

The Scarring Effects of COVID-19 on Household Debt in Thailand

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Abstract

“Is credit given to where credit is due?” This paper examines how economic exposure to COVID affected household credit behavior in Thailand using loan-level panel data from the National Credit Bureau, combined with remotely-sensed night-time light intensity as a proxy for local economic disruption. I find that more COVID-exposed postal codes experienced significantly worse repayment outcomes, with delinquency rising especially strongly for loans originated during the pandemic. At the same time, total outstanding debt often declined in more exposed areas. However, this decline does not appear to reflect healthier household balance sheets. Rather, it is more consistent with tighter effective access to credit, as more exposed borrowers became more likely to make loan inquiries, while also facing a higher probability that those inquiries did not result in new loans. Further product-level results show that these dynamics were not uniform across loan categories — unsecured products such as credit cards and personal loans exhibit clearer signs of repayment distress, while agricultural credit appears more shaped by policy intervention, with compositional shifts toward smaller-amount loans. In addition, borrowers who entered the pandemic with only unsecured debt appear to be systematically more vulnerable to COVID exposure. These findings suggest that COVID-19 affected household credit markets in Thailand through a combination of various channels, including worsening repayment capacity, tighter effective credit supply, and changes in the composition of lending, with effects that react to the end of government debt relief policy and persisting well beyond the initial COVID period. This paper advances the use of remotely-sensed variables in development economics to proxy economic shock at granular geographic scales and holds implications for financial health monitoring and targeted government policy.

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1 Introduction

In recent decades, household debt has emerged as a critical structural issue for policy-makers in numerous emerging and middle-income countries. Household debt plays a double role. On one hand, borrowing can improve the welfare of households through consumption smoothing and financing investment. On the other hand, when debt is persistently high, it can amplify financial fragility and restrict future access to credit, making both households and the broader economy more vulnerable to crises. This tension became especially visible during the COVID-19 pandemic, as many households relied on debt to survive sudden and unpredicted income losses even as their repayment capacity deteriorated.

For Thailand, the persistently high level of household debt has become one of the central macroeconomic challenges facing the country. Even before COVID, the household debt-to-GDP ratio has been climbing steadily, due to greater access to retail credit, prolonged low interest rates, and specific policy episodes that stimulated borrowing, such as the “First-Car Scheme” and the severe 2011 floods (Monetary Policy Committee 2023). COVID and the associated economic downturns exacerbated this problem. Thailand’s household debt-to-GDP ratio peaked at 95.5% at the end of 2021 Q1, among the highest in the region, before slightly dropping to 90.7% at the end of 2023 Q2 (Monetary Policy Committee 2023). In advanced economies, the median ratio rose from 52% in 2008 to 63% in 2016, while among emerging market economies, the ratio increased from 15% to 21% (Alter, Feng, and Valckx 2020). As of 2025, the household debt-to-GDP ratios have risen to 80.5% in advanced economies and 54.1% in emerging markets (Pangsapa, Kongphalee, and Gongsiang 2025). Thailand’s ratio places it not only far above the emerging-market average, but also near the upper bound of levels associated with advanced economies. Thailand’s elevated levels of household debt remains concerning, with a particularly large share of borrowing concentrated in “unproductive” and unsecured forms such as personal loans and credit cards, rather than investments that can create future wealth or income (e.g., home-ownership or education) (Monetary Policy Committee 2023).

Thailand’s high household debt presents acute challenges for vulnerable groups. Households in the lowest income quintile had debt service ratios that were almost twice as high as other income groups, as well as the highest share of credit card and personal loans relative to their household debt (Monetary Policy Committee 2023). As COVID lockdowns and business closures reduced household incomes — especially for vulnerable workers in the tourism, services, and informal sectors — many households turned to additional borrowing to maintain consumption levels. For Thai households, borrowing was the single most impor-

tant strategy to smooth consumption during COVID (Sirisankanan and Kananurak 2025). While overall inequality in the country may not have surged dramatically following COVID, reflecting the result of social protection policies, many households, especially low-income ones, relied more heavily on debt (Chote et al. 2025).

Understanding household debt in Thailand is important not only because of its scale, but also because of its macroeconomic implications. High debt burdens can suppress consumption and growth, increase household sensitivity to shocks, and weaken the effectiveness of monetary policy (Alpanda and Zubairy 2019; Baker 2014, 2018; Debelle 2004; Kim and Lim 2020; Lombardi, Mohanty, and Shim 2017; Zabai 2017). Increases in the household debt also predicts higher unemployment in the medium run (Mian, Sufi, and Verner 2017).

Given these intertwined economic and social risks, studying the drivers and consequences of Thailand’s household debt during COVID becomes essential to design policies that support sustainable recovery and long-run stability. This paper asks three related questions. First, how did COVID-19 exposure affect household debt and repayment outcomes in Thailand? Second, through what mechanisms did these effects operate? Third, how did the impacts vary across heterogeneous borrower groups, loan cohorts, and loan product types?

The paper contributes in several main ways. First, it leverages highly granular loan-level panel data from the National Credit Bureau in Thailand to provide new evidence on household credit dynamics during and after COVID-19, tracking the medium- and long-term impacts up until 2025, longer than most papers in the literature. Second, it introduces a novel measure of local pandemic exposure by exploiting variation in satellite night-time light intensity at the postal code level. This is useful because it captures spatially uneven economic disruption at a much finer scale than regional aggregated administrative data. To the best of my knowledge, this is the first paper to assign a measure of COVID economic shock at the postal code-level using remote sensing techniques. Third, by joining postal code-level COVID exposure to loan-level panel data, I am able to examine how differential localized shocks affect debt and repayment outcomes at fine scales. Lastly, I go beyond debt stocks alone by jointly examining repayment behavior and loan inquiry activity, considering heterogeneity across loan products and borrower characteristics. As such, I paint a detailed picture of how crisis conditions affect both household balance sheets and the functioning of the credit market.

To answer these questions, I estimate event-study specifications that relate household credit outcomes over time to postal code-level COVID exposure. The analysis spans debt holdings, delinquency, loan inquiries, unmet loan inquiries, and new loan origination, and is extended through decompositions by loan product type, loan cohort, and borrower charac-

teristics like pre-COVID reliance on unsecured credit. As such, I am able to trace how more and less COVID-exposed areas diverged dynamically during and after the pandemic.

The results point to several main findings. First, COVID exposure is associated with a deterioration in repayment outcomes, with delinquency rising more strongly in more exposed postal codes, especially for loans originated during the pandemic. Second, the decline in total outstanding debt at the borrower level in more exposed postal codes does not appear to reflect healthier household balance sheets. Instead, it is more consistent with tighter effective access to credit, as indicated by the simultaneous rise in loan inquiries and unmet inquiries. Third, borrowers who enter the pandemic with only unsecured loans appear systematically more vulnerable, and exhibit worse repayment dynamics over time. More broadly, evidence from product-level decompositions shows that these effects were not uniform across loan categories. Combining these results, I find that COVID affected household credit markets in Thailand through a combination of worsening repayment capacity, tighter effective credit supply, and changes in lending composition. Several of the effects materialize upon the expiration of debt relief measures. Many of these effects persist well beyond the initial COVID shock period, showing a “scarring” nature.

The remainder of the paper is structured as follows: Section 2 surveys relevant literature; Section 3 discusses relevant COVID policy in Thailand; Section 4 describes the data used; Section 5 presents the main methodology; Section 6 shows the pertinent results; Section 7 discusses the implications; finally, Section 8 concludes.

2 Literature Review

I situate the paper within three strands of literature: (1) empirical work on the impacts of COVID-19 on household welfare; (2) research on long-term effects of shocks on household trajectories and development dynamics; and (3) impact evaluations on COVID-era policy interventions, particularly debt relief and liquidity support. Across these strands, the common theme is that large shocks can generate persistent and unequal impacts, especially when households are unprepared and enter the crisis with limited buffers. The part less well understood, then, is how these dynamics operate in a highly-leveraged, emerging-market economy like Thailand.

2.1 COVID-19 Impacts on Households

A large body of early literature documents the severe short-run effects of COVID-19 on household welfare. Much of this work relies on high-frequency household surveys, often linked to pre-pandemic baselines, to track changes in employment, income, food security, education, and coping behavior during the pandemic. Across LMICs, this literature shows large and widespread declines in work and income, with particularly severe effects for poorer and more informal households (Bundervoet, Dávalos, and Garcia 2022; Egger et al. 2021). Related firm-level evidence across countries shows sharp declines in sales, widespread temporary closures, and liquidity constraints, especially notable among smaller firms, pointing to both labor market impacts and also spillovers to households (Apedo-Amah et al. 2020).

However, official statistics are often slow and unreliable in emerging economies and informal economies (see, for example, Angrist, Goldberg, and Jolliffe (2021); Glewwe (2007); Gollin and Udry (2021)). In light of this, a second strand of research, especially in LMICs, uses high-frequency proxies of local economic activity to measure COVID exposure. These include night-time lights, mobility indicators, electricity consumption, traffic, and pollution, to capture local disruption in real time (Ai, Zhong, and Zhou 2022; Apedo-Amah et al. 2020; Beyer, Jain, and Sinha 2020; Beyer, Franco-Bedoya, and Galdo 2021; Hale et al. 2021; Lin and Rybnikova 2023). This literature is particularly relevant in settings where administrative or survey-based measures of local shocks are sparse or prone to misreporting. In Thailand, recent studies using the Socio-Economic Survey (SES) show that borrowing became a central coping mechanism during COVID, and that lower-income households became more likely to be indebted after the pandemic, even when inequality was partly cushioned by government social protection (Chote et al. 2025; Sirisankanan and Kananurak 2025).

Overall, this strand of literature establishes that: (1) COVID generated severe short-run welfare losses in LMICs, and that these losses were regressive, hitting poorer and more vulnerable households harder; and (2) borrowing played an important role in household coping during the crisis. However, most of this literature focuses on income, employment, consumption, or self-reported hardship, and typically follows households only over the short run; much less is known about how local COVID exposure translated into medium- and long-run debt dynamics and credit outcomes. This paper addresses that gap by studying household credit outcomes directly.

2.2 Long-term Effects of Shocks and Household Scarring

A second set of literature studies how temporary shocks can have persistent effects on household trajectories. One branch of this work uses household panel data and shocks such as rainfall or conflict to show that transitory adverse events can produce long-lasting effects on consumption and assets (Dercon 2004). Another branch studies early-life shocks, showing that adverse conditions around birth can also leave durable impacts on consumption and income (Almond 2006; Maccini and Yang 2009). As such, even one-time shocks can alter long-run outcomes when households are vulnerable, or lack sufficient means of adjustment.

This literature is complemented by work on poverty traps and nonlinear asset dynamics. In these models, households near a critical threshold may fail to recover from a shock, while better-off households absorb the same shock more easily (Carter and Barrett 2006). Although empirical support for strict poverty traps is mixed, the broader insight that the consequences of shocks depend on pre-shock conditions has strong relevance for household debt. For instance, a large negative income shock in the presence of high existing debt may generate a liabilities-side analogue to an asset-based poverty trap: households may become trapped in persistent debt burdens and restricted access to future credit (Antman and McKenzie 2007; Kraay and McKenzie 2014).

This paper, then, builds upon that intuition by shifting attention from the asset side of household resilience to the liabilities side of the balance sheet. Rather than focusing on consumption or wealth, it examines whether COVID had generated persistent scarring through debt burdens, delinquency, and credit access. Recent evidence from Thailand provides hints of such mechanisms. Post COVID, lower-income households have both weaker assets and higher likelihoods of indebtedness, creating a similar kind of vulnerability emphasized in the poverty trap literature (Chote et al. 2025). Hence, this paper further contributes to the literature on long-run shock dynamics, by showing how pre-existing indebtedness may shape post-shock trajectories for a variety of credit outcomes.

2.3 COVID-era Policy Interventions

A third strand of literature evaluates the effects of pandemic-era policy responses, especially debt moratoria and emergency cash transfers. Research from advanced and emerging economies shows that temporary debt relief can substantially reduce observed default and delinquency during crisis periods (Cherry et al. 2021; Fiorin, Hall, and Kanz 2023). Cross-country evidence documents that over 80% of lower-middle income countries, over 90% of upper-middle income countries, and nearly all high-income countries introduced debt mora-

toria and emergency transfers for households in the face of COVID, showing the widespread nature (Gentilini 2022; World Bank 2022). At the same time, however, cash transfer programs were often of short duration, raising concern that they smoothed immediate distress without fully restoring household balance sheets (Brooks et al. 2022; Gentilini 2022; Londoño-Vélez and Querubín 2022).

Generally, this literature suggests that well-targeted temporary support can prevent catastrophic defaults and stabilize consumption in the short run. However, they may also alter the timing and visibility of distress. This point is especially relevant for a context like Thailand, where debt relief programs were widely used during COVID, and this paper seeks to explore this further.

3 COVID-19 and Related Financial and Credit Policy

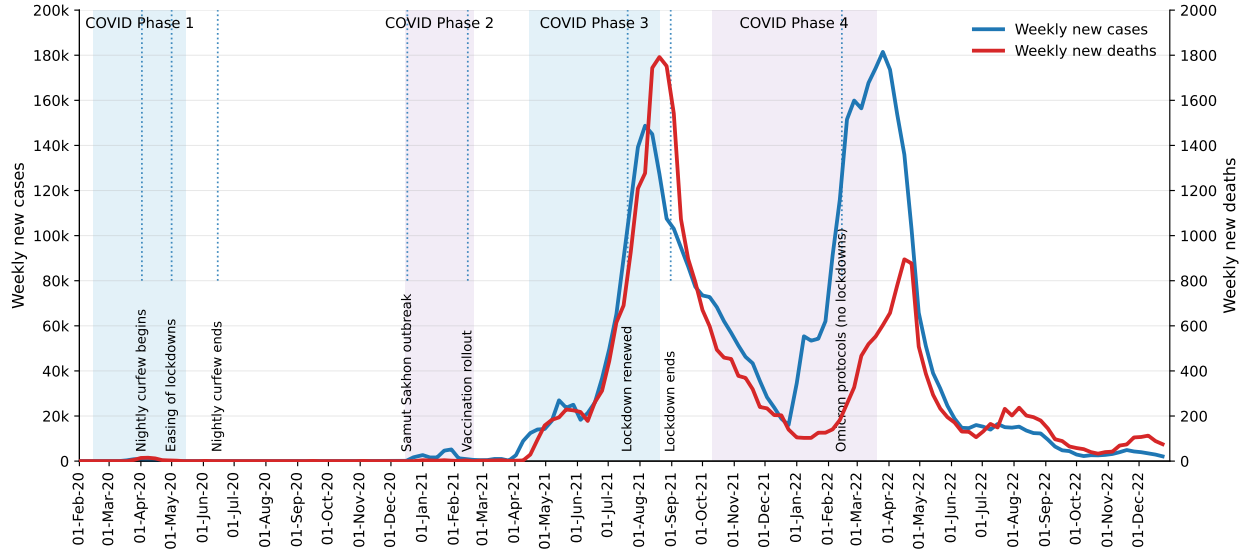
I first document the evolution of the COVID-19 pandemic in Thailand using official case statistics from the Department of Disease Control (DDC), Ministry of Public Health.¹ The dataset contains weekly confirmed cases, recoveries, and deaths at the provincial level from January 2020 to December 2022.

Figure 3.1 provides the epidemiological and policy backdrop for the empirical analysis. It plots weekly new confirmed COVID-19 cases and weekly new deaths in Thailand, alongside major containment-policy implementations (vertical dotted lines) and broader pandemic phases (shaded regions). The figure highlights that the most pronounced deterioration in health outcomes coincides with Phase 3, while Phase 4 is characterized by a large cases wave with comparatively lower mortality, consistent with the shift toward vaccination. As opposed to many Western countries, Thailand was largely successful in containing the case spread and mortality of COVID in 2020 (during Phase 1), through stringent government policies, including lockdowns, nightly curfews, and restriction of inbound tourism. Table 3.1 provides additional details on key COVID mitigation policies implemented in Thailand.

Figure 3.1 also motivates the core identification strategy of the paper. While the pandemic indeed constitutes the underlying shock, the figure suggests that the direct health impact — measured by deaths and severe cases — remained relatively limited compared to many other countries, particularly during Phases 1 and 2, as well as outside the major waves. Instead, the most economically relevant variation arises from the timing and intensity of policy responses, such as lockdowns/curfews and mobility restrictions, which are captured by

1. Refer to Department of Disease Control (2024).

Figure 3.1: COVID-19 Cases, Deaths, and Select Key Policies



Source: Case and mortality counts are plotted based on data from Department of Disease Control (2024). Information on government policies are obtained from official notices and secondary news sources.

Notes: The blue line reports weekly new confirmed cases across Thailand (left axis), and the red line reports weekly new deaths (right axis). Vertical dotted lines indicate major public-health policy milestones (e.g., curfew, lockdown renewal/ending, Omicron protocol shift).

the vertical dotted policy markers and detailed in Table 3.1. The empirical strategy exploits, accordingly, the variation in these policy-induced disruptions, rather than strict epidemiological outcomes. Thus, the key identifying assumption is that changes in household financial outcomes are driven primarily by the economic consequences of COVID policy measures, such as income losses and reduced business activity, and not by direct health shocks and underlying disease dynamics.

Table 3.2 summarizes the key debt relief phases and liquidity support measures implemented by the Bank of Thailand (BOT), the country's central bank, during COVID. The policy response evolved from broad-based, automatic payment moratoria in Phase I (March–June 2020) toward increasingly targeted and sustainability-oriented restructuring frameworks in Phases II and III. Phase I prioritized immediate liquidity preservation through universal payment holidays, whereas Phase II introduced opt-in restructuring mechanisms aimed at medium-term debt sustainability. Phase III, implemented amid the prolonged Delta-wave period, combined expanded liquidity provision with regulatory forbearance to incentivize long-term restructuring. Concurrently, BOT's Soft Loan program provided concessional funding to financial institutions for on-lending to SMEs, thereby mitigating liquidity constraints. Beyond crisis-period interventions, BOT introduced a Long-Term Debt Restructuring Framework in September 2021 to promote sustainable restructuring practices.

Table 3.1: Key COVID-19 Containment Policies in Thailand

Date Effective	Policy / Measure	Description	Scope
12 Mar 2020	Establishment of the CCSA	Creation of the Centre for COVID-19 Situation Administration (CCSA) to centralize coordination of national pandemic response and regulatory measures.	National
26 Mar 2020	State of Emergency	Declaration of nationwide emergency, enabling movement restrictions, business closures, and COVID containment regulations.	National
3–4 Apr 2020	Nationwide Night Curfew	Implementation of nationwide nighttime curfew (10pm–4am) to reduce mobility and social interaction during the first wave.	National
3 May 2020	Phase I Reopening	Initial easing of lockdown measures, allowing phased reopening of selected businesses and public spaces.	National
15 Jun 2020	Curfew Lifted	Termination of nationwide curfew following sustained decline in local transmission.	National
17 Dec 2020	Samut Sakhon Outbreak Controls	Targeted lockdowns, mass testing, and mobility restrictions following an outbreak linked to seafood market cluster.	Targeted (Provincial)
14 Feb 2021	Vaccination Rollout	Launch of national COVID-19 vaccination program, beginning with priority groups.	National
Jul 2021	Renewed Lockdown Measures	Reintroduction of strict containment measures in high-risk provinces during the Delta wave, including mobility limits and business restrictions.	Targeted (High-risk provinces)
31 Aug 2021	Lockdown Extension	Extension of tightened containment measures through end-August amid elevated case counts.	Targeted (High-risk provinces)
1 Nov 2021	International Reopening	Reopening to vaccinated international travelers under testing and quarantine-related protocols.	National (Border policy)
Mid-Feb 2022	Symptom-Based Protocol Shift	Transition toward symptom-based management and reduced reliance on nationwide lockdowns during the Omicron wave.	National
30 Sep 2022	End of Emergency Decree	Termination of nationwide emergency legal framework governing COVID containment measures.	National

Source: Author compilation from official announcements of the Centre for COVID-19 Situation Administration (CCSA), Royal Thai Government Gazette emergency decrees, publications of the Department of Disease Control (DDC), and secondary news sources.

Table 3.2: COVID-19 Debt Relief Phases and Soft Loan Measures in Thailand

Program	Start	End	Key Features
Debt Relief Phase I (automatic)	26 Mar 2020	30 Jun 2020	• Broad-based minimum relief coordinated across FIs • Payment holidays / debt moratorium; temporary repayment reductions • Universal loan coverage; retail borrowers & SMEs (personal, auto, leasing) • Suspended payments not classified as arrears • Automatic enrollment for borrowers; many FIs exceed these minimum requirements
Debt Relief Phase II (opt-in)	1 Jul 2020	31 Dec 2020	• Transition from blanket relief to targeted restructuring; opt-in required • Measures: installment reduction, maturity extension • No lump-sum settlement of deferred principal/accrued interest at expiry • Late payment fees & other charges waived • Focus on medium-term debt sustainability
Debt Relief Phase III (opt-in)	3 Sep 2021	31 Dec 2021	• Addressed prolonged pandemic risks; opt-in required • Expanded liquidity: revised Special Loan regulations (higher credit limits, increased guarantee coverage, reduced fees for high-risk SMEs) • Targeted long-term restructuring with eased asset classification & provisioning requirements • Retail credit regulations temporarily relaxed (higher limits, extended reduced minimum payments, expanded digital loan limits/maturities)
Soft Loan Measures (BOT)	Apr 2020	2022 (phased extensions)	• THB 500bn BOT liquidity facility for on-lending to SMEs (Financial Assistance Emergency Decree) • Eligibility: normal repayment status; credit line $\leq$ THB 500mn per FI as of end-2019 • Max drawdown: 20% of outstanding loans (end-2019); interest rate cap: 2% • Targeted at SMEs in affected sectors/provinces, incl. high-risk firms, to support SME liquidity
Long-Term Debt Restructuring Framework	3 Sep 2021	Ongoing	• Promotes sustainable, tailored debt restructuring • Requires repayment schedules aligned with debtor cash flows, with gradual normalization as income recovers • Conditional relaxation of asset classification and provisioning rules
Persistent Debt / Responsible Lending Measures	1 Jan / 1 Apr 2024	Ongoing	• Structural household debt reform under Responsible Lending framework, introducing targeted treatment for persistent debt (interest-dominant repayment profiles) • Requires structured repayment pathways toward full amortization within defined horizons • Strengthens consumer protection, affordability assessment, and lender accountability

Source: Author compilation from Bank of Thailand (2021a, 2021b, 2023a, 2023b, 2024) and Monetary Policy Committee (2020).

The ongoing Persistent Debt and Responsible Lending measures represent efforts toward preventing chronic debt traps and strengthening prudential consumer lending standards.

Specifically, Debt Relief Phases I–III plays a central role in the identification strategy, representing distinct policy regimes governing borrower support and therefore provide meaningful variation in household debt and loan outcomes. These policy phases are critical for interpreting observed dynamics in debt performance: differences across periods may reflect not only underlying economic conditions, but also the changing structure of policy support. As such, this paper treats these financial policy phases as key policy regimes that could shape borrower outcomes. This enables distinguishing between the mechanical effects of policy interventions and the underlying changes in household financial distress.

Table 3.3 summarizes the main agriculture-specific debt relief and credit measures implemented in Thailand during the COVID-19 period, primarily through the Bank for Agriculture and Agricultural Cooperatives (BAAC), a large government-owned financial institution. These programs combined broad debt moratoria with small emergency liquidity loans and targeted restructuring.

Agriculture is a strategically important sector in Thailand, encompassing more than 7 million households in 2025 and serving as a key foundation of rural livelihoods. However, Thai agricultural households face persistent structural vulnerabilities. As such, credit has become a central financial tool for farm households, with 90% of surveyed farmer households reported being indebted to various lenders, ranging from formal government banks to informal money lenders (Ratanavararak and Chantararat 2023).

At the same time, agriculture in Thailand is one of the most heavily supported sectors of the economy, with the government having long relied on a wide range of interventions, such as subsidies, occupation training, crop insurance support, disaster relief, concessional lending, and debt relief or restructuring schemes. This extensive policy support reflects the economic significance of agriculture, with the implication that the financial behavior and outcomes of agricultural households are heavily shaped by government assistance.

4 Data

This paper incorporates two main categories of data, pertaining to the credit bureau data and COVID exposure data. I describe both categories, with a discussion of the main COVID exposure data, night-time lights, in this section and the secondary supporting data sources in Appendix A.

