MITIGATING A DEMAND SHOCK THROUGH FINTECH*

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Abstract

This paper examines how FinTech helps firms mitigate adverse effects from negative demand shocks. Exploiting variation between U.K. firms' customer base exposure to the cost-of-living crisis, this study investigates the firm adoption and implications of "Buy Now, Pay Later" (BNPL) technology. Employing matched difference-in-differences and triple-differences estimations, results show that firms in industries with demand that is more elastic to the income of young households are more likely to adopt BNPL after the cost-of-living crisis. Further, BNPL-adopting firms show higher sales, profitability, and survival rate compared to non-adopters. The findings speak to the effects of the consumer financial constraints on firm-level FinTech adoption during macroeconomic shocks, and demonstrate how BNPL technology helps mitigate a negative consumer demand shock for firms.
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I INTRODUCTION

"Buy Now, Pay Later" (BNPL), a novel financial technology (FinTech) that enables consumers to split purchases into installments at the point of sale, has been spreading quickly in many countries. So far, most literature has focused on the consumer side by showing that BNPL encourages spending and can lead to overborrowing (e.g., deHaan et al. 2024; Cornelli, Gambacorta, and Pancotto 2023; Guttman-Kenney, Firth, and Gathergood 2023). However, empirical evidence on what drives firms' adoption of BNPL and how this might impact their performance is scant. In this paper, I hypothesize that firms may be particularly interested in adopting BNPL during a negative macroeconomic demand shock when consumers typically cut back on consumption (e.g., Krueger, Mitman, and Perri 2016; Mian and Sufi 2018; Kaplan and Violante 2018; Di Maggio and Kermani 2017). By adopting BNPL, firms can enable liquidity-constrained households to maintain their consumption through installment payments, which in turn can mitigate the negative demand shock effect on their sales and, ultimately, profitability.[1]

The U.K. market provides an ideal setting to examine this hypothesis. First, the U.K. is one of the biggest and fastest-growing BNPL markets in the world. The market size of BNPL has grown by more than 200% per year in the U.K., outpacing the growth rate in other developed countries in Europe, such as Germany and Sweden (Visa 2022). Also, one-in-four adults in the U.K. has made at least one BNPL purchase in their life (FCA 2023). Second, between 2021 and 2022, U.K. inflation surged by more than 10 times to the highest level in four decades, from approximately 1% in 2020 to 10.1% in October 2022. The rapid increase in prices forced consumers to cut back on discretionary spending, which has been dubbed the "cost-of-living crisis" (Harari et al. 2024; ONS 2024b; Ellett, Linda 2024). While inflation also increased in the U.S. and the E.U., peaking at 9.1% and 10.6% in 2022 respectively, both economies experienced a faster subsequent decline. In contrast, U.K. inflation remained above 10% in early 2023 and declined more slowly than in the U.S. and the E.U., making the British cost-of-living crisis uniquely persistent and severe (Eurostat 2025; USBLS 2025). Third, in the U.K., private firms are usually required to disclose their financial statements with firm-level information, an institutional feature not common in other countries, such as the U.S. Altogether, these institutional features allow me to analyze the BNPL adoption more comprehensively.

[1] In this paper, I use the terms households and consumers interchangeably to refer to the end users of goods and services.

Within this setting, I use the cost-of-living crisis as an exogenous shock to consumer spending. In particular, I exploit the variation in exposure to the shock across industries based on the average consumer age. Survey and household expenditure evidence show that younger households, which generally have lower income, limited savings, and more constrained access to credit, experienced the largest decline in real spending among all age cohorts during this crisis (Whelton 2024; Youth Select Committee 2024; Earwaker 2022; Murray and Gunn 2023). As such, industries with a consumer demand more (less) elastic to the income of young households are expected to be more (less) affected by the cost-of-living crisis and are identified as treated (control). To support such conjecture Figure I shows the average weekly household consumption across treated (red) and control (blue) industries around the cost-of-living crisis. While both industry groups show a parallel trend before the crisis, the average spending in treated industries fell sharply during the crisis, confirming the heterogeneous impact of the crisis across industries.

(Insert Figure I here)

Once treated and control industries are identified, I hypothesize that: (1) firms operating in treated industries (treated firms) are relatively more likely to adopt BNPL than those operating in control industries (control firms); and (2) BNPL adoption attenuates the adverse effects of the negative demand shock on firm performance and survival. To test these hypotheses, I create a firm-level BNPL adoption measure using novel website technology data retrieved from BuiltWith Pty Ltd (BuiltWith), which covers a large sample of public and private U.K. firms. With these data, I identify the payment technology used by firms in their online shops. I combine this measure with detailed firmographic and financial statement data from Orbis, spanning from 2017 to 2023. As the crisis started in early 2021 and persisted through mid-2024 (Francis-Devine et al. 2024), I define 2017-2019 as the pre-crisis period, and 2021-2023 as the crisis period.[2] Further, to mitigate the potential concern that firms in the treated and control industries may differ along observable characteristics that also affect BNPL adoption. I use one-to-one propensity score matching (PSM) estimation where each treated firm is matched with one control along several dimensions (i.e., industry, size, age, leverage, cash, and gross profitability). I further require both treated and control firms to have an E-commerce website established before the crisis to rule out the possibility that differences in business models and digital readiness drive the results. The matched final sample counts 1,502 U.K. E-commerce firms, with a balanced number of treated and control firms.

[2]I exclude 2020 to mitigate the concern that the shock of COVID-19 might affect the results.

Using a pairwise matched DID estimation, I find first that firms in industries more exposed to the demand shock are significantly more likely to adopt BNPL during the crisis by approximately eight percentage points. During the crisis, around one-in-five E-commerce firms in the treated industries adopted BNPL, which is twice as large as that in the control sample where approximately one-in-ten firms adopted such technology. This effect, robust to firm, year, and industry-by-year fixed effects, is both statistically and economically significant, suggesting that adoption was a strategic response to weakened consumer demand.

Furthermore, I show that BNPL adopters in treated industries achieve higher turnover, profitability, and survival during the crisis, while non-adopters with the same exposure experience a significant decline. Compared to the control group, BNPL adopters in treated industries experience about 33% higher revenue, whereas non-adopters in the same industries face a 17% decline. Interestingly, when I look at the effect of BNPL adoption at the market level by comparing treated and control industries, I find no significant differences in exit and market concentration after the crisis. This possibly suggests that benefits achieved by adopters offset the possible losses borne by non-adopters. By sustaining firms' revenues during the crisis, BNPL adoption, thus, not only improves firm-level resilience but also mitigates the impact of the crisis at aggregate level.

To further validate the interpretation that firms adopted BNPL to mitigate the negative demand shock, I conduct two more tests. First, I examine whether the observed adoption and performance results could instead be explained by a supply-side channel. For instance, improvements in production efficiency or a reduction in input prices could enhance profitability through the supply channel. Results show no evidence of reductions in the cost-of-goods sold (COGS)-to-turnover ratio among BNPL adopters, ruling out the supply-side explanation. Second, I test whether adoption was more likely among firms closer to financial distress, for whom sustaining sales is the most critical element for survival during a crisis. Results show that the effect of the crisis on BNPL adoption is significantly stronger for firms with lower Altman Z-scores, further supporting the conjecture that adopting BNPL was a strategic response of firms to shield themselves from adverse demand shocks.

Several other tests validate the robustness of the main results. First, one concern could be that firms in treated industries might have the propensity to adopt BNPL, irrespective of the crisis, simply because their typical customers, e.g., younger consumers, are more likely to use BNPL (deHaan et al. 2024). The inclusion of firm-fixed effects should mitigate such concern. Nonetheless, I perform a dynamic difference-in-differences (DiD) specification that shows no evidence of pre-trends in the BNPL adoption outcomes between treated and control firms, supporting the parallel-trends assumption and mitigating this concern.

Second, I verify the validity of the triple-differences (DDD) estimations about the effect of BNPL adoption on firm performance with three alternative tests. First, if treated firms already outperformed the controls before the crisis, irrespective of adopting BNPL, then the DDD results might capture more simply pre-crisis dynamics rather than the BNPL effect. Matching treated and control firms along several observable dimensions might attenuate this concern. Nonetheless, I estimate a dynamic DID model separately for adopters and non-adopters. I find no significant pre-crisis differences between treated and control firms in either group. Second, I examine whether adopters differ systematically from non-adopters even before the crisis by estimating dynamic DID models that compare adopters and non-adopters within treated and control groups. Results show no evidence of significant differences, suggesting that a potential selection bias does not affect the main results. Last, I conduct a Monte Carlo placebo simulation by randomly reassigning treatment status across industries. Results from the simulation confirm that the estimated effects of the baseline regressions are not random variations.

A natural question is why not all firms in treated industries adopted BNPL despite its positive effects on sales and profitability. To answer this question, I exploit a number of cross-sectional differences that might be indicative of the presence of barriers in adopting BNPL. Specifically, I examine the impact of financial constraints, supply chain concentration, and managerial characteristics. First, financial constraints may represent a barrier since BNPL adoption is likely to increase the firm demand for working capital and, as a result, its cost-per-sales. Financially constrained firms may simply lack the internal funds and/or access to external credit to implement and afford this technology. Indeed, results show that financially unconstrained firms are significantly more likely to adopt BNPL, suggesting that BNPL adoption is costly for firms and requires adequate levels of liquidity.

Second, supplier market concentration could limit the ability of firms to adopt BNPL as they may need to expand inventories to meet higher consumer demand. Firms with stronger bargaining power in competitive supplier markets can negotiate better input prices and/or more favorable payment terms, helping them absorb the additional pressure from a higher demand. By contrast, firms in concentrated supplier markets, facing limited flexibility in supplier negotiations, may find it harder to accommodate the increased working capital demands associated with BNPL. Indeed, I find that treated firms are only more likely to adopt BNPL if their suppliers market is competitive. Overall, these two tests suggest that when it comes to adopting BNPL technology, firms trade-off the costs of further pressure on their working capital management with the benefits of a potential increase in their goods demand.

Last, the age of a firm's directors could potentially act as a barrier to BNPL adoption. Previous literature suggests that younger managers are more open to new technology adoption and have higher risk tolerance compared to older managers (e.g., Barker III and Mueller 2002; Acemoglu, Akcigit, and Celik 2022; MacDonald and Weisbach 2004). However, I find that the likelihood of adopting BNPL in response to the crisis is not statistically different between treated firms with younger directors and those with mature directors. Interestingly, these results further support the interpretation that firms adopt BNPL as a response to the crisis rather than as a result of managerial preferences or human capital differences.

Literature Review. The study contributes to four streams of literature. First, it contributes to the emerging literature on the firm's FinTech adoption. For example, Cong, Yang, and Zhang (2024) show that firms with prior digital experiences and stronger production networks are more likely to adopt E-commerce under Covid-19; Higgins (2024) finds that network externalities drive the firm's adoption to point-of-sale terminal; Gao, Marchica, and Petry (2025) suggest awareness to digital technologies and training in digital skills promote firm-level adoption of digital technologies, such as E-commerce and data analytic tools. I add to this literature by showing that firms adopt BNPL in response to weakened consumer demand, suggesting the firm's FinTech adoption decision is directly affected by the liquidity constraints of its consumers.

Second, to the best of my knowledge, my study is the first to document the causal effect of BNPL adoption on firm performance using a large sample of public and private firms. Previous studies examine BNPL mainly from the consumers' perspective, highlighting the effects of BNPL on consumers' spending and borrowing behaviours (e.g., Bian, Cong, and Ji 2023; Di Maggio, Williams, and Katz 2022; Cornelli, Gambacorta, and Pancotto 2023; Guttman-Kenney, Firth, and Gathergood 2023; deHaan et al. 2024; Chen et al. 2024; Laudenbach et al. 2025; Donou-Adonsou and Leslie-Piper 2025; Aidala et al. 2025). The only exception is Berg et al. (2025), they provide experimental evidence using a randomized control trial within a German E-commerce furniture retailer and showing that offering BNPL increases sales through price discrimination. On the contrary, I look at the effects of BNPL adoption from the firm's perspective using a large sample of E-commerce firms and showing a positive side of BNPL adoption on firm performance and resilience during economic downturns.

Third, I provide novel evidence that links consumer credit access to firm outcomes. Evidence from household finance literature shows that expanding consumer credit can affect real economic outcomes, such as housing prices (e.g., Favara and Imbs 2015; Di Maggio and Kermani 2017; Mian and Sufi 2018; Justiniano, Primiceri, and Tambalotti 2019; Adelino, Schoar, and Severino 2025), aggregate employment (e.g., Mian, Sufi, and Verner 2020) and labor outcomes (e.g., Dobbie et al. 2020; Herkenhoff, Phillips, and Cohen-Cole 2021). So far, however, there is little evidence on its effects on the performance of firms, and previous studies have predominantly focused on household mortgages. I differentiate from these studies by using the BNPL availability as a proxy for consumer access to credit and demonstrate that smoother consumer credit access can positively affect firm performance during times of negative demand shocks.

