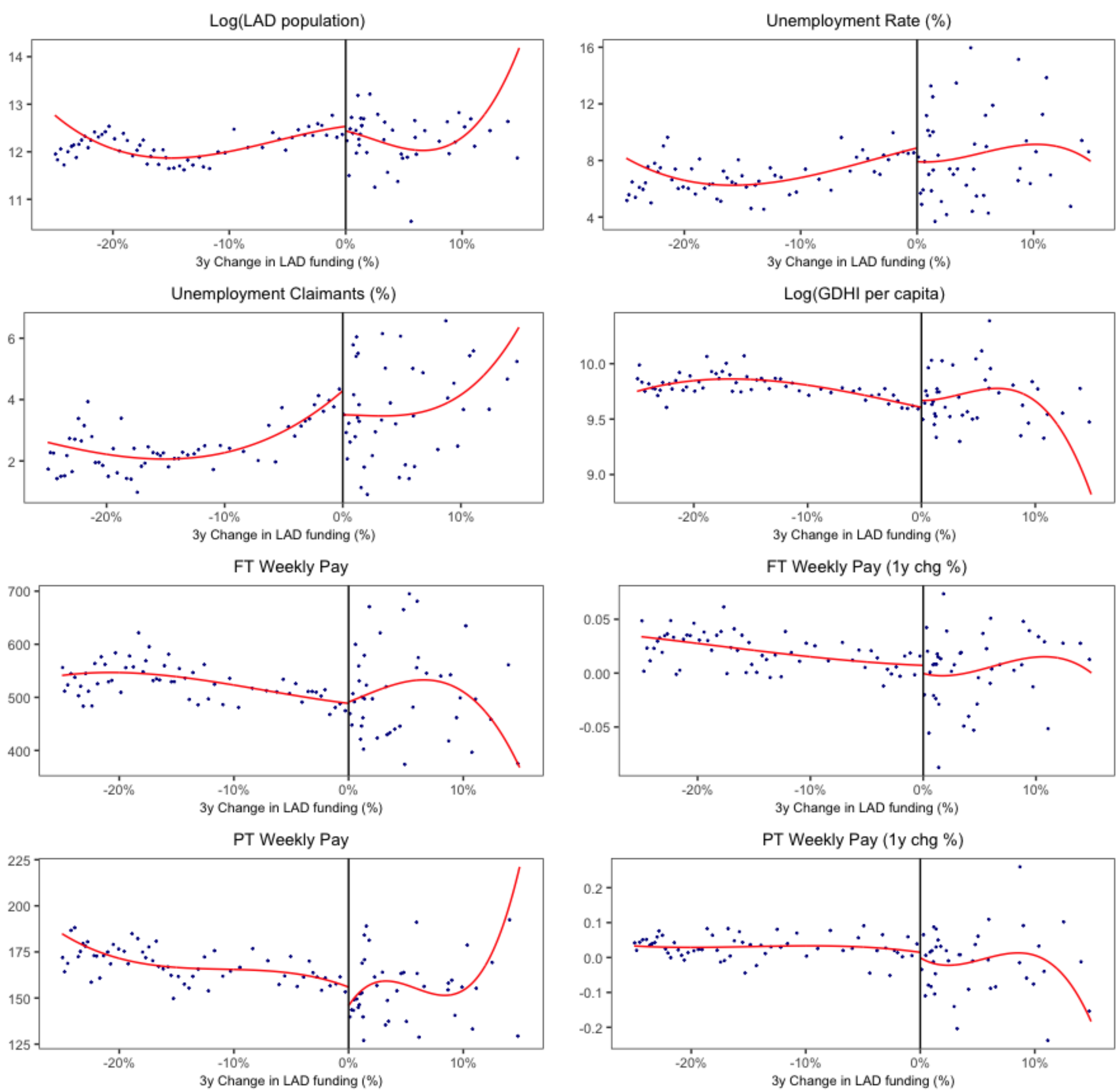


Figure A2: Kaplan-Meier curves of loan performance by length of maturity

Figure shows Kaplan-Meier curves of loan performance for a sample of P2P loans issued in treated and control LADs. Loans are grouped by their maturity (rounded to nearest year), and separate Kaplan-Meier curves are fit for loans belonging to each group. An LAD is considered *treated* if it experienced a negative change in cumulative funding from the central government over the preceding three years ($\Delta Funding < 0$), and is considered *control* if the corresponding change was non-negative ($\Delta Funding \geq 0$). To minimize the effect of confounding factors, the analysis is restricted to loans from LADs whose $\Delta Funding$ is within a bandwidth $h = \pm 25\%$ around the zero cutoff. Loans issued in LADs with $\Delta Funding$ outside these intervals are not considered. For loans belonging to either treatment status, each plot shows the fraction of loans that did not default (i.e, were either fully repaid or outstanding at the end of the sample period) together with 95% confidence intervals as a function of time since their origination.

