FinTech Lending under Austerity

Yan Alperovych[*], Anantha Divakaruni[†], François Le Grand[‡]

June 8, 2024[§]

Abstract

We document shortfalls in public welfare spending as a significant growth driver of peer-to-peer (P2P) lending. By analyzing the asymmetric rollback of the welfare state under the UK's 2010-19 austerity program as shocks to local household incomes, we find that welfare cuts increased demand for P2P consumer loans, especially in areas with greater banking and digital deprivation. P2P loans issued in austerity-affected areas are also costlier, reflecting the platform's risk pricing sensitivity to higher default rates occurring in those areas. Overall, our findings suggest that P2P lending can mitigate welfare spending cuts, particularly aiding households in deprived areas.

JEL classification: D12, D14, G23

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

---

[*]Emlyon Business School. E-mail: alperovych@em-lyon.com

[†]University of Bergen. E-mail: anantha.divakaruni@uib.no

[‡]Rennes School of Business. E-mail: francois.le-grand@rennes-sb.com

[§]We thank Hans Hvide, Hadar Gafni, Nuria Suárez, Alex Groh, Thomas Lambert, Ahmed Nofal, Elena Pikulina, and the participants of the 6^{th} and 7^{th} Entrepreneurial Finance Conference, Cardiff FinTech Conference, EIRC seminar at Emlyon Business School, Southwestern Finance Association 2023 Conference, Eastern Finance Association 2023 Meeting, 39^{th} International Conference of the French Finance Association, and faculty of University of Bergen for helpful comments and feedback. All errors remain our own.

1 Introduction

Credit markets worldwide are experiencing the rapid proliferation of FinTech platforms that leverage innovative technology-driven solutions to streamline the lending process. A growing body of research on this topic has investigated 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, 2022), and the implications of competition between P2P and traditional lenders (de Roure, Pelizzon, and Thakor, 2022). However, factors that determine the rising demand for P2P loans worldwide remain largely understudied.[1]

This paper provides novel evidence that public welfare spending is an important growth driver of P2P lending activity, as such spending can substantially impact the economic conditions of households and shape their demand for external financial assistance. Public welfare mainly targets the poorer strata of society, whose primary constituents – households – not only depend on assistance from the state (Van de Walle, Nead et al., 1995; Mackay and Williams, 2005), but also face significant challenges in accessing traditional finance due to low incomes and poor credit histories (Demirgüç-Kunt and Singer, 2017). Any reduction in public welfare, as is frequently the case under austerity (Alesina et al., 2019), may further restrict households' already limited access to mainstream finance. P2P lending, on the other hand, with its promise to provide small loans with simpler processing of applications and quicker disbursements, claims to promote financial inclusion and meet the financing needs of economically deprived households and individuals (Berg et al., 2022). In this paper, we find a strong connection between public welfare spending, household financial distress, and the demand for P2P loans.

An ideal setting to investigate this question would involve observing how households' borrowing behaviour responds to external shocks to the welfare assistance that they receive from the state. However, identifying the impact of welfare transfers on individual borrowing behavior is very challenging as we do not observe the transfers made to individual households. We overcome this challenge by focusing on a unique setting that captures the effects of public welfare spending on local communities at a highly disaggregated level. We specifically examine public welfare spending in England, with a focus on the spending cuts implemented by the UK central government (CG) during its decade-long *austerity* program whose objec-

[1] See literature reviews by Thakor (2020), Allen, Gu, and Jagtiani (2021), and Berg, Fuster, and Puri (2022) for more information on these topics. According to Ziegler et al. (2021), the volumes of the FinTech consumer and business lending in 2020 amounted to $38 billion (11.9% annual growth between 2016-2020) and $31 billion (43.1% annual growth between 2016-2020) respectively.

tive was to reduce the massive budget deficit occasioned by the 2008 financial crisis. The cuts primarily involved reducing annual welfare grants disbursed by the CG to the local governments of England's 324 local authority districts (LADs).[2,3] These local governments are tasked with providing essential public services including housing benefits, schools, hygiene, safety, and culture in their respective localities. To fund these services, local governments depend heavily on CG grants, which make up to three-fifths of their annual budget on average (Innes and Tetlow, 2015). The prolonged austerity-driven funding cuts led to LADs losing up to 37% of their grants on aggregate between 2009 and 2019 (Atkins and Hoddinott, 2022), forcing local governments to significantly reduce spending on numerous welfare services. We find that following cuts in local government expenditures, households living in austerity-affected LADs experienced increased financial constraints and reduced spending. Thus the impact of austerity was particularly severe on households that were already economically deprived and reliant on welfare benefits from their local governments.[4]

What is then the connection between austerity-driven shocks to households' incomes and their P2P borrowing behaviour? To uncover the economic mechanisms underpinning this question, we formulate a model of loan demand with strategic default, linking austerity-driven funding cuts to the demand for local P2P loans. In our model, rational households receive a certain initial endowment in the first period, but face uncertainty about their private income in the second period. This uncertainty can be seen as the realization of adverse shocks, such as unemployment or illness, resulting in low private income. In this "bad" scenario, the household receives a public welfare transfer, i.e., welfare assistance such as unemployment or disability benefits. However, the welfare transfer is also subject to some uncertainty, reflecting possible variations in the generosity of the state. In order to smooth out consumption amidst uncertain income prospects, the household solicits an unsecured, non-contingent, short-term loan, for example through a P2P lending platform. The P2P lender observes the households' financial situation, but has no possibility to perfectly enforce debt repayment. As such, the household can strategically default on its debt commitment when repaying debt is costlier.

[2]Here we refer to the number of LADs that existed during our sample period of 2007-2020. This number can change over time either because of reorganizations led by the UK government, or because some local authorities decide to merge or split. As of April 1st, 2023, the number of LADs is at 317. See https://bit.ly/3Tpw94D and https://bit.ly/3TKjhI4 (last accessed on March 19th, 2024) for more information on the local government structure and restructurings respectively.

[3]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.

[4]Although the UK austerity program concluded officially in 2019, it is unclear whether CG grants to LADs have increased since then. Details of the official announcement on end of the austerity program can be found here: https://bit.ly/3tqQJFC.

The model's comparative statics characterizes the impact of variation in public welfare transfers on the demand for debt, loan prices (interest rates) and subsequent loan performance (default occurrence). It then yields three empirical predictions about the implications of austerity-driven funding cuts. Namely, the reduction of public welfare transfers leads to a contemporaneous increase in: (i) demand for P2P loans, (ii) interest rates at which these loans are issued, and (iii) fraction of defaulting loans. All three are obviously intertwined. Low public transfers make households poorer and less likely to repay their debt, as default becomes relatively cheaper; this explains (iii). However, the P2P lender anticipates the increase in the risk of default, and charges a higher interest rate, reflecting a higher default premium; this justifies (ii). The demand effect in (i) is much more subtle as it results from the aggregation of two potentially opposing forces. On the one hand, austerity makes households more willing to smooth out their consumption and thus more willing to borrow. On the other hand, the higher interest rate quoted by the P2P lender in times of austerity may discourage the demand for debt. We formally show that the consumption smoothing motive always dominates in the presence of strategic default.

We next test the model 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. Our identification is based on a regression discontinuity (RD) design. Specifically, we compare P2P lending outcomes in LADs that experienced funding cuts (*treated* LADs) with P2P lending outcomes in a group of LADs that experienced non-negative changes in funding (*control* LADs).

The empirical findings are as follows. First, austerity led to greater demand for P2P loans, whereby *treated* LADs witnessed 11% more P2P loan issuance per zipcode by the platform per year (17% in aggregate £) compared to P2P loans issued in zipcodes of similar *control* LADs.[5] These results correspond to our model prediction (i): the demand for debt indeed raises in the context of austerity. Moreover, they also confirm (and are reinforced by) the theoretical prediction regarding the dominance of the consumption smoothing desire over the reluctance of households to borrow at higher interest rates. Thus, in austerity, households end up borrowing more. 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 (ii): austerity induces a higher default premium in loan interest rates. The platform anticipates a

[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.

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 (iii): austerity raises the share of defaulting loans. Income shocks resulting from prolonged funding cuts to LADs 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 to the platform's decision to charge higher interest rates on P2P loans issued to borrowers in LADs experiencing funding cuts.

Concerns regarding the identification and robustness of our results broadly correspond to two potential issues: (i) funding cuts to LADs may be non-randomly distributed between *treated* and *control* LADs due to their active lobbying for funding from the CG; (ii) the results may be driven by the heterogeneity in LAD socioeconomic characteristics, including heterogeneity that we are unable to observe or to control for. To tackle (i), we verify that LAD funding cuts can be considered as quasi-random by analyzing the CG's funding decisions as a function of political alignment between the local and central governments. We find no evidence that some LADs are consistently favored by the CG, or are actively lobbying the CG to influence the allocations of the government grants. Our results are also robust to the exclusion of few LADs that experienced steady decline (increase) in CG grants during the sample period. To solve (ii), our approach is twofold. First, we formally show that treated and control LADs exhibit no systematic differences in their observable socioeconomic characteristics, except in outcomes likely to be affected by the funding cuts. We also find no discontinuities in these characteristics, again with an exception of P2P lending outcomes, between the treated and control LADs. Second, although our results are robust to the inclusion of various controls, we also rule out that our results are driven by unobservable within-LAD heterogeneity (say, among zipcodes within an LAD). We do so 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 here is that zipcodes falling within these 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.

Contributions to literature. 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, 2022; Thakor, 2020; Berg et al., 2022; de Roure et al., 2022; 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., 2022; Fuster et al., 2019, 2022). 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, and 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 (2022), 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. (2023) 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 Conceptual framework

To characterize the demand, pricing, and performance of P2P loans issued in the UK during the austerity period, we develop a theoretical model with a household borrowing from a P2P lending platform in a two-period economy. We subsequently analyze the household's decision to strategically default on its debt, contingent upon the stochastically-determined levels of its private and public welfare incomes. We then present the household's optimization program that leads to several possible equilibria, which, in turn, yield three testable predictions forming the foundation for our empirical analyses. The current section lays down the key theoretical points. Formal details of the model are presented in Appendix C.

2.1 Setup

The economy is two-period and comprises a household that borrows from a P2P lending platform representing the debt market for that household. For the sake of simplicity, we assume that the household has no access to traditional banking and can borrow from the platform only.[6] Moreover, given the focus of this paper, we disregard the household that saves instead of borrowing.

The household is a unit of consumption and in every period is endowed with a total income consisting of two components: a private income from labor, and a possible public welfare transfer. The private income y can either be high at y_h or low at y_l. Receiving y_l is always worse than receiving y_h. Furthermore, when $y = y_l$, the household receives a public welfare transfer T that is either high at T_G or low at T_B. Put differently, there is a welfare state supplementing the household's low income with the transfer. The magnitude of the transfer depends on public redistribution policy and on the state of public finances. We further assume that the welfare state transfers cannot make the household earning y_l better off than the household earning y_h, that is, $0 < y_l + T_B < y_l + T_G < y_h$.

The household's total endowment in every period is thus characterized by an individual state $\{h, l\}$ and an aggregate state $\{G, B\}$. Denote $s \in \{h, l\}$ and $S \in \{G, B\}$ the individual and aggregate states in the first period. Accordingly, $s' \in \{h, l\}$ and $S' \in \{G, B\}$ are the individual and aggregate states in the second period. Individual state switches from s to s' with probability $\rho_{ss'}$. Aggregate state switches from S to S' with probability $\pi_{SS'}$, and is persistent. That is, when the current state is B, it is more likely that the future state will be B rather than G; the same logic applies if the current state is G.[7] Lastly, the processes governing the transition from s to s' and from S to S' are assumed to be independent, i.e., states switch from (s, S) to (s', S') with probability $\rho_{ss'}\pi_{SS'}$.