Fourth, I add to the literature on firm resilience under adverse demand shocks. Previous literature found that firms maintain their performance and avoid exits under the demand shock through adjusting their inventory and labour policies, optimizing prices and markups, and reallocating production lines (e.g., Chevalier, Kashyap, and Rossi 2003; Bernard, Redding, and Schott 2010; Kashyap, Lamont, and Stein 1994; Bils and Kahn 2000; Giupponi, Landais, and Lapeyre 2022; Hart 2023). I contribute to this literature by showing that BNPL, as a FinTech innovation, enables firms to stabilize demand during negative shocks, thereby enhancing firm-level performance and resilience and preventing potential industry-level shakeouts.

The remainder of the paper is organized as follows. Section II explains the institutional details of the cost-of-living crisis and BNPL. Section III describes the research design and the data. Section IV presents the baseline results both at firm- and industry-level. Section V presents the validity and robustness tests. Section VI reports the tests on the mechanisms underlying the baseline results. Section VII discusses the barriers to the firm's adoption of BNPL, and Section VIII concludes the paper.

II INSTITUTIONAL BACKGROUND

II.A The Cost-of-Living Crisis

In the U.K., the cost-of-living crisis is referred to as the period beginning early 2021, when the amount of money people need for essential goods, such as food, shelter, and energy, has been increasing rapidly (Francis-Devine et al. 2024). Between 2021 and 2022, the U.K. experienced a sharp acceleration in inflation, with the Consumer Prices Index including housing cost (CPIH) surging more than tenfold, to 10.1%, as shown in Figure II.[3] The increase in inflation persisted through 2022 and started to fall after October 2022. Still, at the end of 2023, inflation had quadrupled compared to the level at the beginning of 2021. During this period, prices for essential goods and services increased rapidly. For instance, food price inflation peaked at 19.2% in March 2023, which was the highest rate in the U.K. since 1977 (ONS 2024a). Likewise, domestic energy bills more than doubled during this period (Bolton 2025). As the growth of the prices of necessities outpaced wage growth, real incomes declined, forcing households to reduce non-essential spending (Harari et al. 2024; ONS 2024b; Ellett, Linda 2024).

(Insert Figure II here)

Recent developments in macroeconomic and household finance literature suggest that aggregate shocks can have a heterogeneous impact across different cohorts of households (Kaplan and Violante 2018). This heterogeneity plays a central role in the transmission of shocks to the wider economy (e.g., Di Maggio and Kermani 2017; Mian and Sufi 2018). However, empirical evidence is limited on how the difference in responses of households to macroeconomic shocks translate into real economic outcomes for firms, including their revenues, profitability, and survival.

The cost-of-living crisis in the U.K. provides a unique opportunity to empirically

[3]Several shocks, including the energy price shock and supply chain disruptions, contributed to this surge. These confounding shocks are less likely to affect the conclusion of this paper. If energy or supply-side shocks alone were driving the results, treated and control groups would exhibit different movements in their production costs. For example, if the treated (control) group have a lower (higher) exposure to energy shocks, I should observe a lower production cost in the treated when compared to the control group during the crisis. In Section IV, I test this hypothesis explicitly by showing that the COGS-to-Turnover ratio did not change differentially between the two groups, suggesting that variations in input costs are unlikely to explain the main findings.

Another potential cause of the inflation would be the aftermath of COVID-19. I control for that by restricting the sample to E-commerce firms established before the crisis. Thus, treated and control firms have similar exposures to COVID-19. Thus, this event is also less likely to drive the results.

document such evidence. Survey data and household expenditure records indicate that younger households were disproportionately affected by the crisis, reflecting their generally lower incomes, limited precautionary savings, and more constrained access to credit relative to older cohorts. At the end of 2022, a large-scale survey conducted by the Joseph Rowntree Foundation showed that households with a reference person under the age of 30 were three times more likely to report a shortage of essential goods required for daily living, compared to older households (Earwaker 2022). Moreover, the cost of rent increased by approximately 12% in 2022, which further squeezed the disposable income of young households that, on average, spend 47% of their gross income just on rent, corresponding to 14 percentage points above the national average (Murray and Gunn 2023).

This unexpected increase in the cost-of-living forced young households to change their spending patterns more drastically than other age groups. Compared to young households, older age groups have been better able to maintain their spending, due to either their less constrained access to credit or their reliance on pension, which is often inflation-protected (e.g., Brewer, Fry, and Try 2023; Ray-Chaudhuri et al. 2023). In line with this view, the average weekly spending by households under age 30 on non-essential goods and services declined more significantly than that of other age groups (Whelton 2024).[4]

As a result of such change in spending patterns, industries that depend heavily on such discretionary spending are expected to experience more pronounced reductions in demand during this period. Such heterogeneity in response to a crisis creates an interesting setting to explore the differential impact on firms across industries.

[4] I do not define the treated and control group based on the low-income group because, the U.K. government has introduced a bundle of subsidies during the crisis, including cash payments and tax credits, designed exclusively to support this cohort of households (e.g., see: Gov.UK (2023) and Gov.UK (2025)). Such policies were likely to stabilize the spending of low-income households, thereby confounding the effects of the crisis. In contrast, to the best of my knowledge, no policy targeting young people was implemented during the crisis. Further, data from the British Household Panel Survey and the Current Population Survey suggest that, both in the U.K. and the U.S., the distribution of income is similar between young households (20 to 30 years old) and older households (30 to 45 years old) (Ozhamaratli, Kitov, and Barucca 2022). As such, the elasticity measure based on young households' income captures more precisely the industry-level exposure to the crisis and mitigates the concern that confounding government policies might affect the results.

II.B BNPL in the U.K.

BNPL is an unsecured short-term consumer credit arrangement offered at the point of sale, which allows customers to divide payments into installments, typically interest-free if paid on time. The repayment period usually range from 30 to 90 days, and in some cases up to twelve months. A typical BNPL transaction involves three parties: the consumer, the merchant, and the BNPL service provider (platform). When a customer chooses BNPL as the payment method at checkout, the provider pays the merchant the full purchase price minus a transaction fee. This fee represents a credit risk premium since the platform takes all the credit risk of the transaction.[5] The customer then repays the platform in installments, which are interest-free if payments are made on schedule (see Cornelli, Gambacorta, and Pancotto (2023) for a visual illustration).

The BNPL market in the U.K. has grown rapidly in recent years. One-in-four British adults used BNPL at least once in 2023 (FCA 2023). The value of BNPL transactions ranged from around £10 to £3,000, with an average of £68 (Experian 2023). The market is dominated by a few BNPL platforms. The largest platform, Klarna, has obtained more than 80% of the market share (BuiltWith 2025a). In 2024, Klarna reported 11 million active U.K. customers and over 60,000 U.K. merchants (Klarna 2025). The next three major players in this market are Afterpay, PayPal, and Laybuy. Together with Klarna, these large players account for more than 97% of the U.K. BNPL market (BuiltWith 2025a). The BNPL market in the U.K. is very similar to that in the U.S., with a fast growth rate, a highly concentrated structure, and the top five providers controlling more than 95% of the market share, among which Klarna is the largest player (BuiltWith 2025b).

In the U.K., BNPL services still operate outside the scope of formal consumer credit regulation. The platforms do not have to comply with the requirements of the Consumer Credit Act 1974 (CCA), which is the legislation governing other consumer credit products such as credit cards (HM Treasury 2025). Common requirements on other consumer credit products, such as affordability assessments, interest disclosures, or mandatory credit reporting, do not yet apply to BNPL services. Further, using BNPL services does

[5] The transaction fee paid by the merchant for each BNPL transaction is higher than for a credit-card transaction, typically by several percentage points, across different countries (Cornelli, Gambacorta, and Pancotto 2023). In the U.K., credit card transactions cost the merchant around 1.5% to 3.4% (Moore 2025), whereas BNPL transactions often cost more than 5%. For example, Klarna, which is the largest BNPL platform in the U.K. with over 80% of the market shares, charges the merchant 4.99% plus £0.20 per transaction on average (BuiltWith 2025a; Wallid 2025).

not affect the customer's credit scores.[6] As a consequence, BNPL products are more readily accessible, particularly to younger or credit-constrained consumers, compared to credit cards. Recent evidence seems to support this by showing that BNPL users tend to be younger, have lower levels of education, carry higher existing debt burdens, and exhibit weaker credit profiles (Cornelli, Gambacorta, and Pancotto 2023; deHaan et al. 2024).

During the cost-of-living crisis, the demand for BNPL services increased from the customer side as it allows them to sustain consumption by easing short-term credit constraints (Di Maggio, Williams, and Katz 2022; Cornelli, Gambacorta, and Pancotto 2023; Bian, Cong, and Ji 2023).

For firms, however, the decision of whether to adopt BNPL involves a benefit-cost trade-off. Although BNPL can help sustain demand by enabling purchases from liquidity-constrained consumers, it also incurs the additional costs per sale, in the form of a transaction fee paid to the platform, which reduces profit margins. As such, ex ante, it is unclear whether a firm is willing/able to adopt BNPL, even during a crisis. The first part of my paper aims to investigate that decision in more detail.

III METHODOLOGY AND DATA

III.A Identification of Treated and Control Industries

To examine how firms adopt BNPL as a response to the negative demand shock, I define the treated and control firms based on their industry exposure to the cost-of-living crisis. Lim, Kim, and Agarwal (2023) suggest that negative demand shocks do not affect all firms uniformly. Instead, the severity of shocks depends on their demand elasticity. Given that the demand of young households for discretionary goods and services was disproportionately affected by the crisis (Earwaker 2022; Murray and Gunn 2023; Whelton 2024), I define the industries with the demand that is more (less) elastic to income of young people as the treated (control) industries, where young people are those under the age of 30.[7] Specifically, I calculate a measure of income elasticity of demand, E^{u30}, as follows:

[6] The U.K. is initiating regulation for BNPL, which was first announced in 2025 and is expected to be effective in 2026. (See: FCA (2025)). Thus, the regulation governing BNPL is absent during the sample period of this study.

[7] The age of 30 is the youngest cohort available in household consumption data.

$$E_{j,t}^{u30} = \frac{\%\Delta Real\ Consumption_{j,t}^{u30}}{\%\Delta Real\ Income_{t}^{u30}}, \tag{1}$$

where $\%\Delta Real\ Consumption^{u30}$ is the percentage change of the average real consumption of young households ("u30") in each five-digit Standard Industrial Classification (SIC-5) code (j) each year (t); and $\%\Delta Real\ Income^{u30}$ is the percentage change of the average real income of the same young households each year. $E_{j,t}^{u30}$ captures how sensitive each industry's j demand is to changes in the income of young households each year t. For each SIC-5 code, I compute their average demand elasticity between 2002 and 2019, which is the maximum period available before the crisis. Treated (control) industries are then defined as those whose average pre-crisis demand elasticity is above (below) the median distribution across all industries.

Since BNPL is a consumer-facing FinTech that allows the payment to be split into interest-free installments at the checkout, I restrict the sample to industries in which firms can accept individual customer payments through an online checkout interface. Specifically, I exclude industries where transactions are primarily business-to-business or contract-based, including agriculture, construction, manufacturing, wholesale, business services, and video production. Furthermore, I exclude industries with transaction sizes or regulatory features that make short-term installments inapplicable, including real estate, public administration, utility, postal, and repairing. Finally, I exclude industries for membership-related activities, where revenues primarily consist of periodic dues or subscriptions collected via account billing arrangements (e.g., direct debit or standing orders) rather than per-purchase payments. In such industries, BNPL is not applicable.[8] Excluding such industries mitigates the concern that results might be mechanically driven by firms that would not adopt BNPL under any circumstance. As a result, 42 (47) SIC-5 codes are defined as treated (control) industries.[9] Firms operating in the treated (control) industries are then defined as treated (control) firms.

[8] As a verification, I check the business categories listed on Klarna's website. There is no business in any of the excluded industries.

[9] The treated industries that have the highest youth-specific income elasticity of demand are artistic creation (90030), retail sale of sporting equipment in specialized stores (47640), travel agency activities (79110), and retail sale of games and toys in specialized stores (47650); The control industries that have the lowest youth-specific income elasticity of demand are retail sale of medical and orthopaedic goods in specialized stores (47740), retail sale by opticians (47782), Other human health activities (86900), retail sale of textiles in specialized stores (47510).