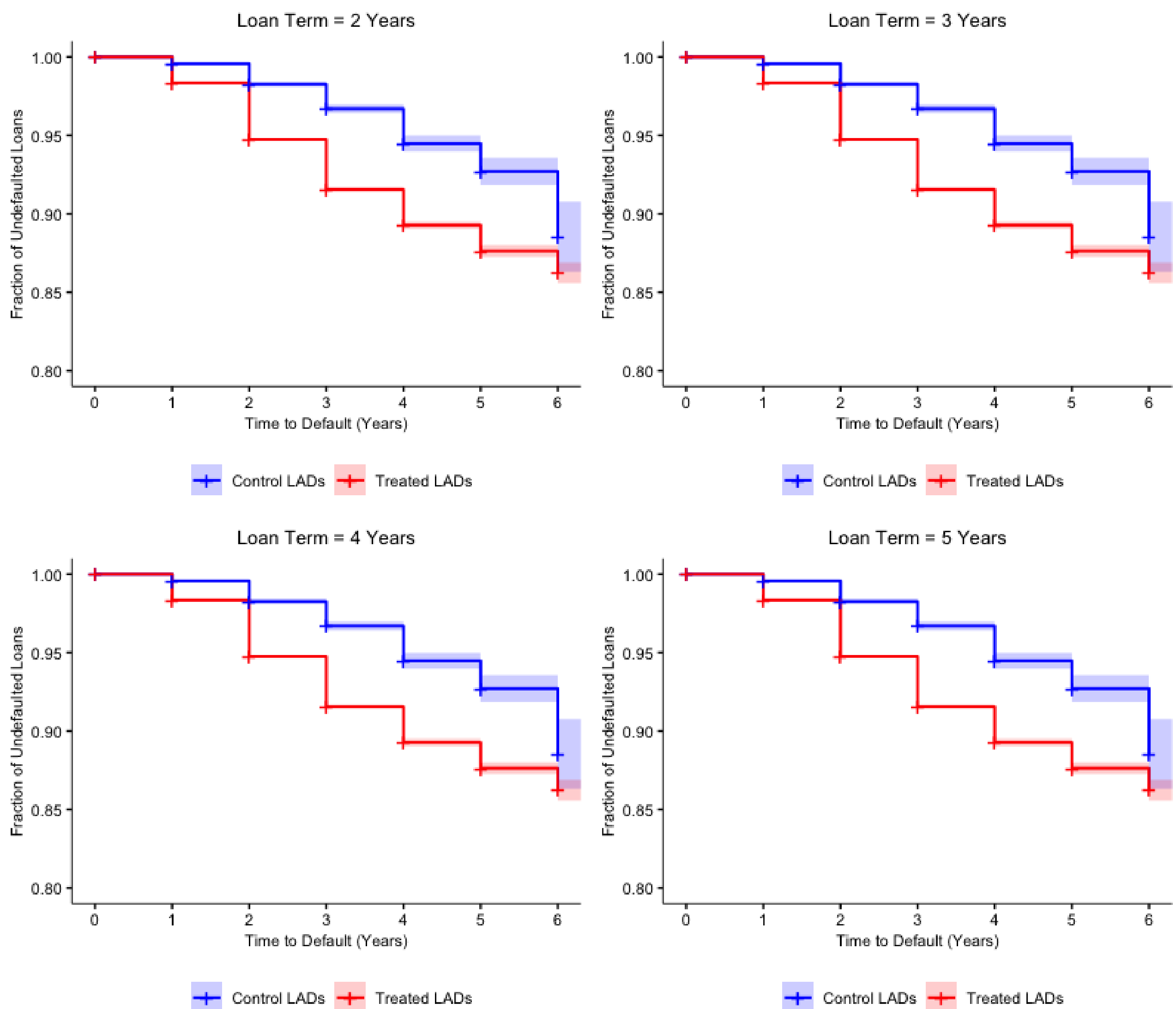


Table A1: Summary statistics

Table reports summary statistics for the full sample of loans obtained from the P2P platform. Panel (a) shows the summary statistics at the individual loan level. Panel (b) shows the summary statistics of loan-level variables split into individual bins by the year-on-year change in central government funding for the LAD in which the loans were issued. Panel (c) shows the final performance status of loan by year of origination. See Section 4.2 for the definitions of variables.

(a) Loan origination

	Mean	SD	Minimum	25 pct	Median	75 pct	Maximum
Loan Amount (£)	7,385	5,775	260	3,060	5,500	10,170	35,000
Term (m)	41.71	16.25	10.00	24.00	36.00	60.00	60.00
Interest (%)	9.52	6.40	2.00	4.30	7.50	13.10	33.65
Repeat Borrower (%)	27.63	44.72	0.00	0.00	0.00	100.00	100.00
Default (%)	4.78	21.33	0.00	0.00	0.00	0.00	100.00
Time to Default (m)	14.66	9.35	1.00	8.00	13.00	19.00	89.00
Loan Recovery (%)	66.44	35.63	0.00	30.57	80.71	100.00	100.00

(b) P2P loan origination and LAD funding change

YoY Funding Change (%)		Loan Amt (£)	Term (m)	Interest (%)	Repeat Loan (%)	Default (%)
[–30%, –20%) *N=11,390*	Mean	7781	43.6	8.7	21.7	6.9
	Median	5880	48.0	6.8	0.0	0.0
	SD	6045	15.6	6.1	41.2	25.3
[–20%, –10%) *N=132,376*	Mean	7146	43.2	8.7	22.6	6.4
	Median	5330	48.0	7.0	0.0	0.0
	SD	5477	15.3	5.8	41.8	24.5
[–10%, 0%) *N=162,149*	Mean	7283	41.7	9.7	27.0	5.2
	Median	5380	36.0	7.6	0.0	0.0
	SD	5736	16.2	6.4	44.4	22.3
[0%, 10%) *N=27,018*	Mean	7574	42.7	8.4	27.7	3.1
	Median	5920	48.0	6.5	0.0	0.0
	SD	5662	15.8	5.9	44.8	17.4
[10%, 20%) *N=13,340*	Mean	6524	41.7	8.4	21.4	3.6
	Median	5120	36.0	6.4	0.0	0.0
	SD	4618	14.9	5.7	41.0	18.6
[20%, 30%) *N=7,304*	Mean	6366	41.2	7.8	19.0	1.4
	Median	5120	36.0	5.9	0.0	0.0
	SD	4389	15.2	4.9	39.2	11.7

(c) P2P loan status by year of origination

Year Issued	Loan Status			
	Active	Completed	Defaulted	Late
2009	0	5,636 (95.6)	258 (4.4)	0
2010	0	9,518 (96.2)	371 (3.8)	0
2011	0	11,649 (98.0)	233 (2.0)	0
2012	0	17,136 (98.2)	310 (1.8)	0
2013	0	32,236 (98.6)	466 (1.4)	2 (0.0)
2014	1,036 (2.8)	34,076 (92.9)	1,534 (4.2)	45 (0.1)
2015	9,267 (12.7)	57,390 (78.8)	5,829 (8.0)	366 (0.5)
2016	20,721 (20.8)	69,250 (69.5)	8,741 (8.8)	911 (0.9)
2017	52,288 (39.1)	70,319 (52.5)	9,479 (7.1)	1,813 (1.4)
2018	84,484 (66.8)	36,427 (28.8)	3,437 (2.7)	2,062 (1.6)
2019	101,389 (89.8)	9,408 (8.3)	579 (0.5)	1,495 (1.3)