To smooth out consumption under low private income, the household solicits an unsecured and non-contingent loan from the P2P lending platform in the first period, and is expected to repay d ($d > 0$) units of wealth in the second period. While the platform observes the amount of debt traded and the endowment status of the household at no cost, it has no perfect enforcement technology. As such, the household can opt to strategically default on its debt repayment in the second period. In case of default, the payoff to the platform is zero, but the household suffers a private cost, equal to a share $\tau > 0$ of the total second-period endowment.[8]

The platform is a risk-neutral financial intermediary with access to financial market paying a constant and risk-free interest rate r at the price $q = (1 + r)^{-1}$. It thus provides a risk-sharing arrangement that allows the household to pay a credit risk premium in accordance with the ex-ante default probability $\delta_{s,S}(d)$. Under these assumptions, the price of a

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

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

[8] It is possible to make the default cost τ endogenous by setting an infinite-horizon model, wherein a defaulter would be prevented from borrowing further (LeGrand and Ragot, 2021).

unit of debt $q_{s,S}(d)$ will be:

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

Accordingly, the interest interest rate paid by the household borrowing d in state (s, S) in the first period is:

$$r_{s,S}(d) = \frac{1}{q_{s,S}(d)} - 1. \tag{2}$$

The timing of the market is as follows. In the first period, the household earns a low private income y_l, which we assume here because we focus on household borrowing rather than saving. The aggregate state is then randomly drawn determining the size of the public welfare transfer T_S ($S \in \{G, B\}$). The household then receives its total first-period endowment of $y_l + T_S$ and decides how much to consume and to borrow. In the second period, once the individual and aggregate 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 the comparison of the household's relative consumption levels. Thus, the household defaults if the consumption enjoyed when defaulting is higher than the one derived when repaying debt.[9] More formally, in state (s', S'), repaying debt d corresponds to the second-period consumption $y_{s'} + T_{S'} \cdot 1_{s'=l} - d$. Respectively, defaulting corresponds to the second-period consumption $(1-\tau)(y_{s'} + T_{S'} \cdot 1_{s'=l})$. 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 is the optimal strategic decision. We will denote by:

$$\overline{d}_{l,S'} = \tau(y_l + T_{S'}), \text{ and } \overline{d}_h = \tau y_h, \tag{3}$$

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 Analysis

Since the household's preference for higher private income is independent of public transfers, the states can be arranged in an increasing order by total household revenue as follows: (l, B), wherein the total endowment is $y_l + T_B$; (l, G), wherein the total endowment is $y_l + T_G$; and h, wherein the total endowment is y_h. Further, from equations (3) and the ranking of aggregate incomes, it can readily be deduced that default thresholds satisfy the following condition (for proof, refer to Appendix C):

$$\overline{d}_h \geq \overline{d}_{l,G} \geq \overline{d}_{l,B} > 0. \tag{4}$$

[9]The household actually compares utility levels. Because of the two-period framework and the time-separability of utility function, this is akin to comparing consumption levels.

It follows that the household's decision about default is determined completely by its debt choice d and by where it fits in condition (4). Four outcomes are distinguishable. First, when $d \leq \overline{d}_{l,B}$, the debt amount is sufficiently modest and will be repaid no matter the household's future financial situation. There is consequently no default on the loan. Second, when $\overline{d}_{l,B} < d \leq \overline{d}_{l,G}$, the debt amount is too large to be repaid in the "poorest" state of low private income y_l and low public transfers T_B. The household hence defaults in state (l, B), but does repay its debt in "better" situations, that is, whenever the public transfer or the private income are high. Third, when $\overline{d}_{l,G} < d \leq d_h$, the debt amount is so large that the household can only repay it upon earning a high private income (in state h). In this case, low private income occasions the household's default no matter the amount of public transfers. Finally, when $d > d_h$, the default is certain, and the platform refuses to lend in the first place.[10]

The case of certain default is of little interest and will not be studied further. The three remaining situations correspond to three 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 probability. The characterization of the equilibria follows.

2.3 Equilibria

The household's utility maximization problem consists in choosing d that maximizes its date-0 intertemporal utility of consumption subject to a budget constraint. We assume that the household is an expected-utility maximizer, with time-separable preferences, a periodic utility u, and a discount factor $\beta > 0$. The function $u : \mathbb{R}_+ \to \bar{\mathbb{R}}$ is assumed to be twice continuously differentiable, strictly increasing and strictly concave. Given these assumptions and the debt price from equation (1), the household's problem in the present state (l, S) can be formally written as:

$$\begin{aligned}\max_{d} \ \{u(y_l + T_S + q_{l,S}(d) \cdot d) &+ \beta\rho_{lh} \max[u((1-\tau)y_h),\ u(y_h - d)] \\ &+ \beta\rho_{ll}\pi_{SB} \max[u((1-\tau)(y_l + T_B)),\ u(y_l + T_B - d)] \\ &+ \beta\rho_{ll}\pi_{SG} \max[u((1-\tau)(y_l + T_G)),\ u(y_l + T_G - d)]\}.\end{aligned} \tag{5}$$

The first term in program (5) corresponds to utility of consumption in the first period while the three other terms reflect the expected discounted future utility. The default equilibria stemming from different combinations of second-period individual and aggregate states (s', S') imply three different formulations of the program (5).[11] As such, to derive testable

[10] That is, the price of debt is null, which is similar to the absence of borrowing.

[11] At this point, we have already discarded the certain default equilibrium.

predictions regarding the effect of public transfers on debt demand, pricing, and performance, we work through each equilibrium separately and combine the insights afterwards.

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

$$q\cdot u'(y_l + T_S + q\cdot d) \leq \beta\rho_{lh}u'(y_h - d) + \beta\rho_{ll}\pi_{SG}u'(y_l + T_G - d) + \beta\rho_{ll}\pi_{SB}u'(y_l + T_B - d), \quad (6)$$

$$d \leq \tau(y_l + T_B). \quad (7)$$

Expression (6) is the Euler equation for the household in the current state (l, S) and corresponds to the first-order condition of program (5). Expression (7) denotes the endogenous borrowing constraint guaranteeing that when facing the obligation to repay d the household does not default ex-post in any state of the world.

Equilibrium in state (l, B). In this equilibrium, the household currently in state (l, S) defaults on its debt repayment in the second period if it obtains a low private income and low public transfer. The corresponding probability of default is $\rho_{ll}\pi_{SB}$. The absence of arbitrage opportunities for the risk-neutral P2P lending platform implies that the debt price and the (net) interest rate charged on the household's debt are, respectively:

$$q_{l,S}(d) = \frac{1 - \rho_{ll}\pi_{SB}}{1 + r}, \quad r_{l,S}(d) = \frac{1 + r}{1 - \rho_{ll}\pi_{SB}} - 1. \quad (8)$$

The interest rate $r_{l,S}(d)$ clearly reflects that the household will default in the second period under state (l, B), but repays its debt otherwise. Obviously, the more likely the state B in the second period, that is, the higher π_{SB}, the higher the interest rate charged. The quantity of debt borrowed must now satisfy the following conditions:

$$\frac{1 - \rho_{ll}\pi_{SB}}{1 + r} \cdot u'(y_l + T_S + \frac{1 - \rho_{ll}\pi_{SB}}{1 + r} \cdot d) \leq \beta\rho_{lh}u'(y_h - d) + \beta\rho_{ll}\pi_{SG}u'(y_l + T_G - d) \quad (9)$$

$$\tau(y_l + T_B) < d \leq \tau(y_l + T_G). \quad (10)$$

Expression (9) is again the Euler equation for a household that defaults in state (l, B) in the second period. Equation (10) formalizes the conditions guaranteeing that the borrower will only default in the state (l, B).

Equilibrium in states (l, B) and (l, G). The last equilibrium characterizes the household defaulting in the second period in state (l, S). Note that in this case, the household obtains a low private income and defaults regardless of the size of public transfers. The corresponding probability of default is then ρ_{ll}, implying that the debt price and the interest rate are, respectively:

$$q_{l,S}(d) = \frac{1-\rho_{ll}}{1+r}, \quad r_{l,S}(d) = \frac{1+r}{1-\rho_{ll}} - 1. \tag{11}$$

Similar to the case of default in the second period under state (l, B), the debt quantity must this time verify the following equations:

$$\frac{1-\rho_{ll}}{1+r} \cdot u'(y_l + T_S + \frac{1-\rho_{ll}}{1+r} \cdot d) \leq \beta \rho_{lh} u'(y_h - d), \tag{12}$$

$$\tau(y_l + T_G) < d \leq \tau y_h, \tag{13}$$

As before, expression (12) is the Euler equation, while inequalities in equation (13) guarantee that the household defaults in the second period in states (l, B) and (l, G) only.

The analysis of these equilibria yields the following proposition regarding the debt demand.

Proposition 1. *The household debt demand is larger in state B (low public transfers) than in state G (high public transfers).*

From equation (8) governing the loan interest rate in the (l, B) equilibrium, and from the assumption of state persistence (see also footnote 7), we deduce our next proposition.

Proposition 2. *The loan interest rate is higher in state B (low public transfers) than in state G (high public transfers), that is $r_{l,B}(d) \geq r_{l,G}(d)$.*

The final proposition denotes the probability that the household defaults on its debt conditional on the size of the public transfer it eventually receives in the second period.

Proposition 3. *The share of defaulting loans is higher in state B (low public transfers) than in state G (high public transfers).*

The formal proofs of these propositions are collected in Appendix C, namely in Sections C.2, C.3, C.4.

2.4 Discussion

The prediction of higher demand for debt under low public transfers is, in fact, less intuitive than it sounds. Indeed, this demand is subject to two potentially opposing forces: consumption smoothing and interest rate. Consumption smoothing implies that the household demands more debt when its total current endowment is low, compared to when its total current endowment is high. This contributes to overall higher (lower) P2P debt demand during periods of low (high) public transfers. However, as also explained above, the household is charged with a higher interest rate under low public transfers, which is likely to have a negative effect on its debt demand. The equilibrium outcome is therefore a horse race between these forces. In Appendix C (Section C.5) we formally show that consumption-smoothing dominates and that demand for P2P loans is higher when households receive lower public transfers.

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. The P2P lending 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 occurring when the household receives a low public transfer in the next period.

3 Background and data

Evaluating the model predictions developed in Section 2 requires data on public welfare transfers to households and their borrowings from P2P loan providers. Absent individual households' financial data, public transfers to households across different aggregate states of the economy are approximated using the quasi-exogenous variation in funding grants allocated annually by the UK CG to LADs in England. We contend that LAD funding and public transfers to households are related because of LADs' dependence on CG grants to deliver essential social and welfare services to their local communities, particularly to those in financial need. Variation in funding being recorded at the LAD level, we must therefore observe short-term borrowing activities of households within and across LADs. Data on such activities come from one of the popular FinTech lending platforms that operated in the UK during our study period.

To provide more details, this section commences with a description of the institutional details of LAD services and their funding mechanisms. Next, we outline the data on LAD funding and our methodology for assessing cuts to LAD funding under austerity. Lastly, we introduce the P2P lending platform.

3.1 Local governments and their funding in England

England is divided into 324 LADs which are essentially sub-national administrative areas, whose respective local administrations are 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 these services, LADs rely on annual Revenue Support Grants from the

CG, on a portion of taxes levied on local commercial properties known as *business rates*,[12] and on *council taxes* levied on local residential properties (Studdert, 2021). 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' finances prompting them to reduce spending on social services and housing benefits (Becker et al., 2017). 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).[13] According to more recent data from the Atkins and Hoddinott (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)" (Atkins and Hoddinott, 2022, p.1).[14]

With no real possibility to borrow to fund their services, LADs faced two options to offset the CG funding cuts. First, they could tap into their financial reserves accumulated during previous years (Brien, 2023; Atkins and Hoddinott, 2022). Utilizing such reserves, if available, can offer vital assistance during unexpected crises such as the COVID-19 pandemic. However, these reserves are designed to bolster LADs' finances during emergencies and cannot replace regular budgeted revenues. Additionally, replenishing them is essential to safeguard LADs against potential future budget shortfalls (Studdert, 2021; Local Government Association, 2022). Reserves are thus usually not considered a sustainable source of funding for LADs

[12]Before 2013, all business rates collected by LADs were transferred to the CG, which subsequently redistributed them back to LADs through the Formula Grant scheme; since 2013, LADs retain a "local share" of up to 50% of business rates, and may further receive a fraction of "central share" still redistributed by the CG through the same Formula Grant scheme as before (Local Government Association, 2015; Department for Communities and Local Government, 2012).

[13]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".

[14]The importance of CG funding for LADs can also 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.

(Innes and Tetlow, 2015). Second, LADs could potentially raise council taxes. However, their ability to do so is limited. According to the 2011 Localism Act, increases in council tax rates cannot exceed 2% per annum without approval through a local referendum (Atkins and Hoddinott, 2022; Sandford, 2023). The 2% cap on the council tax rate increase was effective for 2012–13, raised to 3% for 2018–19, and subsequently brought back to 2% for 2020–22.

Taken together, prolonged 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 has resulted in a decline in public service quality and social benefits provided by LADs. Consequently, economically disadvantaged households dependent on these services likely faced income setbacks. This conjecture aligns with existing evidence indicating that reductions in CG funding adversely affected health and social care services nationwide (Maynard, 2017), and had disproportionate effects on people living in poverty (Cummins, 2018).