III.B Adoption of BNPL during the Crisis

To examine whether firms in industries with higher exposure to the negative demand shock adopted BNPL as a response, I estimate the effect of the crisis on BNPL adoption using a matched DiD framework with firm and time fixed effects, as follows:

$$BNPL_{i,t} = \delta(Crisis_t \times Treated_i) + \mathbf{F_{i,t,j}} + \epsilon_{i,t}, \tag{2}$$

where $BNPL_{i,t}$ is a dummy variable equal to one if the firm i has adopted BNPL on its website in year t and zero otherwise. $Crisis_t$ equals one in the crisis-period (2021–2023) and zero for the pre-period (2017–2019). $Treated_i$ equals one (zero) for firms operating in the treated (control) industries, as defined above. $F_{i,t,j}$ is a matrix of fixed effects including firm (i), year (t), and industry-by-year (j) fixed effects, where industry is defined at the SIC-2 level. Standard errors are clustered at the industry (SIC-5)-by-year level. δ is the coefficient of interest that captures the differential effect of the crisis on the firms' likelihood to adopt BNPL between treated and control firms.

III.C Real Effects of BNPL during the Crisis

Since BNPL offers consumers an accessible way to defer payments, helping sustain their purchases during the crisis period, it could serve as a potential mechanism through which firms mitigate the adverse demand shock. To examine the effects of BNPL adoption on firm performances, I estimate a DDD model as follows:

$$\begin{aligned} Y_{i,t} = {} & \beta_1 \left(Crisis_t \times Treated_i \times BNPL_{i,t}\right) + \beta_2 \left(Crisis_t \times Treated_i\right) \\ & + \beta_3 \left(Treated_i \times BNPL_{i,t}\right) + \beta_4 \left(Crisis_t \times BNPL_{i,t}\right) \\ & + \beta_5 \left(BNPL_{i,t}\right) + \mathbf{F_{i,t,j}} + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

where $Y_{i,t}$ includes *Ln(Turnover)* defined as the natural log of one plus the firm's turnover; *ROA* is defined as the earnings before interest and tax (EBIT) divided by total assets; and *Dissolved*, which is a dummy, equals one if the firm is dissolved or in liquidation in that year and zero otherwise. The triple interaction, β_1, is the coefficient of interest and captures the differential impact on performance during the crisis between BNPL adopters and non-adopters, comparing treated and control industries before and after the crisis. This triple-difference estimate, therefore, provides evidence on whether BNPL adoption might mitigate the adverse impact of the crisis on firms in more affected industries.

The lower-order terms are interpreted as follows: β_2 captures the crisis-period difference in performance between treated and control firms among non-adopters; β_3 captures the difference in performance between treated and control firms that adopt BNPL in the pre-period; β_4 captures the difference between adopters and non-adopters within the control group in the crisis-period; and β_5 captures the difference between adopters and non-adopters within the control group in the pre-period.

III.D Data

I assemble the data for the analysis from three different sources: (1) household-level survey data; (2) BuiltWith Pty Ltd; and (3) Orbis database.

III.D.1 Household-Level Surveys

To construct industry-level young household-specific income elasticity of demand (E^{U30} as in Equation (1), I use data from two official U.K. household surveys published by the Office for National Statistics (ONS). First, the Living Costs and Food Survey (LCF) reports average weekly household expenditure across the Classification of Individual Consumption by Purpose (COICOP) categories by age cohorts.[10] I retrieve the average weekly consumption for households under the age of 30 for each year between 2002 and 2019 and manually map each COICOP category to the corresponding five-digit U.K. SIC codes.[11]

Second, the Household Disposable Income and Inequality (HDII) series reports average disposable income by age cohorts.[12] Since the HDII does not report income for a precise "under-30" cohort, I use the youngest available group (ages 18 to 24) to approximate the income of young households. Both household consumption and disposable income variables are deflated using the CPIH in 2017. I then use the data from these two surveys to construct the industry-level demand elasticity measure, defined as the ratio of the annual percentage change in real consumption to the annual percentage change in real disposable income.

[10] Available on: ONS (2024 c).
[11] In those instances where multiple goods and services are linked to the same SIC code, I use the average value across them.
[12] Available on: ONS (2024 d).

III.D.2 BuiltWith

I construct a firm-level measure of BNPL adoption using data from BuiltWith Pty Ltd following Gao, Marchica, and Petry (2025) and Di Maggio, Williams, and Katz (2022). BuiltWith provides detailed information on web technologies implemented on firm websites. BuiltWith uses web crawlers to regularly scan and record the technologies embedded in websites since 2000. The crawler identifies and tracks the embedded technologies of each website and records the first and last detection dates of each technology.[13] Furthermore, BuiltWith provides a detailed description of each tracked technology and classifies each one into different tags according to their functionality, such as E-commerce, analytics tools, and payment systems. Under each tag, BuiltWith further classifies the technology into detailed categories. BNPL is one of the categories ("Pay Later") under the tag "Payment." Between 2000 and 2023, BuiltWith recorded over 490 million technologies from over 17 million U.K. websites. Among those sites, 80,927 have adopted BNPL. From BuiltWith, I retrieve the historical records of BNPL adoption. Using these records, I construct the BNPL dummy as in Equation (2). Further, BuiltWith provides the name and registration number of each firm that owns the website, allowing their data to be merged with other firm-level databases.

III.D.3 Orbis

Firm-level financial, firmographic, and director information is sourced from Orbis database provided by Moody's. The database provides near-universe coverage of active and historical U.K. public and private companies across the entire spectrum of sizes. From Orbis, I retrieve detailed firm identifiers, including the name, registration number, address, and website URL, along with each firm's legal status (e.g., active, dissolved, in liquidation), which I use to capture firm survivability over the sample period. I also retrieve each firm's U.K. SIC-5 code, which I use to identify the industry in which the

[13]BuiltWith's website crawler works similarly to Google Search by crawling and indexing websites. The crawler robot automatically finds websites on the internet and downloads information from each website ("indexing"). BuiltWith targets to index all country-code top-level domains (ccTLD) as well as any active generic top-level domains (gTLD), such as ".com," ".net," and ".org" in all regions. BuiltWith tracks when technologies are added or removed from a website through either weekly, bi-weekly, or quarterly updates, depending on the activity of the website. Specifically, records are updated weekly for websites with positive technology spending, which is estimated by BuiltWith, bi-weekly for websites with high traffic (identified using ranks such as "Google top 10k sites"), and monthly for active websites. All remaining websites are updated quarterly (BuiltWith 2025). This enables the construction of panel data to track the E-commerce and BNPL adoption status of firms each year.

firm operates and to link firms to the industry-level elasticity measure.

Furthermore, I collect annual financial statement data for each sample firm from Orbis, including the balance sheet and income statement information. I use these data to construct firm-level control variables, including *Size*, defined as the natural logarithm of one plus the total assets; *Age*, defined as the natural logarithm of one plus the firm's age; *Leverage*, defined as the sum of short-term debt and long-term liability divided by total assets; *Cash*, defined as cash divided by total assets; *ROA* as defined above; and *Gross Profitability*, defined as the gross profit divided by the COGS.

In addition, I construct the industry-level exit rate and Herfindahl-Hirschman Index (*HHI*) using the data from Orbis. The exit rate is calculated as the number of firms dissolved or in liquidation divided by the total number of firms in that SIC-5 industry. *HHI* is constructed as the sum of squared sales-based market shares at the industry level.

III.E Sample Construction

I retrieve 73,919 firms operating in the treated and control industries using Orbis database during the sample period from 2017 to 2023.[14] I require the sample firms to have at least one non-missing value of total assets and turnover during the pre-period. This restricted the sample to 8,825 firms.

To mitigate concerns that firms in the treated and control industries differ systematically in business models or digital readiness, I require sample firms to have established an E-commerce website before the crisis using data from BuiltWith.[15] To include both firms that are linked with E-commerce platforms and those with a self-built webstore, I identify the establishment of an E-commerce website as the first detection date of an E-commerce store technology or a checkout button on that website. This filter ensures that both treated and control firms were operating online retail stores before the

[14]For firms with SIC codes that make it impossible to identify the type of goods or services they sell (e.g., SIC 47190: Other retail sale in non-specialized stores), I re-identify their SIC codes using the BuiltWith E-commerce market categories. For example, for E-commerce firms with an ambiguous SIC code but recorded in the "Technology and Computing" category on BuiltWith, I re-identify their SIC code as 47410 (retail sale of computers, peripheral units and software in specialized stores). Similarly, for E-commerce firms with a manufacturing SIC code, I re-identify their SIC codes following the same procedure. This ensures that factory stores are also included in the analysis.

[15]I matched the sample from Orbis to the records retrieved from BuiltWith using a hierarchical approach. First, I merge them using the Companies House registration number if it is available in both databases. Second, for records without a registration number in BuiltWith, I merge them using the website URL. For the remaining unmatched records, I match the legal name and registered address, retaining only exact matches.

shock, mitigating the concern that differences in digital adoption confound estimates of the effect of the crisis on BNPL adoption and firm performance. Moreover, since both groups were actively engaged in E-commerce, unexpected operational disruptions arising from COVID-19, such as social distancing restrictions, are likely to affect them similarly, further limiting potential identification concerns. After this filter, the sample includes 4,466 and 4,285 E-commerce firms established before the crisis in the treated and control industries, respectively.

Panel A in Table I compares the firm characteristics of treated and control groups. Across all dimensions, the two groups of firms appear statistically different. Therefore, I implement a PSM to address concerns that the differences in characteristics between firms in treated and control industries drive the results. The covariates in the PSM are *Size*, *Age*, *Leverage*, *Cash*, *ROA*, and *Gross Profitability*, together with two-digit SIC code dummies. Each treated firm is matched to one control firm based on the propensity score, which is estimated based on the average value of these variables before the crisis, with a caliper of 0.01 and without replacement. The matched sample comprises 1,502 firms, with a balanced number of treated and control firms. Panel B in Table I shows the comparison of firm characteristics after the PSM, confirming that, across all these variables, the treated and control firms are statistically insignificantly different from each other.

(Insert Table I here)

IV RESULTS

IV.A Adoption of BNPL

I begin the firm-level analysis by examining whether firms in industries more exposed to the cost-of-living demand shock are more likely to adopt BNPL in the aftermath of the crisis. Table II presents the baseline results from the matched DiD estimation as in Equation (2). The estimated coefficient on the interaction term is positive and statistically significant at the 1% level in both columns, indicating a higher likelihood of BNPL adoption among firms in treated industries as a response to the crisis. The estimated effect is approximately eight percentage points, which reflects an economically meaningful difference relative to firms in control industries. After the crisis, nearly one in five firms in the treated industries adopted BNPL, which is significantly higher than the adoption rate of approximately one in ten firms in the control industries. This finding provides evidence that firms responded to the cost-of-living crisis by adopting BNPL, consistent with the interpretation that it was used as a tool to manage demand-side pressure.[16]

(Insert Table II here)

IV.B Real Effects of BNPL during the Crisis

Building on the evidence that firms in more exposed industries are more likely to adopt BNPL following the cost-of-living crisis, I next examine whether such adoption helped mitigate the adverse impact of the crisis on firm performance. Table III presents the results estimated by the DDD specification as in Equation (3).

Columns (1) and (2) report the results for *Ln(Turnover)*. Among firms that adopted BNPL, the coefficient of the triple interaction term (*Crisis* $\times$*Treated* $\times$*BNPL*) indicates that revenue in the treated group increased relative to the control by approximately 33% to 35%, significant at the 1% level. Compared to the average revenue of control firms during the pre-period, 33% estimate corresponds to a revenue £2 million higher for the adopters in the treated industries. In contrast, the negative and significant coefficients of the double interaction term (*Crisis* $\times$*Treated*) suggest that firms in treated industries that did not adopt BNPL experienced a larger decline in turnover compared to the control firms that also did not adopt BNPL by approximately 17% to 19%. These results support the conjecture that, during the crisis when purchasing power declines, customers tend to spend more at firms that adopt BNPL compared to firms that did not. In other words, adopting BNPL enabled firms to sustain or even expand their sales in the period of weakened demand.

Columns (3) and (4) report the results for profitability, measured by *ROA*. The positive and statistically significant triple interaction terms indicate that the increase in sales converted into 12% higher profitability for BNPL adopters in treated industries as compared to the control group (Column (3)). In contrast, the negative and significant double interaction terms show that non-adopters in treated industries experienced a larger decrease in their profitability compared to the control ones. This result further supports the idea that BNPL adoption can help firms mitigate the negative impacts of

[16] The result is robust to Probit and Logit models that included the same set of firm-level control variables as used in PSM, together with the year and SIC-2 dummies. The estimated marginal effect (untabulated) shows similar statistical and economic significance as in Table II.

the crisis and maintain their operating performance.