Table 3.3: Agriculture-Specific COVID-19 Debt Relief and Credit Measures in Thailand

Program	Start	End	Key Features
BAAC Debt Moratorium (automatic)	Apr 2020	Mar 2021	• One-year automatic suspension of principal and interest payments due during Apr 2020–Mar 2021 • Covered farmers, agricultural groups/cooperatives, village/community funds, and related rural borrowers • Designed as broad-based agricultural debt relief at the onset of the pandemic
BAAC Emergency Household-Expense Loan	May 2020	30 Jun 2021	• THB 20bn facility for farmers and farmer households affected by COVID-19 • Loan size up to THB 10,000 per borrower • Fixed interest rate of 0.1% per month; maturity up to 2.5 years • Six-month grace period and no collateral requirement • Expanded access to small-ticket liquidity loans in rural areas
BAAC Cashback / Principal-Reduction Measures	1 Dec 2020	31 Mar 2021	• Normal farmer debtors received 20% interest cashback, capped at THB 5,000 • For overdue debtors, refunded interest was applied directly to principal reduction • Repayment schedules were adjusted to better match borrower income flows • Combined short-run relief with targeted restructuring and debt burden reduction
BAAC Third-Wave Moratorium and Disaster Loan	11 May 2021	31 Dec 2021	• Opt-in principal moratorium of 6–12 months for eligible borrowers with debt outstanding before 1 Apr 2021 • Borrowers continued paying interest only during the relief • Separate COVID-19 disaster loan facility of THB 10bn • Disaster loans up to THB 10,000 per borrower, interest rate 0.35% per month, 3-year maturity, six-month grace period, and no collateral • Targeted liquidity support for agricultural households during the prolonged pandemic wave

Source: Author compilation from Bank for Agriculture and Agricultural Cooperatives (2020) and Ministry of Finance (2021a, 2021b).

4.1 Credit Bureau Data

4.1.1 Overview of NCB Data

This paper uses account-level consumer loan data from 2016 to 2024, submitted quarterly to the National Credit Bureau (NCB) by its members.² NCB is the primary credit information provider in Thailand; the data cover essentially all loans from formal financial institutions to ordinary persons in the country.³

The NCB data is ideal for several reasons. First, the data track the vast majority of formal loans to Thai individuals from formal financial institutions. This allows for the data to cover a wide range of the Thai population, as opposed to, for example, data collected from surveys which tend to miss certain subgroups (e.g., those at the low and high tails of the income distribution) and are prone to mis-reported data. Secondly, the wide coverage of loans at the account level, tied to unique borrower identifiers, enables analysis of the loan portfolios of individuals when they borrow from multiple lenders, encompassing many possible loan categories (e.g., home loan, business loan, etc.). Lastly, and perhaps most importantly, the data contain loan account-level panel data that makes possible analysis of household debt at very granular levels. Further, the matching of the loan account-level data to the borrower’s mailing address postal code enables analyzing the heterogeneity of households at very fine geographic scales. In this paper, I consider the borrower’s mailing address postal code to be the same as their residential address postal code.

The NCB data hold account level information on four dimensions: (i) borrower information on age, gender, and postal code of mailing address; (ii) information on the lender, which I group into three general categories: commercial banks,⁴ Special Financial Institutions (SFIs),⁵ and the remaining nonbank financial institutions;⁶ (iii) information on the loan product type, which I group into six mutually-exclusive categories: credit card loans, home

2. The data are as of the end of each quarter, except for the data since August 2020, which are reported monthly. In those cases, I filter the data to March, June, September, and December, corresponding to the end of each quarter.

3. The data do not include loans from the Student Loan Fund, cooperatives, and village funds. Loans from the informal financial sector, such as money lenders or community-based institutions, are not reported to nor represented in NCB data. Additionally, the NCB data do not include loans to juristic persons.

4. In NCB data, commercial banks are defined on a stand-alone basis. That is, for the subsidiaries of commercial banks (e.g., credit card, hire purchase, and leasing companies), if they are also NCB members, then they are filed as separate financial institutions.

5. The Specialized Financial Institutions (SFIs) include: the Government Savings Bank, Government Housing Bank, Export-Import Bank, Small and Medium Enterprise Development Bank, Islamic Bank, and Bank for Agriculture and Agricultural Cooperatives.

6. I refer to the remaining financial institutions as nonbank financial institutions (e.g., credit card companies, hire purchase or leasing companies, insurance companies, and cooperatives).

loans, agricultural loans, hire purchase (HP) loans,⁷ business loans, and personal loans;⁸ and (iv) reported information on the credit line, date of opening, payment installment frequency and amount, outstanding balance, and number of days past due (if it is nonzero). In this paper, I define delinquent loans as those that are more than 90 days past due, and it serves as the key indicator of financial unhealthiness.⁹ Additionally, the NCB separately tracks instances of new loan inquiries initiated by the borrower and instances of credit reviews on existing loans by member financial institutions. I join this inquiry dataset on the main dataset with the unique borrower identifiers common across both data.

Table 4.1 displays an overview of NCB data. At the end of 2025 Q2, the NCB tracked 29.14 million unique borrowers over 92.57 million loan accounts. All together, these represented a total loan amount outstanding of 14.7 trillion baht, or 90% of the 16.3 trillion baht of total household debt in the system. As of 2025 Q2, there were 163 member financial institutions represented in the NCB. Notably, the jump in the tracked results in Table 4.1 between 2016 Q1 and 2016 Q2 is largely reflective of the fact that the Bank for Agriculture and Agricultural Cooperatives (BAAC), a large government-owned bank in Thailand, began submitting borrower data to the NCB after 2016 Q1. While I display summary statistics for 2016 Q1 in this section, I exclude that quarter from my methodology, beginning my analysis in Q2.

Table 4.2 provides some descriptive characteristics of borrowers and loans as of the end of 2025 Q2 (the most recent cohort in the NCB data). The median borrower is 43 years old, and the vast majority of borrowers reside in a postal code that is considered “urban” (see the Footnote in Table 4.2). Further, the plurality of borrowers (27%) reside in Bangkok and its adjacent provinces.¹⁰ The distribution for the credit limit is skewed right, with a median of 44,528 baht but a mean of over half a million baht. Similarly, the current loan balance is skewed right with a median of 16,982 baht but a mean of 146,474 baht. This holds as well for the loan balance for delinquent accounts, which has a median of 35,737 baht but a mean

7. Hire purchase (HP) loans include automobile and motorbike HP loans.

8. Personal loans include personal term loans, personal revolving loans, and other unsecured loans.

9. This definition of delinquent loans is intentionally placed between mere late payment status and the official non-performing loan (NPL) classification used by the Bank of Thailand (BOT). Under BOT regulations, NPL status applies to loans with principal or interest overdue for more than 90 days, as well as loans exhibiting other qualitative indicators of credit impairment under asset classification and provisioning rules (Bank of Thailand 2024). Adopting the 90+ days past due threshold, in line with international banking practice and the literature, provides an objective and economically meaningful indicator of financial distress that is more stringent than counting short-term late payments (e.g., 30-60 days), but less encompassing than the BOT’s formal NPL classification, which additionally incorporates qualitative assessments of credit deterioration that are not well-suited for quantitative regressions.

10. That is: Bangkok, Nonthaburi, Pathum Thani, Nakhon Pathom, Samut Sakhon, and Samut Songkhram.

Table 4.1: Overview of National Credit Bureau (NCB) Data

Quarter	# of FI Members	Borrowers Total (mil.)	Accounts Total (mil.)	Total Loan Outstanding (tril. baht)	Total Loan Past Due (tril. baht)	Newly Delinquent (tril. baht)	New Loan Inquiries (mil.)	Review Inquiries (mil.)
2016Q1	89	17.17	49.05	9.34	0.39	0.08	3.73	10.16
2016Q2	90	20.47	60.62	10.46	0.45	0.09	3.76	12.07
2016Q3	91	20.84	61.74	10.55	0.46	0.11	3.96	12.92
2016Q4	92	21.00	62.02	10.76	0.46	0.10	3.86	16.88
2017Q1	94	20.98	61.87	10.73	0.47	0.08	3.90	12.62
2017Q2	94	21.26	62.41	10.88	0.48	0.14	4.24	14.59
2017Q3	92	21.33	63.60	10.97	0.49	0.12	4.43	12.78
2017Q4	94	21.77	64.48	11.29	0.51	0.08	4.23	14.59
2018Q1	96	21.95	64.87	11.40	0.50	0.08	4.27	16.39
2018Q2	97	22.15	66.60	11.60	0.52	0.11	4.65	15.82
2018Q3	96	22.44	67.44	11.83	0.54	0.10	4.91	17.94
2018Q4	95	22.62	68.68	12.11	0.52	0.11	5.09	16.90
2019Q1	98	22.78	69.90	12.21	0.54	0.09	5.19	15.61
2019Q2	98	23.13	70.90	12.43	0.56	0.16	5.69	16.76
2019Q3	97	23.37	72.13	12.60	0.57	0.16	6.17	16.37
2019Q4	101	23.74	73.15	13.67	0.60	0.14	5.47	19.51
2020Q1	100	23.88	73.62	13.61	0.62	0.14	5.28	19.76
2020Q2	102	24.99	74.62	12.95	0.67	0.08	6.26	23.67
2020Q3	104	25.36	75.64	13.05	0.66	0.06	6.33	22.48
2020Q4	106	25.64	76.21	13.28	0.65	0.09	7.13	20.54
2021Q1	107	26.13	77.42	13.38	0.67	0.10	9.80	19.59
2021Q2	108	26.37	78.68	13.56	0.70	0.11	11.11	19.84
2021Q3	110	26.23	79.25	13.51	0.73	0.15	9.69	16.86
2021Q4	115	26.68	80.04	13.88	0.73	0.11	11.14	23.33
2022Q1	117	26.84	81.32	13.95	0.72	0.10	11.99	21.41
2022Q2	121	27.02	82.13	14.13	0.76	0.27	14.93	21.19
2022Q3	123	27.23	82.72	14.34	0.78	0.17	15.62	22.70
2022Q4	124	27.18	86.09	14.39	0.73	0.14	13.04	21.63
2023Q1	127	27.15	83.38	14.39	0.75	0.13	10.85	20.71
2023Q2	131	27.38	83.75	14.68	0.77	0.18	12.31	22.60
2023Q3	132	27.42	83.71	14.77	0.78	0.17	11.33	22.25
2023Q4	134	27.44	84.33	14.86	0.78	0.17	10.35	21.95
2024Q1	145	27.34	84.41	14.85	0.80	0.17	10.02	21.18
2024Q2	148	27.54	84.76	14.88	0.83	0.18	10.68	20.25
2024Q3	153	27.77	85.27	14.88	0.83	0.18	11.04	21.45
2024Q4	154	27.88	85.32	14.93	0.84	0.18	10.24	23.44
2025Q1	160	27.95	85.88	14.76	0.85	0.12	10.01	22.13
2025Q2	163	29.14	92.57	14.70	0.89	0.16	11.02	22.64

Source: Author's calculations from National Credit Bureau (NCB) data.

Notes: Newly Delinquent Loans are loan accounts that reached 90+ days of principal or interest overdue during that particular quarter (see Footnote 9). New Loan Inquiries is the number of NCB credit reviews for new loans, while Review Inquiries is the number of NCB credit reviews for existing loans.

Table 4.2: Descriptive Statistics of NCB Borrowers and Loans (2025 Q2)

Variable	N	Mean	Std. Dev.	p25	Median	p75
Borrower characteristics						
Age (Years)	29,139,716	44.25	12.73	34	43	53
Urban Postal Code (=1) ^a	26,753,938	0.9112	N/A	N/A	N/A	N/A
Region:						
<i>Bangkok and vicinity (=1)</i>	26,753,349	0.2695	N/A	N/A	N/A	N/A
<i>Central (=1)</i>	26,753,349	0.1969	N/A	N/A	N/A	N/A
<i>North (=1)</i>	26,753,349	0.1509	N/A	N/A	N/A	N/A
<i>Northeast (=1)</i>	26,753,349	0.2587	N/A	N/A	N/A	N/A
<i>South (=1)</i>	26,753,349	0.1240	N/A	N/A	N/A	N/A
Total Loan Outstanding (baht)	29,139,808	504,424	2,891,082	18,164	94,881	442,072
Account-level loan characteristics						
Credit Limit (baht)	92,572,093	500,694	16,692,671	15,000	44,528	144,991
Current Balance (baht)	92,572,093	146,474	949,918	142	16,982	71,772
Utilization Rate ^b	86,653,009	5.91	3,707.47	0.0005	0.5424	0.9444
Delinquent Balance (baht)	9,618,480	128,481	589,914	13,690	35,737	90,289

Source: Author’s calculations from National Credit Bureau (NCB) data.

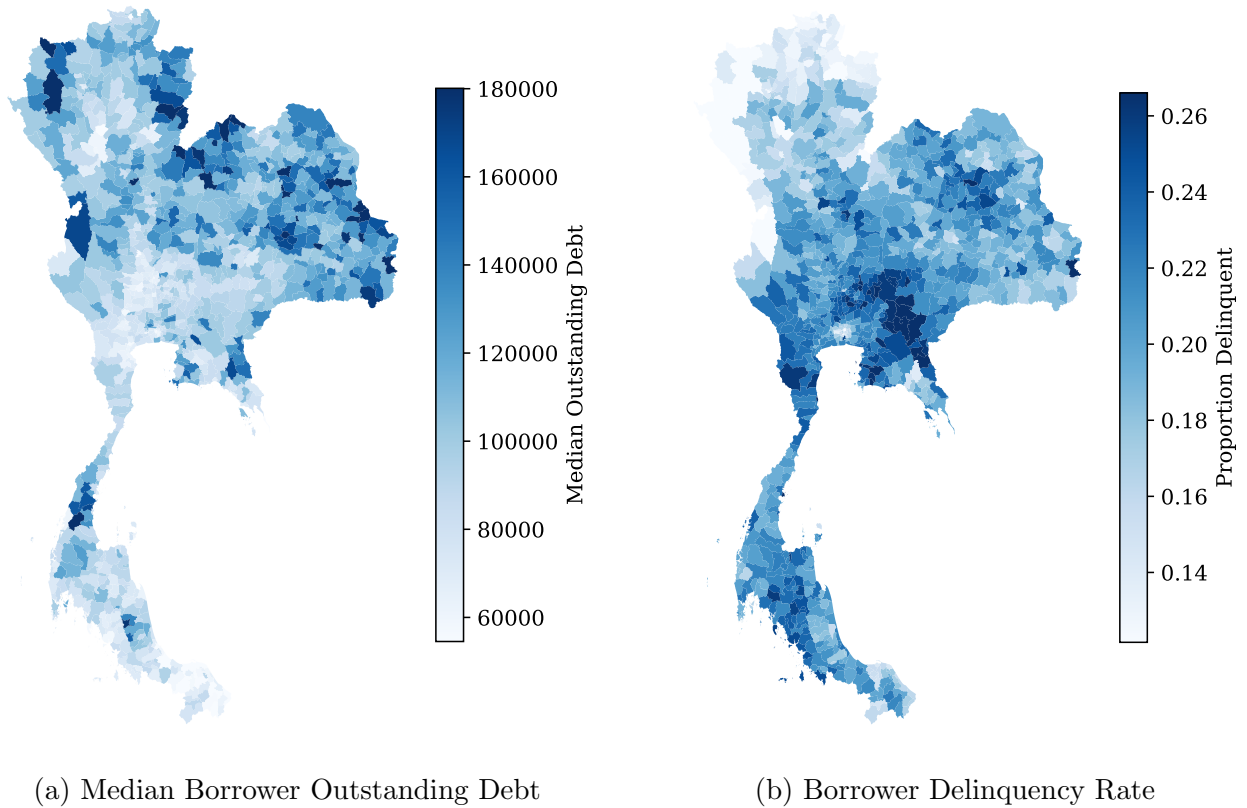
Notes: Summary statistics for borrower characteristics are computed at the borrower level. Summary statistics for loan characteristics are computed at the account level. Percentiles correspond to the empirical distribution.

^a A postal code is urban if more than 50 percent of the area belongs to municipalities. This characterization is much looser than typical convention, as this includes many, for instance, primarily agricultural postal codes. In fact, 88 percent of all postal codes in Thailand are considered “urban”.

^b Utilization rate — defined by the current balance divided by the (non-zero) credit limit — exhibits extreme right-tail outliers for small credit limits. Results are robust to winsorization at the 99th percentile.

of 128,481 baht. The median utilization rate of the account, defined as the current balance divided by the credit limit, is 54.24%. The mean borrower in 2025 Q2 had 3.18 active loan accounts. Aggregating all the loan accounts for each individual, the total loan outstanding per borrower is again skewed right with a median of 94,881 baht and a mean of 504,424 baht.

Figure 4.1: Spatial Distribution of Borrower Debt and Delinquency (2025 Q2)



Source: Author's calculations from National Credit Bureau (NCB) data.

Notes: Median borrower outstanding debt and the indicator for borrower delinquency are calculated at the borrower level, combining all loan accounts held by each borrower. A borrower is delinquent if at least one of their loans is delinquent. Color scales are winsorized at the 2–98% limits.

Figure 4.1 presents the pronounced spatial heterogeneity in both borrowing intensity (measured by the median borrower outstanding debt in each postal code, in panel (a)) and repayment performance (measured by the percent of all borrowers in each postal code with at least one delinquent loan, in panel (b)). While postal codes in Bangkok and surrounding areas generally show lower median outstanding debt than much of the country, delinquency rates form distinct clusters that do not align closely with debt levels. This mismatch indicates that regional repayment risk is influenced by factors beyond the size of borrowing, as there is no clear visual relationship between median outstanding debt and delinquency rates.

Table 4.3: Borrower-level Loan Product Composition and Delinquency (2025 Q2)

Loan product	# Borrowers w/ product	Share of all borrowers ^a	Debt p25 (baht)	Debt med. (baht)	Debt p75 (baht)	Delin. rate ^b
Personal (pl)	21,148,006	0.7257	10,014	44,615	129,152	0.2131
Credit card (cc)	8,128,518	0.2789	2,803	22,041	62,638	0.0850
Hire purchase (hp)	5,515,617	0.1893	167,167	322,454	533,084	0.1483
Agricultural (agri)	2,935,139	0.1007	19,310	109,630	268,745	0.0484
Home (hl)	2,824,328	0.0969	614,620	1,390,357	2,285,367	0.0489
Business (biz)	856,868	0.0294	32,676	142,814	571,503	0.1476

Source: Author's calculations from National Credit Bureau (NCB) data.

Notes: Summary statistics are computed at the borrower-loan type level, aggregating all loan accounts for each loan type within a borrower's portfolio.

^a Shares sum to more than one because borrowers may hold multiple loan products within the same quarter.

^b Delinquency rate is defined as the share of borrowers with this product who are delinquent in at least one loan of that product type in 2025 Q2.

Table 4.3 shows that in 2025 Q2, personal loans were the most prevalent product in the borrower portfolio, with 21.1 million borrowers holding a personal loan (72.6% of all borrowers). Credit cards and hire purchase were also common, held by 27.9% and 18.9% of borrowers, respectively, while agricultural, home, and business loans were comparatively less widespread.

Debt distributions differ sharply across products. Home loans exhibit substantially larger balances than other products, with a median debt of 1.39 million baht, consistent with housing finance being the largest household liability. By contrast, unsecured credit products have smaller typical balances: personal loans have a median of 44.6 thousand baht and credit cards 22.0 thousand baht. Hire purchase and business loans sit in between, with higher upper-quartile balances (p75 of 533 thousand and 572 thousand baht, respectively), reflecting larger financed durables and heterogeneous borrowing needs.

Furthermore, delinquency rates also vary meaningfully across products. Personal loans show the highest delinquency rate (21.3%), followed by hire purchase (14.8%) and business loans (14.8%). Credit cards have a lower delinquency rate (8.5%), and agricultural and home loans show the lowest delinquency (both around 4.9%). Taken together, these patterns suggest that delinquency risk is concentrated in unsecured and semi-secured loan products, while large-balance mortgage borrowing appears comparatively stable in this quarter.

4.1.2 Credit Outcome Variables

Using quarterly loan-level data from the National Credit Bureau (NCB) spanning 2016–2025, I construct four groups of outcome variables, capturing debt dynamics, loan repayment behavior, new borrowing, and credit demand. All variables are defined at the borrower–quarter level (i, q) and, where applicable, at the borrower–quarter–product level (i, q, p) , where product p includes the six loan types.

- **Debt dynamics**

- D_{iq} : Total outstanding debt of borrower i in quarter q , defined as the sum of all reported outstanding balances across all of their loan accounts.
- D_{iqp} : Total outstanding debt of borrower i in quarter q for all of their loan accounts belonging to product p .

- **Loan repayment and delinquency**

- $Delin_{iq}$: Indicator equal to one if borrower i has at least one delinquent loan in quarter q , and zero otherwise.¹¹
- $Delin_{iqp}$: Indicator equal to one if borrower i is delinquent on product p in quarter q .
- $DelinPreLoan_{iq}$: Indicator equal to one if borrower i is delinquent in quarter q on a loan originated prior to the COVID-19 period (i.e., 2019 Q4 or prior).
- $DelinCovidLoan_{iq}$: Indicator equal to one if borrower i is delinquent in quarter q on a loan initiated during or after the COVID-19 period (i.e., 2020 Q1 or after).
- $Minpay_{iq}$: Indicator equal to one if borrower i makes only interest payments in quarter q , such that the outstanding principal does not decline. This variable is primarily relevant for, and calculated using, term loans (home loans, personal term loans, and hire purchase loans).

- **New borrowing**

- $HaveNewLoan_{iq}$: Indicator equal to one if borrower i opens at least one new loan in quarter q .
- $HaveNewLoan_{iqp}$: Indicator equal to one if borrower i opens at least one new loan of product type p in quarter q .

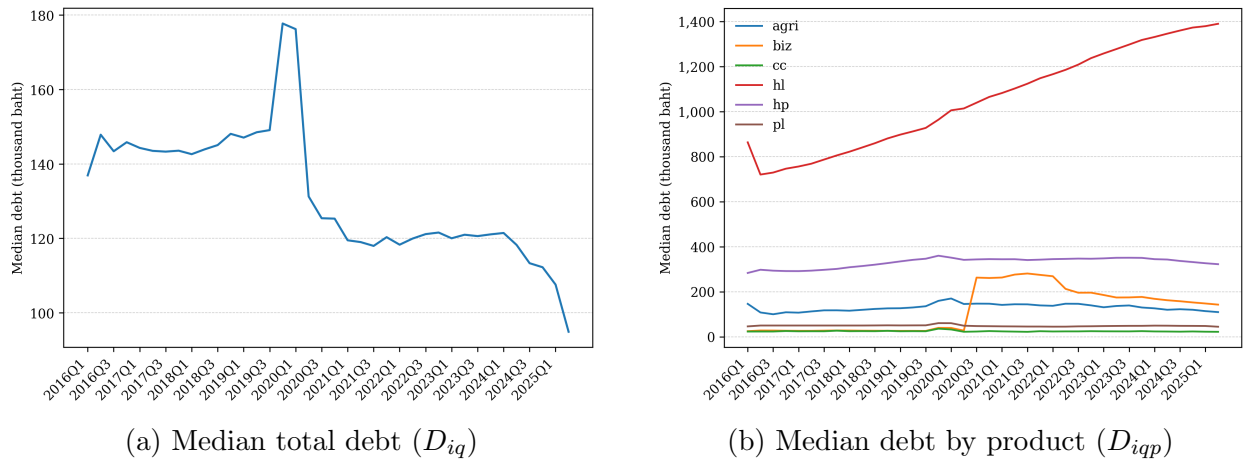
11. Recall the definition of delinquency, as outlined in Footnote 9.

- **Credit demand and unmet demand**

- $HaveInquiry_{iq}$: Indicator equal to one if borrower i generates at least one loan inquiry in quarter q .
- $HaveUnmetInquiry_{iq}$: Indicator equal to one if borrower i generates a loan inquiry in quarter q but does not open a new loan within the subsequent two quarters (i.e., the current quarter or the following quarter). This variable captures unmet or unsuccessful credit demand.

All indicator variables are defined at the borrower–quarter level unless otherwise specified. Product-level variables allow for multi-product borrowing, as indicators may equal one simultaneously across different products within the same quarter, for a given borrower.

Figure 4.2: Evolution of Borrower Debt Level Behavior



Source: Author's calculations from National Credit Bureau (NCB) data.