3.2 Measuring funding cuts to LADs

Funding cuts under the UK's austerity program are measured by analysing annual SFAs allocated to each LAD in England during the period 2007–20. The SFA data is publicly available and was downloaded from the website of the Department for Levelling Up, Housing and Communities (DLUHC) of the UK government.[15] In particular, we use the annual revenue expense budget files from the DLUHC portal to recover the SFAs for all LADs in England during the specified period. We then proceed in two steps.[16] First, we construct a measure of three-year cumulative change in SFA for each LAD–year in our sample as $\Delta Funding_{i,t} = \prod_{k=1}^{3}(1 + r_{i,t+k}) - 1$, where $r_{i,t+k}$ is the annual percentage change in SFA for LAD i between years $t + k - 1$ and $t + k$. Second, for each year, we define *treated* LADs as those that experienced a negative change in cumulative SFA over the preceding three years ($\Delta Funding_{i,t} < 0$) and *control* LADs as those with $\Delta Funding_{i,t} \geq 0$. We further define a dummy variable $NegFunding_{it}$ for each LAD-year to be equal to one for treated LADs and zero for control LADs.

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

[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.

for comparing P2P loan demand between LADs conditional on whether they experienced positive or negative changes in cumulative SFA grants. The remaining few LADs experienced consistently negative changes in cumulative SFA until 2018, suggesting that these areas faced consistent drops in funding. The SFA was increased overall for all LADs in 2019.

[Figure 1]

Recall that under our model's predictions, LAD funding cuts should lead to reductions in public welfare transfers to households, further harming their financial situation. We examine whether funding cuts to LADs impacted local households' financial well-being, utilizing data from the Bank of England's annual NMG Household Finance Survey. The NMG Survey, conducted since 2004, 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).[17] The survey includes two important questions that are relevant for our purposes: (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*). Analysis of responses to these two questions indicates that residents in LADs impacted by austerity, where *NegFunding* equals one, faced tighter financial constraints and cut spending during periods of sustained funding cuts. These findings imply that $\Delta Funding$ correctly predicts local household financial stress within LADs. A detailed discussion of our findings from the NMG household survey can be found in Section D.4 in the Internet Appendix.

Motivations for a three-year window. The decision to estimate three-year cumulative changes in SFA funding is driven by three considerations. First, it is plausible that annual changes in SFA may have a short-lived and inconsequential effect on local residents and their borrowing behavior. At the LAD level, temporary funding cuts can be offset either by available reserves, alternative sources of income, or through a 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. In turn, this rollback in the local welfare state may affect the individuals and their borrowing behaviour. Consider an individual who depends on periodic housing allowances from the LAD and has limited access to mainstream banking. If the SFA to her

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

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 as well. To the extent that LAD reserves, 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 $\Delta \mathit{Funding}$ also makes sense given the characteristics of available data. It enables us to account for longer-term changes in LAD funding as just mentioned, and yet provides us a sufficiently large sample of P2P loans to conduct empirical analyses.[18] Indeed, 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. The three-year time frame is thus a good balance in the trade-off between the time frame used for measuring $\Delta \mathit{Funding}$, and the sample period available for analysis.

Third and finally, if, as discussed above, annual changes in SFA are not suitable, and rolling time frames penalize the size of the sample, why then not use the cumulative change in LAD funding since 2007? It would be available at any point in time, would not occasion any loss of data, and would equally show the aggregate net gain or loss of funds available to LADs. In Figure 1b, we report the aggregate cumulative change in SFA for each LAD per year, starting from 2007 as the baseline year.[19] 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 between-LAD variation in P2P lending outcomes in response to changes in SFA.

[18]The P2P loan sample is formally presented in Section 3.3.

[19]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.

Aggregate cumulative changes in SFA at the LAD level. 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 obtained data on P2P loan origination and performance from the popular FinTech lending platform Zopa, which published information on all approved loans on its website.[20] This information included loan interest rates, maturities, loan amounts, and latest loan status (fully repaid/defaulted/prepaid). Zopa also provided anonymized borrower identifiers and their zipcodes (only up to *postcode district* level for maintaining anonymity).[21] We used the identifiers to detect repeat borrowers who borrowed more than once from the platform. Zipcodes, in turn, allowed mapping the borrowers to their respective LADs.

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 coincided strongly with the austerity program in the UK that led to substantial declines in funding to many LADs.

[Figure 3]

The functioning of the platform. The P2P lending side of Zopa was one of the largest providers of non-bank consumer loans in the UK, with total loan issuance exceeding £4.8

[20] Zopa closed its P2P lending business in 2021, which falls just after the end of our sample period. For details, see `https://www.zopa.com/about/our-story`, (accessed on December 27$^{\text{th}}$, 2023).

[21] No other details on borrowers, such as their age, employment status, and annual income, that the platform used to determine loan approvals are made available.

billion since it commenced operations in March 2005. The platform offered 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 good credit record with no history of insolvency.

To apply for a loan, prospective borrowers were required to visit the platform's website and specify how much they want to borrow and for how long.[22] The applicant had to 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 used these details to access the applicant's credit history and public record information from two credit reference agencies CallCredit and Equifax. This included information on the applicant's previous and current credit agreements, financial assets and liabilities, and court records. The platform used this information to ascertain the applicant's creditworthiness and decide whether to approve or decline the loan application.[23]

The platform made a decision within two business days of submission of the loan application. If the application was approved, the platform would then quote an interest rate that would 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 would then be required to provide identity information such as a bank account and proof of income. The platform used this information to conduct additional background checks, and upon further approval, deposited the loan money into the applicant's bank account within three business days.[24] The platform charged an origination fee and a servicing fee on approved loans.[25]

Money lent to borrowers by Zopa came directly from a pool of investors, who could choose from several investment products offered by the platform based on their risk and return preferences. Funds deposited by investors were placed in a queue, split into smaller chunks,

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

[23] The platform could 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.

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

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

and matched automatically to borrowers by the platform's algorithms. This mechanism achieved sufficient risk diversification by ensuring that each borrower receives no more than 1% from any single investor. Investors received monthly payments of interest and principal on their invested capital, which could be reinvested into the platform.

4 Research design

This section begins by documenting a notable discontinuity in the distribution of P2P loans between treated and control LADs. Next, we outline the regression discontinuity (RD) design used in our empirical analysis. Finally, we identify potential identification issues impacting our RD approach and discuss how we address them.

4.1 P2P loan issuance across treated and control LADs

To motivate our empirical design, Figure 4a plots the distribution of aggregate P2P loans issued per zipcode (matched to its corresponding LAD) in a given year against the running variable $\Delta Funding$.[26] We observe a sharp discontinuous drop in loan origination at the *zero* threshold: there are disproportionately more loans issued in treated LADs with negative $\Delta Funding$ relative to control LADs where $\Delta Funding$ is non-negative.[27]

We further analyze the discontinuity in P2P loan issuance per zipcode–year at the zero threshold using a probability density test developed by McCrary (2008). The null hypothesis of this test is that of a continuous distribution around the threshold while the alternative 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. 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. This confirms a statistically significant discontinuity in P2P loan issuance per zipcode–year at the zero threshold.[28]

[Figure 4]

We also verify that the discontinuity at the zero threshold is not non-random, possibly

[26] 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 LAD with the largest population.

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

[28] In some cases, the McCrary (2008) t-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.

due to some LADs being consistently favored (or alternatively disfavored) in the allocation of SFA. The presence of such biased preferences on the part of the CG may lead to misspecification errors as some LADs will find themselves consistently on one side of the zero threshold (see Becker et al. (2017); Maynard (2017); Fetzer (2019); Atkins and Hoddinott (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) t-test after excluding LADs whose $\Delta Funding$ is consistently above or below zero throughout the sample period. 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 change the baseline results by much as shown in Figure 4b.

Finally, we 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. (2023) 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%). 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., 2023). 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.

4.2 Empirical methodology

Our identification strategy is based on a regression discontinuity (RD) design that compares LADs with negative $\Delta Funding$ (*treated* LADs) to those with non-negative $\Delta Funding$ (*control* LADs) around a zero cutoff (implying $\Delta Funding = 0$). The corresponding baseline specification is as follows:

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

where y represents P2P loan-related outcomes of interest at the zipcode and individual loan levels. At the zipcode level, our analysis considers aggregate loan origination in volume (*Num loans*) and in value (*Sum loans*) in response to changes in $\Delta Funding_{it}$ to the corresponding 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. At the loan level, we investigate the impact of $\Delta Funding_{it}$ on 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 loans to default (*Default*).

The coefficient β_1 represents the mean effect of CG funding cuts to LADs ($NegFunding_{it}$) and is our main parameter of interest. The estimation of β_1 requires strong assumptions about the unknown relationship between y and $NegFunding_{it}$ 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 this problem. First, we restrict the sample to a specific bandwidth h on either side of the cutoff, with $h = \pm 25\%$.[29]. Focusing on LADs within this narrow bandwidth minimizes biases arising from unobservable factors that might be confounded with $NegFunding_{it}$ (Calonico et al., 2014).[30] 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.

X_{it} represents a vector of controls for socioeconomic characteristics at the LAD–year level that can potentially 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.[31] 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).

Table 1a presents descriptive statistics of the main sample used for our analysis.[32] 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.[33] Finally, the mean recovery rate on a loan is 66.44%.[34]

[29] The chosen bandwidth $h =$ very close and below the optimal bandwidth of 27.9% determined using the *rdbwselect* procedure developed by Calonico et al. (2017, 2018). This procedure identifies an optimal bandwidth with the least mean squared error for a given sample. We use heteroskedasticity-robust standard errors and a triangular kernel, which weights observations by their distance to the zero cutoff within a selected bandwidth.

[30] In subsequent analyses, we adopt tighter restrictions and compare P2P lending outcomes within contiguous treated and control LADs sharing a common border to eliminate any remaining identification concerns.

[31] 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.

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

[33] 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.

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

The average zipcode issues nearly 27 loans per year amounting to £198 thousands, of which 3.80% of them default.

[Table 1]

4.3 Concerns regarding the identification and validity

We acknowledge and address several concerns that could potentially weaken our identification strategy. First, although our measurement of funding cuts is based on SFAs, LADs may be able to alleviate funding constraints by tapping into existing financial reserves, raising council taxes, or both. Under this logic, funding cuts to LADs, as we measure them, should be unrelated to P2P lending outcomes. In other words, our estimate of β_1 should not be statistically significant, which is the opposite of our results reported in Section 5. Additionally, in section D.1 of the Internet Appendix, we argue that the ability of LADs to offset cuts in the SFA using unspent reserves or council taxes is rather limited, which further supports the robustness of our results to the mentioned concern. Second, systematic differences in the observable characteristics of treated and control LADs could confound the identification of the causal effect of funding cuts on P2P lending outcomes. In Section D.2, we describe formal tests that were applied revealing no statistical differences along these characteristics between the treated and control LADs in our sample. Third, local administrations overseeing individual LADs may seek to influence funding allocation decisions by the CG, leading to non-random assignment of LADs into the treated and control groups, potentially weakening our RD design. We consider this possibility in Section D.3, and find no evidence of LAD administrations influencing the fund allocation decisions made by the CG.

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. Overall, the results confirm the predictions of the theoretical model: funding cuts to LADs lead to higher demand for P2P loans within the corresponding local zipcodes, higher interest rates on these issued loans, and higher contemporaneous default rates on loans issued previously by the platform with these zipcodes. Finally, in Section 5.4, we present several robustness checks validating our results and show some additional findings.

defaulted.

5.1 P2P loan demand

Table 2 presents OLS estimates of the impact of funding cuts to LADs on aggregate P2P loan origination within constituent zipcodes based on Equation (I). Each specification includes 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. Standard errors are clustered by year to account for correlated shocks across LADs. Independent of how loan origination is measured, treated LADs are found to experience relatively higher demand for P2P loans than control LADs. First, when looking at the volume of loans issuance (*Num loans*), nearly 11% more P2P loans were issued per year on average among zipcodes belonging to treated LADs relative to zipcodes from control LADs, as denoted by the positive coefficients of *NegFunding* in columns (1) and (2). The coefficients are also statistically significant at the 10% and 5% levels respectively. Second, in terms of the value of loans issued (*Sum loans*), columns (4) and (5) highlight that aggregate P2P loan origination per treated zipcode-year was up to 17.8% more on average compared to control LADs. Again, these results are statistically significant at the 5% and 1% levels. Finally, the year-on-year (YoY) growth in *Num loans* and *Sum loans* is respectively 27% and 72% higher in zipcodes belonging to treated LADs relative to those in control LADs, as depicted by significant at the 1% level coefficients in columns (3) and (6).