Further, Columns (5) and (6) report the results for the probability of exit (*Dissolved*). The negative and significant coefficient of the triple interaction terms suggest that firms in the treated group that adopted BNPL are significantly less likely to exit during the crisis period, by approximately 12 percentage points (Column (6)), statistically significant at 1%. In contrast, among non-adopters, firms in the treated industries are more likely to exit compared to the control firms, as indicated by the positive and significant double interaction term. This suggests that improvements in revenue and profitability experienced by BNPL adopters are associated with a higher likelihood of survival during the crisis period.

(Insert Table III here)

IV.C Industry-level Results

The firm-level results in Table III show that BNPL adopters had stronger performance and resilience during the crisis compared with non-adopters, who have similar exposure to the crisis. I next investigate whether these firm-level results are reflected at the industry level. Existing evidence suggests that negative demand shocks lead to higher exit rates and increased market concentration (Dunne, Roberts, and Samuelson 1989; Foster, Grim, and Haltiwanger 2016; Bartik et al. 2024; Kozeniauskas, Moreira, and Santos 2022).

Figure III compares the average exit rates (Panel A) and *HHI* (Panel B) trends across treated and control industries.[17] Despite sharper declines in household demand in treated industries, no significant differences in exit or concentration are observed before or after the crisis. This is consistent with the firm-level DDD results in Table III. The positive outcomes for BNPL adopters balance the negative outcomes for non-adopters, resulting in no significant impacts on exit or concentration at the industry level. This suggests that, on average, BNPL adoption mitigates the impact of the crisis and stabilizes the competition at the industry level under the negative demand shock.

(Insert Figure III here)

[17]To have a comprehensive analysis on the industry-level impacts, both variables are constructed based on all firms available from Orbis.

V VALIDITY TESTS

V.A Parallel Trends

For my identification strategy to yield valid causal inferences, the parallel trends assumption must be satisfied. In this section, I verify this assumption using a set of dynamic DiD specifications, which test the treatment effects across time. First, one concern underlying the results on the BNPL adoption (Table II) is that firms in treated industries may be more prone to adopt BNPL, regardless of the crisis, due to their greater exposure to younger consumers, who are more likely to use BNPL (deHaan et al. 2024). To address this concern, I estimate a dynamic version of Equation (2) where the *Crisis* dummy is replaced by the yearly dummies using 2017 as the baseline year, as follows:

$$BNPL_{i,t} = \sum_{k \neq 2017} \gamma_k (1_{t=k} \times Treated_i) + \mathbf{F_{i,t,j}} + \epsilon_{i,t}, \tag{4}$$

Figure IV reports the yearly estimated coefficients. The pre-crisis coefficients are statistically indistinguishable from zero, indicating no differential trends in BNPL adoption between treated and control industries prior to the shock. This mitigates the concern that the propensity to adopt BNPL is systematically higher in the treated industries compared to the control. This implies that, even for the treated firms, the expected benefits of adopting BNPL did not outweigh the associated costs before the crisis. Only when the cost-of-living crisis intensified the liquidity constraints of young consumers, the BNPL adoption rate in the treated group rises above that of the control group, implying that BNPL adoption was more of a strategic response to the crisis rather than a systematic choice by firms in the treated industries.[18]

(Insert Figure IV here)

I then turn to validating the assumptions underlying the DDD specification. While Figure IA.I shows that treated and control firms follow parallel pre-crisis trends in performance, this evidence alone is not sufficient to establish the validity of the DDD model (Olden and Møen 2022). One potential concern is that firms that choose to adopt BNPL may systematically differ in performance compared to non-adopters, even before the crisis. If BNPL adopters were already outperforming the non-adopters before the crisis, the

[18]To be consistent, I verify the parallel trend assumption also for the *Ln(Turnover)* and *ROA*. As shown in Figure IA.I, no significant difference is found between the treated and control groups for both variables. This evidence supports that the parallel trend condition is likely to be held in the DiD design.

estimated triple-differences coefficients could reflect the pre-existing trend rather than the causal effect of adoption.

To address this, I estimate Equation (4), using *Ln(Turnover)* and *ROA* as the dependent variable, separately for adopters and non-adopters, comparing the performance of treated and control within the group of BNPL adopting and non-adopting firms, respectively. Figure V presents the results. Graphs V.I and V.II show the dynamic coefficients for *Ln(Turnover)* estimated within the BNPL adopter and non-adopter subsamples, respectively. In both groups, the coefficients are statistically insignificant before the crisis, suggesting that treated and control firms within each adoption status followed similar trends prior to the shock. Similar results are observed in Graphs V.III and V.IV, which report the same test for ROA. This mitigates the concern that performance results in Table III are driven by differential pre-crisis trends across industries within the adopter or non-adopter group.

(Insert Figure V here)

A further concern is that the treated firms that adopted BNPL during the crisis were already outperforming or underperforming the non-adopters prior to the crisis, and the DDD estimates could be affected by a selection bias into adoption based on pre-crisis dynamics. To address this concern, I estimate Equation (5), which interacts yearly dummies with the BNPL adoption dummy, separately for the treated and control firms. This dynamic specification allows for a direct test of whether adopters and non-adopters within the same industry group followed parallel trends prior to the crisis:

$$Y_{i,t} = \sum_{k \neq 2017} \gamma_k (1_{t=k} \times BNPL_{i,t}) + \mathbf{F_{i,t,j}} + \epsilon_{i,t}, \tag{5}$$

Figure VI presents the results. Graphs VI.I and VI.II show the dynamic coefficients for *Ln(Turnover)* as a function of BNPL adoption when estimated within the treated and control subsamples, respectively. I find no significant difference between the adopters and non-adopters in both subsamples, suggesting that BNPL adopters and non-adopters are comparable in performance before the crisis. Graphs VI.III and VI.IV present the same estimates for *ROA*. Again, there is no evidence of differences between the adopters and non-adopters before the crisis, in both the treated and control groups. These findings mitigate the concerns that the DDD estimates are driven by selection into BNPL based on pre-crisis performance differences.

(Insert Figure VI here)

Overall, the dynamic DiD estimations provide strong support for the identification strategy. The absence of systematic differences in pre-crisis outcomes across both the treatment and adoption dimensions reinforces the credibility of the DiD and DDD models and strengthens the causal interpretation of the findings related to the firm's adoption of BNPL in response to the cost-of-living crisis and its mitigating effect on performance and resilience.

In addition, the dynamic coefficients during the crisis further highlight the mitigating role of BNPL adoption. Specifically, in Figure V, negative impacts on performance are detected only among non-adopters, whereas the coefficients for adopters remain statistically indistinguishable from zero. Moreover, in Figure VI, when comparing adopters and non-adopters during the crisis, positive coefficients emerge only in the treated group, which faced greater exposure to the crisis relative to their control counterparts. Together, these patterns suggest that BNPL adoption results in higher performance only in industries where the demand shock was most severe, consistent with the interpretation that BNPL adoption effectively shielded firms from the adverse demand shock.

V.B Placebo Test

In addition, to assess the validity of the identification strategy and ensure that the estimated effects are not driven by random patterns in the data, I conduct a Monte Carlo placebo simulation in which I randomly assign the treatment status at the industry level 1000 times with balanced treated and control sample sizes. In each placebo sample, I estimate both the DiD specification for BNPL adoption and the DDD model for firm performance outcomes. The purpose of this simulation is to evaluate whether the actual estimates reported in Tables II and III are unique relative to what would be observed under random treatment assignments.

Table IA.I reports the mean, standard deviation, and 99% confidence intervals of placebo estimates across the 1000 simulations. Panel A presents results for the DiD model and Panel B for the DDD model. For the coefficients of interest, namely the treatment interaction in the DiD model and the triple interaction in the DDD model, the means of the placebo estimations are statistically indistinguishable from zero. In contrast, the real estimates in Tables II and III are economically and statistically significant and are outside the 99% confidence intervals of the simulations. This pattern indicates that the real results are unlikely to have arisen under a random allocation of treatment, which strengthens the causal interpretation of the main findings.[19]

VI ALTERNATIVE CHANNELS

The baseline results in Tables II and III suggest that firms adopted BNPL to mitigate the negative demand shock during the crisis with positive effects on performance and resilience. To validate this interpretation, I conduct two tests. First, I examine whether the observed adoption and performance improvements could instead be explained by a supply-side channel, namely the reduction in production costs or increase in margins. Second, to further support the interpretation that the negative demand shock drives the baseline results, I investigate whether the adoption response was stronger among firms closer to financial distress.

VI.A Cost-Reduction Channel

Within a cost–benefit analysis for BNPL adoption, a firm weighs the additional revenues generated by BNPL against the transaction fees paid to the BNPL provider. These fees reduce the firm's profit margin, so the adoption decision is more attractive when margins are already high (Berg et al. 2025). Controlling for gross profitability in the PSM already mitigates the concern that treated and control firms might have systematically different profit margins. However, if firms in the treated industries had experienced an improvement in production technology or operating efficiency during the crisis, such cost reductions could increase both the profit margins and so the likelihood of adopting BNPL with, ultimately, improvements in performance and resilience, independently from the exogenous demand shock.

To address this alternative explanation, I examine whether the COGS-to-turnover ratio changed differently for BNPL adopters in treated industries during the crisis using the DDD model as in Equation (3). If improvements in performance were primarily driven by a reduction in input costs or overhead expenditures, I would expect to observe a negative and significant coefficient on the triple-interaction term.

Table IV reports the results for the COGS ratio. Across both columns, coefficients

[19] For the lower-order terms (*BNPL* and *Crisis* × *BNPL*), the placebo simulations yield statistically significant estimates, while the actual coefficients in the baseline model are all insignificant. This also reinforces the notion that the identified variation comes from the treatment exposure, rather than from any general differences between adopters and non-adopters or from common time effects.

on the triple interaction are statistically insignificant, as well as for all lower-order terms. These findings suggest that BNPL adopters in the treated industries did not experience any salient reduction in production costs relative to other firms, thereby ruling out the possibility that the observed performance results are driven by the cost-reduction channel.

(Insert Table IV here)

VI.B Financial Distress and BNPL Adoption

To further validate the interpretation that results on both BNPL adoption and firm performance are driven by the firm's response to a demand shock, I examine whether the likelihood of BNPL adoption is higher among firms closer to financial distress. Previous literature suggests that distressed firms at the margin of exit suffer disproportionately during downturns and are highly sensitive to revenue shocks (Opler and Titman 1994). Moreover, they place disproportionately high value on sustaining current revenues, since even a modest loss in cash inflows might trigger liquidation (e.g., Hotchkiss et al. 2008; Clementi and Hopenhayn 2006). Therefore, if firms adopt BNPL to strategically mitigate the negative demand shock, such adoptions should be more pronounced among firms closer to financial distress compared to healthier firms.

To test this hypothesis, I split the sample based on the firm's distance to financial distress, measured by the Altman Z-score (1983) during the pre-period. I define firms closer (further away) to financial distress as those with a lower (higher) than median Z-score. Then, I re-estimate the baseline DID model (Equation (2)) in both subsamples and compare the difference between the treatment effects with a Chow test.

Table V shows that, although the treatment effect is positive and significant in both subsamples (Columns (1) and (2)), the effect is significantly larger in the subsample with lower Z-score (Column (3)). This suggests that firms closer to financial distress are more likely to adopt BNPL during the crisis compared to financially healthier firms, consistent with the interpretation that BNPL adoption is driven by its role in sustaining revenues and mitigating the adverse effects of the demand shock, which is particularly valuable for distressed firms.

(Insert Table V here)

VII BARRIERS TO BNPL ADOPTION

The baseline results suggest that BNPL adoption helped firms in more exposed industries mitigate the adverse effects of the cost-of-living crisis. However, not all firms in the treated industries adopted BNPL, suggesting the existence of barriers that limited the ability or willingness of treated firms to respond to the shock using this tool. In this section, I discuss the impact of several dimensions, including the financial constraints, suppliers concentration, and directors' age.

VII.A Financial Constraints

Previous literature emphasizes the role of financial constraints in shaping a firm's responses to adverse macroeconomic shocks. During crisis periods, financially constrained firms may face heightened barriers to adjustment due to limited internal funds and restricted access to external finance (Campello, Graham, and Harvey 2010; Almeida, Campello, and Weisbach 2004; Hadlock and Pierce 2010). In the context of the cost-of-living crisis, how financial constraints would affect the firm's adoption of BNPL is less obvious. On the one hand, BNPL offers a potential channel to sustain consumer demand, and so firm's sales, by relaxing customer liquidity constraints. On the other hand, BNPL transactions incur additional transaction fees, which may be more difficult for financially constrained firms to absorb.