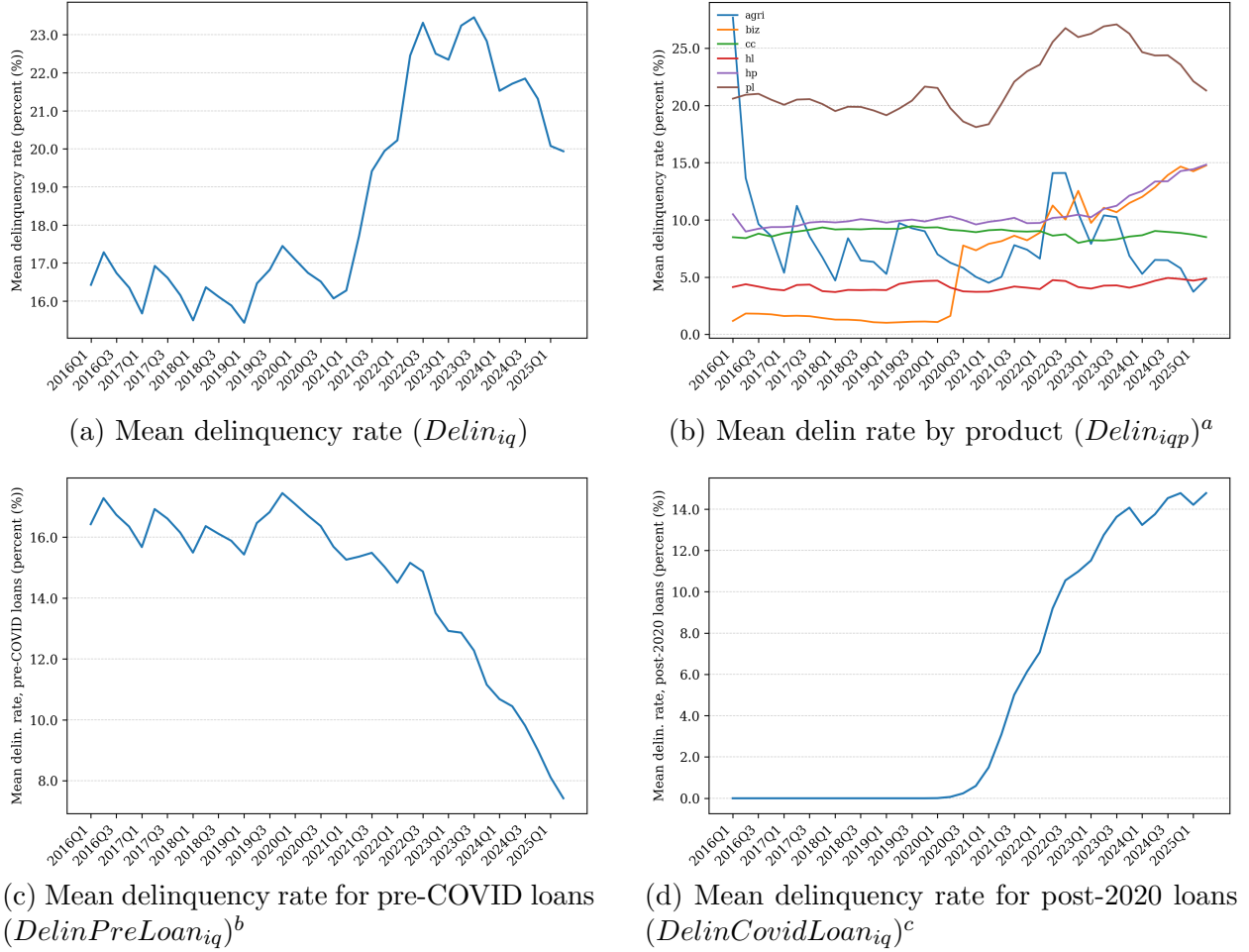
Notes: All outcomes are computed at the borrower-quarter level or at the borrower-quarter-product level. For variables at the borrower-quarter-product level, summary statistics are computed with only borrowers who hold loan product type p in quarter q .

Figure 4.2 shows the evolution of borrower-level debt. Panel (a) shows that the median debt increases gradually from 2016 through 2019, indicating a steady expansion in borrower leverage prior to the COVID-19 period. A noticeable spike occurs around 2020, followed by a sharp adjustment. After 2021, the median debt stabilizes and then gradually declines toward the end of the sample. This pattern suggests that the aggregate debt accumulation slowed dramatically after the pandemic shock, consistent with tighter credit conditions or borrower deleveraging.

Panel (b) is a decomposition by loan product type. Home loans exhibit a persistent upward trend throughout the sample. In contrast, hire purchase and agricultural loans

display more cyclical movements, including visible fluctuations around 2020. Credit card and personal loan balances remain comparatively small and show modest variation over time. Business loans, meanwhile, showed a strong uptick in median balance between 2020 Q2 and 2020 Q3, remaining elevated until slowly declining in 2022.

Figure 4.3: Evolution of Borrower Delinquency Behavior



Source: Author's calculations from National Credit Bureau (NCB) data.

Notes: All outcomes are computed at the borrower-quarter level or at the borrower-quarter-product level. For variables at the borrower-quarter-product level, summary statistics are computed with only borrowers who hold loan product type p in quarter q .

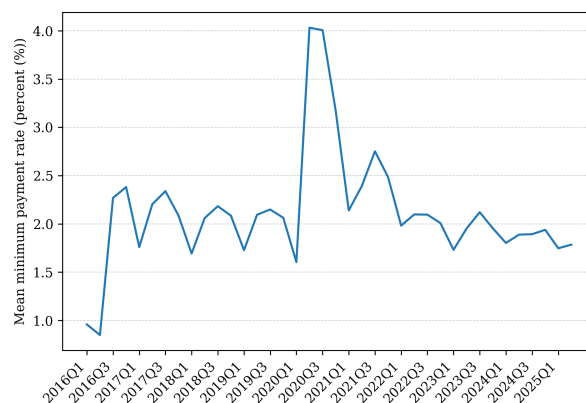
^a $Delin_{iqp}$ for agricultural loans shows a sharp change between 2016 Q1 and 2016 Q2, as discussed in the context of Table 4.1, due to the start of BAAC-reported data to the NCB.

^{b,c} The delinquency rate for loans originating prior to COVID naturally decreases sharply in 2020 Q1, once no new loans enter the sample. Likewise, the delinquency rate for loans originating during COVID or after is naturally zero pre-COVID, as no such loans existed then.

Figures 4.3 and 4.4 present the evolution of borrower repayment behavior and delinquency outcomes. Panels (a) and (b) of Figure 4.3 plot the mean delinquency rate among borrowers, overall ($Delin_{iq}$) and by product ($Delin_{iqp}$). Prior to 2020, overall delinquency remains

relatively stable. Beginning in 2021, however, delinquency increases markedly. Separating loans by product reveals meaningful differences in risk exposure. Agricultural and personal loans display more pronounced fluctuations, while home loans remain comparatively stable throughout the sample, consistent with the long-term structure of home loans. Credit card loans exhibit mild changes in delinquency rates in 2022 and 2023. Business loans show a spike, followed by increasing delinquency rates during the post-pandemic period. Panels (c) and (d) are decompositions by loan cohort, showing the different trajectories for loans that originated before COVID and during/after COVID.

Figure 4.4: Evolution of $Minpay_{iq}$ Repayment Behavior



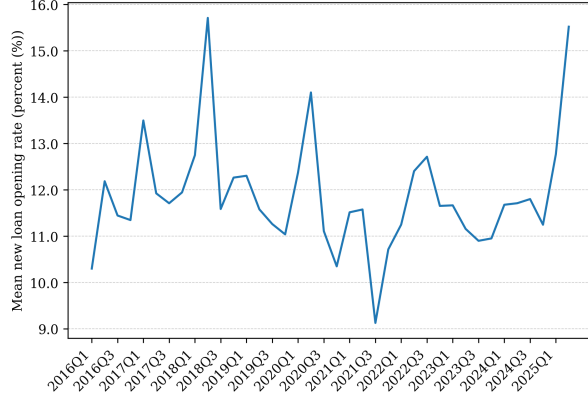
Source: Author's calculations from National Credit Bureau (NCB) data.

Notes: The series reports the borrower-quarter share (percent) making interest-only payments (no principal reduction), primarily relevant and calculated for term loans. This series report the percentage of all borrowers, not just borrowers with term loans, who make interest-only payments.

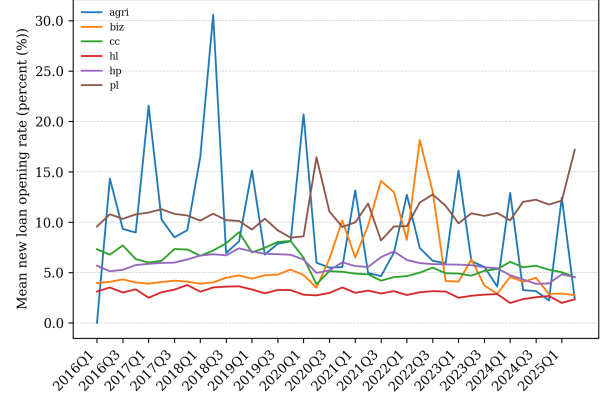
Figure 4.4 displays the mean minimum-payment rate ($Minpay_{iq}$), which captures interest-only payment behavior. The minimum-payment rate increases substantially during 2020, peaking around the height of pandemic-related disruptions. Borrowers defer principal repayment while maintaining loan accounts in current status, consistent with COVID-era Debt Relief policies. Following the pandemic period, the minimum-payment rate gradually declines, but remains above pre-2020 levels for several quarters, thus suggesting a persistent adjustment in repayment behavior.

Figure 4.5 showcases the evolution of loan origination and credit inquiry behavior, where several patterns emerge. First, the share of borrowers with new loans ($HaveNewLoan_{iq}$) fluctuates over the sample period, with noticeable cyclical variation and temporary spikes. The product-level series ($HaveNewLoan_{iqp}$) reveals substantial heterogeneity across loan categories, with some products exhibiting sharper short-run movements, which suggests that some changes in credit expansion may be concentrated in specific market segments rather than broad-based. For instance, the relative share of new openings for agricultural loans,

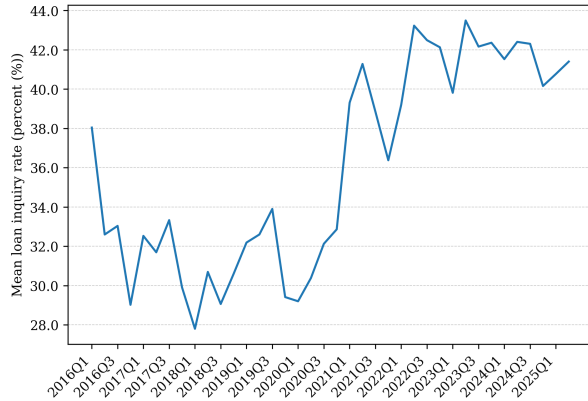
Figure 4.5: Evolution of Borrower Loan Origination and Credit Inquiry Behavior



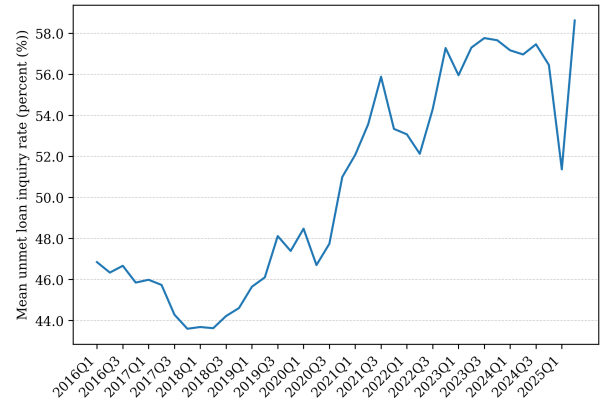
(a) Share of borrowers with new loans ($HaveNewLoan_{iq}$)



(b) Share of borrowers with new loans by product ($HaveNewLoan_{iqp}$)



(c) Share of borrowers with credit inquiries ($HaveInquiry_{iq}$)



(d) Share of borrowers with unmet credit inquiries ($HaveUnmetInquiry_{iq}$)

Source: Author's calculations from National Credit Bureau (NCB) data.

Notes: All outcomes are computed at the borrower-quarter level or borrower-quarter-product level. Product-level summary statistics are computed using only borrowers who held or now hold product type p in quarter q .

while decreasing over time, shows clear cyclical patterns and is a major source of the variation in Panel (a). Business loans have a clear spike early in the COVID pandemic, while the largest spikes in business loans appear in the COVID recovery phase.

Second, credit inquiry activity ($HaveInquiry_{iq}$) shows a clear upward trend over time, particularly in the post-2020 period. This pattern is consistent with greater credit demand, and the sustained elevation in inquiry rates after 2020 suggests structurally higher credit market activity, rather than purely transitory fluctuations. More strikingly, the share of borrowers with unmet credit inquiries ($HaveUnmetInquiry_{iq}$) rises substantially beginning in 2020. The increase in unmet inquiries, particularly relative to overall inquiry rates, may indicate increased loan screening stringency or greater demand pressure in the credit market, both leading to tightening credit conditions. While new loan origination remains relatively stable in aggregate, the rising prevalence of unmet inquiries suggests a potential widening gap between borrower demand and effective credit supply in the system.

4.2 COVID Exposure Data

To measure the variations in the postal code-level economic shock from COVID, I use satellite-based night-time light (NTL) data from the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor onboard the Soumi-NPP satellite, which is jointly operated by NASA and the National Oceanic and Atmospheric Administration (NOAA) of the U.S. government. In particular, I leverage monthly composites of the VIIRS lights produced by the Earth Observation Group (EOG) at the Colorado School of Mines.¹² These monthly composites cover virtually the entire globe, with a resolution of 15 arc seconds (approximately 450 meters at Bangkok’s latitude) per pixel. For each pixel, the VIIRS composites report the luminous intensity in nanowatts/cm²/sr, averaged across all cloud-free nights in a month. I make use of the monthly composites from January 2013 to December 2024, for 12 years of data.

As the measure of the monthly NTL intensity for each postal code, I overlay Thai postal code polygons on the VIIRS pixel grid and compute, for each postal code-month entry, the mean light intensity value for all valid pixels whose centroids fall within the geographic area of that postal code.¹³ Valid pixels are those with an intensity that is non-negative.¹⁴ This

12. For information on the VIIRS dataset and its methodology, refer to Elvidge et al. (2017).

13. As a robustness check, I compute also the 5% trimmed mean and the 5% winsorized mean, where the lowest and highest 5% of valid pixel intensities are either excluded (trimmed mean) or capped at the respective percentile thresholds (winsorized mean). In addition, I calculate the median intensity of valid pixels. Across all three alternative measures of central tendency, the event-study regressions produce similar results, although the corresponding graphs are not reported in this paper.

14. Negative NTL values can occur due to instrument noise, atmospheric correction artifacts, airglow

yields a monthly NTL time series for each postal code.

Because the VIIRS composites report only the average of the intensities from cloud-free days in a given month, distortions in the lights data for Thailand are possible during the monsoon season, generally starting in late May or early June and ending in October. Such distortions arise from there being fewer cloud-free nights to average over, and the remaining cloud-free nights may have data that is contaminated. Given the widespread and intense nature of this distortion, I filter out all the postal code-month entries where less than 90% of the pixels in that postal code are marked as valid.

It is important to note that there may also be other sources of distortion in the data associated with, for instance, atmospheric effects or other meteorological phenomena. The analysis in this paper accounts for these distortions to the extent that they follow seasonal patterns; however, if these distortions do not follow a pattern, and if the timing and scale of these effects are correlated with the onslaught of COVID, then the VIIRS composites may misattribute these effects to COVID.

For each postal code, I compute the average annual NTL value from all remaining valid postal code-month entries in that year. I then fit a linear trend to the annual averages of NTL values from 2013 to 2024. The COVID-NTL exposure is quantified as the average logarithmic deviation between the expected NTL values based on the fitted trend and the observed yearly-averaged NTL values, for 2020 and 2021.¹⁵ This mechanism separates the negative shock in NTL experienced during COVID from the general, long-term growth trends for each postal code.

Although a natural alternative is to estimate the trend using only pre-pandemic annual NTL data (2013–2019), this approach proves unstable in this context. The pre-COVID window is relatively short and, importantly, NTL data are inherently noisy at the postal code level, even after taking annual averages, leading to highly sensitive and erratic fitted values, particularly when allowing for nonlinear (e.g., quadratic) trends. Additionally, NTL growth in this setting reflects sustained structural expansion, consistent with rising factory and business counts, which is often closer to exponential than quadratic in shape (See Figures A.1 and A.3). As a result, quadratic detrending using only pre-COVID years produces

background subtraction, or data processing, where the monthly average may average out near-zero values into negative numbers.

15. That is, $Exposure_{NTL} = \frac{1}{2} \sum_{t \in \{2020, 2021\}} [\log(NTL_{trend,t}) - \log(NTL_{actual,t})]$. This ordering when taking the difference ensures that $Exposure_{NTL}$ is more positive (i.e., more negatively impacted by COVID) for postal codes that saw a larger drop in NTL compared to expected, and vice versa. Further, using log differences is preferable because they provide a symmetric and scale-invariant measure of relative change, and approximate percentage changes while avoiding distortions from large NTL values or asymmetry between increases and decreases.

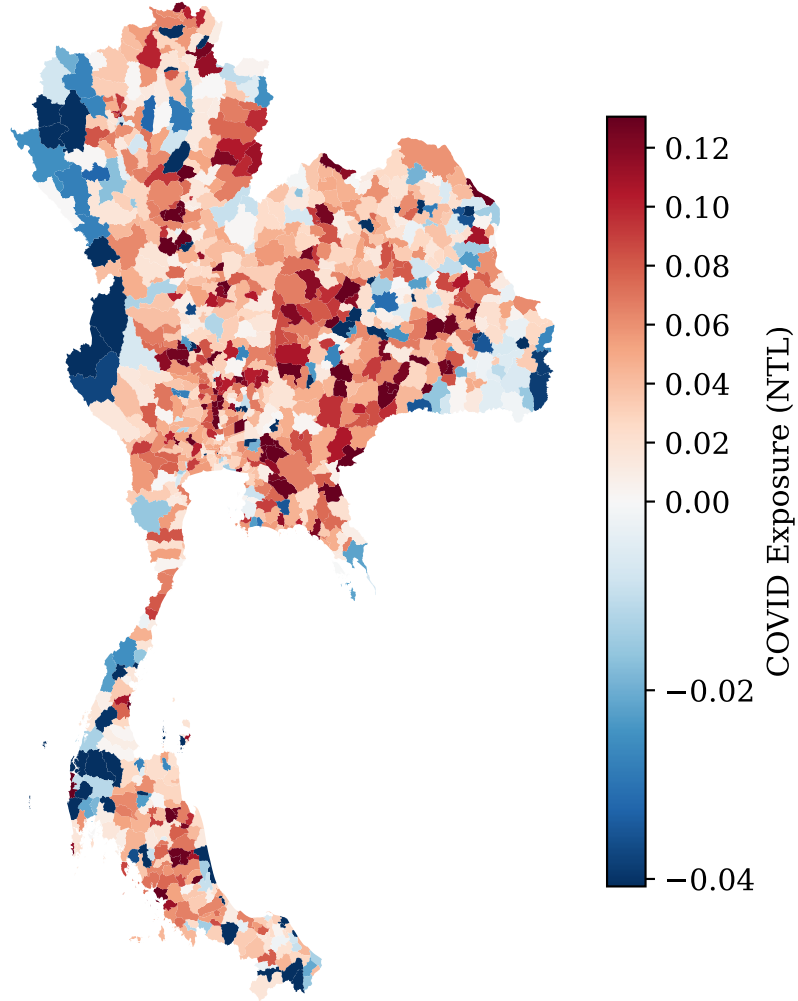
implausible counterfactual paths and exaggerated deviations. Estimating the trend over the full 12-year sample (2013 to 2024) instead provides a more stable and empirically grounded representation of long-run economic activity at the postal code level, which allows COVID to appear as a temporary deviation from that long-run trajectory rather than driving a new and permanent trend itself post-COVID. This approach, therefore, reduces noise-driven overfitting while preserving cross-sectional variation in pandemic exposure.

The motivation for using NTL as a high-frequency, spatially detailed proxy for local economic activity and human mobility is grounded in recent literature. A large body of literature has shown that luminosity at night strongly correlates with economic output, and is particularly useful in contexts where official statistics are noisy, unreliable, or experience lags in reporting. Early work established that satellite-observed lights can proxy GDP growth and spatial output at the country and subnational levels (Chen and Nordhaus 2011; Henderson, Storeygard, and Weil 2012; Pérez-Sindín, Chen, and Prishchepov 2021). More recent evaluations focusing on VIIRS, compared to sensors from the previous-generation U.S. Air Force Defense Meteorological Satellite Program (DMSP), show that VIIRS’s higher resolution and dynamic range improve the estimation of economic activity, particularly in urban regions (Chen and Nordhaus 2019). In particular, GDP growth measurements from national accounting are often less precise for low- and middle-income countries, and the incorporation of NTL can improve such measurements (Hu and Yao 2022). In the context of Thailand, provincial-level results show a strong and statistically significant correlation between nighttime light intensity and GPP growth, which remains robust even after controlling for several factors, including population density and the relative size of the agricultural and manufacturing sectors (Chaiwat 2016).

During COVID, NTL has been extensively used to capture short-run disruptions to activity. Studies in India and Morocco show that changes in nightlights track national output and electricity usage closely, and can also predict the short-term economic impact of pandemic-related supply and demand shocks with relatively low error (Beyer, Franco-Bedoya, and Galdo 2021; Dasgupta 2022; Roberts 2021). And at subnational and city levels, NTL co-moves with mobility indicators and clearly reflects lockdown and curfew policies, as documented for several countries (Deng et al. 2022; Stokes and Román 2022). Further studies have combined NTL with land-use data to show that commercial areas dim while residential areas sometimes brighten, consistent with expected changes in work and mobility patterns during COVID lockdowns (Liu et al. 2020; Wang et al. 2022). NTL has additionally been shown to be correlated with COVID mortality (Yoneoka et al. 2024; Zhang et al. 2022). Beyond COVID, NTL has also been used to detect sudden natural disruptions, such as the

2015 Nepal earthquakes, and subsequent recovery patterns, confirming their sensitivity to sharp changes in economic and human activity (Gao et al. 2020; Tveit, Skoufias, and Strobl 2022).

Figure 4.6: Spatial Distribution of COVID Exposure based on Night-Time Light



Source: Author's calculations based on VIIRS satellite night-time light data.

Notes: This map displays $Exposure_{NTL}$. Exposure is measured using detrended log night-time light intensity at the postal code level. The color scale is winsorized at the 5–95% limits; postcodes with missing values are shown in light gray. More positive COVID exposure signifies that the postal code was more impacted by COVID (i.e., the NTL during COVID was lower than the expected NTL).

Figure 4.6 illustrates the spatial distribution of COVID exposure ($Exposure_{NTL}$) across postal codes, measured using detrended log night-time light (NTL) intensity. The exposure measure captures deviations in local economic activity during the pandemic, relative to expected levels. More positive values (more red) indicate a larger contraction in NTL intensity

during COVID, and thus greater local economic disruption.

The spatial pattern of exposure is heterogeneous across Thailand. Even with the same region or province, urban and industrialized regions exhibit substantial variation, which can reflect localized differences in economic structure and also their vulnerabilities to mobility restrictions. Several clusters of high exposure postal codes are visible in metropolitan and manufacturing-intensive areas, which is consistent with the concentration of service-sector and export-oriented activity that was particularly sensitive to pandemic-related disruption. At the same time, some peripheral and rural postal codes display relatively low or even negative exposure values, suggesting either resilience or weaker pre-pandemic growth trends. This is also consistent with internal migration from urban to rural areas — or “reverse migration” — during COVID, in line with Sukasem and Phutthanuphap (2021), who found that in 2020, around 2 million people left Bangkok and other large cities to return to their hometowns from February to April alone, based on mobile phone data, compared to the average net labor migration of 0.6 to 0.8 million people per year.

This observed heterogeneity is central to the empirical strategy of this paper. The postal code-level exposure measure provides plausibly exogenous variation in the local economic shocks that can be linked to borrower-level outcomes in NCB data, especially since $Exposure_{NTL}$ is computed over 2020 and 2021, while the event-study window in the NCB data extends to 2025, ensuring that exposure is predetermined with respect to subsequent borrower outcomes. And because NTL captures broad-based economic activity rather than sector-specific performance, it offers a high-frequency proxy for localized income and demand shocks that are unlikely to be driven by individual borrower credit conditions.

Section A in the Appendix provides three pieces of related data. In particular, Section A.1 discusses administrative data on factory activity. Section A.2 examines administrative data on business activity. Section A.3 explores a constructed index on the stringency of COVID containment policies. Section A.4 incorporates these three sources to further validate the use of NTL for this paper’s empirical strategy.