[Table 2]

We verify that these results are not driven by the rising popularity and adoption of P2P lending at a macro level. For this purpose, we scale both measures of loan origination, *Num loans* and *Sum loans*, by the corresponding aggregate P2P loan origination estimates at the national level during the same year. The regression results on these outcomes are presented in A2 of the Internet Appendix. Scaled P2P loan volume in treated zipcodes is higher by nearly 14% on average relative to corresponding zipcodes in control LADs. Similarly, the scaled total value of P2P loans issued in treated zipcodes is higher on average by 27% compared to that issued in control zipcodes during the same year. These results highlight that our findings are robust to cross-sectional aggregate trends in P2P lending, and that funding cuts to LADs have indeed contributed to a sharp rise in P2P loan demand.

We interpret the results of Tables 2 and A2 as demand-driven, implying that the impact of *NegFunding* on P2P loan demand is ostensibly causal in nature. 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 each year. 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 diversifies every 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.

Impact of banking and internet access on P2P loan origination. While the regression estimates in Tables 2 and A2 control for several local socioeconomic characteristics at the LAD level, it is possible that the extent of financial and digital inclusion among residents living in a given area might moderate the demand for P2P loans. We therefore investigate how variation in access to banking (proxying financial inclusion) and the internet (proxying digital inclusion) 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.[35] Similarly, internet speed proxies the extent of digital inclusion among households in a given area. 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.[36]

[Table 3]

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 use 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 3 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 columns (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

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

[36] 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`.

branch coverage. Columns (5) and (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, our results indicate that cuts in LAD funding under austerity led to higher demand for P2P loans. Moreover, this demand is stronger in areas that are the most deprived in terms of access to mainstream banking and the Internet. The evidence presented in this section is therefore consistent with Proposition 1 suggesting that funding cuts to LADs foster greater demand for P2P loans from within the local population.

5.2 P2P loan interest rate

Table 4 reports OLS estimates of the impact of *NegFunding* on the interest rates charged by the P2P platform on individual loans. 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*), loan maturity (*Loan Term*), and repeat borrower status (*Repeat Borrower*) as additional controls. Standard errors clustered by year are reported in parentheses.

Columns (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 columns, 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. Column (3) shows that new borrowers in treated LADs pay about 40 bps higher interest rate on a loan relative to new borrowers from control LADs. In comparison, column (4) shows that repeat borrowers in treated LADs pay only 17 bps higher interest rates than those from control LADs, but the effect 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 was likely using the repeat borrower status as a means to reduce information asymmetry: when the platform knows the borrower from prior interactions, 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 her loan in much higher.[37]

[37]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*

[Table 4]

In economic terms, Table 4 indicates that borrowers generally pay slightly higher spreads of up to 1.2 bps on average per one log-month increase in loan maturity. Loan spreads are also lower by 2.2–2.4 bps on average per one log-pound increase in loan size.[38]

Overall, the results in this section are consistent with Proposition 2, which states that the P2P platform anticipates higher default probabilities for debt issued to borrowers from austerity-affected LAD. This ex-ante expectation of a higher default rate due to the funding constraints faced by the borrower's LAD translates into a higher default premium that correspondingly increases the cost of borrowing.

5.3 P2P loan performance

Lastly, we analyse 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, this analysis allows us to interpret whether the ex-ante pricing of P2P loans by the platform, as outlined in Section 5.2, is contingent, at least partially, on the contemporaneous incidence of defaults among P2P loans issued previously within the same LAD.

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 employ a stacked regression approach following Franks et al. (2020) to analyse the incidence of default.[39] As a robustness check, we also compare the results obtained from the stacked regression method against estimates obtained from the Cox proportional hazards model. Each of these analyses are described below.

Stacked regressions. Under this method, we estimate the per-period probability of default for each loan–year, rather than the raw probability of default for a given loan. We accordingly 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.

---

per 100 businesses, and *NegFunding* $\times$ *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.

[38] One plausible explanation is that Zopa limits loan amounts in relation to the borrowers' income. For instance, the amount lent could be such that the monthly repayments do 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.

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

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:

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

Panel 5a reports GLM logit estimates of the stacked regression specification. Columns (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. Moreover, the estimated effect of *NegFunding* implies that the default probability of an average loan increases by about 39% in LADs subject to treatment.[40,41]

In columns (3) and (4), we once again split the sample into loans issued to new and repeat borrowers. The coefficient of *NegFunding* in column (3) implies that new borrowers in the treated LAD-year group have 1.42 ($= e^{0.345}$) more odds of defaulting than similar borrowers in the control LAD-year group. We find no 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 the funding cuts as exogenous shocks to local household incomes, and utilizes contemporaneous information on loan defaults in a given LAD when pricing new loans issued to borrowers from the same area. A possible mechanism that explains this platform behavior is the persistence of aggregate states as postulated in Section 2. According to this conjecture, the platform anticipates that funding cuts, once initiated, will likely persist in the subsequent periods, and adjusts the pricing of new loans

[40] 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.

[41] 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.

accordingly based on prevailing local household conditions.

[Table 5]

Cox proportional hazards models. For the sake of robustness, we verify that the stacked regression results are consistent with P2P loan default probabilities estimated 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 Panel 5b. Loans in treated LADs are 2.31–2.87 times as likely to default as similar loans in control LADs at any given time from origination. Conversely, loans issued to repeat borrowers are at least 0.38 times as likely to default as loans issued on similar terms to new borrowers. After splitting the sample by repeat borrower status, new (repeat) borrowers in treated LADs appear to be 2.97 (1.53) as likely to default on average as new (repeat) borrowers in control LADs. These effects are statistically significant only in the case of new borrowers.

[Figure 5]

To further illustrate the Cox hazard estimates, we plot, in Figure 5, the Kaplan-Meier curves representing the fractions of un-defaulted loans from their origination date for treated and control LADs separately.[42] The curves clearly show that the fraction of loans that default at any given time in treated LADs is much higher than the fraction of loans that eventually default in control LADs. In fact, approximately 10% (5%) of loans issued in treated (control) LADs tend to default within the first three years of origination.

Taken together, our findings indicate that loans issued to borrowers in treated LADs are more likely to default than those in control areas. These results are robust to the manner in which default probabilities are estimated, and are consistent with theoretical predictions outlined in Proposition 3.

5.4 Robustness checks and additional analyses

In section 4.2 we emphasized that systematic but observable differences between LADs do not weaken our identification strategy. However, LADs may vary in their socioeconomic characteristics in many ways that are unobservable. In this section, we first demonstrate that the potential presence of such factors does not weaken our causal interpretation of *NegFunding* on P2P lending. Next, we check whether the observed patterns in P2P loan demand and outcomes are driven by broader regional macroeconomic trends.

[42] Figure A1 in the Internet Appendix presents Kaplan-Meier curves for loans with different maturities.

5.4.1 Unobservable differences across LADs and contiguous zipcodes

Even though we control for observable socioeconomic conditions at the LAD level, unobserved heterogeneity in economic conditions among zipcodes within LADs could still weaken the causal interpretation of *NegFunding* on P2P lending. This would occur if these unobservable differences are correlated with funding cuts and are driving the observed differences in P2P loan origination, pricing, and performance across treated and control LADs at the same time.

We verify that this is not the case by running 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. That is, 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.

[Table 6]

Table 6 reports results of the analyses on contiguous LADs using $d \leq 10$km 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.[43]

In addition to this formal treatment, we can also emphasize that our estimates of *NegFunding* are robust throughout all our analyses, indicating that the role of unobservable heterogeneity is likely to be minimal. 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 Δ*Funding* and their interactions with *NegFunding*, as well as LAD and year fixed effects.[44]

5.4.2 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 groupings such as the English re-

[43] These results are presented in Section B of the Internet Appendix.

[44] 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.

gions. For example, LADs in the London region may have experienced correlated trends in CG funding, which are distinct from other regions, because commonalities in their socioeconomic characteristics may lead them to have similar funding requirements to support their respective 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 determine whether such regional patterns exist, 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 $\Delta Funding$ and a categorical variable representing the region to which the LAD belongs. We keep everything else 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 regional heterogeneity in the response of P2P loan demand to the austerity-led funding cuts to LADs.

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 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 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.

References

Alesina, A., O. Barbiero, C. Favero, F. Giavazzi, and M. Paradisi (2015): "Austerity in 2009–13," *Economic Policy*, 30, 383–437.

Alesina, A., C. Favero, and F. Giavazzi (2019): "Effects of Austerity: Expenditure- and Tax-Based Approaches," *Journal of Economic Perspectives*, 33, 141–62.

Alesina, A., C. A. Favero, and F. Giavazzi (2018): "Climbing Out of Debt," *Finance & Development*, 55, 6–11.

Allen, F., X. Gu, and J. Jagtiani (2021): "A Survey of Fintech Research and Policy Discussion," *Review of Corporate Finance*, 1, 259–339.

Anderson, G., P. Bunn, A. Pugh, and A. Uluc (2016): "The Bank of England/NMG Survey of Household Finances," *Fiscal Studies*, 37, 131–152.

Atkins, G. and S. Hoddinott (2022): "Local Government Funding in England." Institute for Government, https://www.instituteforgovernment.org.uk/explainers/local-government-funding-england, Accessed: 2022-02-19.

Balyuk, T., A. N. Berger, and J. Hackney (2020): "What is Fueling FinTech Lending? The Role of Banking Market Structure," SSRN working paper.

Bartlett, R., A. Morse, R. Stanton, and N. Wallace (2022): "Consumer-Lending Discrimination in the FinTech Era," *Journal of Financial Economics*, 143, 30–56.

Becker, S. O., T. Fetzer, and D. Novy (2017): "Who Voted for Brexit? A Comprehensive District-Level Analysis," *Economic Policy*, 32, 601–650.

Berg, T., A. Fuster, and M. Puri (2022): "FinTech Lending," *Annual Review of Financial Economics*, 14, 187–207.

Blumenstock, J. E., N. Eagle, and M. Fafchamps (2016): "Airtime Transfers and Mobile Communications: Evidence in the Aftermath of Natural Disasters," *Journal of Development Economics*, 120, 157–181.

Blyth, M. (2013): *Austerity: The History of a Dangerous Idea*, Oxford University Press.

Brien, P. (2023): "Local Government Finances." Research Briefing Number 08431, House of Commons Library.

Buchak, G., G. Matvos, T. Piskorski, and A. Seru (2018): "Fintech, Regulatory Arbitrage, and the Rise of Shadow Banks," *Journal of Financial Economics*, 130, 453–483.

Calonico, S., M. D. Cattaneo, and M. H. Farrell (2018): "On the Effect of Bias Estimation on Coverage Accuracy in Nonparametric Inference," *Journal of the American Statistical Association*, 113, 767–779.

Calonico, S., M. D. Cattaneo, M. H. Farrell, and R. Titiunik (2017): "rdrobust: Software for Regression-Discontinuity Designs," *The Stata Journal*, 17, 372–404.

Calonico, S., M. D. Cattaneo, and R. Titiunik (2014): "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs," *Econometrica*, 82, 2295–2326.

Cameron, A. C. and P. K. Trivedi (2005): *Microeconometrics: Methods and Applications*, Cambridge University Press.

Cattaneo, M. D., N. Idrobo, and R. Titiunik (2019): *A Practical Introduction to Regression Discontinuity Designs: Foundations*, Cambridge University Press.

Célerier, C. and A. Matray (2019): "Bank-Branch Supply, Financial Inclusion, and Wealth Accumulation," *The Review of Financial Studies*, 32, 4767–4809.

Cummins, I. (2018): "The Impact of Austerity on Mental Health Service Provision: A UK Perspective," *International Journal of Environmental Research and Public Health*, 15, 1145.

de Roure, C., L. Pelizzon, and A. Thakor (2022): "P2P Lenders versus Banks: Cream Skimming or Bottom Fishing?" *The Review of Corporate Finance Studies*, 11, 213–262.

Demirgüç-Kunt, A. and D. Singer (2017): "Financial Inclusion and Inclusive Growth: A Review of Recent Empirical Evidence," Policy Research Working Paper 8040, World Bank.