To investigate the role played by financial constraints in the likelihood to adopt BNPL, I compare different subsamples of firms based on their levels of financial constraints. Following previous literature (e.g., Beck, Demirgüç-Kunt, and Maksimovic 2005; Hadlock and Pierce 2010), I use firm size, employment, and firm age as indicators of financial constraint. Smaller and younger firms typically face tighter borrowing constraints due to weaker balance sheets, shorter credit histories, and limited collateral. Specifically, I split the sample into more financially constrained (below the median) and less financially constrained (above the median) based on their *Size*, log-transformed *number of employees*, and *Age*, respectively, during the pre-period. Then, I re-estimate the baseline DiD model (Equation 2) separately for each subsample pair and compare the difference between treatment effects with a Chow test.

Table VI reports the results. Across all three proxies (Panels A, B, and C), I find that the likelihood of BNPL adoption is significantly higher among treated firms compared to the control firms in both subsamples. However, the Chow tests in Column (3) suggest that the magnitude of the estimated coefficients is consistently larger in the less constrained group. These results suggest that, although financially constrained firms responded to the demand-side pressures of the crisis by adopting BNPL, their capacity to do so was limited by restricted access to external financing, whereas unconstrained firms were better positioned to implement an adaptive strategy during the crisis. Overall, these results highlight the role of financial constraints in shaping a firm's ability to undertake adaptive measures during periods of economic disruption.

(Insert Table VI here)

VII.B Supplier Concentration

In addition to financial constraints, supply chain structure may also influence a firm's ability to respond to demand shocks through the adoption of BNPL. Offering BNPL would impose additional pressure on the firm's working capital since the firm may need to scale up inventory to meet the higher volume of sales. Firms with greater bargaining power over their suppliers may be more able to manage this additional pressure by negotiating more favorable trade credit terms (Chod, Lyandres, and Yang 2019). In contrast, firms with a constrained bargaining power in the supply market may have limited ability to control input costs or payment timing, making it more difficult to accommodate the working capital demands associated with BNPL adoption.

To examine how the supplier concentration influenced BNPL adoption during the crisis, I construct an industry-level measure of supplier concentration (SC) using customer–supplier relationship data collected from FactSet. First, for each SIC-5 industry j in the sample, I identify its supplier industries s from FactSet. For each supplier industry, I calculate its Herfindahl–Hirschman Index (HHI) based on the turnover shares of firms within that supplier industry. This captures the degree of concentration in each supplier industry s.

I then measure the revenue dependence of each supplier industry s on the focal customer industry j. For each supplier firm k in industry s and each customer firm c in industry j, I observe the percentage of the supplier's total revenue attributable to sales to that customer, denoted as *%Revenue*. The revenue dependence, denoted as RD, is defined as:

$$RD_{s,j} = \sum_{k=1}^{N_s} \sum_{c=1}^{N_j} \%\text{Revenue}_{c,k} \tag{6}$$

where N_s is the number of firms in the supplier industry s, and N_j is the number of firms in the customer industry j. The weight assigned to supplier industry s for customer industry j is measured as the share of RD in the total RD across all supplier industries serving j, given by:

$$weight_{s,j} = \frac{RD_{s,j}}{\sum_{s=1}^{S} RD_{s,j}} \tag{7}$$

Finally, *SC* is defined as the weighted average of the *HHI* of its supplier industries, to capture both the degree of concentration of its supply industry and its dependency on that supply industry:

$$SC_{j,t} = \sum_{s=1}^{S_j} HHI_{s,t} \times \text{weight}_{s,j} \tag{8}$$

This measure captures both the degree of concentration in the supplier industry and the relative importance of each supplier industry to the focal customer industry. Higher values of *SC* indicate greater reliance on a small number of highly concentrated suppliers, whereas lower values suggest a more competitive and diversified supplier base. Then, I divide the sample based on the pre-period average *SC* using the sample median as a cutoff. Firms with an *SC* higher (lower) than the median are defined as having a concentrated (competitive) supplier market. I then re-estimate the baseline DiD model (Equation (2)) for both subsamples and compare the estimated treatment effects between them with a Chow test.

Table VII shows that the positive and significant treatment effect on BNPL adoption holds only in the subsample of firms operating in industries with relatively competitive supplier markets (Column (1)), while the treatment effect is insignificant in the subsample with a concentrated supplier market (Column (2)). This result suggests that firms with greater bargaining power in their supply chain are more capable of adopting BNPL during the crisis. By contrast, firms facing concentrated supplier markets may lack the flexibility to accommodate additional working capital pressure, limiting their ability to adopt BNPL in response to the demand shock.

(Insert Table VII here)

An important concern is that the observed BNPL adoption effects in Table II could reflect differences in supplier concentration rather than variations in demand-side exposure to the crisis if the treated industry has a supplier market that is systematically more competitive than the control industry. To address this concern, I test whether the supplier concentration evolved differently over time between treated and control industries by estimating an industry-level dynamic model. Specifically, I re-estimate the dynamic model as a modified version of Equation (4) at the SIC-5 level:

$$SC_{j,t} = \sum_{k \neq 2017} \gamma_k^{SIC} (1_{t=k} \times Treated_j^{SIC}) + \mathbf{F_{j,t}^{SIC}} + \epsilon_{i,t}, \tag{9}$$

where $Treated^{SIC}$ equals one (zero) for the treated (control) industries. F^{SIC} includes industry and year fixed effects. Standard errors are clustered at the industry level.

Figure IA.II reports the yearly estimated coefficients. They are statistically insignificant across all years in the sample period, suggesting that treated and control industries have similar levels of bargaining power or switching costs in the upstream supply market. Furthermore, they were likely to experience similar exposure to shocks transmitted through the supplier channel. This further implies that supply chain disruptions caused by COVID-19 or Brexit are unlikely to confound the results, as any such disruptions would have affected both groups in a comparable manner. Overall, this evidence mitigates the concern that the main results are driven by differences in supplier concentration rather than by differential exposures to the crisis.

(Insert Figure IA.II here)

VII.C Directors' Age

Previous corporate governance literature suggests that the age of managers affects a firm's adoption of new technology. Younger managers are generally found to be more open to innovation and change, reflected in greater R&D spending and the adoption of more frontier technologies (e.g., Barker III and Mueller 2002; Acemoglu, Akcigit, and Celik 2022). On the other hand, older managers may be more risk-averse or lack the human capital to adopt emerging technologies (MacDonald and Weisbach 2004). As such, if the managerial human capital and attitude toward novel technologies drive the firm's BNPL adoption decision, a higher likelihood of adoption should be observed among firms with younger directors.

To test this hypothesis, I collected the directors' information from Orbis to construct a director-firm-year level panel and classify firms based on the age of their directors in the pre-crisis period.[20] Specifically, I compare firms with young and mature directors, where a firm is classified as having younger directors if at least one director was under the age of 50 before the crisis, while it is classified as having mature directors if all directors are above 50. I re-estimate the baseline DiD model (Equation (2)) and compare the treatment effects across the two subsamples with a Chow test.

Table VIII presents the results of the subsample test based on the directors' ages. Across both groups, I find positive and statistically significant coefficients on the interaction term, indicating that firms in exposed industries are more likely to adopt BNPL under the crisis, regardless of their directors' age. The Chow test in Column (3) confirms that the magnitudes of the estimated effects are similar across the two subsamples. This result suggests, in the context of BNPL, that both younger and more mature directors responded similarly. Thus, BNPL is less likely to be a discretionary innovation in which its adoption decision is influenced by individual preferences, but rather a strategic response to the demand-side pressures triggered by the cost-of-living crisis.

(Insert Table VIII here)

Overall, this section provides evidence to understand the heterogeneity of adoption of BNPL during the crisis. Firms that are not constrained financially or have greater bargaining power in the supply market are more likely to adopt BNPL. In contrast, director age has no impact on adoption. These results highlight the importance of financial resources and flexibility in the supply chain in enabling firms to implement adaptive strategies during crisis periods, while managerial attitudes toward technology have limited influence.

VIII CONCLUSION

Using a matched DiD and DDD identification strategy, this study examines how BNPL adoption affects U.K. firms during the cost-of-living crisis. Exploiting variation in exposure to the young consumer demand shock across industries, I find that firms in highly affected industries are significantly more likely to adopt BNPL in the aftermath of the crisis. Moreover, I find that BNPL adopters sustain higher revenue and profitability and

[20] In the U.K., directors are the individuals legally responsible for running a firm and who have a duty to promote its success.

are significantly less likely to exit than comparable non-adopters, which suggests that BNPL effectively offsets negative shock and enhances firm resilience. These effects are not explained by pre-existing trends, cost-reduction strategies, or spurious correlation, as confirmed through dynamic specifications and placebo tests.

I also explore potential barriers that prevent firms from adopting BNPL. The adoption of BNPL is concentrated among firms with fewer financial constraints and greater supply chain bargaining power, suggesting that the potential of absorbing the higher costs and working capital demand is crucial for adopting this fintech solution. By contrast, director age had no significant effect on adoption, indicating that differences in managerial human capital did not affect a firm's decision to adopt BNPL under the negative shocks.

This study makes four key contributions. First, it extends the literature on FinTech adoption by showing that firm decisions to adopt BNPL during a macroeconomic shock are affected by the profile of their customer base. Specifically, firms operating in industries with demand that is elastic to young consumers are likely to adopt BNPL, highlighting the role of consumer-side factors in technology diffusion. Second, it provides the first large-sample causal evidence on the firm-level effects of BNPL adoption, showing that adoption significantly improves sales, profitability, and survival during the crisis. Third, it provides novel evidence linking consumer credit access to firm outcomes, showing that expanding liquidity at the point of sale can stabilize firm performance during downturns. Fourth, it contributes to the literature on firm adjustment to adverse demand shocks by showing that BNPL adoption serves as a novel margin that stabilizes demand through easing consumer liquidity constraints. Overall, these findings bridge household finance and firm dynamics and highlight the importance of consumer-facing financial innovation in enhancing business resilience.

From a policy perspective, the findings of this paper suggest that consumer-facing FinTech, such as BNPL, can play a positive role during macroeconomic downturns by sustaining household consumption and firm revenues. However, the benefits are unevenly distributed: financially constrained firms and those with concentrated supplier bases are less able to benefit from BNPL during the crisis. Overall, policymakers should recognize BNPL's potential to enhance firm resilience and industry stability, and consider regulatory frameworks that improve access to such tools for constrained firms.

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FIGURES

Figure I
Average Weekly Household Consumption

This figure reports the average weekly consumption of U.K. households in the treated (red) and the control (blue) industries before and during the crisis. Treated (Control) industries are those with the demand elastic (inelastic) to young household's income.

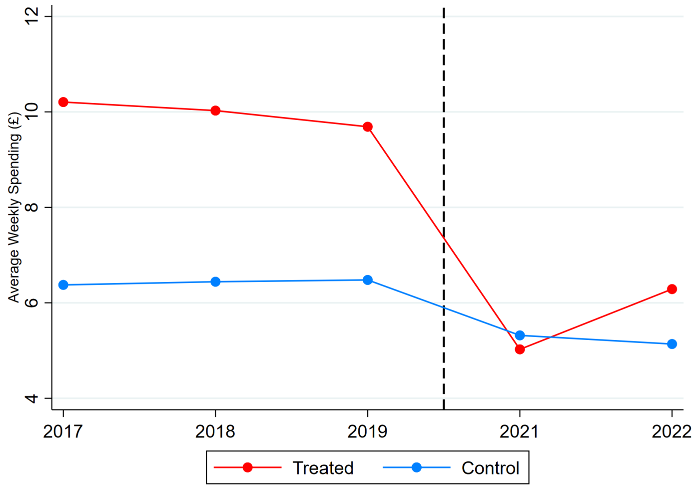
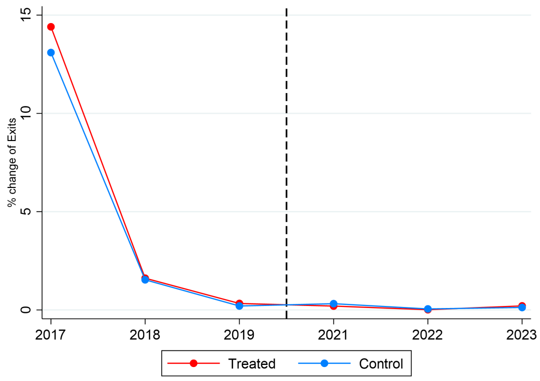


Figure II
Consumer Prices Index including Housing Costs

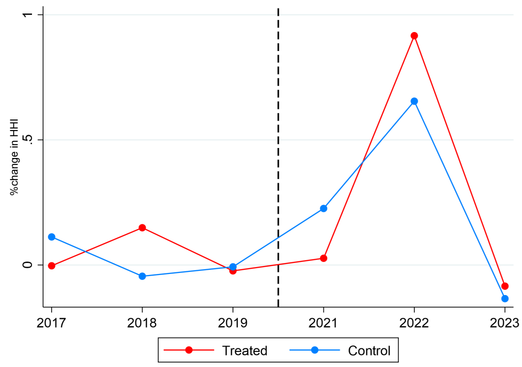
This figure reports the monthly Consumer Prices Index including housing costs (CPIH) from 2017 to 2023. The data are from the ONS consumer price inflation time series.