5 Methodology

To estimate the impact of COVID on household debt dynamics, I implement an event study design with continuous treatment intensity (COVID exposure), at the borrower level, with individual fixed effects. The baseline specification is then as follows:

$$y_{it} = \delta_i + \gamma_t + \sum_{k \neq -1} \beta^k (\mathbf{1}\{t - t_0 = k\} \times Exposure_{NTL,i}) + \varepsilon_{it} \quad (5.1)$$

where i indexes unique borrowers, t indexes calendar time in the NCB data in quarters, δ_i are individual fixed effects, and γ_t are quarter-year fixed effects. The term $\mathbf{1}\{t - t_0 = k\}$ is an event-time indicator equal to one if period t is k quarters relative to the COVID onset at time t_0 (2020 Q1), and zero otherwise. Standard errors are clustered at the postal code level. I use $Exposure_{NTL,i}$, the postal code level of COVID exposure for borrower i , as defined in Footnote 15. I estimate dynamic treatment effects by interacting COVID exposure with event-time indicators. The event time k ranges from $k = -15$ (2016 Q2) to $k = 21$ (2025 Q2), inclusive. The omitted period is the quarter immediately before COVID onset, $k = -1$ (2019 Q4), allowing the desired coefficients β^k to trace pre-trends and post-COVID dynamics. This event study excludes 2016 Q1 due to the entry of the BAAC into NCB data, as explained in Section 4.1.1.

To construct a clean measure of local COVID exposure, I freeze each borrower’s residential postal code to their 2019 Q4 postcode and extrapolate this to prior and future quarters. I use this fixed location to merge in their postal code COVID-NTL exposure. This design choice is consciously made to ensure that observed changes in borrower outcomes are not mechanically driven by endogenous mobility during COVID (e.g., borrowers moving away from severely affected areas, or relocating in response to job losses or restrictions). Freezing location also avoids time-varying measurement error from inconsistent address updating in credit bureau reporting. This reduces selection concerns; if mobility responds to COVID severity or household financial distress, allowing postal codes to change for a borrower over time would mix treatment effects with selective migration.

Additionally, I restrict the sample to borrowers who appear in the NCB data in 2019 Q4 or earlier, which implies that the analysis excludes “new entrants” to the credit bureau during COVID or later. This exclusion yields a stable borrower cohort, observed before the shock and followed through the post-COVID period. This restriction is standard in the literature because it reduces compositional changes in the sample over time. If new borrowers enter during/after the shock, the sample composition (credit access, risk profile, etc.) can shift mechanically, making it difficult to interpret changes in financial outcomes as true responses to COVID exposure rather than changes in who is being observed.¹⁶ Recent econometric work emphasizes that compositional changes can bias DiD estimators if not accounted for

16. The no-compositional change assumption, also referred to as the stationarity assumption, is used in many widely-cited DiD papers. See, for example, Abadie (2005), Callaway and Sant’Anna (2021), and Heckman, Ichimura, and Todd (1997).

(Sant’Anna and Xu 2026). Therefore, the estimates in this paper describes how COVID affected the debt outcomes of borrowers who were already active in the formal credit market prior to the pandemic.

The NCB data tracks the universe of formal borrowers in Thailand (23.74 million as of 2019 Q4, as shown in Table 4.1); however, due to computing power limitations, it is not feasible to use the entire sample. As a result, I pull a stratified random sample with 1000 unique borrowers from each postal code, with 947 postal codes in the country, for a total of nearly 1 million borrowers. As this paper primarily concerns itself with the impacts of differences of COVID exposure at the postal code level, using a stratified random sample ensures that the results are not dominated by high-population, high-borrower concentration postal codes, while still maintaining sufficient statistical power.

As such, this event-study structure enables: (1) testing for parallel pre-trends; (2) estimating the short-run impacts during 2020–21; and (3) examining the medium and long-run persistence (“scarring”) in 2022 and beyond. Additionally, the quarterly time interval enables a direct comparison to the timing of the three Debt Relief regimes outlined in Table 3.2. The design leverages cross-sectional variation in COVID exposure intensity, as measured by the NTL shock. Because individual fixed effects absorb all time-invariant borrower characteristics (e.g., income level, baseline credit risk, etc.), the identification comes from the differential changes over time between more- and less-exposed borrowers. The inclusion of time fixed effects absorbs national macroeconomic trends and policy changes.

6 Results

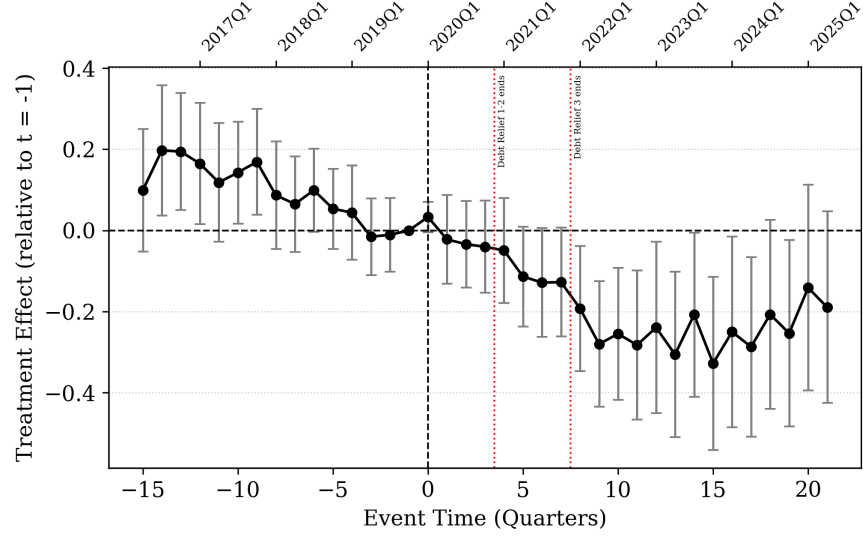
6.1 Baseline Results

I examine the four sets of outcomes capturing different dimensions of household financial behavior described in Section 4.1.2.

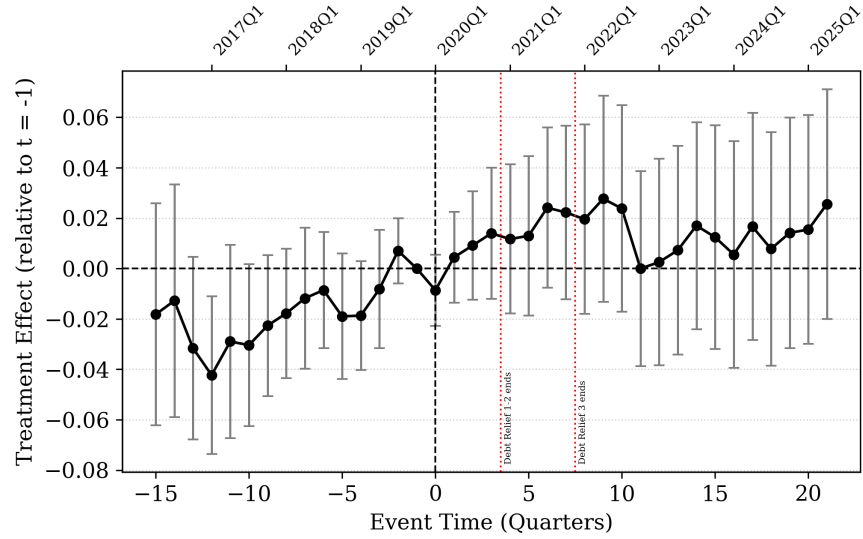
Figure 6.1 presents the event-study estimates for the main borrowing and repayment outcomes: total outstanding log debt, $\ln D_{iq}$, in panel (a), and the delinquency rate, $Delin_{iq}$, in panel (b). The coefficients are normalized relative to period immediately proceeding COVID (2019 Q4), and the vertical red lines mark the end of Debt Relief Phases I–II and the end of Debt Relief Phase III.¹⁷

17. I group Phases I and II since they were each of relatively short duration, and Phase II is in many ways a continuation of Phase I.

Figure 6.1: Dynamic Effects of COVID Exposure on Borrowing and Repayment



(a) Total outstanding log debt ($\ln D_{iq}$)



(b) Delinquency rate ($Delin_{iq}$)

Source: Author's calculations using National Credit Bureau (NCB) and night-time lights data.

Notes: Vertical gray bars denote 95% confidence intervals based on standard errors clustered at the postal code level. The first set of vertical red dots marks the end of Debt Relief Phases I and II, at the end of 2020. The second set of vertical red dots marks the end of Debt Relief Phase III, at the end of 2021.

Panel (a) shows a substantial decline in total outstanding log debt in more COVID-exposed postal codes over the post-COVID period. The estimated effect becomes increasingly negative after the onset of the pandemic and suddenly falls further after the end of Debt Relief Phase III, and remains below zero throughout much of the later post-period. Substantively, this pattern suggests that borrowers in more COVID-affected areas carry less outstanding debt across all of their accounts after the shock. On its own, this could be interpreted as deleveraging; however, taken together with the broader evidence on credit demand and unmet borrower discussed later, a more plausible option is credit contraction in the system. Debt falls in harder-hit areas not because households are necessarily financially healthier, but because the access to credit becomes more restricted. The observed rapid decline in the estimated effect immediately following the end of Phase III suggests that the debt relief policies softened this effect during the periods in which they were active.

The results are robust to the inclusion of increasingly granular geographic time controls. Comparing the baseline specification without geographic time fixed effects to specifications that include region-by-quarter and province-by-quarter fixed effects (see panel (a) and panel (b) in Appendix Figure C.1, respectively), the overall pattern of the estimated coefficients remains broadly similar, although the magnitudes are slightly attenuated. Similar results hold upon conducting robustness checks with other sets of outcome variables for region-by-quarter and province-by-quarter fixed effects. This suggests that, while some portion of the baseline estimates may reflect province-level time-varying shocks, these are not the primary drivers of the results.

At the same time, panel (a) shows that the pre-period coefficients are not flat. Before the COVID shock, the estimated coefficients are mostly positive, with 5 quarters significantly so, and exhibit a downward drift toward zero as the event date approaches. This suggests a non-trivial pre-trend in debt across areas with varying COVID exposure. I therefore interpret the post-period decline in debt with caution. In particular, the estimates in the figure likely capture some continuations or reversals of pre-existing differential trends, in addition to the effect of COVID exposure and withdraw of debt relief policies. However, although the pre-period coefficients display some drift, the joint test fails to reject the null that they are jointly equal to zero ($p = 0.285$). This suggests that while the visual pre-trend warrants additional caution, the evidence against parallel trends is statistically limited. This is fair, since the parallel trends assumption seems to hold especially well for the several quarters proceeding COVID.

Panel (b) presents the estimates for the delinquency rate $Delin_{iq}$, which display a more plausible event-study pattern. The pre-period estimates are mostly negative (although not

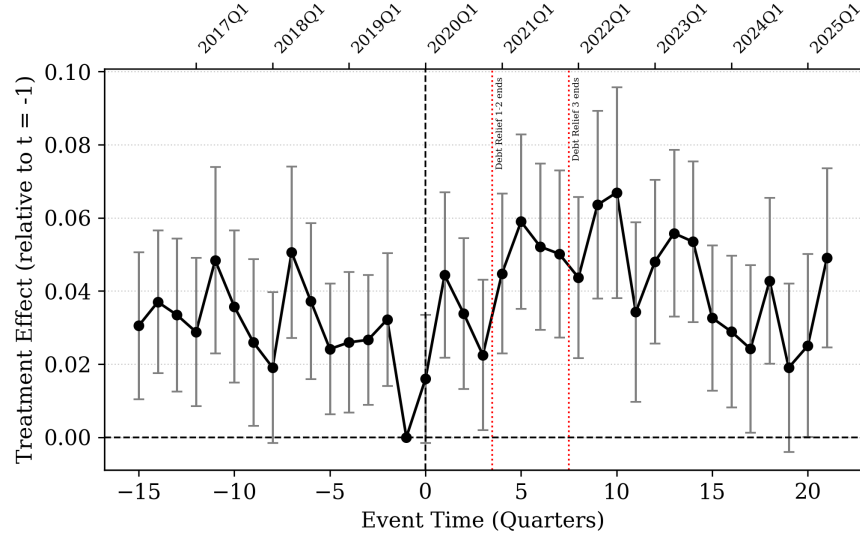
significantly so, with the exception of one quarter) and trend upward toward zero as COVID approaches, but remain relatively close to zero in the quarters immediately prior to the start of COVID. Likewise, the joint test fails to reject the null that the pre-period coefficients are jointly equal to zero ($p = 0.114$). At the onset of COVID, the treatment effect increases and becomes positive, indicating that more COVID-exposed postal codes experienced worse repayment performance, although it is not significant. This persists into the early post-period and remains elevated thereafter.

A notable feature of panel (b) is that the treatment effect on delinquency increases after the COVID shock, but does not continue rising indefinitely. Rather, the point estimates flatten somewhat after the end of Debt Relief Phase III. This pattern is consistent with a break in the post-shock delinquency trajectory. One interpretation is that the underlying distress initially worsened sharply during COVID, but the observed heterogeneity later stabilized because the composition of borrowers changed. In particular, if riskier borrowers became less likely to obtain or retain credit following the end of debt relief policies, then the measured delinquency among borrowers could flatten even if financial stress remains elevated. This mechanism is consistent with a selection effect, and when matched with panel (a), is especially convincing. Indeed, the break in the delinquency trajectory occurs approximately two quarters after the break in the debt trajectory, and this lag is consistent with the definition of delinquency being at least 90 days past due (see Footnote 9), as delinquency status materializes around two quarters afterward.

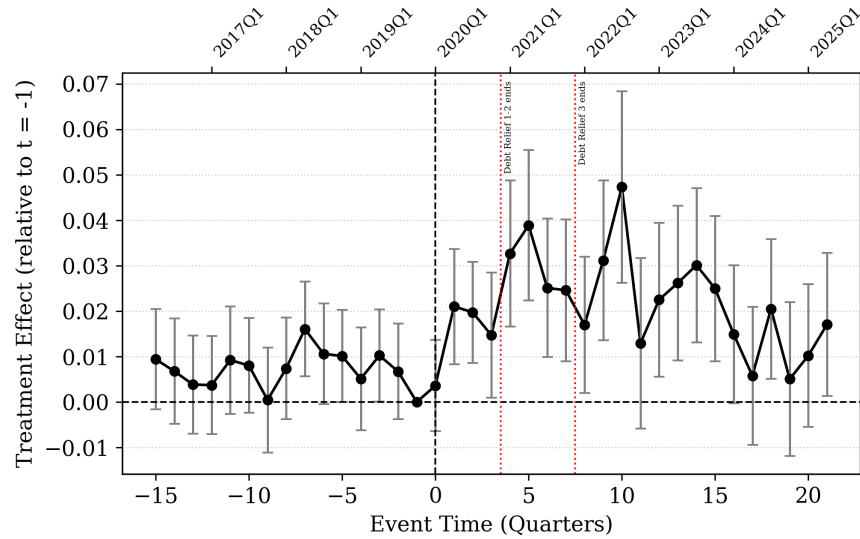
In general, Figure 6.1 suggests two main findings. First, debt falls sharply in more COVID-exposed areas, especially after the end of debt relief, consistent with a contraction in credit access. Second, delinquency rises after the shock, indicating worsening repayment abilities, but the later flattening of the delinquency path suggests that observed repayment outcomes are shaped by borrower distress — and also changes in which borrowers remain in the credit market. I explore this further using inquiry-based measures and loan-cohort evidence.

To better understand whether the post-COVID adjustment reflects weaker demand for borrowing or a tighter credit supply, Figure 6.2 examines two intermediary outcomes: the share of borrowers with at least one loan inquiry, *HaveInquiry_{iq}*, and the share of borrowers with unmet loan inquiry, *HaveUnmetInquiry_{iq}*. Panel (a) plots the coefficients for *HaveInquiry_{iq}*. The post-period estimates are generally positive, suggesting that borrowers in more COVID-exposed postal codes became more likely to make loan inquiries after the onset of the pandemic. The increase is especially visible after the end of Debt Relief Phases II and III, and inquiry activity remains elevated for many of the subsequent quarters. Gener-

Figure 6.2: Dynamic Effects of COVID Exposure on Loan Inquiry and Access



(a) Share of borrowers with loan inquiry ($HaveInquiry_{iq}$)



(b) Share of borrowers with unmet inquiry ($HaveUnmetInquiry_{iq}$)

Source: Author's calculations using National Credit Bureau (NCB) and night-time lights data.

Notes: Vertical gray bars denote 95% confidence intervals based on standard errors clustered at the postal code level. The first set of vertical red dots marks the end of Debt Relief Phases I and II, at the end of 2020. The second set of vertical red dots marks the end of Debt Relief Phase III, at the end of 2021.

ally, this pattern suggests that there was higher demand for credit in more severely affected areas, likely reflecting the greater liquidity needs during and after the pandemic.

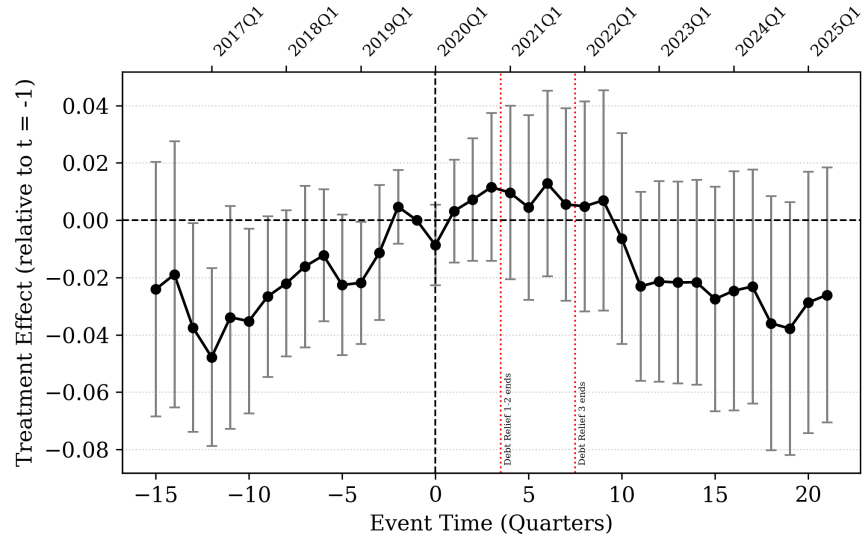
However, the pre-period in panel (a) is not flat. Most pre-treatment coefficients are already positive relative to the omitted quarter, and they fluctuate at a non-trivial distance from zero, which weakens a strict parallel trends interpretation. One likely reason is the choice of the omitted quarter: because all coefficients are normalized relative to $t = -1$, an unusually low value for inquiries in 2019 Q4, as observed in Figure 4.5, would mechanically shift much of the pre-period upward. As such, the positive pre-period coefficients may partly reflect the fact that the omitted quarter is a poor benchmark, rather than a smooth underlying trend. The joint test of the pre-period coefficients, however, rejects the null that they are jointly equal to zero ($p = 0.012$), suggesting that these estimates are sensitive to pre-period specification and should be interpreted cautiously.

Panel (b) presents the estimates for *HaveUnmetInquiry_{iq}*. In contrast to *HaveInquiry_{iq}*, the pre-period here is better behaved and supports the parallel trends assumption (joint test yields $p = 0.165$). The coefficients before treatment remain relatively close to zero, with no strong systematic drift. After the onset of COVID, the estimates rise and become more clearly positive, with the increase becoming more pronounced after the end of Debt Relief Phase II and remaining elevated well into later quarters. This, therefore, indicates that in more COVID-exposed areas, a larger share of borrowers made inquiries that did not result in a loan opening. Moreover, the pattern in panel (b) in the post-period generally mirrors that of panel (a) but is more amplified, suggesting that households continue to seek credit, but a growing share of that demand goes unmet. This is most consistent with a credit rationing mechanism; if, hypothetically, lenders had approved loans at roughly the same rate in the post-period, thereby increasing credit supply, then the treatment effect for *HaveUnmetInquiry_{iq}* would have been expected to be flatter in that period as well.

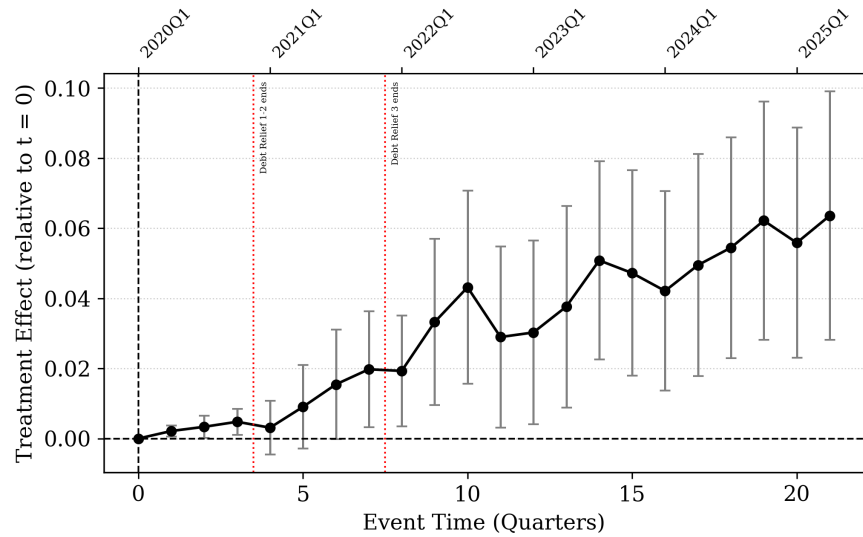
This interpretation also helps reconcile the decline in debt documented in Figure 6.1. If the more exposed postal codes experience both elevated loan inquiry activity and higher incidence rates of unmet loan demand, then lower observed debt is unlikely to reflect improved borrower balance sheets alone. Rather, the influence from a tighter credit supply and stricter screening in harder-hit areas becomes more plausible.

Figure 6.3 examines repayment dynamics separately for two loan cohorts: loans originating before the onset of COVID (*DelinPreLoan_{iq}*) and loans originating starting 2020Q1 (*DelinCovidLoan_{iq}*). This decomposition helps distinguish whether post-pandemic repayment patterns reflect the evolution of pre-existing debt, or the performance of newly originated loans under pandemic conditions.

Figure 6.3: Dynamic Effects of COVID Exposure on Loan Repayment by Cohort



(a) Delinquency rate on pre-COVID loans ($DelinPreLoan_{iq}$)



(b) Delinquency rate on COVID-era loans ($DelinCovidLoan_{iq}$)

Source: Author's calculations using National Credit Bureau (NCB) and night-time lights data.

Notes: Vertical gray bars denote 95% confidence intervals based on standard errors clustered at the postal code level. The first set of vertical red dots marks the end of Debt Relief Phases I and II, at the end of 2020. The second set of vertical red dots marks the end of Debt Relief Phase III, at the end of 2021.

The panels, however, should be interpreted differently, since the underlying cohorts are defined asymmetrically. Panel (a) plots $DelinPreLoan_{iq}$, and since this outcome is defined with only loans originating before 2020 Q1, the post-COVID path reflects repayment behavior within a fixed pre-pandemic loan pool, and not the performance of newly issued loans. In this setting, the event-study coefficients can still be examined for pre-treatment dynamics (the joint test yields $p = 0.058$), and do show some movement toward zero as the pandemic approaches.

In the post-period, panel (a) shows that the treatment effect on delinquency for pre-COVID loans rises modestly around the onset of COVID, but then declines after the end of Debt Relief Phase III, and finally becomes more negative in the later post-period, although without significance. At first glance, this could read as an improvement in repayment performance among pre-existing loans; however, since the pre-COVID loan cohort is mechanically fixed, this decline should not be interpreted simply as evidence that borrowers in more COVID-exposed areas became more able to repay. As time passes, the cohort becomes increasingly selected, and the remaining pool becomes less representative of the original distribution, and potentially tilted toward performing loans. The later decline in the treatment effect, therefore, is more plausibly interpreted as reflecting selection and survivorship bias in the loan pool, and not an improved broad recovery in underlying financial conditions for more COVID-exposed postal codes relative to less-exposed postal codes.

An alternative interpretation is that the reduced access to new borrowing after Debt Relief Phase III improved repayment capacity on existing loans, as borrowers were less able to take on additional debt. This explanation, however, is less consistent with the evidence presented earlier. In particular, loan inquiry activity increases in more COVID-exposed areas, as does the share of unmet inquiries, suggesting that borrowers continue to seek credit, but face tighter supply constraints. This pattern, therefore, points toward heightened liquidity needs, and not necessarily improved financial health. Hence, in this context, the decline in delinquency for pre-COVID loans is more plausibly driven by selection and survivorship within the loan pool, rather than a genuine improvement in repayment capacity.