Department for Communities and Local Government (2012): "A Plain English Guide to Business Rates Retention: Local Government Finance Bill," https://assets.publishing.service.gov.uk/media/5a79017f40f0b679c0a07cb0/2182624.pdf, Accessed: 2023-12-21.

Dobbie, W., A. Liberman, D. Paravisini, and V. Pathania (2021): "Measuring Bias in Vonsumer Lending," *The Review of Economic Studies*, 88, 2799–2832.

Erel, I. and J. Liebersohn (2022): "Can FinTech Reduce Disparities in Access to Finance? Evidence from the Paycheck Protection Program," *Journal of Financial Economics*, 146, 90–118.

Fetzer, T. (2019): "Did Austerity Cause Brexit?" *The American Economic Review*, 109, 3849–3886.

Fitzgerald, A. (2018): "Querying the Resilient Local Authority: The Question of 'Resilience for Whom?'," *Local Government Studies*, 44, 788–806.

Franks, J., N. Serrano-Velarde, and O. Sussman (2020): "Marketplace Lending, Information Aggregation, and Liquidity," *The Review of Financial Studies*, 34, 2318–2361.

Fuster, A., P. Goldsmith-Pinkham, T. Ramadorai, and A. Walther (2022): "Predictably Unequal? The Effects of Machine Learning on Credit Markets," *Journal of Finance*, 77, 5–47.

Fuster, A., M. Plosser, P. Schnabl, and J. Vickery (2019): "The Role of Technology in Mortgage Lending," *The Review of Financial Studies*, 32, 1854–1899.

Goncharov, I., V. Ioannidou, and M. C. Schmalz (2023): "(Why) Do Central Banks Care about Their Profits?" *Journal of Finance*, 78, 2991–3045.

Gopal, M. and P. Schnabl (2022): "The Rise of Finance Companies and FinTech Lenders in Small Business Lending," *The Review of Financial Studies*, 35, 4859–4901.

Innes, D. and G. Tetlow (2015): "Delivering Fiscal Squeeze by Cutting Local Government Spending," *Fiscal Studies*, 36, 303–325.

Kerr, W. R. and R. Nanda (2009): "Democratizing Entry: Banking Deregulations, Financing Constraints, and Entrepreneurship," *Journal of Financial Economics*, 94, 124–149.

Lee, D. S. and T. Lemieux (2010): "Regression Discontinuity Designs in Economics," *Journal of Economic Literature*, 48, 281–355.

LeGrand, F. and X. Ragot (2021): "Sovereign Default and Liquidity: The Case for a World Safe Asset," *Journal of International Economics*, 131, 103462.

Local Government Association (2015): "Business rate retention: the story continues," https://www.local.gov.uk/sites/default/files/documents/business-rate-retention-s-96f.pdf, Accessed: 2023-12-21.

——— (2022): "Council Funding," https://www.local.gov.uk/council-funding, Accessed: 2022-05-19.

Mackay, R. and J. Williams (2005): "Thinking about Need: Public Spending on the Regions," *Regional Studies*, 39, 815–828.

Mas, I. and O. Morawczynski (2009): "Designing Mobile Money Services: Lessons from M-PESA," *innovations*, 4, 77–91.

Maynard, A. (2017): "Shrinking the State: The Fate of the NHS and Social Care," *Journal of the Royal Society of Medicine*, 110, 49–51.

McCrary, J. (2008): "Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test," *Journal of Econometrics*, 142, 698–714.

Mezzanotti, F., N. Crouzet, and A. Gupta (2023): "Shocks and Technology Adoption: Evidence from Electronic Payment Systems," *Journal of Political Economy*, Forthcoming.

Phillips, D. (2014): "Business as Usual. The Barnett Formula, Business Rates and Further Tax Devolution," IFS Briefing Note BN155, The Institute for Fiscal Studies.

Sandford, M. (2023): "Council Tax: Local Referendums," Research Briefing Number 05682, House of Commons Library.

Studdert, J. (2021): "Local Government Explained Part 3: How are Councils Funded?" .

SUEYOSHI, G. T. (1995): "A Class of Binary Response Models for Grouped Duration Data," *Journal of Applied Econometrics*, 10, 411–431.

SURI, T. AND W. JACK (2016): "The Long-Run Poverty and Gender Impacts of Mobile Money," *Science*, 354, 1288–1292.

TANG, H. (2019): "Peer-to-Peer Lenders Versus Banks: Substitutes or Complements?" *The Review of Financial Studies*, 32, 1900–1938.

THAKOR, A. V. (2020): "Fintech and Banking: What do we Know?" *Journal of Financial Intermediation*, 41, 100833.

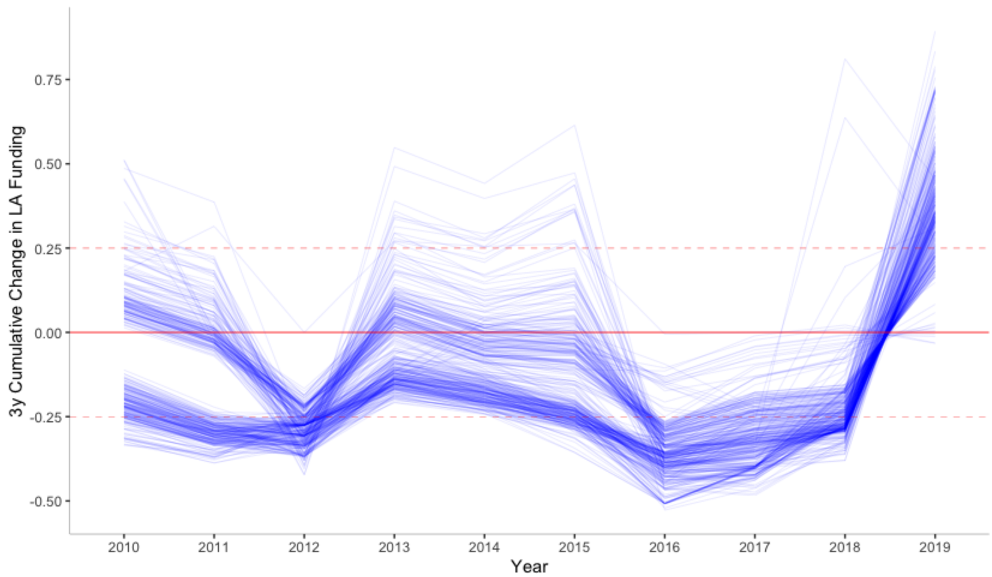
VAN DE WALLE, D., K. NEAD, ET AL. (1995): *Public Spending and the Poor: Theory and Evidence*, The Johins Hopkins University Press for the World Bank.

ZIEGLER, T., R. SHNEOR, K. WENZLAFF, K. SURESH, F. F. DE CAMARGO PAES, L. MAMMADOVA, C. WANGA, N. KEKRE, S. MUTINDA, B. W. WANG, C. L. CLOSS, B. ZHANG, H. FORBES, E. SOKI, N. ALAM, AND C. KNAUP (2021): "The 2nd Global Alternative Finance Market Benchmarking Report," University of Cambridge Judge Business School, Cambridge Centre for Alternative Finance.

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)

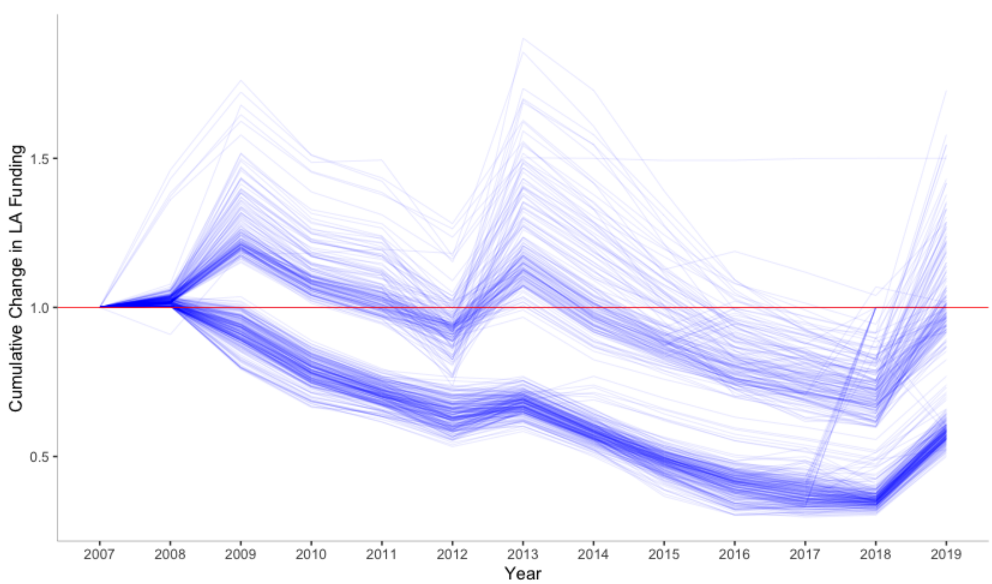
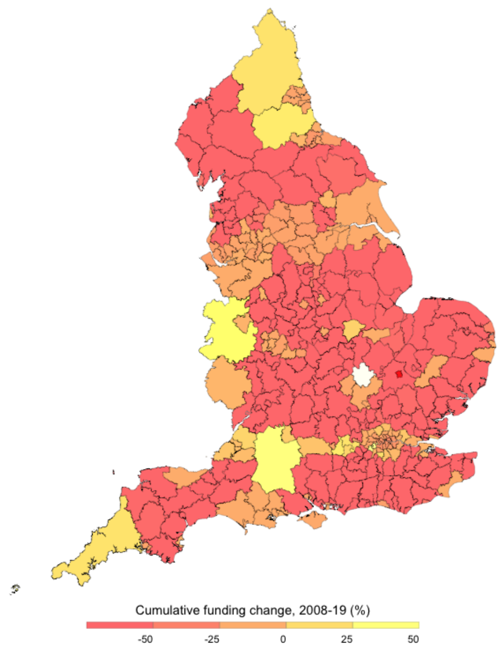


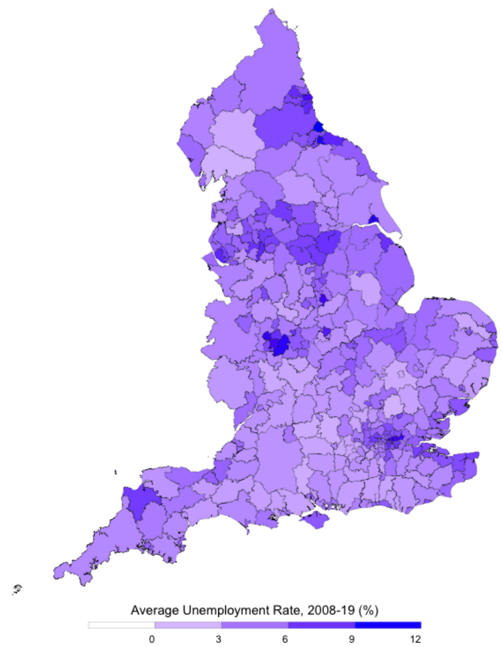
Figure 2: Distribution of select LAD characteristics.

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.

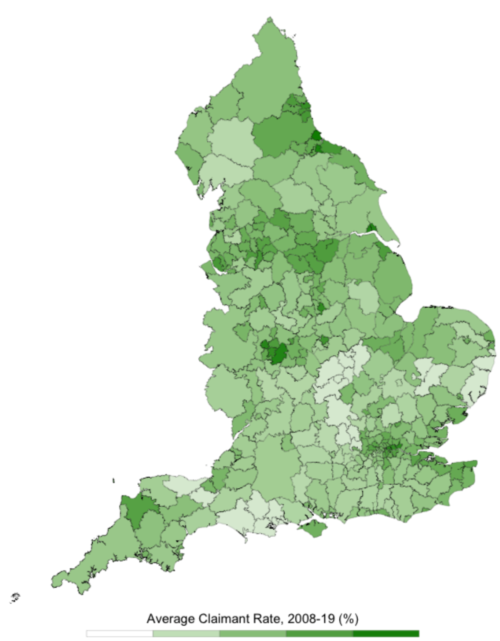
(a) Cumulative change in LAD funding (SFA)



(b) Unemployment rate



(c) Jobseekers' allowance claimants



(d) Log(GDHI)

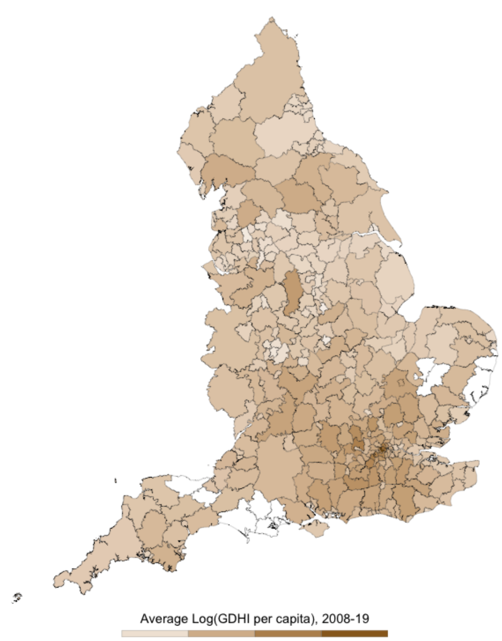


Figure 3: P2P loan origination by year

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).