Figure III
Industry-level Impacts of the Crisis

This figure reports the industry-level outcomes in the treated (red) and the control (blue) industries before and after the crisis. Graph A reports the yearly average percentage change in the number of exits. A firm is exiting if its status becomes 'dissolved' or 'in liquidation' in that year. Graph B reports the yearly percentage change in the HHI. HHI is calculated as the sum of the squared market shares of all firms within an industry, defined at the 2-digit SIC level. Market share is defined as a firm's turnover divided by the total industry turnover.



(I) Graph A: %Change in Exits



(II) Graph B: %Change in HHI

Figure IV
Dynamic Models for BNPL Adoption

This figure reports the results from the model estimation:

$$BNPL_{i,t} = \sum_{k \neq 2017} \gamma_k (1_{t=k} \times Treated_i) + \mathbf{F_{i,t,j}} + \epsilon_{i,t}$$

where $BNPL_{i,t}$ is a dummy equal to one if the firm i has adopted BNPL on its website in year t and zero otherwise. $Treated_i$ equals one (zero) for firms operating in the treated (control) industries $\mathbf{F_{i,j,t}}$ is a matrix of fixed effects including firm and industry (SIC-2) -by-year fixed effects. All regressions are estimated on a propensity score matched sample using the pre-program period average values of *Size, Age, Leverage, Cash, ROA, Gross Profitability* and 2-digit U.K.-SIC dummies as covariates. Each treated firm is matched with one unique control firm. Standard errors are clustered at the industry-by-year level. The vertical axis shows the estimated coefficients. The horizontal axis shows the years. p-values are reported for each coefficient.

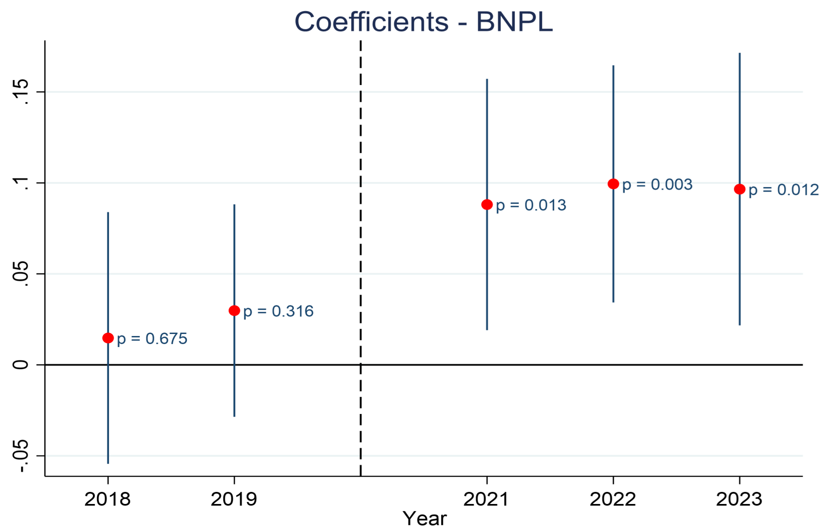


Figure V
Dynamic Models for Real Outcomes by BNPL Adoption Status

This figure reports the results from the model estimations:

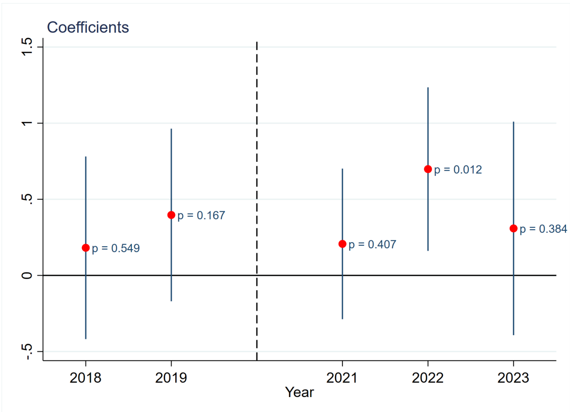
$$Y_{i,t} = \sum_{k \neq 2017} \gamma_k (1_{t=k} \times Treated_i) + \mathbf{F_{i,t,j}} + \epsilon_{i,t} \quad \text{for } i \text{ such that } BNPL_{i,t} = 1 \quad (A),$$

and

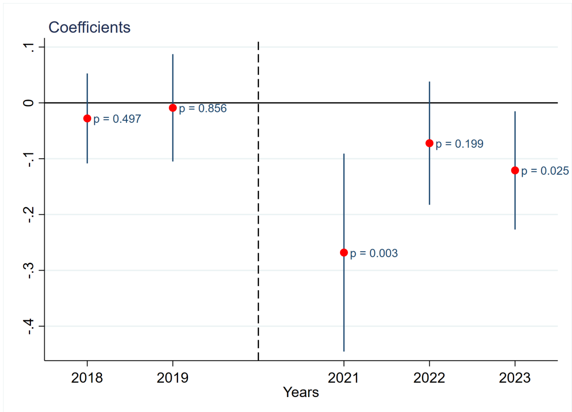
$$Y_{i,t} = \sum_{k \neq 2017} \gamma_k (1_{t=k} \times Treated_i) + \mathbf{F_{i,t,j}} + \epsilon_{i,t} \quad \text{for } i \text{ such that } BNPL_{i,t} = 0 \quad (B),$$

Where $Y_{i,t}$ includes *Ln(Turnover)*, defined as the natural log of one plus the firm's turnover; *ROA*, defined as the earning before interest and tax (EBIT) divided by total assets. $Treated_i$ equals one (zero) for firms operating in the treated (control) industries. $\mathbf{F_{i,j,t}}$ is a matrix of fixed effects including firm and industry (SIC-2) -by-year fixed effects. $BNPL_{i,t}$ is a dummy equal to one if the firm i has adopted BNPL on its website in year t and zero otherwise. Equation A (B) is estimated on the subset of firm-years with (without) BNPL. Columns (1) and (2) display the coefficients and p-values from Equation (A) and (B) using *Ln(Turnover)* and *ROA* as dependent variables, respectively. All regressions are estimated on a propensity score matched sample using the pre-program period average values of *Size, Age, Leverage, Cash, ROA, Gross Profitability* and 2-digit U.K.-SIC dummies as covariates. Each treated firm is matched with one unique control firm. Standard errors are clustered at the industry-by-year level. The vertical axes show the estimated coefficients. The horizontal axes show the years. p-values are reported for each coefficient.

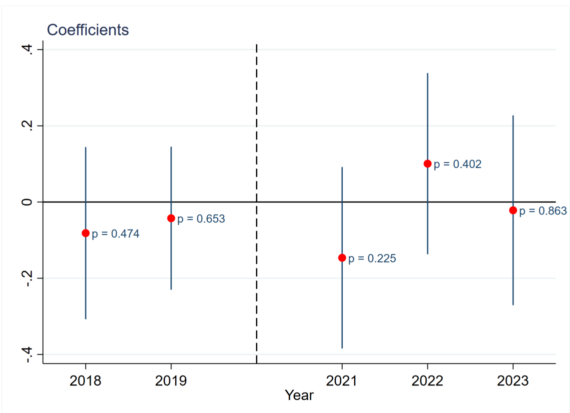
(1) Equation (A): Firm-years with BNPL	(2) Equation (B): Firm-years without BNPL



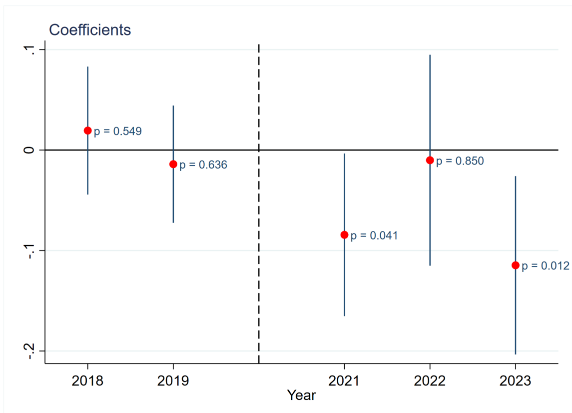
(I) $Ln(Turnover)$



(II) $Ln(Turnover)$



(III) ROA



(IV) ROA

Figure VI
Dynamic Models for Real Outcomes by Treatment Status

This figure reports the results from the model estimation:

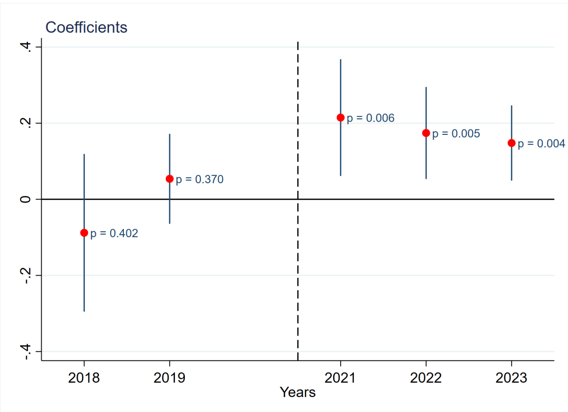
$$Y_{i,t} = \sum_{k \neq 2017} \gamma_k (1_{t=k} \times BNPL_{i,t}) + \mathbf{F_{i,t,j}} + \epsilon_{i,t} \quad \text{for } i \text{ such that } Treated_i = 1 \quad (A),$$

and

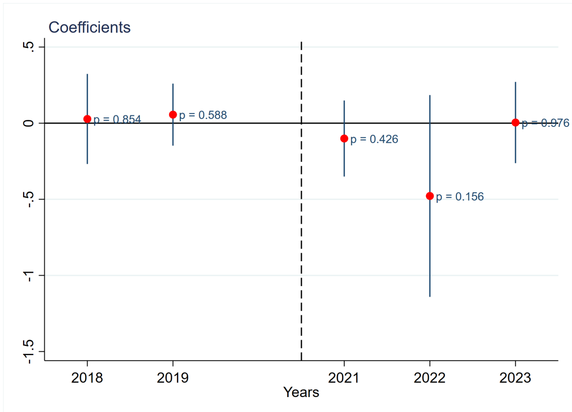
$$Y_{i,t} = \sum_{k \neq 2017} \gamma_k (1_{t=k} \times BNPL_{i,t}) + \mathbf{F_{i,t,j}} + \epsilon_{i,t} \quad \text{for } i \text{ such that } Treated_i = 0 \quad (B),$$

Where $Y_{i,t}$ includes *Ln(Turnover)*, defined as the natural log of one plus the firm's turnover; *ROA*, defined as the earning before interest and tax (EBIT) divided by total assets. $BNPL_{i,t}$ is a dummy equal one if the firm i has adopted BNPL on its website in year t and zero otherwise. $\mathbf{F_{i,j,t}}$ is a matrix of fixed effects including firm and industry (SIC-2) -by-year fixed effects. $Treated_i$ equals one (zero) for firms operating in the treated (control) industries. Equation A (B) is estimated on the treated (control) sample. Columns (1) and (2) display the coefficients and p-values from Equation (A) and (B) using *Ln(Turnover)* and *ROA* as dependent variables, respectively. All regressions are estimated on a propensity score matched sample using the pre-program period average values of *Size, Age, Leverage, Cash, ROA, Gross Profitability* and 2-digit U.K.-SIC dummies as covariates. Each treated firm is matched with one unique control firm. Standard errors are clustered at the industry-by-year level. The vertical axes show the estimated coefficients. The horizontal axes show the years. p-values are reported for each coefficient.