Panel (b) presents $DelinCovidLoan_{iq}$. Unlike the main event-study specifications, the COVID-era loan cohort does not exist before 2020 Q1, so its estimated path should be interpreted as the evolution of delinquency relative to the cohort's initial period (2020 Q1), rather than as a treatment effect identified from pre-treatment parallel trends.¹⁸ In this manner, panel (b) displays a clear and persistent increase in the treatment effect on delin-

18. The use of 2020 Q1 as the omitted reference quarter does not challenge the validity, since I define delinquent loans as those more than 90 days past due, as per Footnote 9. As such, even loans that originated at the very beginning of 2020 Q1 would not be flagged as delinquent until at least 2020 Q2.

quency among COVID-era loans over time. The estimates start near zero in the reference period, and rise steadily through the post-pandemic quarters, with an especially pronounced increase after the expiration of debt relief, even so after Phase III. For borrowers in more COVID-impacted postal codes, these loans became progressively more likely to become delinquent relative to less-impacted areas. Since these are newly originated loans that extended under pandemic and recovery conditions, the rising path supports the view that COVID-era borrowing for more pandemic-exposed borrowers was riskier from the onset, and became progressively more fragile as policy support became expired.

6.2 Loan Product Type Analysis

I next examine how these dynamics vary across the six types of loan products: agricultural loans, business loans, credit card, home loans, hire purchase loans, and personal loans. I present the most salient results for debt dynamics and delinquency outcomes.

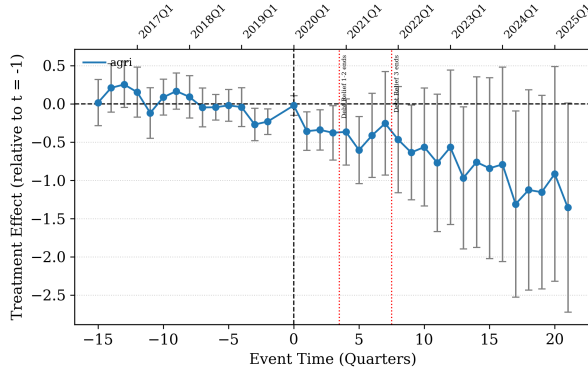
Figure 6.4 decomposes the response of log outstanding debt by loan product type ($\ln D_{iqp}$), which makes clear that the aggregate decline in log debt shown in Figure 6.1 masks substantial heterogeneity across products. At the same time, the credibility of product-level estimates differ across panels, since product-level debt series are noisier and sometimes display stronger pre-existing trends than the aggregate outcomes. As such, this figure is interpreted as a mix of stronger and weaker evidence on how the composition of credit changed in more COVID-exposed postal codes. The joint test p -values for each are shown in the table notes.

A first set of products shows patterns that are broadly consistent with post-COVID contraction for borrowers more impacted by COVID. In panel (a), agricultural loan debt declines sharply over the post-pandemic period, suggesting substantially lower outstanding agricultural debt in more exposed postal codes. Although the post-period decline is economically large, there is a pronounced downward pre-trend. The post-period decline, therefore, possibly reflects both pandemic-era adjustment and pre-existing differential trends.

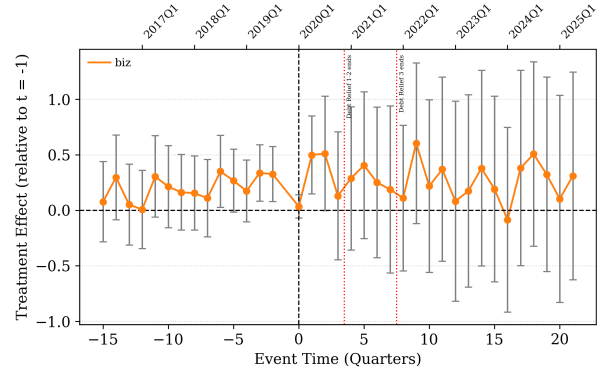
Among the product categories, the evidence for home loans in panel (d) is more persuasive. After the pandemic, the estimates effects turn negative, with a particular marked decline around the end of Debt Relief Phase III. This pattern is consistent with a genuine contraction in home loan debt in more COVID-exposed areas, which substantially suggests that longer-term or more difficult-to-obtain forms of borrowing became less prevalent after the pandemic and the withdrawal of policy support.

A second set of products points instead towards relative expansion or substitution into other forms of credit. In panel (c), credit card debt remains positive throughout much of

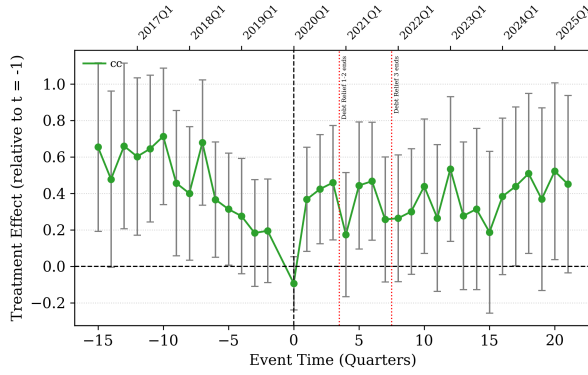
Figure 6.4: Dynamic Effects of COVID Exposure on Outstanding Debt by Loan Type



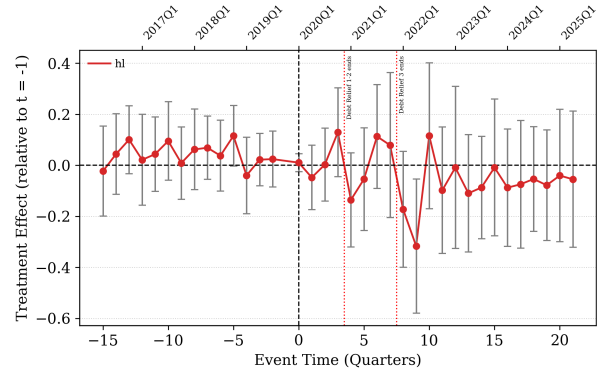
(a) Agricultural loans



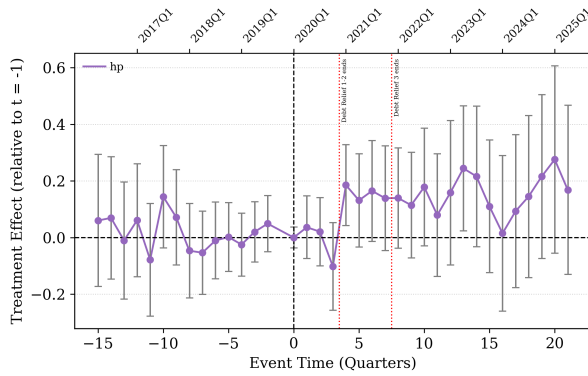
(b) Business loans



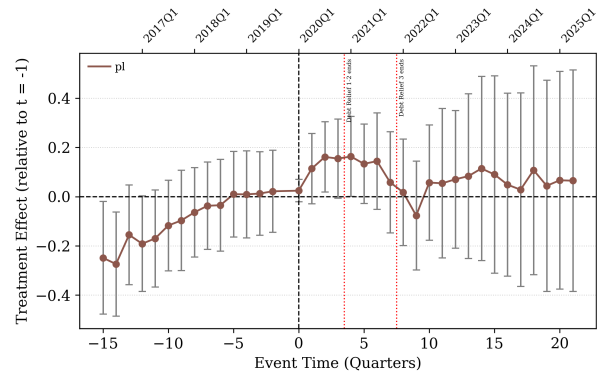
(c) Credit card loans



(d) Home loans



(e) Hire purchase loans



(f) Personal loans

Source: Author's calculations using National Credit Bureau (NCB) and night-time lights data.

Notes: Vertical gray bars denote 95% confidence intervals based on standard errors clustered at the postal code level. The first set of vertical red dots marks the end of Debt Relief Phases I and II, at the end of 2020. The second set of vertical red dots marks the end of Debt Relief Phase III, at the end of 2021.

Conducting joint tests on the pre-period coefficients for each yields the following: agriculture loan: $p = 0.063$; business loan: $p = 0.069$; credit card: $p = 0.003$; home loan: $p = 0.713$; hire purchase loan: $p = 0.132$; personal loan: $p = 0.586$.

the post-period and appears to trend upward after declining toward zero around the onset of COVID. This is consistent with the idea that borrowers in harder-hit areas shifted towards more flexible, revolving credit. However, the pre-period in panel (c) is clearly not flat; it is elevated well before treatment and trends down steadily as the shock approaches. As such, the post-COVID increase should not be read as clean, causal evidence; rather, the figure suggests that for more exposed areas, credit card debt was more resilient than other loan types and may have served as an margin of adjustment during and after the pandemic shock.

In panel (e), the hire purchase loans provides cleaner evidence of expansion, with a cleaner pre-period. After the end of Debt Relief Phase II, the coefficients become positive and remain mostly so thereafter. Among the product types, this emerges as one of the most credible examples of post-COVID increase in product-specific debt for more exposed borrowers. It is possible that rather than uniformly reducing borrowing, such borrowers may have reallocated to certain forms of installment or asset-linked credit, even as total debt declined.

For personal loans in panel (f), despite the coefficients in the pre-period rising steadily from negative values to zero, showing some pre-period pattern, conducting a joint test of pre-period coefficients yielding $p = 0.586$. This suggests that the coefficients are not jointly different from zero. Indeed, the parallel trends assumption holds especially strong when considering the several quarters immediately proceeding 2020 Q1. I therefore interpret the post-period coefficients with some caution. After the onset of COVID, the treatment effect remains mildly positive for several quarters, then dips around the end of Debt Relief Phase III. The personal loan estimates, therefore, provide some evidence of expansion in this loan category for more COVID-impacted borrowers during the disease period itself, but does not provide clean evidence of long-term contraction or expansion.

The remaining category, business loans in panel (b), is more ambiguous. The coefficients are generally positive both before and after COVID, and are highly volatile and imprecisely estimated, providing limited evidence of a post-pandemic change in business-loan debt.

Overall, Figure 6.4 is most consistent with a mechanism of a composition change in borrowing, rather than a uniform departure from credit markets. In particular, postal codes more exposed to COVID appear to reduce borrowing in some categories, while maintaining or increasing debt in others in sustained ways, particularly more flexible (credit card) or installment-based products (hire purchase). As such, aggregate debt can fall, even as some margins of credit use remain active or elevated.

Of note, a striking feature of Figure 6.4 is the rapid response of credit card borrowing following the onset of COVID. In panel (c), credit card debt quickly becomes elevated upon

the beginning of the pandemic, suggesting that borrowers in more COVID-exposed areas relied on revolving credit as an immediate liquidity buffer. This pattern is in agreement with the idea that credit cards function as a “first line of defense” during income shocks, allowing households to smooth consumption when other forms of credit are less immediately accessible.¹⁹ A similar, though more muted, pattern is observed for personal loans in panel (f), where borrowing rises in the early post-period before stabilizing, indicating that they also served as an adjustment margin, albeit with greater frictions than credit cards.

By contrast, agricultural loan debt in panel (a) declines sharply in the post-period. While this may initially appear as a simple contraction in borrowing, the pattern is more plausibly driven by changes in loan structure. In the Thai context, policy initiated by the Bank for Agriculture and Agricultural Cooperatives (BAAC) combined debt moratoria and restructuring with the provision of small emergency loans, often capped at relatively low levels of up to 10,000 baht per person (see Table 3.3). Consistent with this, the number of agricultural loan originations increased for more exposed postal codes (see Appendix Figure C.2) while median agricultural loan amount outstanding declined. This suggests a shift in the composition of agricultural loans: if, for more exposed borrowers, total agricultural debt decreases while the number of agricultural loans increases, then the average loan size should sharply decrease.

This interpretation is reinforced by the heterogeneity results in Appendix Figure C.3, with the desired triple interaction coefficients presented in panel (c). In particular, COVID exposure persistently reduces total outstanding log debt more for borrowers with pre-COVID agricultural loans, indicating that the aggregate decline in debt is not broad-based but instead driven disproportionately by agricultural households.²⁰

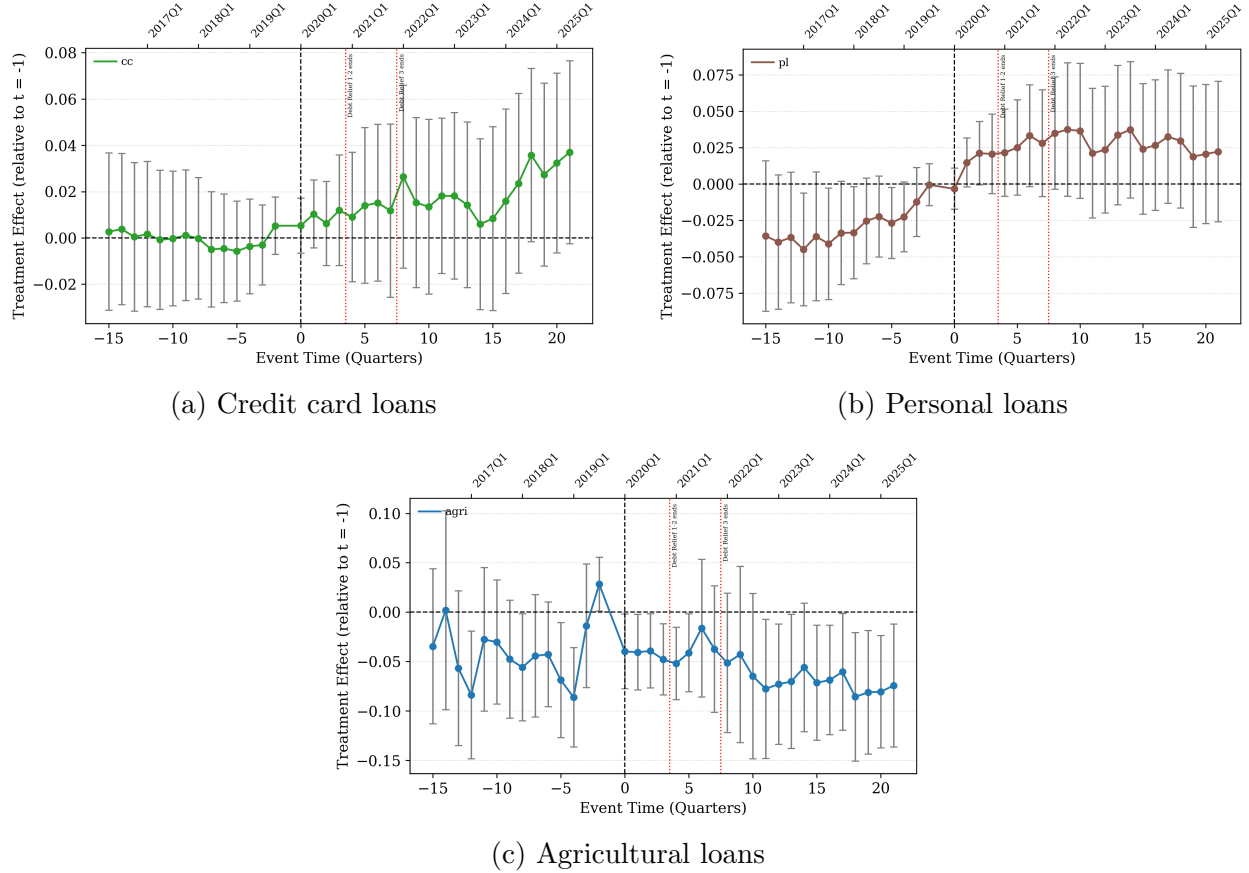
Taken together, these results suggest a shift in the structure of agricultural credit supply toward smaller loan sizes. One possible explanation is that larger loans became less prevalent in more COVID-exposed areas, consistent with a contraction at the intensive margin of lending, either due to tighter screening or changes in lending practices during the pandemic. However, the available evidence does not allow for a clean separation of supply and demand forces, as I cannot discern loan inquiry and unmet loan inquiry information at the loan product level from available data, although I do show that a greater share of borrowers have unmet aggregate credit demand in more COVID-exposed postal codes (recall Figure

19. Indeed, recall that the treatment effect on unmet loan inquiries is significantly positive during these quarters, as shown in Figure 6.2.

20. It is also possible to qualitatively reach the same conclusion from Figure 6.4 with a back-of-the-envelope calculation. The decomposition by product type shows that the magnitude of the negative treatment effect when looking at agricultural loans in isolation is much larger than the magnitudes for other types and dominates them if added together. Figure C.3 presents formal statistical support for this observation.

6.2). As such, rather than attributing this pattern solely to more cautious bank behavior for agricultural loans, I interpret the results as reflecting a combination of policy-driven lending adjustments and potential tightening at the intensive margin of lending.

Figure 6.5: Dynamic Effects of COVID Exposure on Delinquency by Loan Type



Source: Author's calculations using National Credit Bureau (NCB) and night-time lights data.

Notes: Vertical gray bars denote 95% confidence intervals based on standard errors clustered at the postal code level. The first set of vertical red dots marks the end of Debt Relief Phases I and II, at the end of 2020. The second set of vertical red dots marks the end of Debt Relief Phase III, at the end of 2021.

Conducting joint tests on the pre-period coefficients for each yields the following: credit card: $p = 0.993$; personal loan: $p = 0.609$; agricultural loan: $p = 0.0001$.

To examine whether repayment distress evolved differently across loan products, Figure 6.5 presents event-study estimates for delinquency separately for credit card loans, personal loans, and agricultural loans ($Delin_{iqp}$). These first two loan categories are especially informative, as they represent important forms of borrowing that are not specifically tied to specific groups (e.g., farmers, home owners, or business owners). And unlike several of the debt-by-product specifications, their pre-treatment dynamics are relatively well-behaved. In particular, the joint tests of the pre-period coefficients fail to reject the null that the coeffi-

cients are jointly equal to zero for each product separately ($p = 0.993$ for credit cards and $p = 0.609$ for personal loans). Additionally, I include the estimates when considering only agricultural loans, which I previously show drive much of the negative treatment effect for overall debt levels D_{iq} . The other loan categories — business loans, home loans, and hire purchase — show no significant patterns in delinquency in the post-period.

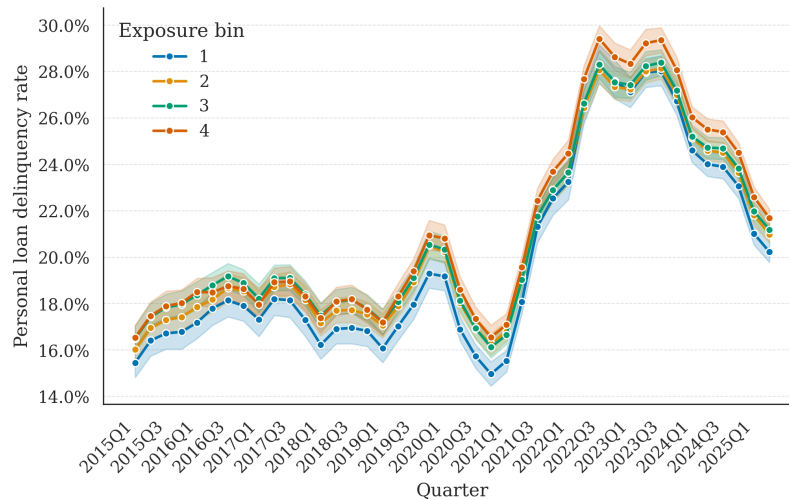
Panel (a) shows the event-study coefficients for credit card delinquency, with estimated effects close to zero in the pre-period and no systematic drift. The rise becomes more visible after the end of Debt Relief Phase II and remains elevated following the end of Phase III, although the treatment effects for individual quarters are not statistically significant, likely due to insufficient power. This pattern suggests that, in more COVID-exposed postal codes, delinquency on credit card borrowing increased persistently after the shock. This result aligns with the view that households in harder-hit areas relied more heavily on revolving credit as an immediate liquidity buffer and experienced greater repayment difficulty on these balances over time, with these results lasting years after COVID. This is consistent with my interpretation of Figure 6.4 for the levels of credit card debt.

Panel (b), meanwhile, presents the corresponding results for personal loan delinquency. As with credit cards, the pre-period coefficients are jointly insignificant, although visually they display somewhat more movement. In the post-period, the treatment effects rise from zero to marginally significant positive values and stay elevated thereafter. Compared to aggregate delinquency results, the personal loan estimates point to a clearer and more sustained deterioration in repayment performance for borrowers more exposed to COVID. This suggests that personal loans were an important channel, through which COVID-related financial distress translated into higher delinquency.

Figure 6.6 provides a complementary view of personal loan results by plotting, descriptively, delinquency rates over time for postal codes grouped into four COVID-exposure bins. The figure shows that delinquency in this category for all groups rises after the pandemic, but does so more sharply for the more exposed bins, especially from 2022 to 2024, in line with Figure 6.5. Likewise, in 2020 and 2021, the delinquency rate for the lowest-exposed bin consistently lie below the other three exposure bins. Figure 6.6 should not be interpreted causally, but does illustrate the economic magnitude and persistence of the widening delinquency rate gap in personal loans.

Returning to Figure 6.5, panel (c) presents the estimates for agricultural loan delinquency, which exhibits a different pattern from credit card and personal loans, with delinquency declining in more exposed areas in the post-period. Although this plot shows obvious non-flat pre-period dynamics, the heterogeneity results in Appendix Figure C.4 provide additional

Figure 6.6: Evolution of Personal Loan Delinquency by COVID Exposure Quartiles



Source: Author's calculations using National Credit Bureau (NCB) and night-time lights data.

Notes: The first exposure bin represents postal codes with COVID exposure in the bottom quartile (i.e., least impacted), and analogously for the other three. Solid lines show estimated personal loan delinquency rates by COVID exposure bin. Shaded areas represent 95% confidence intervals around the estimates.

context. In particular, the triple interaction coefficients in panel (c), which capture the differential effect of COVID exposure for borrowers with pre-COVID agricultural loans, do not display strong systematic pre-trends and indeed remain relatively close to zero prior to the pandemic. In the post-period, however, these coefficients become increasingly negative, indicating that agricultural borrowers in more exposed areas experience relatively lower delinquency rates compared to other borrowers — a result that is long-lasting.

This result is in line with earlier evidence of policy intervention in agricultural credit. In particular, debt moratoria and restructuring programs, alongside the provision of smaller emergency loans from the BAAC, likely reduce measured delinquency, while simultaneously lowering average loan sizes. These findings suggest that repayment distress following COVID is concentrated in unsecured credit segments, like credit cards and personal loans, while agricultural loan outcomes are shaped by agriculture-specific policy that enabled them to move in an opposite direction.

6.3 Additional Heterogeneity Analysis

An important question is whether the effect of COVID-related local distress differed across borrowers depending on their pre-pandemic credit structure. In particular, borrowers who relied exclusively on unsecured debt before COVID may have been financially more

fragile, and therefore more vulnerable to local income shocks during the pandemic.