Table A2: LAD funding and scaled aggregate P2P loan origination

Table presents regression discontinuity OLS estimates of the effect of LAD funding cuts on scaled aggregate P2P loan origination. All models follow the specification outlined in Equation I. The dependent variable in models 1 and 2 is the the log ratio of number of P2P loans issued at the zipcode level relative to aggregate number of loans issued at the national level during the same year. The dependent variable in models 3 and 4 is the log ratio of value of loans (in £) issued at the zipcode level relative to the aggregate value of loans issued at the national level during the same year. *NegFunding* is a dummy equal to one for *treated* LADs that experienced a negative change in cumulative funding from the central government over the preceding three years ($\Delta Funding < 0$), and zero for *control* LADs that experienced a non-negative change in cumulative funding over the past three years ($\Delta Funding \geq 0$). To minimize the effect of confounding factors, the analysis is restricted to loans from LADs whose $\Delta Funding$ is within a bandwidth h $= \pm 25\%$ around the zero cutoff. See Section 4.2 for definitions of the other variables. All regressions include up to the second-order polynomial terms of $\Delta Funding$ and their interactions with *NegFunding*, as well as LAD and year fixed effects. Standard errors are clustered by year and reported in parentheses. ***, **, * indicate 1%, 5%, and 10% significance levels respectively.

Dependent Variables:	$\log \frac{\text{Num loans}_{zip,t}}{\text{Num loans}_{national,t}}$		$\log \frac{\text{Sum loans}_{zip,t}}{\text{Sum loans}_{national,t}}$	
	(1)	(2)	(3)	(4)
NegFunding	0.139**	0.136***	0.277***	0.274***
	(0.043)	(0.040)	(0.058)	(0.055)
Log(Funding per capita$_{t-1}$)	-0.149	-0.104	-0.166	-0.125
	(0.116)	(0.088)	(0.121)	(0.095)
Log(GDHI per capita)	1.87**	1.64**	1.63**	1.42**
	(0.741)	(0.589)	(0.693)	(0.557)
Unemployment (%)	-1.75	-1.42	-2.51	-2.21
	(1.37)	(1.17)	(1.39)	(1.24)
Unemp Claimants (%)	0.007	0.027	-0.058	-0.039
	(0.146)	(0.133)	(0.195)	(0.186)
Log(LAD population$_{t-1}$)		1.32		1.2
		(0.759)		(0.744)
$\log \frac{\text{Num loans}_{lad,t-1}}{\text{Num loans}_{national,t-1}}$	0.798***	0.797***		
	(0.078)	(0.079)		
$\log \frac{\text{Sum loans}_{lad,t-1}}{\text{Sum loans}_{national,t-1}}$			0.676***	0.675***
			(0.088)	(0.088)
Local authority FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,749	4,749	4,749	4,749
Adjusted R^2	0.715	0.715	0.605	0.606
Control zipcodes mean	-5.859	-5.859	-5.931	-5.931
Control zipcodes SD	1.452	1.452	1.542	1.542

Table A3: LAD funding, P2P loan interest rate, and the role of banking and internet access

Table presents regression discontinuity OLS estimates of the effect of LAD funding cuts on the interest rates charged on individual P2P loans. All models follow the specification outlined in Equation I. The dependent variable *interest rate spread* is measured as the difference between the actual P2P loan interest rate and the UK gilt yield of the closest maturity prevailing at the time of origination. *NegFunding* is a dummy equal to one for *treated* LADs that experienced a negative change in cumulative funding from the central government over the preceding three years ($\Delta Funding < 0$), and zero for *control* LADs that experienced a non-negative change in cumulative funding over the past three years ($\Delta Funding \geq 0$). To minimize the effect of confounding factors, the analysis is restricted to loans from LADs whose $\Delta Funding$ is within a bandwidth $h = \pm 25\%$ around the zero cutoff. For a given year, the number of bank branches per LAD is scaled separately by local population size (*bank branches per 1000 individuals*) and number of local businesses (*bank branches per 100 businesses*). Data on bank branch coverage are from the Office for National Statistics. Similarly, for a given year, *mobile internet speed* is the average mobile broadband download speed measured in megabits per second per LAD. Data on internet access are from ThinkBroadband Limited. All regressions include the control variables described in Section 4.2, up to the second-order polynomial terms of $\Delta Funding$ and their interactions with *NegFunding*, as well as LAD and year fixed effects. Standard errors are clustered by year and reported in parentheses. ***, **, * indicate 1%, 5%, and 10% significance levels respectively.

Dependent Variable:	Interest Rate Spread								
	All Loans			New Borrowers			Repeat Borrowers		
	Banking Access		Internet Access	Banking Access		Internet Access	Banking Access		Internet Access
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NegFunding	0.298***	0.301***	0.303***	0.349***	0.355***	0.357***	0.095	0.083	0.087
	(0.085)	(0.089)	(0.088)	(0.098)	(0.101)	(0.099)	(0.191)	(0.199)	(0.200)
Bank branches (per 1000 individuals)	0.008*			0.007*			0.013*		
	(0.004)			(0.004)			(0.006)		
NegFunding × Bank branches (per 1000 individuals)	0.002			0.004			-0.005		
	(0.004)			(0.005)			(0.005)		
Bank branches (per 100 businesses)		0.003			0.003			0.001	
		(0.002)			(0.002)			(0.004)	
NegFunding × Bank branches (per 100 businesses)		0.0006			0.0008			0.001	
		(0.002)			(0.002)			(0.003)	
Internet speed			0.0005			0.0004			0.0003
			(0.0004)			(0.0004)			(0.0006)
NegFunding × Internet speed			0.0004			0.0002			0.001
			(0.0005)			(0.0004)			(0.0008)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Polynomials	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Local authority FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	170,171	170,171	170,020	130,516	130,516	130,387	39,655	39,655	39,633
Adjusted R^2	0.129	0.129	0.129	0.139	0.139	0.139	0.110	0.110	0.110

Table A4: LAD funding, P2P loan performance, and the role of banking and internet access