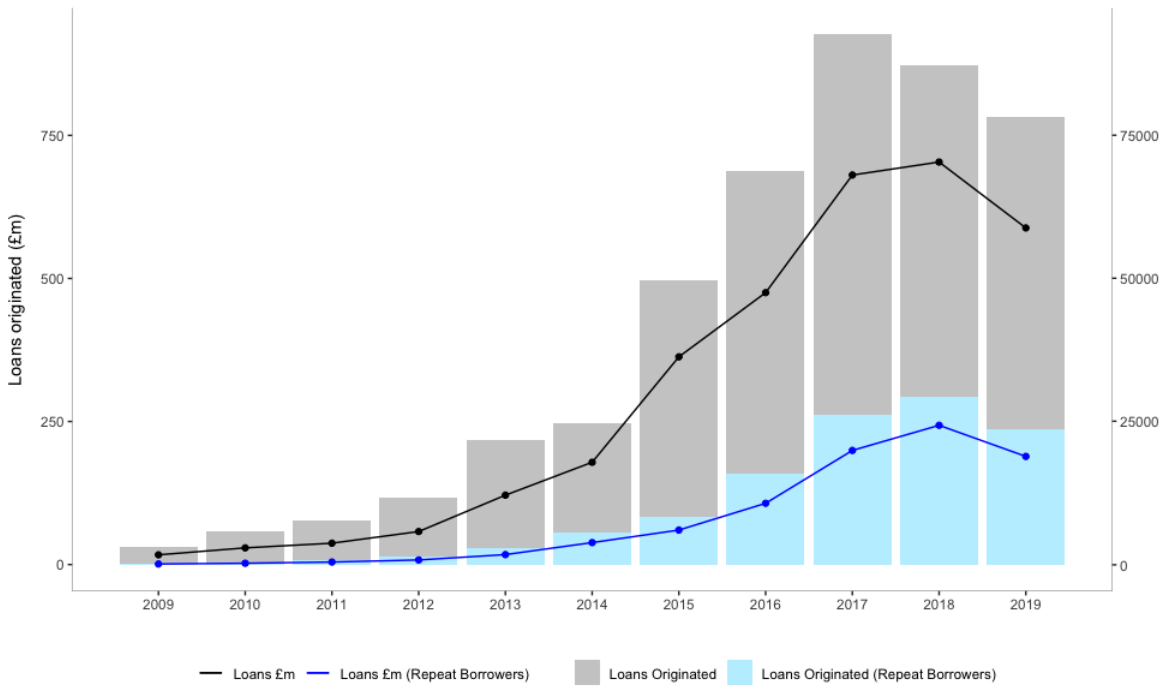
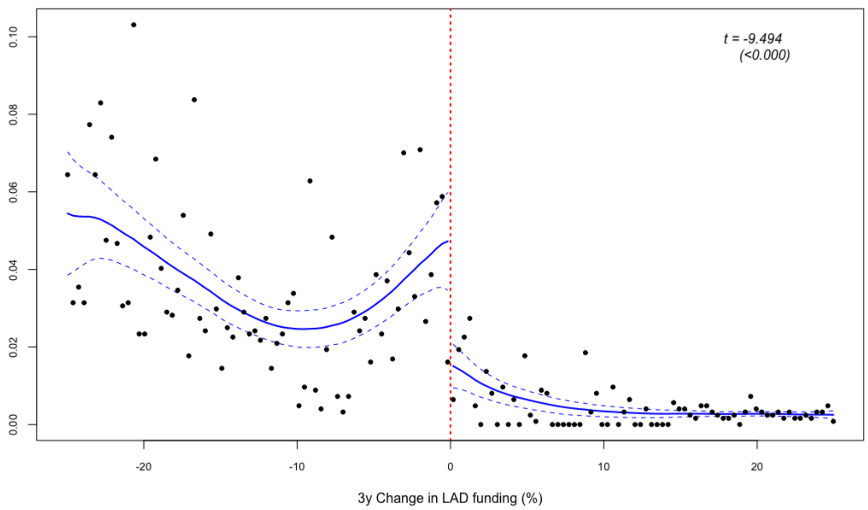


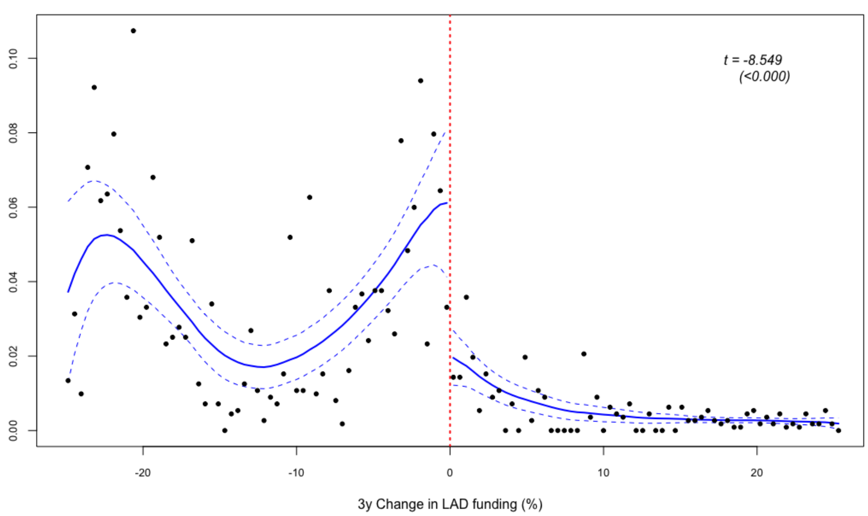
Figure 4: Distribution of UK central government funding to LADs

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

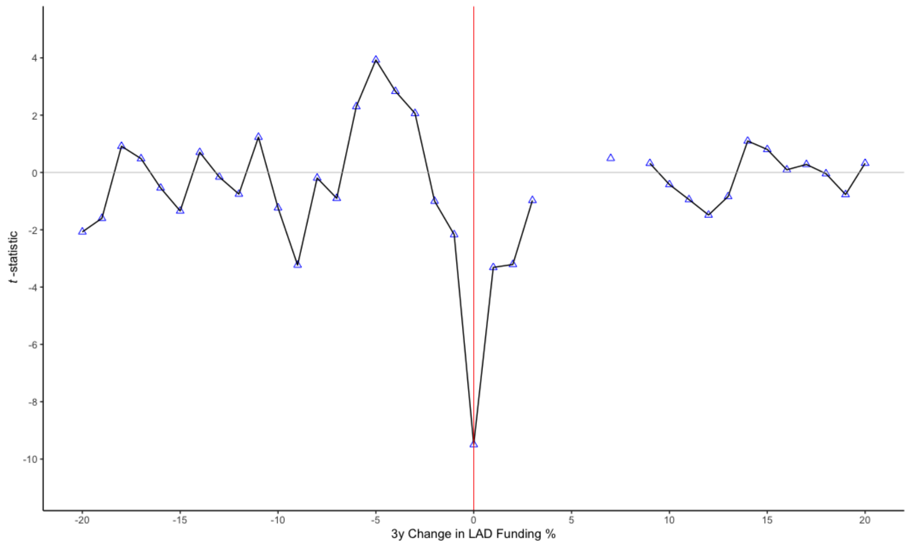


Figure 5: Kaplan-Meier curves of loan performance

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.

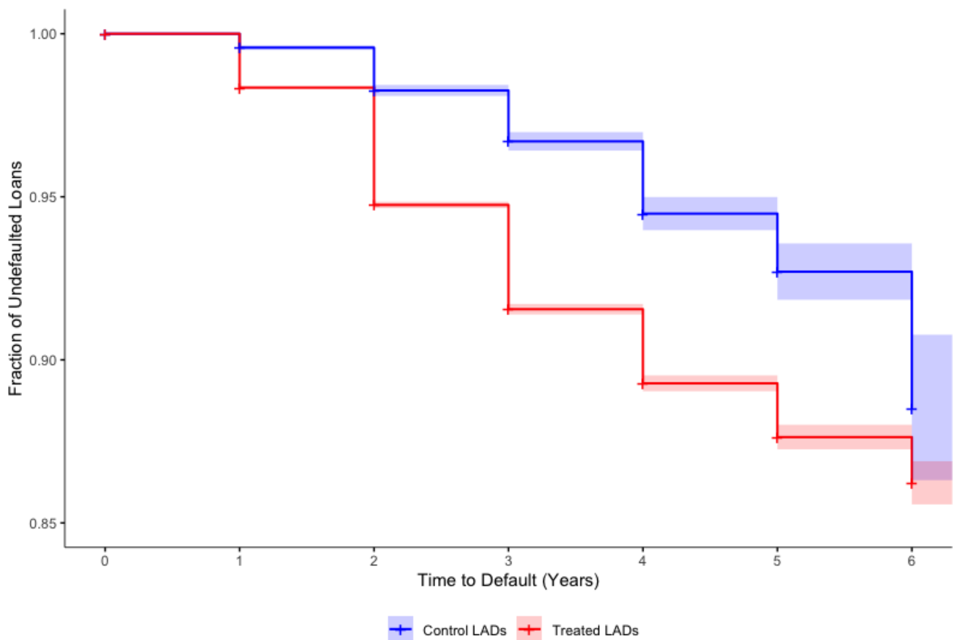


Table 1: Summary statistics

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	
Observations (loans)	152,654		25,629			

Table 2: 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 3: 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 4: 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 5: 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 6: 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: 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.

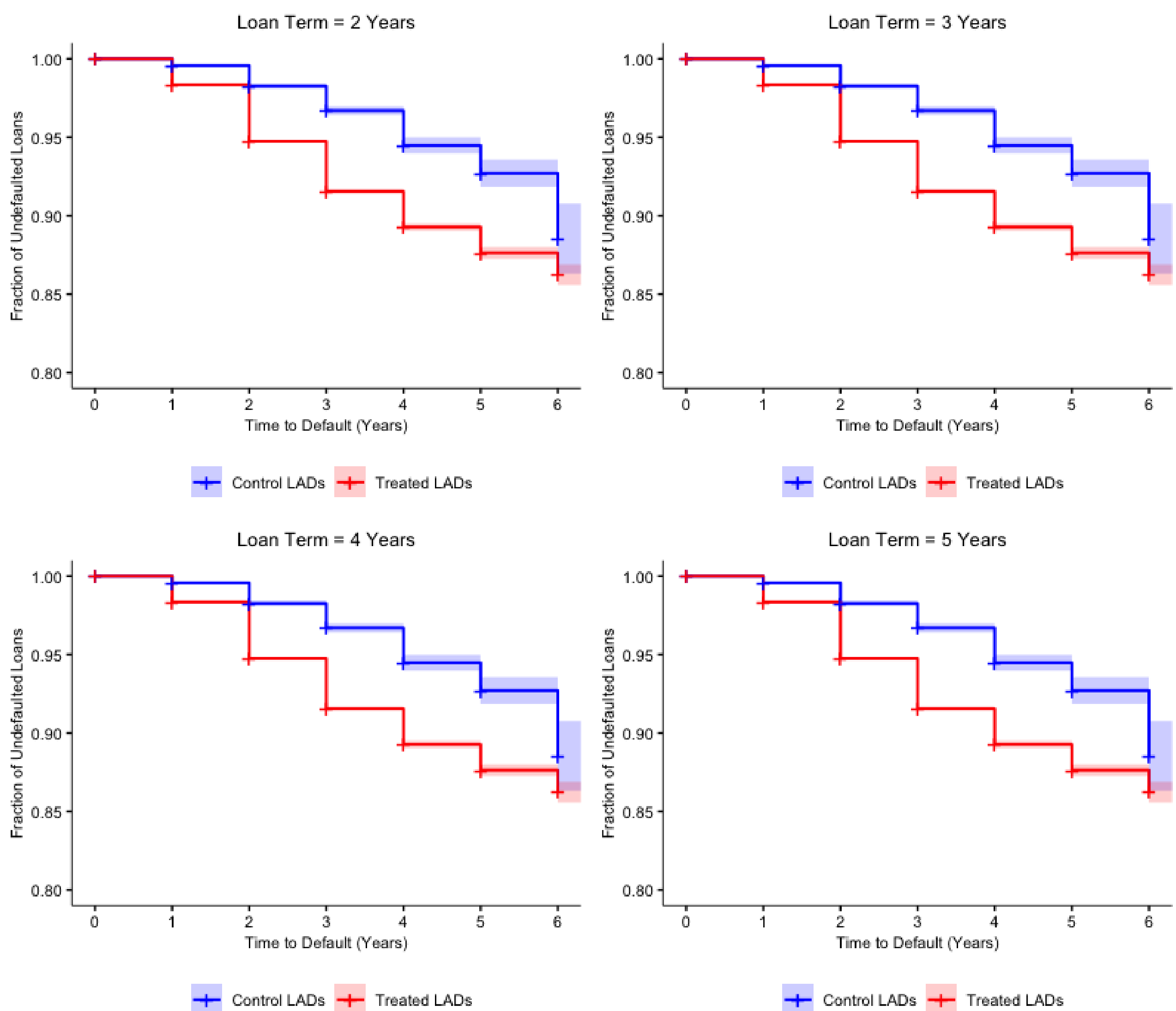


Table A1: Summary statistics

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

	Loan Status			
Year Issued	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 = ±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 Robustness checks: 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 = ±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