I extend the baseline specification by interacting the COVID NTL exposure proxy with a binary indicator for borrowers who held only unsecured debt in the two years prior to the pandemic (approximately 18.3% of the sample). The outcome variable, $DelinCovidLoan_{iq}$, is a binary indicator equal to one if borrower i was delinquent in quarter q , for loans that originated starting in 2020 Q1. I estimate a borrower fixed-effects linear probability model, which allows the coefficients on the interaction terms to be interpreted directly as changes in delinquency probability. This approach is also convenient in the present setting, because the specification contains a large number of time interactions, while fixed-effects nonlinear binary models would be comparatively more difficult to estimate and interpret.²¹

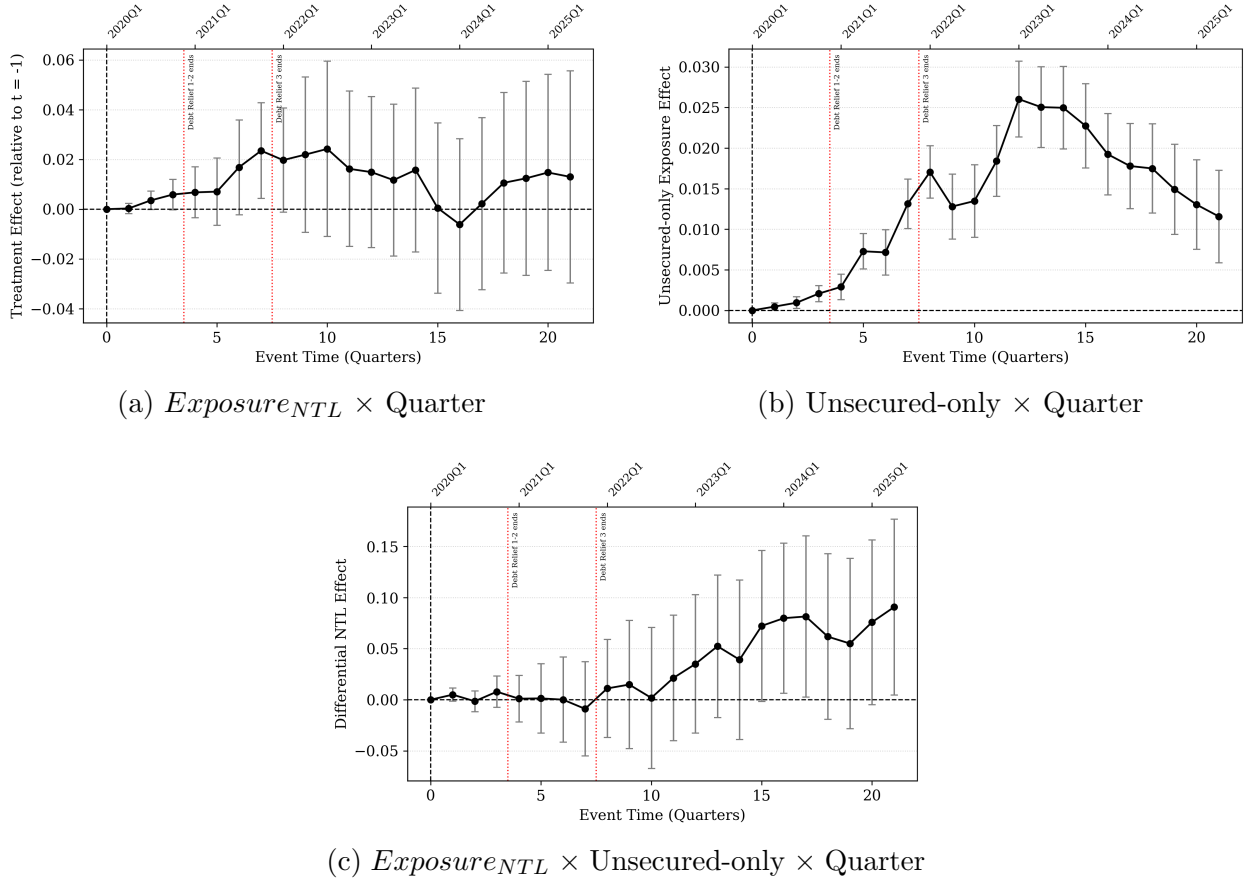
Because the borrower fixed effects absorb time-invariant borrower characteristics, the standalone coefficient on the unsecured-only indicator is not separately identified. The coefficient on $Exposure_{NTL}$ is also omitted. Accordingly, the parameters of interest are the time-varying interaction terms. As before, this specification does not include a pre-COVID period; it describe how the relationship between COVID exposure and delinquency evolved across quarters within the COVID-period loan sample, relative to the omitted baseline period (2020 Q1, or $t = 0$).

Figure 6.7 presents the estimated coefficients from this heterogeneity specification. Panel (a) plots the interaction between COVID exposure and period indicators for the reference group (borrowers with loans other than unsecured loans). These estimates are generally small and statistically imprecise, with a limited evidence of positive exposure effect in 2021. This suggests that, for the reference group, the relationship between local COVID exposure and delinquency does not vary strongly across most quarters.

Panel (b), meanwhile, shows the interaction between the unsecured-only indicator and period indicators. These coefficients are positive and statistically significant in nearly all periods, indicating that borrowers who held only unsecured debt before COVID experienced a systematically larger increase in delinquency over the COVID period relative to other borrowers, with the increase peaking in 2023. This pattern points to a clear form of heterogeneity in delinquency dynamics by pre-pandemic credit composition.

21. In estimating the effect on $DelinCovidLoan_{iq}$, I note a potential selection issue, since a borrower can only become delinquent on a loan originated during or after COVID if they were approved for such a loan in the first place. If the loan approval process differs between borrowers who held only unsecured loans prior to COVID and those who held secured loans, this could bias the estimates. However, estimating an analogous heterogeneity specification using $HaveNewLoan_{iq}$ as the outcome reveals no significant differences in the effect of COVID exposure on post-2020 Q1 loan origination rates across these two borrower groups, which mitigates this concern.

Figure 6.7: Dynamic Heterogeneity in the Effect of COVID Exposure on $DelinCovidLoan_{iq}$



Source: Author's calculations using National Credit Bureau (NCB) and night-time lights data.

Notes: Each figure plots coefficient estimates and 95% confidence intervals from the borrower fixed-effects specification. All paths are relative to the cohort's initial period $t = 0$ (2020 Q1). Vertical dashed lines mark the end of Debt Relief 1–2 and Debt Relief 3. Standard errors are clustered at the postal-code level. Panel (a) shows the period-specific effect of NTL exposure on delinquency for the reference group. Panel (b) shows the delinquency differential over time for borrowers with only unsecured pre-COVID debt. Panel (c) shows the additional differential effect of NTL exposure for unsecured-only borrowers relative to the reference group.

Panel (c) reports the triple interaction between COVID exposure, unsecured-only status, and period indicators. These coefficients are mostly close to zero and imprecisely estimated in the earlier periods, but become positive and statistically significant in several later quarters. Thus, there is suggestive evidence that the effect of COVID exposure on delinquency became stronger for unsecured-only borrowers later in the COVID period. But because the estimates are not uniformly significant across all quarters, I interpret the evidence as indicating a later-period amplification of exposure effects, rather than a consistently stronger effect throughout the entire timeframe.

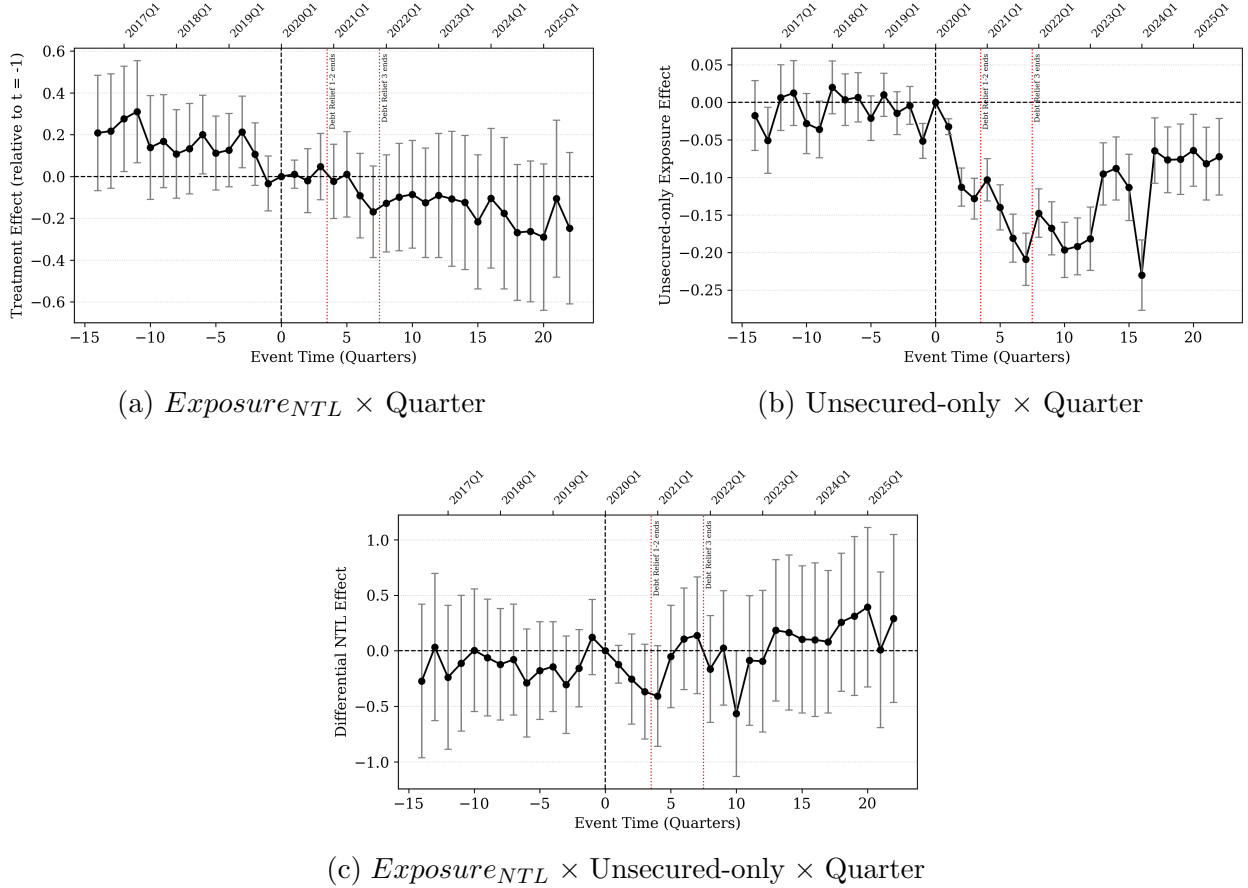
I next examine whether the relationship between local COVID exposure and borrower outcomes differs by pre-pandemic credit composition, using $\ln D_{iq}$ as the dependent variable. In contrast to the earlier *DelinCovidLoan_{iq}* specification, this regression includes both pre- and post-period observations, allowing the dynamic pattern of heterogeneous effects to be assessed relative to an omitted baseline period. The absorbed coefficients and the three coefficients of interest mirror that of the *DelinCovidLoan_{iq}* specification.

These results delineated in Figure 6.8 provide limited overall evidence of heterogeneous exposure effects by pre-COVID credit composition. The coefficients on the triple interaction between COVID exposure, unsecured-only status, and period indicators are generally statistically insignificant. However, during the COVID period, the triple-interaction coefficients are negative and marginally significant in several quarters, with particularly notable estimates in quarter 10. This pattern suggests that in some COVID-period quarters, borrowers who held only unsecured debt prior to the pandemic may have exhibited a somewhat weaker response of $\ln D_{iq}$ to COVID exposure, relative to the reference group. However, since these estimates are only marginally significant, and are not consistently observed across all quarters, the evidence should be interpreted as suggestive rather than conclusive.

In contrast, the interaction between unsecured-only status and the period indicators is negative and statistically significant in most post-baseline quarters, falling drastically from the onset of COVID. This implies that borrowers who held only unsecured debt prior to COVID experienced systematically lower values of $\ln D_{iq}$ relative to other borrowers over much of the post period. As such, the primary form of heterogeneity in this specification appears to operate through differences in the time path of the outcome across groups, rather than through a sharply different response to COVID exposure.

It is worth noting that the coefficients on the interaction between COVID exposure and period indicators for the reference group are positive and statistically significant in several pre-baseline periods, but are generally insignificant in the post period. Accordingly, while the pre-period triple interactions do not indicate strong differential pre-trends across borrower

Figure 6.8: Dynamic Heterogeneity in the Effect of COVID Exposure on Outstanding Debt



Source: Author's calculations using National Credit Bureau (NCB) and night-time lights data.

Notes: Each figure plots coefficient estimates and 95% confidence intervals from the borrower fixed-effects specification. All paths are relative to the cohort's initial period $t = -1$ (2019 Q4). Vertical dashed lines mark the end of Debt Relief 1–2 and Debt Relief 3. Standard errors are clustered at the postal-code level. Panel (a) shows the period-specific association between NTL exposure and $\ln D_{iq}$ for the reference group. Panel (b) shows the differential time path of $\ln D_{iq}$ for borrowers with only unsecured pre-COVID debt. Panel (c) shows the additional differential effect of NTL exposure for unsecured-only borrowers relative to the reference group.

groups, some instability in the baseline-group NTL coefficients suggests that the dynamic pattern should be interpreted cautiously.

7 Discussion

The main results point to a common mechanism across the different outcome sets: in postal codes that were more exposed to COVID, household credit worsened, primarily through repayment distress and tighter effective access to credit, rather than through a simple or uniform rise or fall in borrowing. The clearest evidence comes from unmet inquiry rates and the performance of COVID-era loans. Some other specifications, such as debt stock, show non-flat pre-period dynamics, and therefore should be read with additional caution. Even so, the broad evidence suggests that local pandemic exposure impacted household balance sheets through both financial distress and changes in the function of the credit market, in line with the general literature (see, for example, Bernanke (2018) and Mian, Rao, and Sufi (2013)).

A central conclusion is that total outstanding debt often declined in more COVID-exposed areas, but does not serve as evidence that these harder-hit areas were financially healthier. Debt balances were heavily shaped by transfers and payment relief programs, such as the three debt relief phases outlined in Table 3.2. In Thailand, the central bank and financial institutions introduced broad relief measures for retail borrowers, including reductions in interest-rate ceilings for credit card and personal loans, debt moratoria, lower repayment burdens, maturity extensions, and wider debt-restructuring options. These policies were explicitly designed to preserve liquidity, and to prevent temporary illiquidity problems from immediately turning into delinquent debt. As such, this payment support, combined with lender caution, muted observed balances even while underlying repayment capacity worsened.

The set of inquiry results strengthen this interpretation. In more COVID-exposed areas, borrowers became more likely to make loan inquiries, and yet a larger share of those inquiries goes unmet. This observed pattern is difficult to reconcile with a pure decline in credit demand; instead, it is more so consistent with heightened need for liquidity, combined with tighter lender screening. This stylized conclusion aligns with the pandemic credit-supply literature: in a survey of 11 countries, Bodovski et al. (2021) show that household lending standards tightened considerably during COVID, and that countries that implemented more substantial loan guarantee measures saw lending standards tighten less. The evidence points to a flight-to-safety response by lenders; households in more exposed locations continue to seek credit, but are less likely to translate that demand into realized borrowing.

The cohort and product decompositions adds nuance to the argument. The cohort results suggest that repayment deterioration, measured by delinquency, is stronger for loans originated during the pandemic than for pre-COVID loans. This is expected, as new loans extended under pandemic conditions are more exposed to a fragile recovery path. The product decomposition points toward to the same direction: the aggregate fall in debt masks a reallocation across products. For instance, agricultural loan debt appears to contract more clearly for more COVID-exposed borrowers, whereas credit card and hire purchase debt are comparatively more resilient. The relative persistent of flexible products, then, can be understood as substitution at the margin under stress to more flexible forms of credit, and not an uniform withdrawal from credit markets.

Agricultural loans stand out as a distinct case. Agricultural debt declines more sharply than other loan categories, suggesting that a larger share of the treatment effect on aggregate debt is concentrated in this sector. This does not, however, imply a simple collapse in agricultural lending. Earlier results show that the number of agricultural loans rises in more COVID-exposed areas even as total agricultural balances fall, suggesting sharp reductions in average loan size. This is consistent with the policy interventions from the Bank for Agriculture and Agricultural Cooperatives (BAAC), which combined debt moratoria and restructuring with small, emergency loans. Hence, the results appears not to be from a contraction in demand, but more a compositional shift to smaller, policy-driven loans.

The agricultural delinquency results also move in opposite directions from the unsecured products, namely, credit card and personal loans. While delinquency rates for these products rises in more exposed areas, agricultural delinquency declines and stays relatively lower. This does not necessarily suggest that agricultural borrowers were less impacted from COVID; rather, the more plausible explanation is that they were partially shielded by BAAC policy and changes in loan composition towards smaller loans, which are easier to service. In that sense, the agricultural sector appears different because policy interventions reshaped how stress manifested in the data, not because the underlying stress disappeared.

The heterogeneity results support this interpretation. Borrowers with pre-COVID agricultural loans experience more pronounced declines in total debt in response to COVID exposure than other borrowers, indicating that the aggregate debt contraction is driven disproportionately by agricultural households. Concurrently, these borrowers exhibit relatively lower delinquency rates in exposed areas than the non-agriculture group. This appears consistent with sector-specific intervention and a shift toward smaller loans. By contrast, borrowers who entered the pandemic with only unsecured loans consistently show worse delinquency dynamics and lower debt paths. The strongest heterogeneity result is there-

fore not that unsecured-only borrowers always have a larger COVID-exposure elasticity in each quarter; rather, they appear systematically more vulnerable over the COVID period, consistent with evidence on COVID-era financial fragility in the U.S. and Thailand (Chote et al. 2025; Clark, Lusardi, and Mitchell 2021; Monetary Policy Committee 2023).

One important limitation is that not all results in this paper are equally strong. Several specifications display non-flat pre-period coefficients, and so the corresponding post-COVID paths are better interpreted as suggestive than conclusive. Additionally, I use night-time lights as a proxy for local economic exposure. Although the choice is much grounded in literature and I provide extensive additional validation, it is not the perfect measure for local household shocks. Gibson et al. (2021), for example, claim that the quality of NTL varies by data source and location, and that performance is weaker at smaller spatial units and lower-density areas.²² Further research to uncover the ideal measurement at a very granular scale (e.g., at the postal-code level) is needed in this field. Even so, using NTL, I consistently show that spatially uneven pandemic exposure is associated with tighter credit access and worse repayment outcomes for many loan products.

The policy implications directly follow. Crisis-period debt relief can successfully mute observed delinquency in the short run, but it can also make balance-sheet stress difficult to detect if policymakers only focus on standard stock measures, such as total outstanding debt. In this paper, I show that distress becomes visible first through rising delinquency on certain products, failed access to new credit, and weaker performance of COVID-era loans, not just expanding balances. This promotes the monitoring of a broader set of credit market indicators during crises, for example, with inquiry-based measures and the performance of newly originating loans. Additionally, this paper suggests that adequate policy support can materially reshape the measured outcomes in particular sectors, as the agriculture case appears to show, but that such insulation should not be confused with a full resolution of underlying financial vulnerability. Further, programs should be targeted towards borrowers with weaker *ex ante* credit structures, as this is the segment that appears most vulnerable in the data when local shocks materialize and temporary debt relief measures expire.

Another central finding is that the effects of COVID exposure on household financial outcomes are not purely transitory. Instead, they display a pronounced, long-term component. The deterioration in repayment outcomes and unmet credit demand extend well beyond the initial shock period, and remains evident even during and after the recovery phase, in a “scarring” way. In particular, the divergence in delinquency outcomes across exposure

22. I use the newer VIIRS data for this paper, which Gibson et al. (2021) argues is better than the previous-generation DMSP data for this issue, but still not perfect.

levels and the sustained increase in unsuccessful borrowing attempts are consistent with a mechanism in which the pandemic exacerbated pre-existing financial fragility in a high-debt environment like Thailand. Hence, households in more affected areas remain constrained, even as aggregate conditions improve, pointing towards a form of debt overhang.

This persistence also holds crucial implications for how pandemic-era policy interventions should be interpreted. Short-term debt relief measures appear to have been effective in smoothing outcomes during the periods in which they were active, as suggested by the relatively muted responses in many outcomes prior to the expiration of Debt Relief Phase III. The subsequent deterioration in repayment outcomes and the strong, continued evidence of credit rationing indicate that these measures did not fully resolve the underlying balance sheet weaknesses. Instead, they primarily delayed the adjustment process, preventing immediate loan default, but leaving the borrower vulnerability and lack of realized credit access largely intact.

From a policy perspective, these findings suggest that short-term stabilization tools alone are not sufficient to address the consequences of a large and uneven shock like COVID. In Thailand, where household debt levels are already elevated, and a large share of borrowing is unsecured, policies that focus on temporary repayment relief may reduce short-run distress, but risk prolonged financial fragility. More durable solutions are likely to require targeted debt restructuring and improve credit allocation that avoids both excessive tightening and indiscriminate expansion, with sizable focus on borrowers with weaker pre-shock credit structures, as they appear especially susceptible to long-run adverse effects from the economic shocks.

8 Conclusion

This paper examines the effects of COVID-19 exposure on household credit behavior in Thailand, using loan-level credit bureau panel data combined with spatial variation in pandemic intensity represented by night-time lights. I employ an event-study framework with borrower fixed effects to trace the dynamic relationship between postal code-level COVID exposure and several dimensions of household financial outcomes, including debt holdings, repayment behavior, credit demand, and realized access to credit. I further extend the analysis by examining heterogeneity across loan cohorts, loan product types, and borrower characteristics.

The results point to three core findings. First, COVID exposure is associated with

a deterioration in repayment outcomes, with delinquency strongly rising in more exposed areas, especially for loans that originated after the start of the pandemic. Second, the declines in total outstanding debt experienced in more COVID-impacted postal codes are likely not driven by improved household balance sheets, but rather by a contraction in the effective credit access. This interpretation is supported by the simultaneous rise in loan inquiries and unmet inquiries. Third, those borrowers who entered the pandemic with only unsecured debt appear to be systematically more vulnerable. More broadly, the product-level results show that these effects were not uniform across loan product-type categories. In particular, agricultural debt and delinquency move differently from unsecured products, which is consistent with sector-specific policy intervention from the BAAC and a shift towards smaller loans, and not a simple improvement in borrower financial conditions in that sector. As such, these findings suggest that COVID affected Thai household credit markets through a combination of worsening repayment capacity, tighter credit supply, and changes in lending composition. Just as important, these effects of COVID exposure appear to be “scarring,” lasting well beyond the initial shock period.

These results have important policy implications. Although debt relief measures and liquidity support likely mitigated short-term distress, they primarily delayed, rather than eliminated, underlying financial vulnerabilities. As such, policies aimed at addressing the consequences of large shocks need to move beyond just temporary relief and focus on long-term solutions. In particular, identifying and supporting financially fragile borrowers, such as those relying heavily on unsecured credit, is crucial for a more resilient recovery. Additionally, there is a need to monitor a broader set of credit-market indicators, such as inquiry-based measures and performances of newly originated loans. Lastly, the agricultural loan results indicate that targeted sectoral interventions can drastically reshape measured outcomes, although they should not be confused with a complete resolution of underlying stress.

I acknowledge several limitations. The use of night-time lights as a proxy for local economic exposure captures spatial variation in economic activity at extremely fine scales, but is not a perfect depiction of household-level income shocks. Additionally, some specifications exhibit non-flat pre-trend dynamics, which necessitates caution in interpreting certain estimates. Despite these, however, the broadly consistent results from multiple outcomes and specifications support the main conclusions of this paper.

Further research could build on this analysis in several directions. First, setting the pre-period to be the average of several quarters, or annual averages, may remove the risk associated with choosing one quarter to serve as the baseline. Second, conducting more formal structural-break tests could determine if the patterns of treatment effects change

significantly around specific quarters, such as after the expiration of Debt Relief Phase III. Third, incorporating direct measures of household income or sectoral exposure would help identify more precisely the channels through which COVID exposure affects financial outcomes. Fourth, linking borrower data to lender-level information would shed additional light on the relative roles of credit demand and supply, as well as lender screening processes across more and less exposed areas.

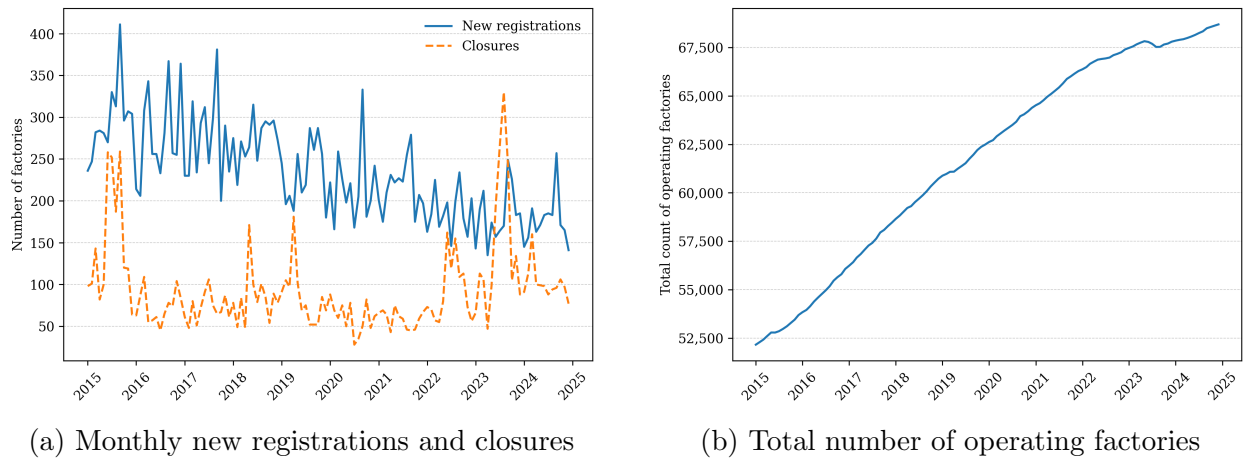
A Appendix: Secondary COVID Exposure Data

A.1 Factory Closure Data

To capture real-sector disruptions in the industrial and manufacturing segments during COVID, I use administrative data on factory registrations and de-registrations, obtained from the Department of Industrial Works, a branch of Thailand’s Ministry of Industry.²³

These data are presented at the postal code and monthly levels, which are used to construct: (i) the number of newly registered factories in a given month; (ii) the number of de-registered factories in the same month; and (iii) the cumulative stock of registered factories at the end of each month. The factory data are available from the start of 2015 through the end of 2024.