Table presents regression discontinuity logit estimates of the effect of LAD funding cuts on the performance of individual P2P loans. All models follow the specification outlined in Equation II. The dependent variable is a dummy equal to one if, after origination, the loan went into default and zero if it was fully repaid or outstanding at the end of the sample period. *NegFunding* is a dummy equal to one for *treated* LADs that experienced a negative change in cumulative funding from the central government over the preceding three years ($\Delta Funding < 0$), and zero for *control* LADs that experienced a non-negative change in cumulative funding over the past three years ($\Delta Funding \geq 0$). To minimize the effect of confounding factors, the analysis is restricted to loans from LADs whose $\Delta Funding$ is within a bandwidth $h = \pm 25\%$ around the zero cutoff. For a given year, the number of bank branches per LAD is scaled separately by local population size (*bank branches per 1000 individuals*) and number of local businesses (*bank branches per 100 businesses*). Data on bank branch coverage are from the Office for National Statistics. Similarly, for a given year, *mobile internet speed* is the average mobile broadband download speed measured in megabits per second per LAD. Data on internet access are from ThinkBroadband Limited. All regressions include the control variables described in Section 4.2, up to the second-order polynomial terms of $\Delta Funding$ and their interactions with *NegFunding*, as well as LAD, issue year, and loan performance year fixed effects. Standard errors are clustered by year and reported in parentheses. ***, **, * indicate 1%, 5%, and 10% significance levels respectively.

Dependent Variable:	Default								
	All Loans			New Borrowers			Repeat Borrowers		
	Banking Access		Internet Access	Banking Access		Internet Access	Banking Access		Internet Access
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NegFunding	0.310**	0.344***	0.323**	0.306**	0.347***	0.336**	0.518	0.385	0.405
	(0.111)	(0.118)	(0.121)	(0.102)	(0.111)	(0.123)	(0.361)	(0.501)	(0.353)
Bank branches (per 1000 individuals)	0.177			0.035			0.087		
	(0.228)			(0.266)			(0.851)		
NegFunding × Bank branches (per 1000 individuals)	-0.107			-0.214			-0.667		
	(0.320)			(0.340)			(0.856)		
Bank branches (per 100 businesses)		0.097			0.088			-0.061	
		(0.068)			(0.093)			(0.494)	
NegFunding × Bank branches (per 100 businesses)		-0.033			-0.018			-0.105	
		(0.090)			(0.120)			(0.538)	
Internet speed			0.037			0.027			0.105
			(0.047)			(0.056)			(0.089)
NegFunding × Internet speed			-0.007			-0.0007			-0.078
			(0.046)			(0.055)			(0.052)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Polynomials	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Local authority FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Issue Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Performance Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	465,864	465,864	465,864	363,766	363,766	363,766	98,498	98,498	98,498
Adjusted R^2	0.052	0.052	0.052	0.053	0.053	0.054	0.053	0.053	0.053

Table A5: P2P loan origination by region and LAD type

Table reports summary statistics of the P2P loan origination by region and LAD type. For *Num loans* and *Sum loans* columns, figures in parentheses represent proportions (in %) of the total number of P2P loans in the sample. For the *Num loans (new borrowers)* and *Sum loans (new borrowers)* columns, figures in parentheses represent proportions (in %) of the respective *Num loans* or *Sum loans*.

Region	LAD Type	Num loans	Num loans (new borrowers)	Sum loans (£m)	Sum loans (£m) (new borrowers)
East	Shire District	42,276 (10.6%)	31,237 (73.9%)	314.6 (10.9%)	228.7 (72.7%)
	Unitary	11,024 (2.8%)	8,277 (75.1%)	80.5 (2.8%)	59.3 (73.6%)
East Midlands	Shire District	34,926 (8.7%)	2,5587 (73.3%)	246.7 (8.5%)	177.0 (71.8%)
	Unitary	7,977 (2.0%)	6,082 (76.2%)	54.6 (1.9%)	40.9 (74.9%)
London	Inner London Borough	16,180 (4.1%)	12,632 (78.1%)	120.1 (4.2%)	91.5 (76.2%)
	Outer London Borough	37,831 (9.5%)	29,817 (78.8%)	293.9 (10.2%)	229.6 (78.1%)
North East	Metropolitan District	9,917 (2.5%)	7,312 (73.7%)	66.4 (2.3%)	47.8 (72.0%)
	Unitary	4,217 (1.1%)	3,057 (72.5%)	28.8 (1.0%)	20.1 (69.9%)
North West	Metropolitan District	37,321 (9.3%)	27,800 (74.5%)	251.4 (8.7%)	183.3 (72.9%)
	Shire District	16,833 (4.2%)	12,281 (73.0%)	117.0 (4.0%)	83.5 (71.4%)
	Unitary	6,183 (1.6%)	4,548 (73.6%)	44.2 (1.5%)	32.2 (73.0%)
South East	Shire District	52,265 (13.1%)	38,639 (73.9%)	408.3 (14.1%)	296.9 (72.7%)
	Unitary	18,956 (4.7%)	14,309 (75.5%)	147.8 (5.1%)	110.1 (74.5%)
South West	Shire District	15,744 (3.9%)	11,455 (72.8%)	112.1 (3.9%)	79.4 (70.8%)
	Unitary	20,615 (5.2%)	15,277 (74.1%)	147.8 (5.1%)	107.2 (72.5%)
West Midlands	Metropolitan District	17,982 (4.5%)	13,555 (75.4%)	122.8 (4.2%)	90.9 (74.0%)
	Shire District	10,844 (2.7%)	8,084 (74.6%)	76.7 (2.7%)	55.9 (72.9%)
	Unitary	66 (0.0%)	47 (71.2%)	0.6 (0.0%)	0.4 (76.4%)
Yorkshire & Humber	Metropolitan District	29,655 (7.4%)	21,873 (73.8%)	199.3 (6.9%)	143.9 (72.2%)
	Shire District	2,733 (0.7%)	1,989 (72.8%)	20.0 (0.7%)	14.5 (72.6%)
	Unitary	6,212 (1.6%)	4,498 (72.4%)	43.2 (1.5%)	30.5 (70.8%)

Table A6: LAD funding across England regions and scaled aggregate P2P loan origination

Table presents regression discontinuity OLS estimates of the effect of LAD funding cuts on scaled aggregate P2P loan origination across England regions. All models follow the specification outlined in Equation I. The dependent variable in models 1 and 2 is the the log ratio of number of P2P loans issued at the zipcode level relative to aggregate number of loans issued at the national level during the same year. The dependent variable in models 3 and 4 is the log ratio of value of loans (in £) issued at the zipcode level relative to the aggregate value of loans issued at the national level during the same year. *NegFunding* is a dummy equal to one for *treated* LADs that experienced a negative change in cumulative funding from the central government over the preceding three years ($\Delta Funding < 0$), and zero for *control* LADs that experienced a non-negative change in cumulative funding over the past three years ($\Delta Funding \geq 0$). To minimize the effect of confounding factors, the analysis is restricted to loans from LADs whose $\Delta Funding$ is within a bandwidth h = ±25% around the zero cutoff. See Section 4.2 for definitions of the other variables. All regressions include up to the second-order polynomial terms of $\Delta Funding$ and their interactions with *NegFunding*, as well as region and year fixed effects. Standard errors are clustered by year and reported in parentheses. ***, **, * indicate 1%, 5%, and 10% significance levels respectively.