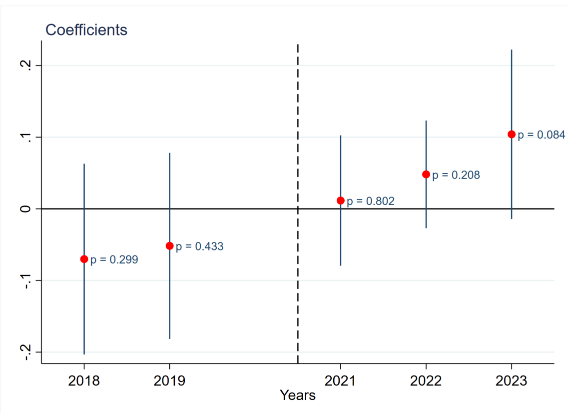
(1) Equation (A): Treated sample | (2) Equation (B): Control sample



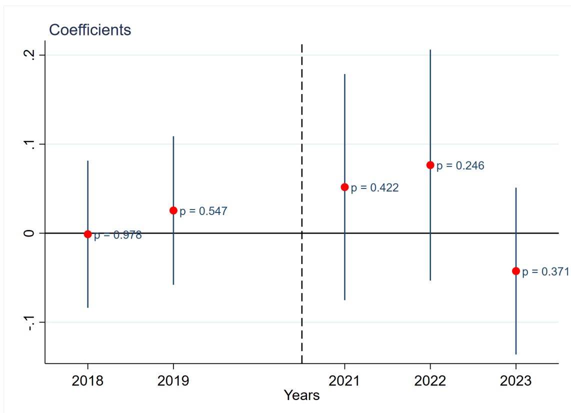
(I) $Ln(Turnover)$



(II) $Ln(Turnover)$



(III) ROA



(IV) ROA

TABLES

Table I
Sample Characteristics Before and After the PSM

This table reports firm-level characteristics of treated (Columns (1) - (3)) and control firms (Columns (4) - (6)) in the pre-period before (Panel A) and after (Panel B) propensity score matching (PSM). The last column (Diff) reports differences in the characteristics between treated and control firms with t-statistics in parentheses from two-tailed, two-sample t-tests of the difference in means. Treated (Control) firms are those operating in industries with demand elastic (inelastic) to young household's income. *Size* is the natural logarithm of one plus the firm's total assets. *Age* is the natural logarithm of one plus the firm's age. *Cash* is the ratio of cash to total assets. *Leverage* is the sum of short-term debt and long-term liability divided by total assets. *ROA* is the earnings before interest, and tax (EBIT) divided by the firm's total assets. *Gross Profitability* is the gross profit divided by COGS. *p-score* is the probability of being treated estimated via a logit model using the pre-program average values of *Size, Age, Leverage, Cash, ROA, Gross Profitability* and 2-digit U.K.-SIC dummies as covariates. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Before PSM						
	Treated (N= 37,061)			Control (N= 35,282)			
	(1)	(2)	(3)	(4)	(5)	(6)	(1 - 4)
Variables	Mean	Median	Std. dev.	Mean	Median	Std. dev.	Diff
Size	10.350	10.879	3.542	10.661	11.080	3.644	-0.311***
							(-10.61)
Age	1.689	1.782	1.072	1.819	1.939	1.092	-0.130***
							(-15.67)
Cash	0.389	0.278	0.345	0.360	0.251	0.330	0.028***
							(8.24)
Leverage	0.432	0.046	1.176	0.411	0.050	1.204	0.021**
							(2.06)
ROA	-0.032	0.033	0.895	-0.039	0.043	0.925	0.007
							(0.35)
Gross Profitability	3.491	0.745	10.821	2.674	0.754	7.881	0.817***
							(2.98)
p-score	0.652	0.812	0.267	0.349	0.281	0.185	0.303***
							(37.49)

(Continued on next page)

Table I
Sample Characteristics Before and After the PSM (cont'd)

	Panel B: After PSM						
	Treated (N= 751)			Control (N= 751)			
	(1)	(2)	(3)	(4)	(5)	(6)	(1 - 4)
Variables	Mean	Median	Std. dev.	Mean	Median	Std. dev.	Diff
Size	14.429	15.180	2.822	14.328	15.321	2.952	0.101
							(0.68)
Age	2.742	2.889	0.927	2.685	2.832	0.935	0.058
							(0.20)
Cash	0.228	0.127	0.248	0.221	0.129	0.244	0.007
							(0.567)
Leverage	0.527	0.244	0.988	0.562	0.203	1.343	-0.035
							(-0.58)
ROA	0.021	0.060	0.793	0.010	0.064	0.768	0.011
							(0.27)
Gross Profitability	1.742	0.671	4.918	2.104	0.665	7.279	-0.362
							(1.13)
p-score	0.430	0.300	0.239	0.433	0.300	0.243	-0.003
							(-0.22)

Table II
Likelihood of BNPL Adoption

This table shows the results from the model estimation:

$$BNPL_{i,t} = \delta(Crisis_t \times Treated_i) + \mathbf{F_{i,t,j}} + \epsilon_{i,t}$$

where $BNPL_{i,t}$ is a dummy equal to one if the firm i has adopted BNPL on its website in year t and zero otherwise. $Crisis_t$ equals one in years during the cost-of-living crisis (2021-2023) and zero otherwise. $Treated_i$ equals one (zero) for firms operating in the treated (control) industries. $\mathbf{F_{i,j,t}}$ is a matrix of fixed effects including firm, year, and industry (SIC-2) -by-year fixed effects. All regressions are estimated on a propensity score matched sample using the pre-program period average values of *Size, Age, Leverage, Cash, ROA, Gross Profitability* and 2-digit U.K.-SIC dummies as covariates. Each treated firm is matched with one unique control firm. t-statistics (in parentheses) are calculated from standard errors clustered at the industry-by-year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
	$BNPL$	$BNPL$
$Crisis \times Treated$	0.079***	0.080***
	(3.51)	(4.14)
Observations	8,827	8,827
Adj. R^2	0.436	0.447
Firm FE	Yes	Yes
Year FE	Yes	No
Industry-by-Year FE	No	Yes

Table III
Real Outcomes

This table shows the results from the model estimation:

$$Y_{i,t} = \beta_1 \left(Crisis_t \times Treated_i \times BNPL_{i,t}\right) + \beta_2 \left(Crisis_t \times Treated_i\right) + \beta_3 \left(Treated_i \times BNPL_{i,t}\right) + \beta_4 \left(Crisis_t \times BNPL_{i,t}\right) + \beta_5 \left(BNPL_{i,t}\right) + \mathbf{F_{i,t,j}} + \varepsilon_{i,t}$$

Where $Y_{i,t}$ includes *Ln(Turnover)*, defined as the natural log of one plus the firm's turnover; *ROA*, defined as the earning before interest and tax (EBIT) divided by total assets; And *Dissolved*, which is a dummy equals one if the firm is dissolved or in liquidation in that year and zero otherwise. $Crisis_t$ equals one in years during the cost-of-living crisis (2021-2023) and zero otherwise. $Treated_i$ equals one (zero) for firms operating in the treated (control) industries. $BNPL_{i,t}$ is a dummy equal one if the firm i has adopted BNPL on its website in year t and zero otherwise. $\mathbf{F_{i,j,t}}$ is a matrix of fixed effects including firm, year, and industry (SIC-2) -by-year fixed effects. All regressions are estimated on a propensity score matched sample using the pre-program period average values of *Size, Age, Leverage, Cash, ROA, Gross Profitability* and 2-digit U.K.-SIC dummies as covariates. Each treated firm is matched with one unique control firm. t-statistics (in parentheses) are calculated from standard errors clustered at the industry-by-year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(Turnover)	*Ln(Turnover)*	*ROA*	*ROA*	*Dissolved*	*Dissolved*
$Crisis \times Treated \times BNPL$	0.351***	0.334***	0.134**	0.119*	-0.119*	-0.116*
	(3.05)	(2.95)	(2.19)	(1.86)	(-1.87)	(-1.82)
$Crisis \times Treated$	-0.186***	-0.167***	-0.092***	-0.082***	0.016**	0.016**
	(-3.12)	(-3.46)	(-3.35)	(-2.99)	(2.19)	(2.24)
$Treated \times BNPL$	0.002	-0.013	-0.059	-0.061	0.086	0.082
	(0.02)	(-0.10)	(-0.97)	(-0.96)	(1.41)	(1.34)
$Crisis \times BNPL$	-0.079	-0.125	-0.004	-0.012	0.076	0.075
	(-0.92)	(-1.48)	(-0.13)	(-0.41)	(1.20)	(1.18)
$BNPL$	-0.038	-0.011	0.010	0.014	-0.070	-0.066
	(-0.35)	(-0.10)	(0.28)	(0.40)	(-1.17)	(-1.10)
Observations	5,043	5,043	5,091	5,091	8,827	8,827
Adj. R^2	0.960	0.962	0.491	0.494	0.069	0.070
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No
Industry-by-Year FE	No	Yes	No	Yes	No	Yes

Table IV
Test of the Cost-Reduction Channel

This table shows the results from the model estimation:

$$Y_{i,t} = \beta_1 \left(Crisis_t \times Treated_i \times BNPL_{i,t}\right) + \beta_2 \left(Crisis_t \times Treated_i\right) + \beta_3 \left(Treated_i \times BNPL_{i,t}\right) + \beta_4 \left(Crisis_t \times BNPL_{i,t}\right) + \beta_5 \left(BNPL_{i,t}\right) + \mathbf{F_{i,t,j}} + \varepsilon_{i,t}$$

Where $Y_{i,t}$ includes *COGS-to-Turnover*, defined as the cost-of-goods-sold divided by turnover. $Crisis_t$ equals one in years during the cost-of-living crisis (2021-2023) and zero otherwise. $Treated_i$ equals one (zero) for firms operating in the treated (control) industries. $BNPL_{i,t}$ is a dummy equal one if the firm i has adopted BNPL on its website in year t and zero otherwise. $\mathbf{F_{i,j,t}}$ is a matrix of fixed effects including firm, year, and industry (SIC-2) -by-year fixed effects. All regressions are estimated on a propensity score matched sample using the pre-program period average values of *Size, Age, Leverage, Cash, ROA, Gross Profitability* and 2-digit U.K.-SIC dummies as covariates. Each treated firm is matched with one unique control firm. t-statistics (in parentheses) are calculated from standard errors clustered at the industry-by-year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) *COGS-to-Turnover*	(2) *COGS-to-Turnover*
$Crisis \times Treated \times BNPL$	0.009	0.019
	(0.41)	(0.81)
$Crisis \times Treated$	0.011	0.010
	((1.21)	(1.34)
$Treated \times BNPL$	-0.020	-0.027
	(-0.88)	(-1.18)
$Crisis \times BNPL$	-0.005	-0.011
	(-0.31)	(-0.68)
$BNPL$	0.009	0.016
	(0.492)	(0.992)
Observations	4,849	4,849
Adj. R^2	0.838	0.842
Firm FE	Yes	Yes
Year FE	Yes	No
Industry-by-Year FE	No	Yes

Table V
BNPL Adoption Conditional on Distance to Financial Distress

This table shows the results from the model estimation:

$$BNPL_{i,t} = \delta(Crisis_t \times Treated_i) + \mathbf{F_{i,t,j}} + \epsilon_{i,t}$$

where the model is separately estimated on subsamples of firms characterized by their distance to financial distress, measured by Altman Z-score. Firms that are closer to financial distress ('Low Z-score) are those with a Altman Z-score measured over the pre-period that is lower than the median, while firms that are further from financial distress ('High Z-score') are those with a Altman Z-score measured over the pre-period that is higher than the median. $BNPL_{i,t}$ is a dummy equal to one if the firm i has adopted BNPL on its website in year t and zero otherwise. $Crisis_t$ equals one in years during the cost-of-living crisis (2021-2023) and zero otherwise. $Treated_i$ equals one (zero) for firms operating in the treated (control) industries. $\mathbf{F_{i,j,t}}$ is a matrix of fixed effects including firm, year, and industry (SIC-2) -by-year fixed effects. All regressions are estimated on a propensity score matched sample using the pre-program period average values of *Size, Age, Leverage, Cash, ROA, Gross Profitability* and 2-digit U.K.-SIC dummies as covariates. Each treated firm is matched with one unique control firm. t-statistics (in parentheses) are calculated from standard errors clustered at the industry-by-year level. Chow test results for the difference between estimated coefficients across the pair subsamples based on the Altman Z-score are reported in brackets at the bottom of each sub-panel ('F-test'). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)
	$BNPL$
Subsamples by Altman-Z scores	*Reported coefficient:* $Crisis \times Treated$
Low Z-score	0.107***
	(5.75)
High Z-score	0.047**
	(2.12)
Diff (High - Low)	-0.060***
F-test	[15.56]
Observations	8,720
Firm FE	Yes
Industry-by-Year FE	Yes