	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 ≤ 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

This section is organized as follows. In Section C.1, we start with recalling some elements and some notation of the model and prove inequality (4). In Section C.2, we demonstrate that Proposition 1 holds in each of the three equilibria we study: the no-default one, the (l, B) one, and the (l, B) and (l, G) ones. In Section C.3, we prove that Proposition 2 holds; it is, in fact, a rather direct consequence of the analysis of the three equilibria. Section C.4 provides proofs of Proposition 3. Finally, in Section C.5, we analytically derive how the two opposing forces – consumption smoothing and interest rate – drive debt demand.

C.1 Proof of inequality (4)

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 also recall that we 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 price of debt $q_{s,S}(d)$ is given by equation (1) in the main text.

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 (3), as well as the ranking of inequality (4).

C.2 Proof of Proposition 1

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 of cutoff thresholds $\overline{d}_h \geq \overline{d}_{l,G} \geq \overline{d}_{l,B} > 0$. 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.

The no-default equilibrium. In this equilibrium, the household currently in state (l, S) will repay its debt under all circumstances. The quantity of debt d borrowed by the household must satisfy the following two conditions, which are equations (6) and (7) of the main text:

$$
\begin{aligned}
qu'(y_l + T_S + qd) &\leq \beta\rho_{lh}u'(y_h - d) + \beta\rho_{ll}\pi_{SG}u'(y_l + T_G - d) \\
&\quad + \beta\rho_{ll}\pi_{SB}u'(y_l + T_B - d), \qquad \text{(C1)}\\
d &\leq \tau(y_l + T_B). \qquad \text{(C2)}
\end{aligned}
$$

Expression (C1) is the Euler equation, while inequality (C2) 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 (C2) 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_{lh}, the household gets a high income y_h independent of the aggregate state, and the intertemporal rate of substitution is $\beta u'(y_h - d)/u'(y_l + T_S + qd)$.
2. With probability $\rho_{ll}\pi_{SG}$, the household receives a low income y_l but a high public transfer, hence the intertemporal rate of substitution is $\beta u'(y_l+T_G-d)/u'(y_l+T_S+qd)$.
3. With probability $\rho_{ll}\pi_{SB}$, the household receives a low income y_l and a low public transfer, and the intertemporal rate of substitution is $\beta u'(y_l + T_B - d)/u'(y_l + T_S + qd)$.

If equation (C2) 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 (C1) and hence ruling out this equilibrium. In that case, the household will borrow as much as it can while not defaulting.[45] A necessary condition for d to be positive (and hence to be debt and not saving) is:

$$qu'(y_l + T_S) \geq \beta\rho_{lh}u'(y_h) + \beta\rho_{ll}\pi_{SG}u'(y_l + T_G).$$

Finally, we verify that the debt choice in the absence of default (hence the solution of (C1)–(C2)) is decreasing with T_S. First, if the debt choice is determined by (C1), deriving (C1)

[45] Both conditions (C1) and (C2) can hold with equality for some specific parameter values that imply that the constrained choice $\tau(y_l + T_B)$ is also optimal.

with respect to T_S yields:

$$\frac{\partial d}{\partial T_S} = \frac{-qu''(y_l + T_S + qd)}{q^2 u''(y_l + T_S + qd) + \beta\rho_{lh}u''(y_h - d) + \beta\rho_{ll}\pi_{SG}u''(y_l + T_G - d) + \beta\rho_{ll}\pi_{SB}u''(y_l + T_B - d)},$$

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 also holds). Finally, note that 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. This proves Proposition 1 for the no-default case.

Equilibrium with default in state $(\boldsymbol{l}, \boldsymbol{B})$. In this equilibrium, the household defaults in state (l, B) but repays in states (l, G) and h.

The debt d verifies the conditions (9) and (10) specified in the main text. Equation (10) is the Euler equation for an household 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 (C1): (i) the debt price, and (ii) a default (hence a zero payoff) with probability $\rho_{ll}\pi_{SB}$.

Inequalities of equation (10) 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 (9) and the default condition (10) must hold with equality.

Similar to the no-default case, the derivative of (9) with respect to T_S is given by:

$$\frac{\partial d}{\partial T_S} = \frac{-\frac{1-\rho_{ll}(1-\pi_{SG})}{1+r}u''(y_l + T_S + \frac{1-\rho_{ll}(1-\pi_{SG})}{1+r}d)}{\left(\frac{1-\rho_{ll}(1-\pi_{SG})}{1+r}\right)^2 u''(y_l + T_S + \frac{1-\rho_{ll}(1-\pi_{SG})}{1+r}d) + \beta\rho_{lh}u''(y_h - d) + \beta\rho_{ll}\pi_{SG}u''(y_l + T_G - d)},$$

and is also negative. Following the same steps as in the the no-default case proves Proposition 1 in the (l, B)-equilibrium.

Equilibrium with default in states $(\boldsymbol{l}, \boldsymbol{B})$ and $(\boldsymbol{l}, \boldsymbol{G})$. In this equilibrium, the household defaults upon receiving a low income, independent of the public transfer (i.e., in states (l, B) and (l, G)). The debt quantity d must verify the equations (12) and (13). Similar to the previous equilibria, (12) is the Euler equation, while inequalities in equation (13) guarantee that the household defaults in states (l, B) and (l, G) but repays in state h (independently of the aggregate state). Again, at least one of equations (12) and (13) must hold with equality.

Similarly to the other two cases, the derivative of (12) with respect to T_S is given:

$$\frac{\partial d}{\partial T_S} = \frac{-\frac{1-\rho_{ll}}{1+r} u''(y_l + T_S + \frac{1-\rho_{ll}}{1+r} d)}{\left(\frac{1-\rho_{ll}}{1+r}\right)^2 u''(y_l + T_S + \frac{1-\rho_{ll}}{1+r} d) + \beta \rho_{lh} u''(y_h - d)},$$

which is again negative. Following the same steps as in the the no-default case proves Proposition 1 in this equilibrium.

C.3 Proof of Proposition 2

The no-default equilibrium. In this equilibrium, the household will repay its debt under all circumstances. In the absence of default, the household faces a price $q(d, s) = (1+r)^{-1} = q$, and hence a constant interest rate $r_{l,S} = r$. The interest rate being independent of the aggregate state, we deduce that Proposition 2 holds in this equilibrium.

Equilibrium with default in state (l, B). In this equilibrium, the household defaults in state (l, B) but repays in states (l, G) and h. The absence of arbitrage opportunities for the risk-neutral intermediary result in the price $q_{l,S}(d)$ of equation (8), reflecting that the household will repay the loan if it gets a high income (with probability ρ_{lh}), or if it gets a low income but the aggregate state is good (with probability $\rho_{ll}\pi_{SG}$). Equivalently, this corresponds to the interest rate of equation (8) too. Using the interest rate expression, we deduce that $r_{l,B}(d) \geq r_{l,G}(d)$ iff

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

or $\pi_{GG} \geq \pi_{BG} = 1 - \pi_{BB}$. This always holds because of the assumption of aggregate state persistence (see footnote 7). We deduce from the above that $r_{l,B}(d) \geq r_{l,G}(d)$, which proves Proposition 2 in the case of the (l, B)-equilibrium.

Equilibrium with default in states (l, B) and (l, G). The household only repays in state h independently of the aggregate state realization. The debt price and the interest rate are given by equation (11) in the main text, which is independent of the current aggregate state as in the no-default case. We thus deduce that Proposition 2 holds in this equilibrium.

Remark. The aggregate state effectively affects the interest rate only through the (l, B) equilibrium. In the other two equilibria, the interest rate is constant with respect to the aggregate risk.

C.4 Proof of Proposition 3

The proof and the mechanism are similar to those of Proposition 2. We denote by $\mu_{S'|(l,S)}$ the share of agents currently in state (l,S) who will default in the second period in (aggregate) state S'.

In the no-default equilibrium, this share is null independently of the next-period aggregate state. Under the (l,B) and (l,G) equilibrium, the default occurs whenever the household remains in state l and is independent of the aggregate state. Hence, $\mu_{B|(l,S)} = \mu_{G|(l,S)} = \rho_{ll}$.

In the (l,B) equilibrium, the household currently in state (l,S) will default on its debt in the next period if it obtains a low income while the aggregate state is bad, hence the default probability equal to $\rho_{ll}\pi_{SB}$. Conversely, the share of default in tomorrow's state B is ρ_{ll}, while it is null in tomorrow's state G: $\mu_{B|(l,S)} > \mu_{G|(l,S)}$.

Furthermore, we can interpret the default probability $\rho_{ll}\pi_{SB}$ as the ex-ante share of default in state S. The default is more likely, when the probability of the "bad" state B is higher. Since aggregate states are persistent, the default is ex ante more likely in state B.

This proves Proposition 3.

C.5 What are the two forces driving debt demand?

We explain in the main text that the household's P2P debt demand is subject to two possibly opposing forces: consumption smoothing and interest rate. We formalize this point below in the case of the $(l,B)-$equilibrium – but the point could similarly be made for any other equilibrium. In the case of an interior debt demand d, the demand is determined by the following Euler equality for an household in state (l,S):

$$\frac{1}{1+r_{l,S}}u'(y_l + T_S + \frac{1}{1+r_{l,S}}d) = \beta\rho_{lh}u'(y_h - d) + \beta\rho_{ll}\pi_{SG}u'(y_l + T_G - d), \tag{C3}$$

where $r_{l,S} = \frac{1+r}{1-\rho_{ll}(1-\pi_{SG})} - 1$ is the interest rate in this equilibrium.

First, we can observe that the income level in the current period, equal to $y_l + T_S$, is lower or equal to income in the next period, which is at y_h or $y_l + T_G$. This generates a consumption smoothing motive as the household would like to borrow to close this intertemporal income gap. As this gap is larger in current state B than in current state G, so is the consumption smoothing motive, which is thus higher in current state B than in current state G.

Second, the increase in the interest can reduce the demand for debt. Indeed, the derivative of the Euler equation (C3) with respect to the interest rate $r_{l,S}$ yields:

$$
\begin{aligned}
&-\left(\beta\rho_{lh}u''(y_h-d)+\beta\rho_{ll}\pi_{SG}u''(y_l+T_G-d)+\frac{1}{(1+r_{l,S})^2}u''(y_l+T_S+\frac{1}{1+r_{l,S}}d)\right)\frac{\partial d}{\partial r_{l,S}}\\
&=-\frac{1}{(1+r_{l,S})^2}(u'(y_l+T_S+\frac{1}{1+r_{l,S}}d)+\frac{d}{1+r_{l,S}}u''(y_l+T_S+\frac{1}{1+r_{l,S}}d)),
\end{aligned}
$$

which shows that $\frac{\partial d}{\partial r_{l,S}}$ can be negative and that debt demand can decrease with the interest rate. For instance, it is always negative when the intertemporal elasticity of substitution is greater than 1, i.e., when $-c\frac{u''(c)}{u'(c)} \leq 1$ for all $c > 0$ (which is a standard assumption in the literature). In that case, since $r_{l,B} > r_{l,G}$ (see Proposition 2), the interest rate effect contributes to the reduction of the demand for debt in current state B compared to current state G.