Dependent Variables:	$\log \frac{\text{Num loans}_{lad}}{\text{Num loans}_{national}}$		$\log \frac{\text{Sum loans}_{lad}}{\text{Sum loans}_{national}}$	
	(1)	(2)	(3)	(4)
NegFunding	0.203***	0.204**	0.411**	0.412**
	(0.073)	(0.084)	(0.176)	(0.186)
NegFunding × Region West Midlands	0.012	0.046	0.133	0.178
	(0.167)	(0.161)	(0.180)	(0.185)
NegFunding × Region East	-0.314***	-0.286***	-0.323**	-0.286*
	(0.068)	(0.061)	(0.157)	(0.168)
NegFunding × Region North East	-0.149*	-0.115	-0.194***	-0.146
	(0.077)	(0.094)	(0.075)	(0.107)
NegFunding × Region London	0.108*	0.097	0.042	0.027
	(0.064)	(0.074)	(0.063)	(0.075)
NegFunding × Region North West	-0.150	-0.173	-0.245***	-0.275***
	(0.165)	(0.181)	(0.074)	(0.106)
NegFunding × Region South East	-0.057	-0.041	-0.077	-0.055
	(0.057)	(0.065)	(0.080)	(0.105)
NegFunding × Region South West	-0.219***	-0.225***	-0.280*	-0.289*
	(0.065)	(0.076)	(0.154)	(0.174)
NegFunding × Region Yorkshire and the Humber	0.200**	0.196**	-0.016	-0.021
	(0.095)	(0.096)	(0.155)	(0.164)
Controls	Yes	Yes	Yes	Yes
Polynomials	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,749	4,749	4,749	4,749
Adjusted R^2	0.708	0.709	0.592	0.593

B Contiguous zipcodes

Table B1: LAD funding and aggregate P2P loan origination across contiguous zipcodes

Tables present regression discontinuity OLS estimates of the effect of funding cuts to LADs on P2P loan origination. The analysis is performed on a restricted sample of P2P loans issued in zipcodes located within 20 and 30 kilometers on either side of the border along contiguous LADs that differ in treatment status. The regression estimates are based on the specification outlined in Equation I. The dependent variables are measures of P2P loan origination at the zipcode level. *NegFunding* is a dummy equal to one for *treated* LADs that experienced a negative change in cumulative funding from the central government over the preceding three years ($\Delta Funding < 0$), and zero for *control* LADs that experienced a non-negative change in cumulative funding over the past three years ($\Delta Funding \geq 0$). To minimize the effect of confounding factors, the analysis is restricted to LADs whose $\Delta Funding$ is within a bandwidth h = ±25% around the zero cutoff. See Section 4.2 for definitions of the other variables. All regressions include up to the second-order polynomial terms of $\Delta Funding$ and their interactions with *NegFunding*, as well as LAD and year fixed effects. Standard errors are clustered by year and reported in parentheses. ***, **, * indicate 1%, 5%, and 10% significance levels respectively.

(a) Distance to border ≤ 20 km

Dependent Variables:	log(Num loans)		$\log \frac{\text{Num loans}_{lad}}{\text{Num loans}_{national}}$		log(Sum loans)		$\log \frac{\text{Sum loans}_{lad}}{\text{Sum loans}_{national}}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NegFunding	0.052*	0.059**	0.069**	0.076**	0.094*	0.092*	0.082**	0.077**
	(0.022)	(0.020)	(0.021)	(0.021)	(0.046)	(0.043)	(0.031)	(0.029)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	24,631	23,631	23,873	22,892	24,631	23,631	23,873	22,892
Adjusted R^2	0.822	0.812	0.581	0.581	0.714	0.710	0.457	0.458

(b) Distance to border ≤ 30 km

Dependent Variables:	log(Num loans)		$\log \frac{\text{Num loans}_{lad}}{\text{Num loans}_{national}}$		Log(Sum loans)		$\log \frac{\text{Sum loans}_{lad}}{\text{Sum loans}_{national}}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NegFunding	0.068**	0.075***	0.082***	0.088***	0.120**	0.122**	0.108**	0.105**
	(0.020)	(0.018)	(0.017)	(0.017)	(0.038)	(0.035)	(0.033)	(0.031)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	31,646	30,450	30,638	29,461	31,646	30,450	30,638	29,461
Adjusted R^2	0.815	0.813	0.575	0.578	0.708	0.704	0.454	0.456

Table B2: LAD funding and P2P loan interest rates across contiguous zipcodes

Tables present regression discontinuity OLS estimates of the effect of funding cuts to LADs on P2P loan interest rates. The analysis is performed on a restricted sample of P2P loans issued in zipcodes located within 20 and 30 kilometers on either side of the border along contiguous LADs that differ in treatment status. The regression estimates are based on the specification outlined in Equation I. The dependent variable *interest rate spread* is measured as the difference between the actual P2P loan interest rate and the UK gilt yield of the closest maturity prevailing at the time of origination. *NegFunding* is a dummy equal to one for *treated* LADs that experienced a negative change in cumulative funding from the central government over the preceding three years ($\Delta Funding < 0$), and zero for *control* LADs that experienced a non-negative change in cumulative funding over the past three years ($\Delta Funding \geq 0$). To minimize the effect of confounding factors, the analysis is restricted to LADs whose $\Delta Funding$ is within a bandwidth h = $\pm$25% around the zero cutoff. See Section 4.2 for definitions of the other variables. All regressions include up to the second-order polynomial terms of $\Delta Funding$ and their interactions with *NegFunding*, as well as LAD and year fixed effects. Standard errors are clustered by year and reported in parentheses. ***, **, * indicate 1%, 5%, and 10% significance levels respectively.