Figure A.1: Factory Entry, Exit, and Total Operating Establishments



Source: Author’s calculations based on Department of Industrial Works administrative data.

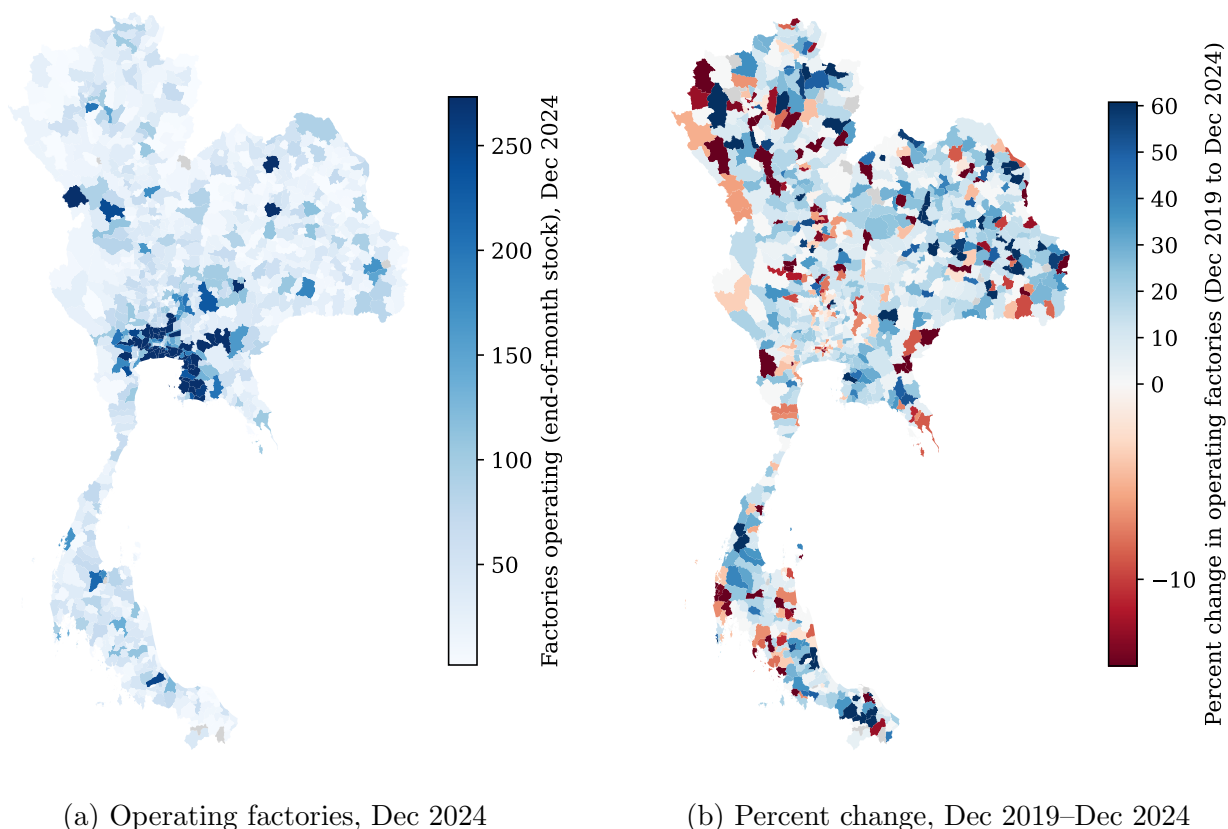
Notes: The data presented are the aggregates across all postal codes in Thailand.

Figure A.1 presents monthly factory registrations and closures alongside the total stock of operating factories. The left panel shows that new registrations consistently exceed closures over most of the sample period, although both series exhibit substantial volatility. The number of new registrations generally shows a decrease over time, while the number of closures increases slightly starting in 2022. The right panel indicates a steady upward trend in the total number of operating factories, although the rate of growth decreases be-

23. Based on the Factory Act, Amendment No. 2 (B.E. 2562/2019), a “factory” is a building, place, or vehicle that uses machinery with a total power of 50 horsepower or more, or employs 50 workers or more (with or without machinery). Refer to Department of Industrial Works (2025). This is more restrictive than the prior criteria, which defined a “factory” as having either 5 or more horsepower or 7 or more workers. Data from pre-2019 are adjusted to match the current (2019) criteria.

ginning in 2022. Despite short-run fluctuations in entry and exit flows, the stock of active establishments grows persistently over time.

Figure A.2: Spatial Distribution of Operating Factories and Post-Pandemic Change



Source: Author's calculations based on Department of Industrial Works administrative data.

Notes: Color scales are winsorized at the 5–95% limits; postcodes with missing values are shown in light gray.

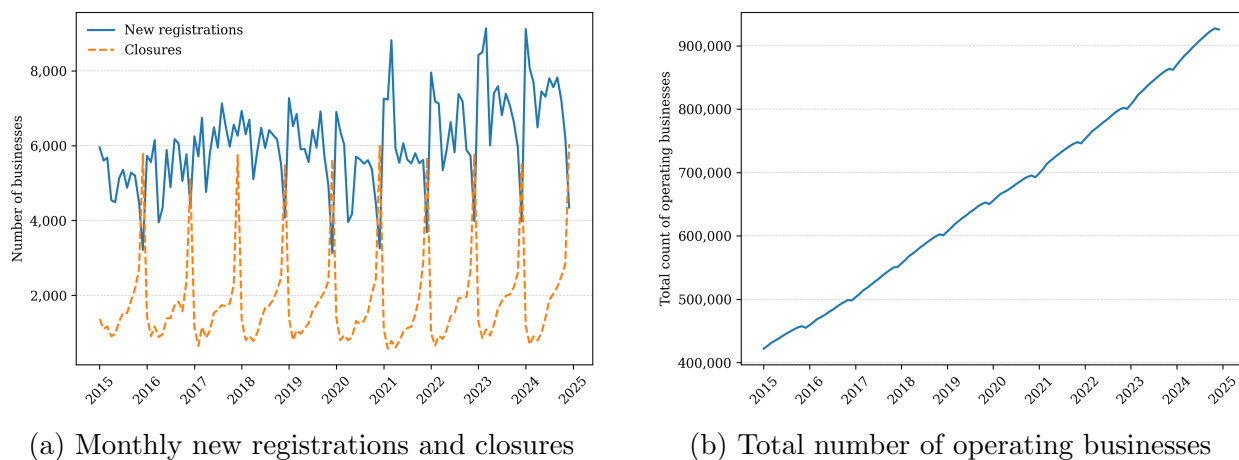
Figure A.2 illustrates the spatial distribution of operating factories across Thai postcodes and their evolution over the post-pandemic period. Panel (a) maps the end-of-month stock of operating factories in December 2024. Factory activity is highly concentrated in major urban and industrial corridors, particularly in the Bangkok metropolitan area and surrounding provinces. Secondary clusters are visible in parts of the Eastern Economic Corridor (Rayong, Chon Buri, and Chachoengsao provinces, which are adjacent to Bangkok on the eastern side of the Gulf) and selected provincial centers, while much of the rural interior exhibits relatively low factory density. Panel (b) presents the percent change in operating factories between December 2019 and December 2024, where the spatial pattern of change is heterogeneous. While some industrial clusters experienced continued expansion, other areas saw stagnation or contraction. Growth appears uneven even within established manufacturing regions, for

example, with some parts of the Bangkok metropolitan region exhibiting net decreases, thus suggesting localized adjustments rather than a uniform national recovery.

A.2 Business Closure Data

To capture the disruptions for the broader business sector, which is particularly relevant for services and small enterprises in both urban and rural areas, I leverage administrative data from the Department of Business Development, under Thailand’s Ministry of Commerce.²⁴ Using the business data record, again at the postal code-month level, I construct the analogous measures of the count of newly registered businesses, de-registered businesses, and the stock of active businesses at the month-end. The business data are available from the start of 2015 through the end of 2024.

Figure A.3: Business Entry, Exit, and Total Operating Establishments



Source: Author’s calculations based on Department of Business Development administrative data.

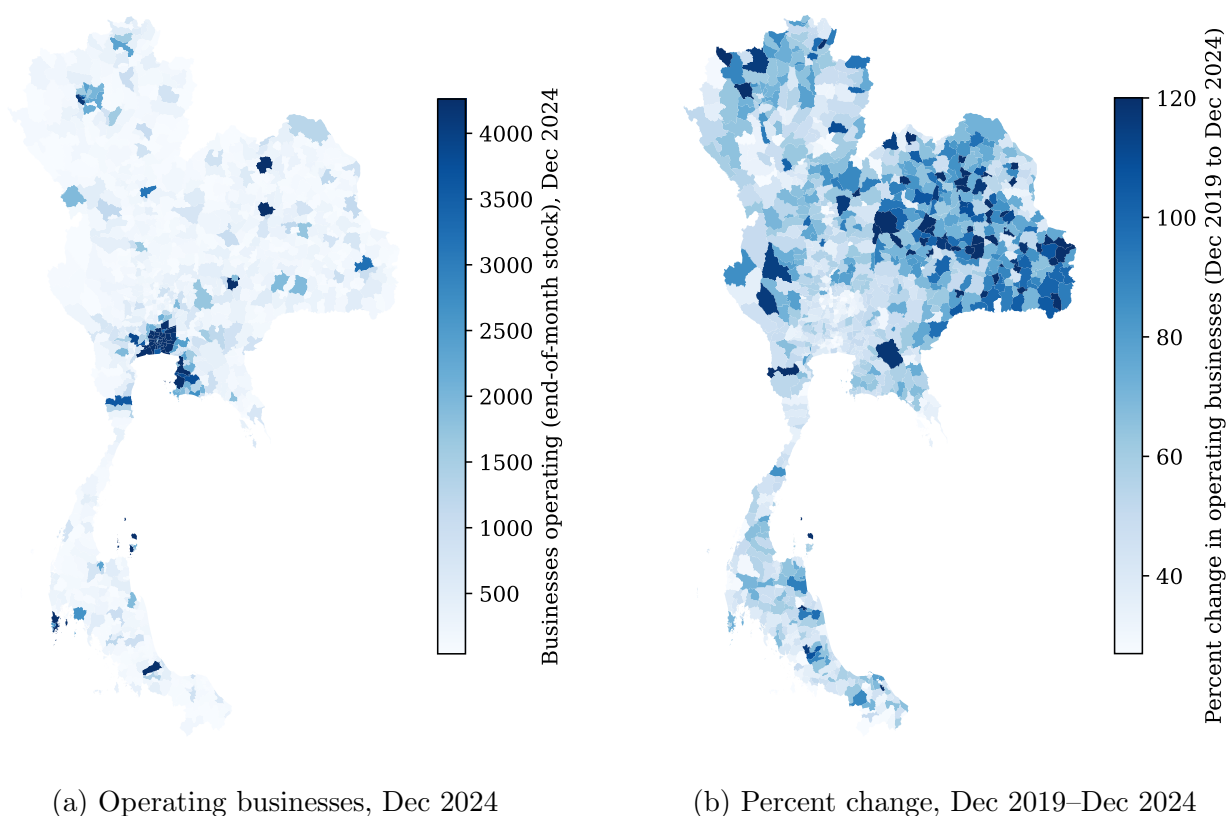
Notes: The data presented are the aggregates across all postal codes in Thailand.

Figure A.3 presents monthly business registrations and de-registrations together with the total stock of operating businesses. The left panel shows substantial seasonality in both entry and exit, with closures exhibiting pronounced year-end spikes. Despite this volatility, new registrations generally exceed closures throughout the sample period, implying sustained net business formation in the aggregate of Thailand. Entry activity trends upward over time, particularly in the post-2020 period, but has a slight dip in 2020 and early 2021. The right panel indicates a steady and persistent increase in the total number of operating

24. This includes sole proprietorships, partnerships, and limited companies, registered and regulated by the Department of Business Development (DBD) under the Ministry of Commerce, primarily under provisions of the Civil and Commercial Code and other relevant laws. Refer to Department of Business Development (2025).

businesses in the country. This suggests a continued expansion of the formal business sector. In particular, the short-run fluctuations in flows in the left panel do not translate into sustained contractions in the overall stock.

Figure A.4: Spatial Distribution of Operating Businesses and Post-Pandemic Change



Source: Author's calculations based on Department of Business Development administrative data.

Notes: Color scales are winsorized at the 5–95% limits; postcodes with missing values are shown in light gray.

Figure A.4 illustrates the spatial distribution of operating businesses and their post-pandemic evolution across postal codes in Thailand. Panel (a) maps the end-of-month stock of operating businesses in December 2024. As shown, business activity is highly concentrated in the Bangkok metropolitan area and major provincial centers, with substantially lower counts in rural and peripheral regions. The spatial distribution reflects the strong concentration of formal economic activity and service-sector establishments in major cities. Panel (b), meanwhile, presents the percent change in operating businesses between December 2019 and December 2024. Unlike the level distribution, the growth pattern is more spatially dispersed. Many postal codes outside the Bangkok core exhibit relatively strong expansion, particularly in parts of the Northeast. In fact, the Bangkok region saw relatively low growth

in the number of formally registered businesses, in percentage terms. This suggests that post-pandemic business formation and recovery were not confined solely to traditional urban centers. It should be noted that all postal codes saw positive growth in the number of operating businesses between December 2019 and December 2024; the 1st percentile of postal codes by percent change showed a 7.5% increase, while the 5th percentile showed a 27.0% increase.

A.3 Provincial Stringency Index

To capture the intensity of COVID-19 non-pharmaceutical interventions (NPIs) across space and time,²⁵ I use the Provincial Stringency Index (PSI) compiled by the Puey Ungphakorn Institute for Economic Research (PIER) at the Bank of Thailand.²⁶ The PSI is a daily index, compiled at the provincial level for all 77 provinces, and is specifically designed to measure the stringency of COVID-19 containment measures, adapting the methodology of the Oxford Stringency Index (OSI) to Thai institutions and data.²⁷

Rojayaroon et al. (2021) construct the PSI by coding, on a daily basis, the set of NPIs in force in each province, using official regulations from the Center for COVID-19 Situation Administration (CCSA) of Thailand and provincial orders. The PSI follows the same conceptual framework as the OSI, where each daily measure is coded on an ordinal scale (e.g., no measure, recommended, required for some groups, required for all). The measures are combined into a daily composite indicator that is normalized from 0 (no restrictions) to 100 (most stringent measures).

Relative to the national-level OSI, the PSI extends the coverage into two crucial ways. First, the PSI is coded separately for each province, allowing for more spatial variation in stringency, as the CCSA classified provinces into different risk categories and provincial governments imposed additional measures. The OSI, meanwhile, records only two levels of stringency (either nationwide or in parts of the country). Secondly, in addition to the seven core OSI categories (school closures, workplace closures, public event cancellations, restrictions on gatherings, public transport closures, stay-at-home orders, and domestic travel restrictions), the PSI includes a richer set of business- and place-specific restrictions.²⁸

25. Non-pharmaceutical interventions (NPIs) are public-health measures that reduce transmission without the use of medications or vaccines, such as masking, physical distancing, isolation, quarantine, and limits on gatherings.

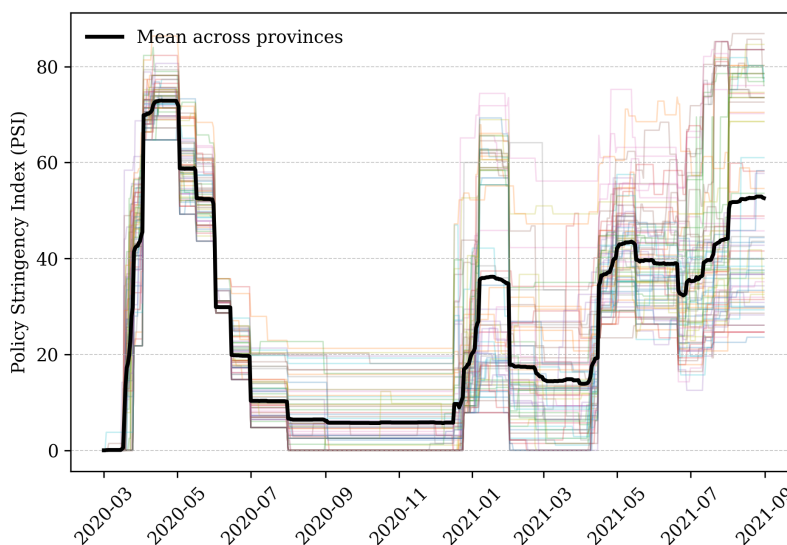
26. For information on the PSI and its methodology, refer to Rojayaroon et al. (2021).

27. For information on the OSI and its methodology, refer to Hale et al. (2021).

28. These cover, for example, restaurants and bars, shopping malls, fresh markets and convenience stores, beauty and massage parlors, entertainment venues, public venues (parks, sports facilities, exhibition centers),

The PSI provides both the underlying measure-by-measure data, as well as a daily composite PSI for each province from March 1, 2020 to August 31, 2021. The composite index tracks the evolution of the pandemic policies, which Rojayaroon et al. (2021) show closely follows infection waves and explain mobility patterns (from Apple and Google mobility indices) better than the national-level OSI.

Figure A.5: Provincial COVID-19 Policy Stringency Index (PSI)



Source: Plotted based on data from the PSI (Rojayaroon et al. 2021).

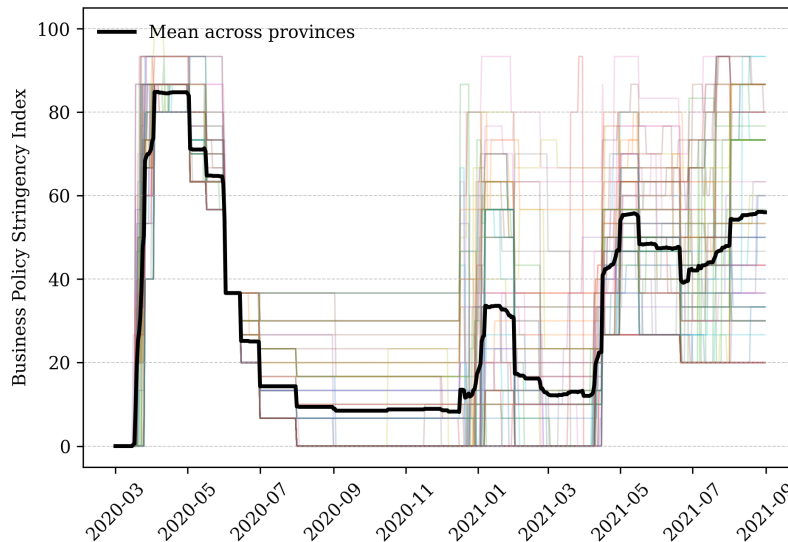
Notes: Thin colored lines show the daily PSI for each province. The thick black line represents the cross-province mean PSI. The index is normalized to range from 0 (no restrictions) to 100 (maximum stringency).

Figure A.5 shows the daily evolution of the PSI across provinces. The thin lines represent province-specific measures, while the thick line denotes the cross-province average for the country. The PSI rises sharply in early 2020, reflecting the introduction of nationwide containment policies, which included mobility restrictions, business closures, and curfews. The index reaches its first peak during the initial pandemic wave and then declines gradually as restrictions are relaxed. A second increase is observed around early 2021, corresponding to renewed containment measures in response to subsequent outbreaks. Although the timing of major policy shifts is broadly synchronized across provinces, we observe noticeable heterogeneity in the intensity and duration of restrictions. For instance, some provinces maintain higher stringency levels for longer periods, suggesting localized policy responses to varying infection dynamics.

Based on the PSI, I construct the sub-index for the stringency of business-related con-
work-from-home policies, curfews, bans on alcohol sales, border-crossing controls, and orders to close factories or worker camps in which infections were detected.

tainment measures, where the aggregate score is normalized on the same scale as the main PSI from Rojayaroon et al. (2021).²⁹ That is, for the aggregate business PSI, 0 represents no restrictions and 100 represents the most stringent measures.

Figure A.6: Provincial Business-Specific Policy Stringency Index (Business PSI)



Source: Author's calculations based on the PSI.

Notes: Thin colored lines show the daily Business Policy Stringency Index (business.PSI) for each province. The thick black line represents the cross-province mean. The index aggregates five categories of business closure measures and is normalized to range from 0 (no restrictions) to 100 (maximum stringency).

Figure A.6 presents the evolution of the business PSI sub-score. The index rises sharply in early 2020, reflecting widespread mandatory business closures during the initial pandemic wave. Stringency declines gradually through late 2020 as restrictions ease, before increasing again during subsequent outbreak waves in 2021. Although provincial policy timing is broadly synchronized, there is considerable cross-province heterogeneity in the intensity and duration of business restrictions. This becomes particularly evident in later waves, when some provinces reimpose stringent closures while others maintain relatively moderate measures. Dispersion across provinces is naturally greater than in Figure A.5, as the score now averages over fewer components. However, when comparing business PSI scores across provinces, we observe substantially more variation in 2021 than during the initial peak in

29. I construct the business PSI as follows: $\frac{1}{5}(B_1 \times 50 + B_2 \times 33.33 + B_3 \times 33.33 + B_4 \times 33.33 + B_5 \times 33.33)$. This insures that all the components receive equal weight in the business PSI score. Here, B_1 represents closure of restaurants and bars (scored from 0–2); B_2 represents closure of shopping malls (scored from 0–3); B_3 represents closure of fresh markets, flea markets, community markets, community retail stores, and convenience stores (scored from 0–3); B_4 represents closure of beauty salons, hair salons, barber shops, beauty clinics, spas, and massage parlors (scored from 0–3); and B_5 represents closure of pubs, massage parlors, game arcades, and internet cafes (scored from 0–3).

2020, suggesting meaningful heterogeneity in how businesses resumed operations during the later phases of COVID.

A.4 Validation of VIIRS Night-Time Lights

Before using VIIRS NTL as a proxy for local economic activity, I validate the measurement against independent “ground” truth data on factory and business activity, as well as COVID-era policy stringency.

I first test whether NTL intensity (as measured by the luminous intensity of each pixel) co-move with real-sector activity at the postal code-month level. Specifically, I estimate regressions of the form

$$\ln(NTL_{pt}) = \alpha_p + \gamma_{my} + \beta \ln(Activity_{pt}) + \epsilon_{pt} \quad (\text{A.1})$$

where $Activity_{pt}$ is either the stock of operating factories or the stock of operating businesses in postal code p and at end-of-month t ; α_p are postal code fixed effects; and γ_{my} are month-year fixed effects. Standard errors are clustered at the postal code level; results are also robust to clustering at the province level.

The results show a tight positive association between NTL and business activity. A 1 percent increase in the number of operating businesses is associated with roughly a 0.20 percent increase in NTL intensity, significant at the 1% level and an adjusted R^2 of about 0.98 (See Table B.2). For factories, the relationship is weaker but still positive in aggregate. The elasticity of NTL with respect to the number of operating factories is around 0.03 and weakly statistically significant overall, though close to zero in non-urban postal codes (See Table B.1).

To probe heterogeneity, I interact the factory and business stock with an indicator for urban postal codes. For factories, the slope is negative but small in non-urban areas and becomes positive in urban locations when the interaction is included. The implied elasticity in urban postal codes is approximately 0.04. For businesses, both urban and non-urban slopes are positive, with a stronger association in urban postal codes (baseline elasticity is around 0.16 in non-urban postal codes and around 0.21 in urban postal codes). Both of these patterns are intuitive; business and factory stock are more tightly linked to night-time luminosity in denser, more commercialized areas, whereas rural factories are less plentiful than rural businesses and may also operate on schedules or technologies less visible in the NTL signal (hence the negative baseline coefficient value).

I further examine if NTL luminosity responds to (i) policy intensity and (ii) administrative evidence of local economic disruption (registered business closures). I estimate panel regressions at the postal code–month level, using provincial level PSI data, of the form:

$$\begin{aligned}
y_{pt} = & \alpha_p + \gamma_{my} \\
& + \sum_{s \in \{Covid, Reopening\}} \left[\beta_s (\mathbf{1}\{t \in s\} \times PSI_r) + \delta_s (\mathbf{1}\{t \in s\} \times \ln(BizDens_p)) \right. \\
& \quad \left. + \theta_s (\mathbf{1}\{t \in s\} \times PSI_r \times \ln(BizDens_p)) \right] \\
& + \epsilon_{pt}
\end{aligned} \tag{A.2}$$

where p indexes the postal code level, r indexes the province level, and my indexes month-year. α_p are postal code fixed effects, and γ_{my} are month-year fixed effects. The business density is calculated as the average number of registered businesses between 2015 and 2019 (pre-COVID period) from the monthly Department of Business Development administrative data. For s , the COVID period is set to be in 2020 and 2021, when restrictions and economic disruption were most acute, while the Reopening period is 2022 and after, to test whether areas that experienced more stringent restrictions in 2020–21 also display persistent differences afterwards.