Overall, this formally shows that the debt demand results from two possibly opposing forces and that the relationship between P2P debt demand and public transfers is, in fact, not straightforward: the (positive) consumption smoothing effect is stronger in current state B than in current state G, while the interest rate effect can lower the debt demand in current state B compared to current state G. Note however, that under Proposition 1 (proved in Appendix C.2), the demand for debt is always higher in current state B than in current state G, regardless the interest rate, and hence that the consumption smoothing effect effect always dominates the interest rate effect.

D 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.

D.1 The focus on Settlement Funding Assessment

As described in Section 3, we are interested in the causal effect of $\Delta \mathit{Funding}$ 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 (Atkins and Hoddinott, 2022; Sandford, 2023). 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 $\Delta \mathit{Funding}$ and do not include council taxes and reserves in our main analyses.[46]

D.2 Falsification tests

Another important concern is that 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 say observable socioeconomic characteristics from LADs just above the cutoff, then such differences might be positively correlated with $\Delta \mathit{Funding}$ as well as the outcomes of interest pertaining to P2P lending, thereby invalidating our RD design. We run two tests to verify the validity of our RD design in light of these concerns.

First, we check for the presence of discontinuities in observable socioeconomic characteristics of treated and control LADs near the cutoff. The presence of such discontinuities would imply that the effect of funding cuts on the P2P lending outcomes is likely to be confounded. Figure D1 in this Internet Appendix presents a graphical illustration of the RD effects for several observable LAD characteristics that are not associated directly with

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

Δ*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.

Second, Table 1b compares P2P lending and socioeconomic characteristics of treated LADs that have Δ*Funding* in $[-25\%, 0\%)$ interval with control LADs having Δ*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 Δ*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 Δ*Funding* , which likely affects P2P lending outcomes.

D.3 Can LADs influence CG funding decisions?

Individual LADs may also exhibit differences along political lines in ways unobservable to the researcher. For instance, certain LADs may engage in proactive lobbying efforts with the CG to secure additional grants, a situation that could lead to their exclusion from the treatment group. In a formal context, such a scenario suggests that certain LADs wield significant political influence over the allotment of CG welfare transfers, thereby rendering our RD design invalid.

To directly address this concern, having access to annual data detailing the political lobbying efforts of LAD governments concerning the allocation of SFA would be the ideal solution. Unfortunately, such information is not publicly available. Therefore, we employ an indirect approach by scrutinizing the political compositions of government representatives within individual LADs and the CG. Our underlying assumption is that the effectiveness of lobbying by an LAD for SFA may be higher when the same political party holds the majority at both the LAD and CG levels. Conversely, when there is a lack of sufficient political alignment between the LAD and CG, lobbying for SFA may face greater challenges. Hence, if LAD governments do indeed possess the capacity to influence CG funding decisions through their lobbying efforts, we would anticipate a negative correlation between political alignment and funding reductions.

To test this hypothesis, we utilize data sourced from the UK Election Statistics obtained from the House of Commons Library. Our approach begins by constructing annual series detailing the government representatives compositions of both LAD and CG (i.e., members of the House of Commons). Following this, we generate binary variables that identify the predominant political party in LAD governments, namely the Conservatives, Labour, or

Liberal Democrats. We then proceed to create two distinct measures of political alignment between each LAD and the CG. The first measure, denoted as *Same Major Party (LAD & CG)* is a binary variable assigned the value of one when the same political party holds the majority of member seats in both the LAD and CG governments, and zero otherwise. The second measure, labeled as *Political Alignment (CG/LAD)*, precisely quantifies the level of political alignment by accounting for simultaneous variations in the seat distribution held by the dominant party within an LAD and the CG. It is expressed as a ratio where the numerator denotes the proportion of seats controlled by the majority party in the House of Commons, while the denominator represents the proportion of seats held by the majority party in the LAD government. We multiply this ratio with an indicator function that assumes a value of 1 when the same political party holds the majority in both the CG and LAD parliaments and -1 otherwise. A positive value for *Political Alignment (CG/LAD)* signifies that the same political party enjoys a majority in both the CG and LAD parliaments, while a negative value indicates the opposite. Furthermore, the magnitude of *Political Alignment (CG/LAD)* provides insight into the relative strength of majorities within the CG and LAD parliaments, respectively.

To investigate whether political alignment influences SFA decisions, we conduct regression analyses with the dependent variables as $\Delta Funding$ as well as the year-on-year change in SFA against *Same Major Party (LAD & Center)* and *Political Alignment (Nat/LAD)*. Additionally, we also test whether LAD-level socioeconomic factors including unemployment rate, percentage of unemployment claimants of CG welfare benefits, and per-capita gross domestic household income impact SFA decisions.

The results are presented in Table D1 in this Internet Appendix. In Panel (a), it is evident that none of the dummy variables representing the majority parties in power within LADs exhibit statistical significance. This indicates that, in general, annual SFA decisions by the CG do not correlate with any of the three major political parties holding power at the LAD level. Furthermore, the coefficients of both *Same Major Party (LAD & CG)* and *Political Alignment (CG/LAD)* are statistically insignificant. Consequently, there is no supporting evidence to suggest that closer ties between political parties at the LAD and CG levels contribute to influencing SFA decisions. Additionally, local socioeconomic conditions do not have any discernible association with SFA decisions either. In Panel (b), we replicate the same analysis using $\Delta Funding$ over the preceding three years as the dependent variable. Consequently, our independent variables comprise three-year averages of LAD-specific socioeconomic factors. Once again, all coefficients exhibit statistical insignificance. Taken together, these findings suggest there is very limited scope for LAD governments (and political representatives at the local level) to influence SFA decisions of the CG.

D.4 Did the funding cuts increase household financial distress?

We check 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.[47] 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.

The results are presented in Table D2. 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.

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

Figure D1: 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.

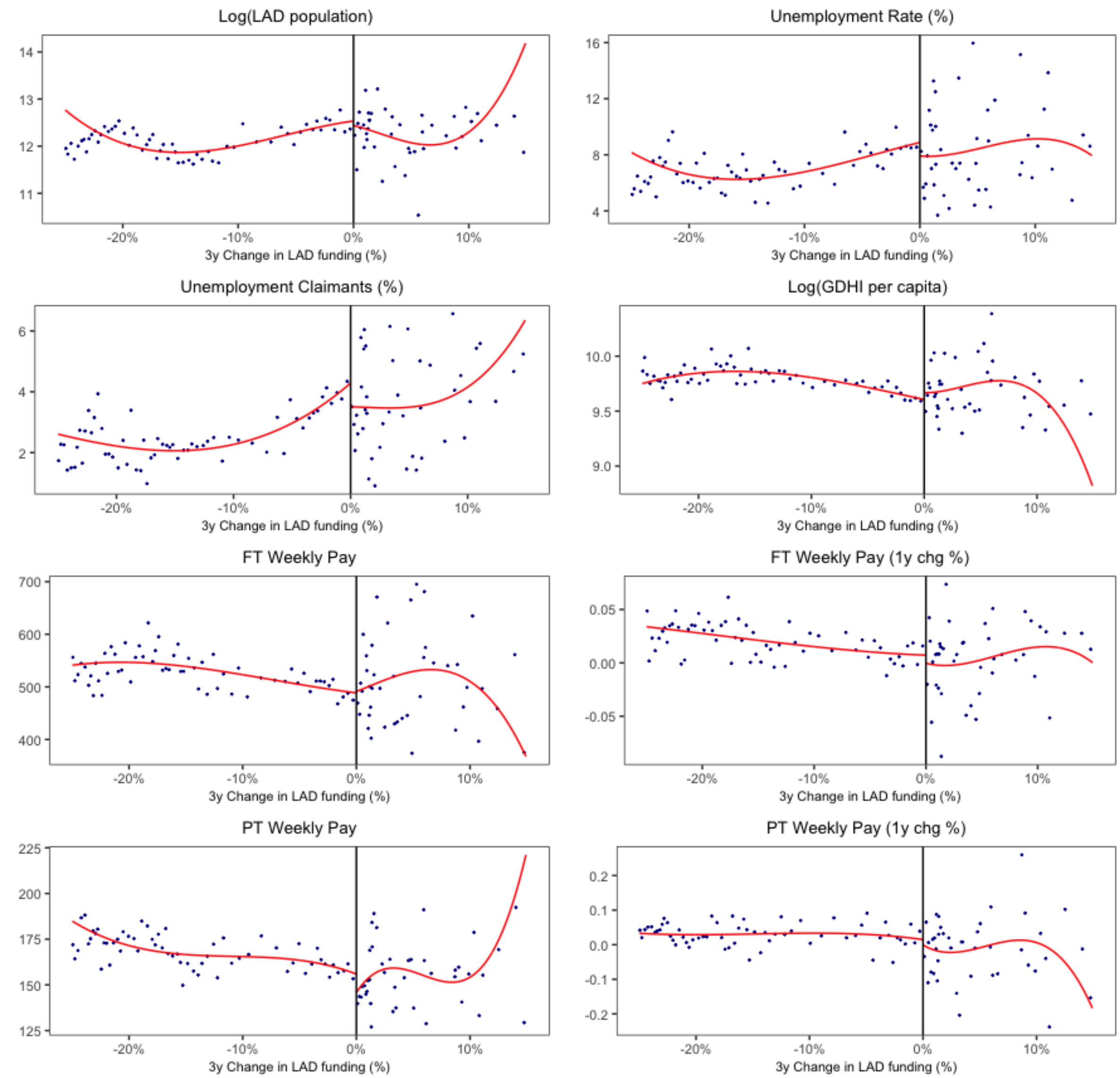


Table D1: Do political and socioeconomic factors determine LAD funding?

Table presents OLS regression estimates of the impact of political alignment between LAD and the CG parliaments on the SFA allocation decisions by the CG. Data for this analysis is based on the UK Election Statistics, drawn from the House of Commons Library. The dependent variable in Panel (a) is the annual rate of change in SFA funding for a given LAD (Δ*Funding* (YoY)); the dependent variable in Panel (b) is the cumulative change in funding (Δ*Funding* (3y)) in a given LAD over the preceding three years. *Major Party LAD (Conservative)*, *Major Party LAD (Labour)*, *Major Party LAD (Lib Dem)* are dummy variables equal to one whenever the corresponding party holds majority in the LAD parliament. *Same Major Party (LAD & CG)* is a binary variable that takes the value of one when the same party holds the majority of seats in both the LAD and CG parliaments. *Political Alignment (CG/LAD)* is the signed relative strength of majorities in the CG and LAD parliaments. See Section D.3 for the formal definition of this variable and Section 4.2 for definitions of other variables. Regressors in Panel (a) are in levels of the corresponding variables; regressors in Panel (b) are three year averages of the corresponding variables. All models include the LAD and year fixed effects. Standard errors are clustered by year and reported in parentheses. ***, **, * indicate 1%, 5%, and 10% significance levels respectively.

(a) YoY change in LAD funding

Dependent Variable:	ΔFunding (YoY)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Major Party LAD (Conservative)	-0.002					
	(0.016)					
Major Party LAD (Labour)	-0.006					
	(0.013)					
Major Party LAD (Lib Dem)	0.029					
	(0.025)					
Same Major Party (LAD & CG)		0.011				
		(0.016)				
Political Alignment (CG/LAD)			0.006			
			(0.009)			
Unemployment (%)				0.785		
				(0.528)		
Unemp Claimants (%)					0.040	
					(0.029)	
Log(GDHI per capita)						-0.132
						(0.107)
Local authority FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,171	4,171	4,171	3,628	3,594	3,702
Adjusted R^2	0.756	0.756	0.756	0.769	0.788	0.530

(b) 3y cumulative change in LAD funding

Dependent Variable:	ΔFunding (3y)				
Model:	(1)	(2)	(3)	(4)	(5)
Same Major Party 3y Avg (LAD & CG)	0.011				
	(0.007)				
Political Alignment 3y Avg (CG/LAD)		0.004			
		(0.004)			
Unemployment 3y Avg (%)			0.432		
			(0.412)		
Unemp Claimants 3y Avg (%)				0.017	
				(0.016)	
Log(GDHI per capita 3y Avg)					-0.105
					(0.067)
Local authority FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	3,466	3,466	2,839	2,993	3,027
Adjusted R^2	0.761	0.761	0.780	0.790	0.705

Table D2: 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