(a) Distance to border $\leq$ 20 km

	All Loans			New Borrowers	Repeat Borrowers
	(1)	(2)	(3)	(4)	(5)
NegFunding	0.293***	0.229***	0.277***	0.249***	0.085
	(0.096)	(0.085)	(0.088)	(0.093)	(0.139)
Log(Loan Amount)	-1.48***	-1.48***	-1.48***	-1.55***	-1.24***
	(0.032)	(0.033)	(0.033)	(0.039)	(0.069)
Log(Loan Term)	0.163***	0.183***	0.184***	0.105	0.841***
	(0.063)	(0.063)	(0.063)	(0.072)	(0.122)
Repeat Borrower	-0.824***	-0.800***	-0.633***		
	(0.054)	(0.056)	(0.077)		
NegFunding × Repeat Borrower			-0.295**		
			(0.125)		
Observations	48,241	46,795	46,795	39,152	7,643
Adjusted R^2	0.193	0.197	0.197	0.199	0.181

(b) Distance to border $\leq$ 30 km

	All Loans			New Borrowers	Repeat Borrowers
	(1)	(2)	(3)	(4)	(5)
NegFunding	0.313***	0.244***	0.292***	0.278***	0.052
	(0.094)	(0.084)	(0.088)	(0.092)	(0.141)
Log(Loan Amount)	-1.48***	-1.48***	-1.49***	-1.55***	-1.26***
	(0.030)	(0.031)	(0.031)	(0.037)	(0.067)
Log(Loan Term)	0.173***	0.193***	0.194***	0.115	0.850***
	(0.061)	(0.061)	(0.061)	(0.069)	(0.119)
Repeat Borrower	-0.818***	-0.794***	-0.625***		
	(0.052)	(0.054)	(0.078)		
NegFunding × Repeat Borrower			-0.289**		
			(0.122)		
Observations	51,143	49,590	49,590	41,447	8,143
Adjusted R^2	0.193	0.197	0.197	0.198	0.184

Table B3: LAD funding and P2P loan defaults across contiguous zipcodes

Tables present regression discontinuity estimates of the effect of funding cuts to LADs on individual P2P loan performance using the Cox proportional hazard model. The analysis is performed on a restricted sample of P2P loans issued in zipcodes located within 20 and 30 kilometers on either side of the border along contiguous LADs that differ in treatment status. The regression estimates are based on the specification outlined in Equation II. The dependent variable is a dummy equal to one if, after origination, the loan went into default and zero if it was fully repaid or outstanding at the end of the sample period. *NegFunding* is a dummy equal to one for *treated* LADs that experienced a negative change in cumulative funding from the central government over the preceding three years ($\Delta Funding < 0$), and zero for *control* LADs that experienced a non-negative change in cumulative funding over the past three years ($\Delta Funding \geq 0$). To minimize the effect of confounding factors, the analysis is restricted to LADs whose $\Delta Funding$ is within a bandwidth h $= \pm 25\%$ around the zero cutoff. See Section 4.2 for definitions of the other variables. All regressions include up to the second-order polynomial terms of $\Delta Funding$ and their interactions with *NegFunding*, as well as LAD and year fixed effects. Standard errors are clustered by year and reported in parentheses. ***, **, * indicate 1%, 5%, and 10% significance levels respectively.

(a) Distance to border $\leq$ 20 km

	Default probability			
	(1)	(2)	(3)	(4)
NegFunding	0.507***	0.528***	0.481***	0.476***
	(0.101)	(0.101)	(0.101)	(0.101)
Interest Rate	0.158***	0.163***	0.162***	0.175***
	(0.003)	(0.003)	(0.003)	(0.003)
Repeat Borrower	-0.363***	-0.307***	-0.332***	-0.32***
	(0.066)	(0.067)	(0.067)	(0.067)
Log(Loan Amount)				0.384***
				(0.029)
Other controls	No	Yes	Yes	Yes
Local authority FE	Yes	Yes	Yes	Yes
Loan Performance Year FE	No	No	Yes	Yes
Observations	48,377	48,377	48,377	48,377
Log Likelihood	-26834.71	-26585.96	-26519.43	-26440.58
LR Test (χ^2)	3543.56***	4041.06***	4174.12***	4331.82***

(b) Distance to border $\leq$ 30 km

	Default probability			
	(1)	(2)	(3)	(4)
NegFunding	0.529***	0.534***	0.487***	0.487***
	(0.103)	(0.102)	(0.101)	(0.105)
Interest Rate	0.159***	0.164***	0.163***	0.177***
	(0.003)	(0.003)	(0.003)	(0.003)
Repeat Borrower	-0.357***	-0.298***	-0.323***	-0.309***
	(0.065)	(0.065)	(0.065)	(0.065)
Log(Loan Amount)				0.396***
				(0.028)
Other controls	No	Yes	Yes	Yes
Local authority FE	Yes	Yes	Yes	Yes
Loan Performance Year FE	No	No	Yes	Yes
Observations	51,200	51,200	51,200	51,200
Log Likelihood	-28132.47	-27873.93	-27802.97	-27716.76
LR Test (χ^2)	3683.07***	4200.14***	4342.06***	4514.49***