Table VI
BNPL Adoption Conditional on Financial Constraints

This table shows the results from the model estimation:

$$BNPL_{i,t} = \delta(Crisis_t \times Treated_i) + \mathbf{F_{i,t,j}} + \epsilon_{i,t}$$

where the model is separately estimated on subsamples of firms characterized by financial constraints. Financial constraints are defined by the mean value of *Size* in the pre-period (2017-2019) where 'Small' ('Large') firms are those with *Size* below (above) median (Panel A); by firms' average number of employees in the pre-period where 'Few' ('Many') employees are firms with the total number of employees below (above) the median (Panel B); by *Age* in 2013 where 'Young' ('Mature') firms are those with *Age* below (above) median (Panel C). $BNPL_{i,t}$ is a dummy equal to one if the firm i has adopted BNPL on its website in year t and zero otherwise. $Crisis_t$ equals one in years during the cost-of-living crisis (2021-2023) and zero otherwise. $Treated_i$ equals one (zero) for firms operating in the treated (control) industries. $\mathbf{F_{i,j,t}}$ is a matrix of fixed effects including firm, year, and industry (SIC-2) -by-year fixed effects. All regressions are estimated on a propensity score matched sample using the pre-program period average values of *Size, Age, Leverage, Cash, ROA, Gross Profitability* and 2-digit U.K.-SIC dummies as covariates. Each treated firm is matched with one unique control firm. t-statistics (in parentheses) are calculated from standard errors clustered at the industry-by-year level. Chow test results for the difference between estimated coefficients across the pair subsamples based on financial constraints are reported in brackets at the bottom of each sub-panel ('F-test'). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Reported coefficient: $Crisis \times Treated$					
Panel A: Firm Size		*Panel B: Number of Employees*		*Panel C: Firm Age*	
	(1)		(2)		(3)
	$BNPL$		$BNPL$		$BNPL$
Small	0.032**	Few	0.053***	Young	0.059***
	(2.14)		(3.44)		(2.79)
Large	0.135***	Many	0.121***	Mature	0.104***
	(5.24)		(4.50)		(5.04)
Diff (Large - Small)	0.103***	Diff (Many - Few)	0.068***	Diff (Mature - Young)	0.045*
F-test	[27.66]	F-test	[8.19]	F-test	[3.82]
Observations	8,827	Observations	7,324	Observations	8,486
Firm FE	Yes	Firm FE	Yes	Firm FE	Yes
Industry-by-Year FE	Yes	Industry-by-Year FE	Yes	Industry-by-Year FE	Yes

Table VII
BNPL Adoption Conditional on Supplier Concentration

This table shows the results from the model estimation:

$$BNPL_{i,t} = \delta(Crisis_t \times Treated_i) + \mathbf{F_{i,t,j}} + \epsilon_{i,t}$$

where the model is separately estimated on subsamples of firms characterized by supplier concentration. Supplier concentration is proxied by the weighted average of the HHI of the firm's supplier industries. The weight assigned to a supplier industry for a given customer industry is calculated as the supplier's revenue dependence on that customer industry, divided by the total revenue dependence of all supplier industries linked to the same customer industry. Firms with 'Competitive' ('Concentrated') supplier market are those with the supplier concentration during the pre-period (2017-2019) lower (higher) than the median. $BNPL_{i,t}$ is a dummy equal one if the firm i has adopted BNPL on its website in year t and zero otherwise. $Crisis_t$ equals one in years during the cost-of-living crisis (2021-2023) and zero otherwise. $Treated_i$ equals one (zero) for firms operating in the treated (control) industries. $\mathbf{F_{i,j,t}}$ is a matrix of fixed effects including firm, year, and industry (SIC-2) -by-year fixed effects. All regressions are estimated on a propensity score matched sample using the pre-program period average values of *Size, Age, Leverage, Cash, ROA, Gross Profitability* and 2-digit U.K.-SIC dummies as covariates. Each treated firm is matched with one unique control firm. t-statistics (in parentheses) are calculated from standard errors clustered at the industry-by-year level. Chow test results for the difference between estimated coefficients across the pair subsamples based on supplier concentrations are reported in brackets at the bottom of each sub-panel ('F-stat'). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)
	$BNPL$
Subsamples by Supplier Concentration	*Reported coefficient:* $Crisis \times Treated$
Competitive	0.140***
	(5.09)
Concentrated	0.002
	(0.17)
Diff (High - Low)	-0.138***
F-test	[21.57]
Observations	8,207
Firm FE	Yes
Industry-by-Year FE	Yes

Table VIII
BNPL Adoption Conditional on Directors' Age

This table shows the results from the model estimation:

$$BNPL_{i,t} = \delta(Crisis_t \times Treated_i) + \mathbf{F_{i,t,j}} + \epsilon_{i,t}$$

where the model is separately estimated on subsamples of firms characterized by directors' age. Directors' age is based on the age of the firm's directors where firms with younger directors ('Young Directors') are those with at least one director who is under the age of 50, while firms with mature directors ('Mature Directors') are those with all directors aged above 50 during the pre-period (2017-2019). $BNPL_{i,t}$ is a dummy equal to one if the firm i has adopted BNPL on its website in year t and zero otherwise. $Crisis_t$ equals one in years during the cost-of-living crisis (2021-2023) and zero otherwise. $Treated_i$ equals one (zero) for firms operating in the treated (control) industries. $\mathbf{F_{i,j,t}}$ is a matrix of fixed effects including firm, year, and industry (SIC-2) -by-year fixed effects. All regressions are estimated on a propensity score matched sample using the pre-program period average values of *Size, Age, Leverage, Cash, ROA, Gross Profitability* and 2-digit U.K.-SIC dummies as covariates. Each treated firm is matched with one unique control firm. t-statistics (in parentheses) are calculated from standard errors clustered at the industry-by-year level. Chow test results for the difference between estimated coefficients across the pair subsamples based on directors' age are reported in brackets at the bottom of each sub-panel ('F-test'). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)
	$BNPL$
Subsamples by Directors' Age	*Reported coefficient:* $Crisis \times Treated$
Young Directors	0.076***
	(3.68)
Mature Directors	0.081***
	(4.05)
Diff (High - Low)	0.005
F-test	[0.12]
Observations	8,821
Firm FE	Yes
Industry-by-Year FE	Yes

Internet Appendix for

"MITIGATING A DEMAND SHOCK THROUGH FINTECH"

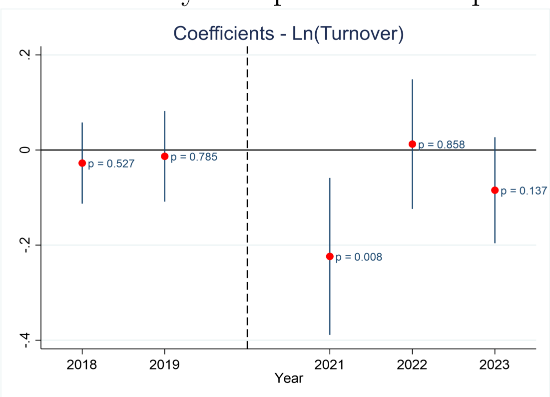
This Internet Appendix includes results from supplementary and robustness tests not reported in the paper.

Figure IA.I
Dynamic model for Real Outcomes

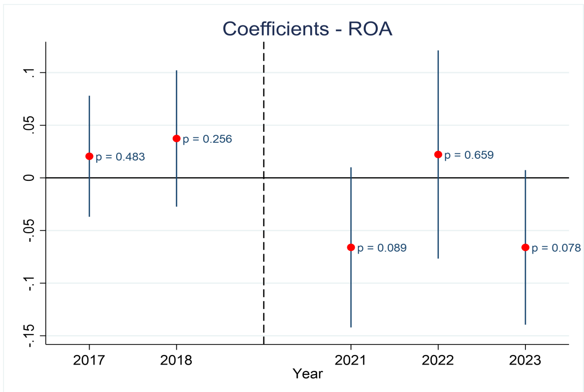
This figure reports the results from the model estimation:

$$Y_{i,t} = \sum_{k \neq 2017} \gamma_k (1_{t=k} \times Treated_i) + \mathbf{F_{i,t,j}} + \epsilon_{i,t}$$

Where $Y_{i,t}$ includes *Ln(Turnover)*, defined as the natural log of one plus the firm's turnover; *ROA*, defined as the earning before interest and tax (EBIT) divided by total assets. $Treated_i$ equals one (zero) for firms operating in the treated (control) industries. $\mathbf{F_{i,j,t}}$ is a matrix of fixed effects including firm and industry (SIC-2) -by-year fixed effects. Graph A and B show estimated coefficients of *Ln(Turnover)* and *ROA*, respectively. All regressions are estimated on a propensity score matched sample using the pre-program period average values of *Size, Age, Leverage, Cash, ROA, Gross Profitability* and 2-digit U.K.-SIC dummies as covariates. Each treated firm is matched with one unique control firm. Standard errors are clustered at the industry-by-year level. The vertical axes show the estimated coefficients. The horizontal axes show the years. p-values are reported for each coefficient.



(I) Graph A: $Ln(Turnover)$



(II) Graph B: ROA

Figure IA.II
Dynamic model for Supplier Concentration

This figure reports the results from the model estimation:

$$SC_{j,t} = \sum_{k \neq 2017} \gamma_k^{SIC}(1_{t=k} \times Treated_j^{SIC}) + \mathbf{F^{SIC}_{j,t}} + \epsilon_{i,t}$$

Where $SC_{j,t}$ is proxied by the weighted average of the *HHI* of the firm's supplier industries. The weight assigned to a supplier industry for a given customer industry is calculated as the supplier's revenue dependence on that customer industry, divided by the total revenue dependence of all supplier industries linked to the same customer industry. $Treated_i^{SIC}$ equals one (zero) for the treated (control) industries. $\mathbf{F}_{j,t}^{SIC}$ is a matrix of fixed effects including industry (SIC-5) and year fixed effects. Standard errors clustered at the industry level. The vertical axes show the estimated coefficients. The horizontal axes show the years. p-values are reported for each coefficient.

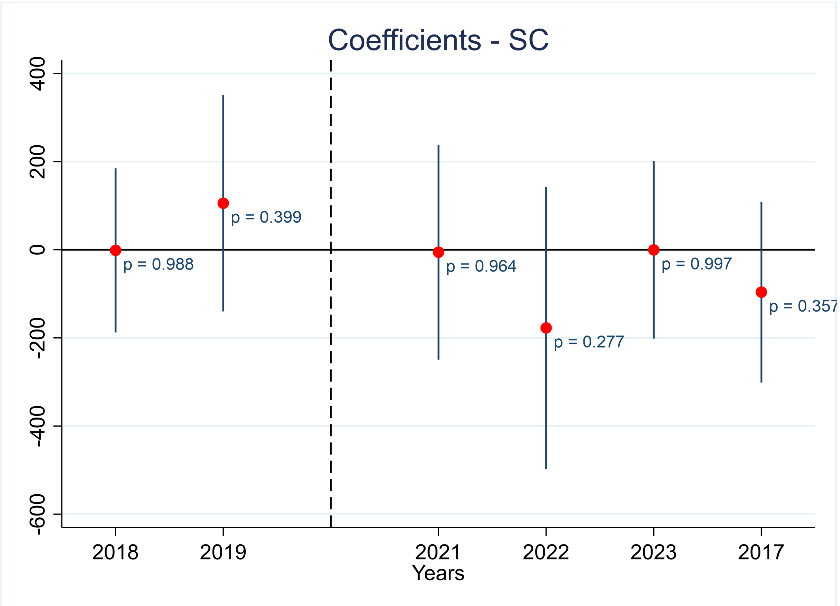


Table IA.I
Monte Carlo Simulation

This table reports the results from Monte Carlo Simulations. The treatment status is randomly assigned at the industry-level 1,000 times. In each placebo sample, I estimate both the DiD specification for BNPL adoption (Panel A) and the DDD model for firm performance outcomes (Panel B). Columns (1) to (4) report the mean, standard deviation, and 99th percent confidence intervals (CI) of the 1,000 placebo coefficients, respectively. The *t*-statistic from a *t*-test on the null hypothesis that the mean is equal to zero is reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: DiD Model				
Dependent Variable: *BNPL*	Mean	Std. dev.	99% CI-	99% CI+
$Crisis \times Treated$	0.001	0.062	-0.004	0.001
	(0.274)			
Panel B: DDD Models				
Dependent Variable: *Ln(Turnover)*	Mean	Std. dev.	99% CI-	99% CI+
$Crisis \times Treated \times BNPL$	0.000	0.157	-0.013	0.013
	(0.07)			
$Crisis \times Treated$	0.003	0.081	-0.003	0.010
	(1.27)			
$Treated \times BNPL$	-0.006	0.134	-0.017	0.005
	(-1.39)			
$Crisis \times BNPL$	0.058***	0.085	0.051	0.065
	(21.63)			
$BNPL$	-0.016***	0.077	-0.022	-0.009
	(-6.43)			
Dependent Variable: *ROA*	Mean	Std. dev.	99% CI-	99% CI+
$Crisis \times Treated \times BNPL$	-0.004	0.102	-0.012	0.004
	(-1.19)			
$Crisis \times Treated$	0.000	0.043	-0.003	0.004
	(0.26)			
$Treated \times BNPL$	0.001	0.095	-0.007	0.008
	(0.25)			
$Crisis \times BNPL$	0.058***	0.095	-0.007	0.008
	(33.79)			
$BNPL$	-0.028***	0.051	-0.032	-0.024
	(-17.21)			