C Proofs of Proposition 1

We recall that the debt market is organized through a risk-neutral P2P lending platform that has access to a financial market paying a constant and risk-free interest rate r. We denote by $q = (1+r)^{-1}$ the related price. We further assume that the amount traded and the income status of each household can be observed by the P2P platform at no cost. Denote d ($d > 0$) the debt level, or equivalently the number of units of wealth that the borrowing household should repay in the second period, conditional on no default. The household pays a credit risk premium in accordance with its expected default probability in state (s, S), denoted by $\delta_{s,S}(d)$. We assume that the payoff in case of default is zero. Thanks to the risk-sharing arrangement, the price of debt $q_{s,S}(d)$ will be:

$$q_{s,S}(d) = q(1 - \delta_{s,S}(d)). \tag{C1}$$

When the state in the next period is (s', S'), the household's income in the second period consists of private income $y_{s'}$ and of public transfer $T_{S'}$ that will be paid if the household's private income is low (i.e., if the indicator function $1_{s'=l}$ is equal to 1). Thus, the second period income will be equal to $y_{s'} + T_{S'} \cdot 1_{s'=l}$. If d is repaid, the household's second period consumption will be $y_{s'} + T_{S'} \cdot 1_{s'=l} - d$. Alternatively, if the household defaults on its debt, the second period consumption will be $(1-\tau)(y_{s'} + T_{S'} \cdot 1_{s'=l})$, because of the default cost τ. The household will decide to default if it is better off to default rather than repay the outstanding debt. Formally, the household chooses to default iff $(1-\tau)(y_{s'} + T_{S'} \cdot 1_{s'=l}) > y_{s'} + T_{S'} \cdot 1_{s'=l} - d$, or iff $d > \tau(y_{s'} + T_{S'} \cdot 1_{s'=l})$. We thus deduce the cutoff thresholds of equation (1), as well as the ranking of inequality (2)

We assume that the household has time-separable preferences, with periodic utility u and discount factor $\beta > 0$. The function $u : \mathbb{R}_+ \to \bar{\mathbb{R}}$ is assumed to be twice continuously differentiable on $(0, \infty)$. The household's utility maximization problem consists in choosing d that maximizes its date-0 intertemporal utility subject to a budget constraint. Using the debt price from equation (C1), the household's problem in state (s, S) can formally be written as follows:

$$\begin{aligned} \max_{d \geq 0} \; u(y_s + T_S - q_{s,S}(d)d) &+ \beta\rho_{sh} \max(u((1-\tau)y_h), u(y_h - d)) \\ &+ \beta\rho_{sl}\pi_{SG} \max(u((1-\tau)(y_l + T_G))), u(y_l + T_G - d)) \\ &+ \beta\rho_{sl}\pi_{SB} \max(u((1-\tau)(y_l + T_B))), u(y_l + T_B - d)). \end{aligned} \tag{C2}$$

Despite its simplicity, the economy features four different types of equilibria, characterized by the unique cases in which default occurs. These depend on the position of d in the ranking inequality $\overline{d}_h \geq \overline{d}_{l,G} \geq \overline{d}_{l,B} > 0$. The first case corresponds to $d \leq \overline{d}_{l,B}$ and involves no default. The second case corresponds to $\overline{d}_{l,B} < d \leq \overline{d}_{l,G}$ and involves default in the second period if the state is (l, B). The third case is $\overline{d}_{l,G} < d \leq \overline{d}_h$ and means default in the second period if the state is (l, B) or (l, G). The fourth case $d > d_h$ corresponds to default in all states of the world in the second period, i.e., certain default. The price of debt is then null (and is similar to an absence of borrowing). This last case is of little interest and will not be studied further.

We introduce some additional notation before examining these equilibria separately. $r_{s,S}(d) := \frac{1}{q_{s,S}(d)} - 1$ is the interest rate paid by the household borrowing d in state (s, S) in the first period; $\mu_{S'|(s,S)}$ is the probability that the household having state (s, S) will default in the next period in state S'. Assuming a continuum of ex-ante identical agents, the law of large numbers for the continuum implies that $\mu_{S'|(s,S)}$ is also equal to the share of agents currently in state (s, S) who will default in the second period in (aggregate) state S'.

The no-default equilibrium. In this equilibrium, the household currently in state (s, S) will repay its debt under all circumstances. In the absence of default, the share of ex-post default $\mu_{S'|(s,S)} = 0$ independently of future state (s', S'). Similarly, the household faces a price $q(d, s) = (1 + r)^{-1} = q$, and hence an interest rate $r_{s,S} = r$. The quantity of debt d borrowed by the household must satisfy the following two conditions:

$$\begin{aligned} qu'(y_s + T_S \cdot 1_{s=l} + qd) \leq \beta\rho_{sh}u'(y_h - d) + \beta\rho_{sl}\pi_{SG}u'(y_l + T_G - d) \quad &\text{(C3)} \\ + \beta\rho_{sl}\pi_{SB}u'(y_l + T_B - d), \quad & \\ d \leq \tau(y_l + T_B). \quad &\text{(C4)} \end{aligned}$$

Equation (C3) is the Euler inequality for the household in state (s, S), which corresponds to the first-order condition of the household's program (C2). Expression (C4) denotes the endogenous borrowing constraint guaranteeing that when borrowing d the household does not want to default ex-post in any state of the world. If the household is not constrained from borrowing (i.e., if expression (C4) is a strict inequality), then the first-order condition will hold with equality, reflecting that the household's debt choice is unconstrained. In that case, the household's valuation of debt can be interpreted as follows: the price of debt q is equal to the debt payoff, discounted by the factor β, and multiplied by the expected intertemporal rate of substitution between consumption in the next period and consumption today. The expected intertemporal rate of substitution is the sum of three terms:

1. With probability ρ_{sh}, the household gets a high income y_h independent of the aggregate state, and the intertemporal rate of substitution is $u'(y_h - d)/u'(y_s + T_S \cdot 1_{s=l} + qd)$.

2. With probability $\rho_{sl}\pi_{SG}$, the household receives a low income y_l but a high public transfer, hence the intertemporal rate of substitution is $u'(y_l + T_G - d)/u'(y_s + T_S \cdot 1_{s=l} + qd)$.
3. With probability $\rho_{sl}\pi_{SB}$, the household receives a low income y_l and a low public transfer, and the intertemporal rate of substitution is $u'(y_l + T_B - d)/u'(y_s + T_S \cdot 1_{s=l} + qd)$.

If equation (C4) holds with equality, the household is credit-constrained. It would like to borrow more but cannot unless it opts to default, implying that the Euler equation will be different from (C3). In that case, the household will borrow as much as it can while not defaulting.[43] A necessary condition for d to be positive (and hence to be debt and not saving) is:

$$qu'(y_s + T_S \cdot 1_{s=l}) \geq \beta\rho_{sh}u'(y_h) + \beta\rho_{sl}\pi_{SG}u'(y_l + T_G).$$

Finally, we can verify that the debt choice in the absence of default (hence the solution of (C3)–(C4)) is decreasing with T_S. First, if the debt choice is determined by (C3), deriving (C3) with respect to T_S yields:

$$\frac{\partial d}{\partial T_S} = \frac{-qu''(y_s + T_S \cdot 1_{s=l} + qd)1_{s=l}}{q^2u''(y_s + T_S \cdot 1_{s=l} + qd) + \beta\rho_{sh}u''(y_h - d) + \beta\rho_{sl}\pi_{SG}u''(y_l + T_G - d) + \beta\rho_{sl}\pi_{SB}u''(y_l + T_B - d)},$$

which is negative. Hence, if debt choices are interior in states B and G, and since $T_B < T_G$, we deduce that d is higher in state B than in state G. Second, if the debt choice is interior in state G, but not in state B, we will also have a higher debt in state B than in state G. Third, if both choices are constrained, then debt is the same in both states (and the result holds). Finally, note having an interior debt choice in state B and a constrained one in state G is not possible (since it would contradict that the interior debt choice is decreasing with T_S). Overall, we deduce that debt demand is higher in state B than in state G (point 1 of Proposition 1).

Equilibrium with default in state (l, B). In this equilibrium, the household currently in state (s, S) will default on its debt in the next period if it obtains a low income while the aggregate state is bad. Formally, default will occur with probability $\mu_{S'|(s,S)} = \rho_{sl}1_{S'=B}$, implying that default is more "likely" in state B than G (point 3 of Proposition 1). The absence of arbitrage opportunities for the risk-neutral intermediary result in the following

[43] Both conditions (C3) and (C4) can hold with equality for some specific parameter values that imply that the constrained choice $\tau(y_l + T_B)$ is also optimal.

price:

$$q_{s,S}(d) = \frac{1 - \rho_{sl}(1 - \pi_{SG})}{1 + r}, \tag{C5}$$

suggesting that the household will repay the loan if it gets a high income (with probability ρ_{sh}), or if it gets a low income but the aggregate state is good (with probability $\rho_{sl}\pi_{SG}$). Equivalently, this corresponds to the following interest rate:

$$r_{s,S}(d) = \frac{1 + r}{1 - \rho_{sl}(1 - \pi_{SG})} - 1.$$

We deduce from the above that $r_{s,B}(d) \geq r_{s,G}(d)$ (point 2 of Proposition 1). Indeed, $r_{s,B}(d) \geq r_{s,G}(d)$ iff

$$\frac{1 + r}{1 - \rho_{sl}(1 - \pi_{BG})} \geq \frac{1 + r}{1 - \rho_{sl}(1 - \pi_{GG})}$$

or $\pi_{GG} \geq \pi_{BG} = 1 - \pi_{BB}$. This always holds because of the assumption of aggregate state persistence (see footnote 6).

The debt d verifies the conditions (3)–(5) specified in the main text. Equation (3) is the Euler equation for an agent that will default in state (l, B). The right hand-side of this equation includes only two terms that correspond to the two states h and (l, G) in which debt will be repaid. This Euler equation has two main differences compared to the no-default Euler equation (C3): (i) the debt price, and (ii) a default (hence a zero payoff) with probability $\rho_{sl}\pi_{SB}$.

Equations (4) and (5) are the conditions guaranteeing that the household will only default in the state (l, B). As in the no-default equilibrium, at least one equation between the Euler equation (3) and the default condition (4) must hold with equality.

Similar to the no-default case, we verify that debt demand is higher in state B than in state G (point 1 of Proposition 1). The derivative of (3) with respect to T_S is given by:

$$\frac{\partial d}{\partial T_S} = \frac{-\frac{1-\rho_{sl}(1-\pi_{SG})}{1+r} u''(y_s + T_S \cdot 1_{s=l} + \frac{1-\rho_{sl}(1-\pi_{SG})}{1+r} d) 1_{s=l}}{\left(\frac{1-\rho_{sl}(1-\pi_{SG})}{1+r}\right)^2 u''(y_s + T_S \cdot 1_{s=l} + \frac{1-\rho_{sl}(1-\pi_{SG})}{1+r} d) + \beta\rho_{sh} u''(y_h - d) + \beta\rho_{sl}\pi_{SG} u''(y_l + T_G - d)},$$

and is also negative. The rest of the proof is similar to the no-default case.

Equilibrium with default in states $(\boldsymbol{l}, \boldsymbol{B})$ and $(\boldsymbol{l}, \boldsymbol{G})$. We finally focus on the last equilibrium in which the household defaults upon receiving a low income, independent of the public transfer (i.e., in states (l, B) and (l, G)). Default thus occurs with probability $\mu_{S'|(s,S)} = \rho_{sl}$. The debt price and interest rate are:

$$q_{s,S}(d) = \frac{1-\rho_{sl}}{1+r},$$
$$r_{s,S}(d) = \frac{1+r}{1-\rho_{s,l}},$$

since the household only repays in state h. Similar to the default in state (l, B), the debt quantity must verify the following equations:

$$\frac{1-\rho_{sl}}{1+r} u'(y_s + T_S \cdot 1_{s=l} + \frac{1-\rho_{sl}}{1+r} d) \leq \beta \rho_{sh} u'(y_h - d), \tag{C6}$$
$$d \leq \tau y_h, \tag{C7}$$
$$d > \tau(y_l + T_G). \tag{C8}$$

Like in the previous cases, equation (C6) is the Euler equation, while inequalities (C7) and (C8) guarantee that the agent defaults in states (l, B) and (l, G) only. Again, at least one of equations (C6) and (C7) must hold with equality. This suggests that either the debt choice is unconstrained and the Euler equation (C6) holds with equality, or the agent is borrowing constrained and (C7) holds with equality.

As in the other two cases, we verify that debt demand is higher in state B than in state G (point 1 of Proposition 1). The derivative of (C6) with respect to T_S is given:

$$\frac{\partial d}{\partial T_S} = \frac{-\frac{1-\rho_{sl}}{1+r} u''(y_s + T_S \cdot 1_{s=l} + \frac{1-\rho_{sl}}{1+r} d) 1_{s=l}}{\left(\frac{1-\rho_{sl}}{1+r}\right)^2 u''(y_s + T_S \cdot 1_{s=l} + \frac{1-\rho_{sl}}{1+r} d) + \beta \rho_{sh} u''(y_h - d)},$$

which is again negative. The rest of the proof is once again similar to that of the no-default case.