Outcomes y_{pt} are (1) the monthly NTL luminosity series at the postal code level, after removing invalid data; (2) the monthly count of business closures per postal code, obtained from the business de-registration data; and (3) the monthly business closure rate, measured as the monthly closures divided by the pre-COVID business density.

The policy exposure PSI_r is measured at the province level r , using: (1) the mean daily PSI index during 2020–21, and (2) high-stringency exposure, measured as the number of days with the PSI index being at least 50 during 2020–21. I also distinguish between composite PSI (obtained from Rojayaroon et al. (2021)), and business PSI components (which I construct based on data from Rojayaroon et al. (2021), as per Footnote 29), since business-restricting measures should map more directly into business operations and night-time activity.

Tables B.3 and B.4 outlines these results. The results show that NTL intensity responds to policy restrictions in the expected direction, particularly when policy exposure is measured using high-stringency days (Column 1). When exposure is defined as the average PSI level over 2020–2021, the estimated COVID interaction is negative but statistically weak (Panels A and B). In contrast, when policy exposure is measured using the number of days with PSI at least 50, the relationship becomes significantly negative (Panels C and D). This pattern suggests that night-time lights respond most strongly to periods of intense, binding

restrictions, rather than to moderate fluctuations in policy stringency averaged over time. This interpretation is consistent with the mechanisms underlying night-time luminosity; the largest reductions in economic activity, such as shortened operating hours and temporary closures of establishments, occur during periods of strict lockdown measures, which reduce NTL intensity.

Additionally, I find that exposure to high-stringency restrictions during 2020–2021 is associated with persistently lower NTL intensity during the reopening period. The reopening-period interaction with high-stringency exposure is negative and statistically significant for NTL (Column 1 in Table B.4). This is consistent with longer-lasting effects of pandemic restrictions, such as permanent closures of venues and persistent behavioral changes in consumption and mobility, including in tourism. Although these estimates should not be interpreted as causal evidence of long-term economic scarring, they do reinforce the interpretation that NTL captures meaningful variation in realized local activity.

A second validation exercise reveals that PSI exposure aligns closely with business closure outcomes. In the closure regressions (Column 3 in Tables B.3 and B.4), the interaction between COVID and mean PSI exposure is positive and statistically significant (Panels A and C). These estimates indicate that areas with higher exposure to pandemic restrictions experienced more registered business closures during the COVID period. Two additional patterns strengthen the credibility of this relationship. First, the estimated effects are larger when using the business-specific PSI measure (Panels B and D), rather than the broader composite, which follows the expectation that restrictions targeting business operations should more directly affect business outcomes than policies affecting other sectors, such as education or public gatherings. Second, exposure measured by high-stringency days (Panel D) also more strongly predicts closures during the COVID period, suggesting that periods of strict restrictions were particularly disruptive for firms. The positive coefficient in Column 3 (Panels B and D) on the interaction between the COVID period and pre-COVID business stock indicates that business closures increased more strongly in areas with higher pre-pandemic firm density, consistent with the disproportionate impact of COVID-19 restrictions on dense service-sector clusters. This could be because postal codes that have high business presence prior to COVID are more susceptible to the negative economic impacts of COVID policy restrictions, or if firms there operate with higher competition and tighter margins. The regressions using business closure rates (Column 4) yield mostly small and statistically insignificant coefficients. This is unsurprising, as closure rates are mechanically small: the denominator, the average stock of registered firms pre-COVID, is large and non-varying.

These validation exercises show that NTL reacts systematically to the intensity of COVID-

era restrictions, particularly during high-stringency regimes, and that the same policy measures predict administrative business closures in the expected direction. These results support interpreting postal code-level NTL deviations from expected levels as a credible, high-frequency proxy for realized local economic disruption during the pandemic.

B Appendix: Additional Tables

Table B.1: Night-time Lights and Factory Activity

	Split Sample			Interaction
	Overall	Urban	Non-Urban	Pooled
	(1)	(2)	(3)	(4)
	ln(NTL)	ln(NTL)	ln(NTL)	ln(NTL)
ln(Factory Stock)	0.0302*	0.0342*	0.00106	-0.0261**
	(0.0173)	(0.0188)	(0.0423)	(0.0114)
Urban $\times$ ln(Factory Stock)				0.0648***
				(0.0119)
Constant	0.115**	0.103*	0.194*	0.109***
	(0.0559)	(0.0619)	(0.116)	(0.0152)
Observations	75038	66252	8785	75038
Adjusted R^2	0.978	0.978	0.976	0.978

Notes: Columns (1)–(3) estimate the relationship separately for the full sample, urban areas, and non-urban areas. Column (4) estimates the pooled specification with an interaction between the urban indicator and the number of operating factories. All regressions include postal code and month-year fixed effects. Standard errors clustered at the postal code level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.2: Night-time Lights and Business Activity

	Split Sample			Interaction
	Overall	Urban	Non-Urban	Pooled
	(1)	(2)	(3)	(4)
	ln(NTL)	ln(NTL)	ln(NTL)	ln(NTL)
ln(Business Stock)	0.203***	0.215***	0.134***	0.163***
	(0.0178)	(0.0199)	(0.0369)	(0.00717)
Urban $\times$ ln(Business Stock)				0.0463***
				(0.00606)
Constant	-0.827***	-0.893***	-0.463***	-0.831***
	(0.0901)	(0.102)	(0.169)	(0.0245)
Observations	76496	67300	9195	76496
Adjusted R^2	0.978	0.978	0.976	0.978

Notes: Columns (1)–(3) estimate the relationship separately for the full sample, urban areas, and non-urban areas. Column (4) estimates the pooled specification with an interaction between the urban indicator and the number of operating businesses. All regressions include postal code and month-year fixed effects. Standard errors clustered at the postal code level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3: Effects of PSI Exposure Across COVID Stages: Mean PSI Exposure

	(1) ln(NTL)	(2) ln(NTL)	(3) Biz closures	(4) Biz closure rate
<i>Panel A: Mean composite PSI exposure (2020–21)</i>				
COVID (2020–21) × Mean PSI	-0.0031 (0.0021)	0.0005 (0.0025)	0.0710* (0.0372)	0.0001 (0.0001)
Reopening (2022+) × Mean PSI	-0.0044 (0.0031)	-0.0006 (0.0042)	0.0134 (0.0517)	-0.0001 (0.0001)
COVID (2020–21) × ln(Biz Density)		-0.0345** (0.0137)	0.2783 (0.1909)	0.0004 (0.0004)
Reopening (2022+) × ln(Biz Density)		-0.0559** (0.0214)	0.0684 (0.2642)	-0.0009 (0.0007)
COVID (2020–21) × Mean PSI × ln(Biz Density)		-0.0002 (0.0004)	-0.0164* (0.0084)	-0.0000 (0.0000)
Reopening (2022+) × Mean PSI × ln(Biz Density)		0.0000 (0.0007)	-0.0027 (0.0121)	0.0000 (0.0000)
Constant	0.2551*** (0.0384)	0.3295*** (0.0528)	1.5744*** (0.4132)	0.0051*** (0.0014)
<i>Panel B: Mean business PSI exposure (2020–21)</i>				
COVID (2020–21) × Mean biz PSI	-0.0022 (0.0017)	0.0020 (0.0019)	0.0879** (0.0380)	0.0001 (0.0001)
Reopening (2022+) × Mean biz PSI	-0.0027 (0.0026)	0.0035 (0.0038)	0.0596 (0.0661)	-0.0000 (0.0001)
COVID (2020–21) × ln(Biz Density)		-0.0288** (0.0119)	0.4405** (0.2141)	0.0005 (0.0005)
Reopening (2022+) × ln(Biz Density)		-0.0386* (0.0217)	0.4209 (0.3692)	-0.0007 (0.0006)
COVID (2020–21) × Mean biz PSI × ln(Biz Density)		-0.0004 (0.0003)	-0.0207** (0.0089)	-0.0000 (0.0000)
Reopening (2022+) × Mean biz PSI × ln(Biz Density)		-0.0006 (0.0007)	-0.0141 (0.0156)	0.0000 (0.0000)
Constant	0.2373*** (0.0328)	0.2842*** (0.0482)	1.0151* (0.5917)	0.0047*** (0.0014)
Observations	76497	76497	114000	114000

Notes: Panel A uses mean composite PSI exposure during 2020–2021, while Panel B uses mean business-specific PSI exposure during the same period. Columns (1) and (2) use NTL intensity interacted with period indicators as the dependent variable. Columns (3) and (4) use business closure counts and closure rates, respectively.

Business firm density is measured as the logarithm of the average number of firms in the postal code area between 2015 and 2019 (pre-COVID). Business closure rate is the number of business closures divided by the business firm density.

All regressions include postal code and month-year fixed effects. Standard errors are clustered at the province level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4: Effects of PSI Exposure Across COVID Stages: High-Stringency Days

	(1) ln(NTL)	(2) ln(NTL)	(3) Biz closures	(4) Biz closure rate
<i>Panel C: Number of days PSI ≥ 50 (2020–21)</i>				
COVID (2020–21) $\times$ Days PSI ≥ 50	-0.0006** (0.0003)	-0.0003 (0.0004)	0.0073* (0.0039)	0.0000 (0.0000)
Reopening (2022+) $\times$ Days PSI ≥ 50	-0.0009** (0.0004)	-0.0005 (0.0007)	0.0010 (0.0054)	-0.0000 (0.0000)
COVID (2020–21) $\times$ ln(Biz Stock)		-0.0393*** (0.0071)	0.0186 (0.0796)	0.0003 (0.0003)
Reopening (2022+) $\times$ ln(Biz Stock)		-0.0541*** (0.0109)	0.0103 (0.1008)	-0.0006* (0.0003)
COVID (2020–21) $\times$ Days PSI $\geq 50 \times$ ln(Biz Stock)		0.0000 (0.0001)	-0.0016* (0.0009)	-0.0000 (0.0000)
Reopening (2022+) $\times$ Days PSI $\geq 50 \times$ ln(Biz Stock)		0.0000 (0.0001)	-0.0002 (0.0012)	0.0000 (0.0000)
Constant	0.2392*** (0.0169)	0.3410*** (0.0288)	1.8777*** (0.1775)	0.0049*** (0.0007)
<i>Panel D: Number of days business PSI ≥ 50 (2020–21)</i>				
COVID (2020–21) $\times$ Days biz PSI ≥ 50	-0.0005** (0.0002)	-0.0002 (0.0003)	0.0089** (0.0036)	0.0000 (0.0000)
Reopening (2022+) $\times$ Days biz PSI ≥ 50	-0.0007** (0.0003)	-0.0001 (0.0005)	0.0060 (0.0062)	-0.0000 (0.0000)
COVID (2020–21) $\times$ ln(Biz Stock)		-0.0379*** (0.0085)	0.1716* (0.0917)	0.0003 (0.0004)
Reopening (2022+) $\times$ ln(Biz Stock)		-0.0472*** (0.0124)	0.2394 (0.1512)	-0.0007 (0.0004)
COVID (2020–21) $\times$ Days biz PSI $\geq 50 \times$ ln(Biz Stock)		0.0000 (0.0000)	-0.0021** (0.0008)	-0.0000 (0.0000)
Reopening (2022+) $\times$ Days biz PSI $\geq 50 \times$ ln(Biz Stock)		-0.0000 (0.0001)	-0.0014 (0.0015)	0.0000 (0.0000)
Constant	0.2453*** (0.0205)	0.3304*** (0.0309)	1.4722*** (0.2284)	0.0050*** (0.0010)
Observations	76497	76497	114000	114000

Notes: Panel C measures the exposure as the number of days with composite PSI greater than or equal to 50 during 2020–2021. Panel D measures the exposure as the number of days with business-specific PSI greater than or equal to 50. Columns (1) and (2) use NTL intensity interacted with period indicators as the dependent variable. Columns (3) and (4) use business closure counts and closure rates, respectively.

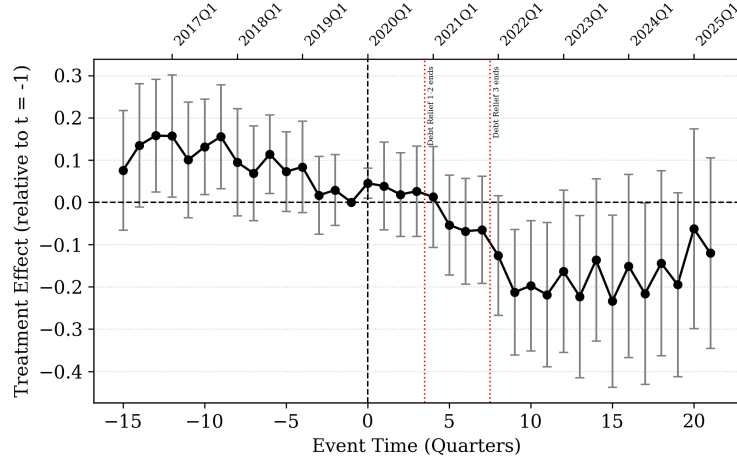
Business firm density is measured as the logarithm of the average number of firms in the postal code area between 2015 and 2019 (pre-COVID). Business closure rate is the number of business closures divided by the business firm density.

All regressions include postal code and month-year fixed effects. Standard errors are clustered at the province level.

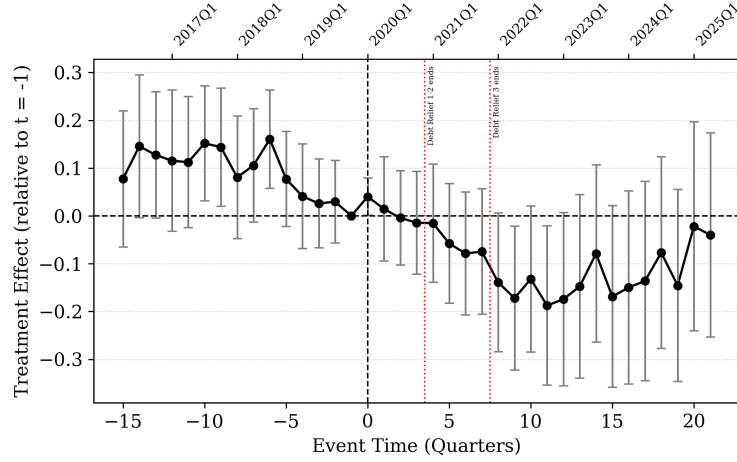
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Appendix: Additional Figures

Figure C.1: Dynamic Effects of COVID Exposure on Outstanding Debt with Fixed Effects



(a) $\ln D_{iq}$ with region-by-quarter FE

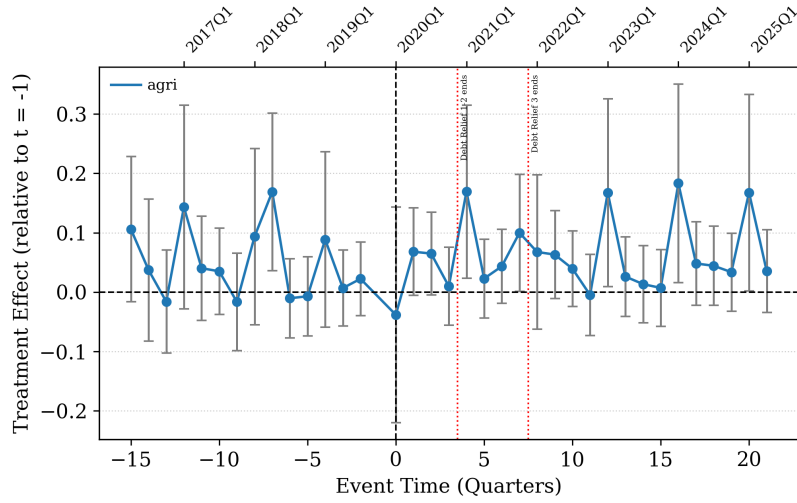


(b) $\ln D_{iq}$ with province-by-quarter FE

Source: Author's calculations using National Credit Bureau (NCB) and night-time lights data.

Notes: The specification in panel (a) includes region-by-quarter fixed effects, which control for common time shocks at a broad regional level (with five regions in Thailand). The second specification includes province-by-quarter fixed effects, which flexibly absorb all province-specific shocks in each quarter (with 77 provinces in Thailand).

Figure C.2: Dynamic Effects of COVID Exposure on New Agricultural Loan Origination

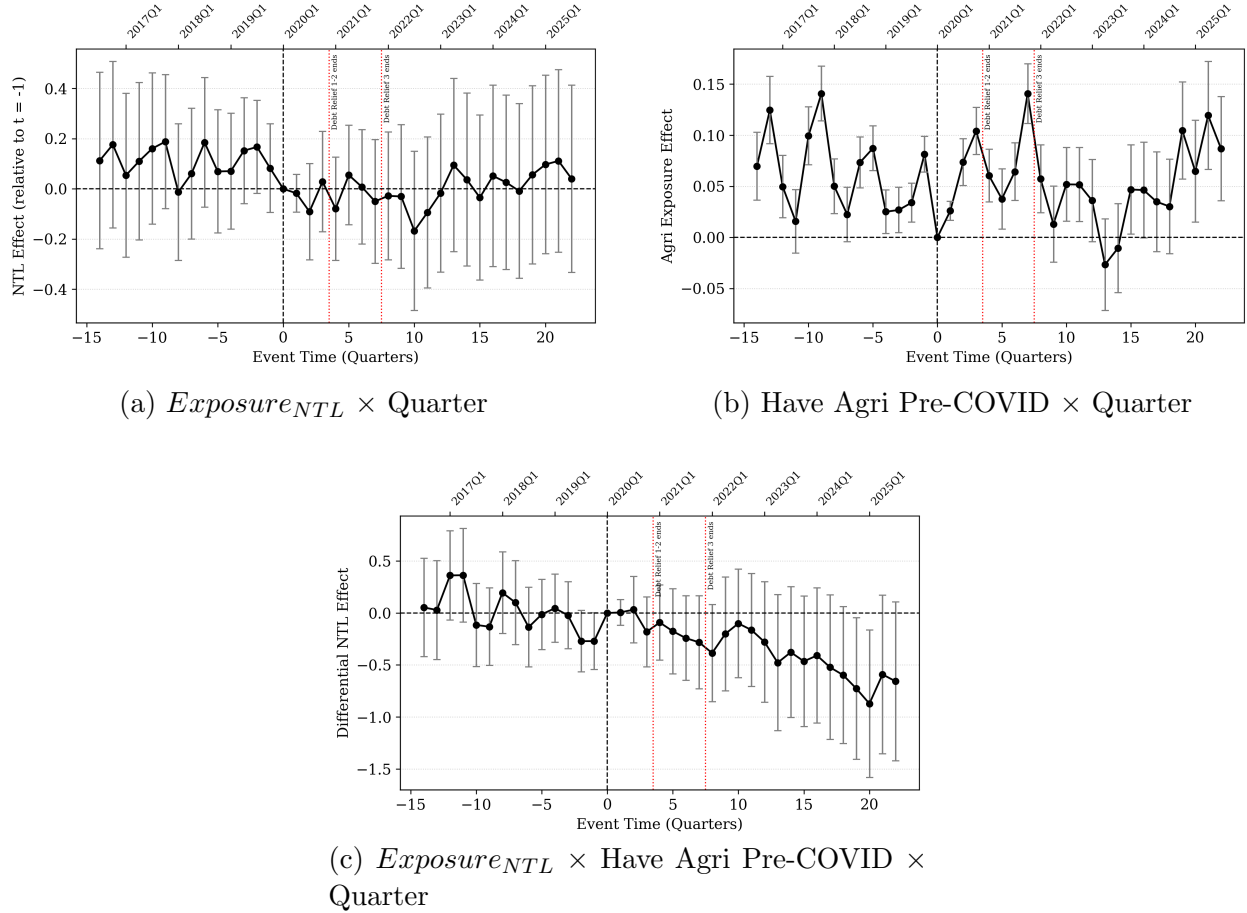


Source: Author's calculations using National Credit Bureau (NCB) and night-time lights data.

Notes: The outcome variable is the proportion of borrowers who have a new agricultural loan opening in each quarter. Vertical gray bars denote 95% confidence intervals based on standard errors clustered at the postal code level. The first set of vertical red dots marks the end of Debt Relief Phases I and II, at the end of 2020. The second set of vertical red dots marks the end of Debt Relief Phase III, at the end of 2021.

Conducting joint tests on the pre-period coefficients for yields $p = 0.231$.

Figure C.3: Event-Study Estimates of Outstanding Debt with Pre-COVID Agricultural Heterogeneity

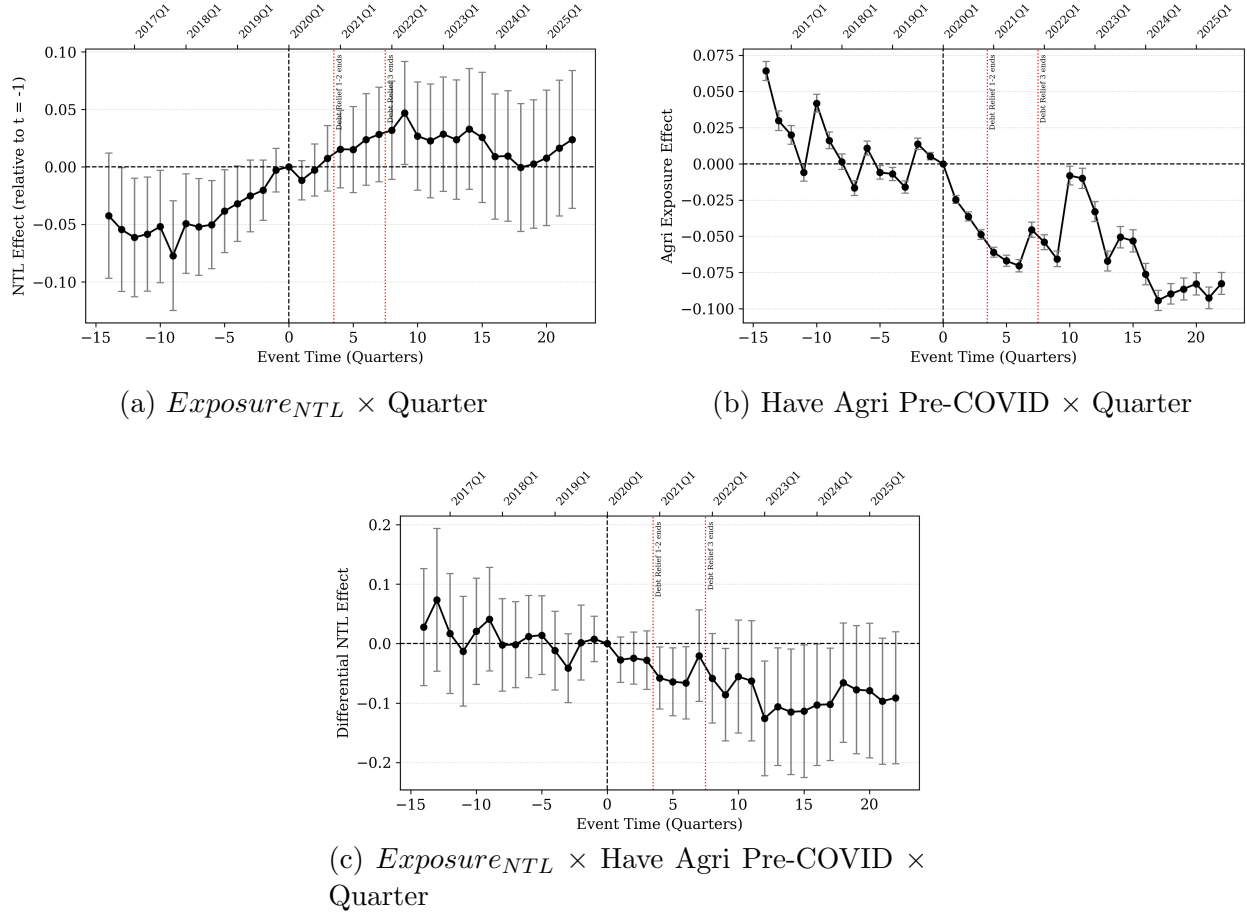


Source: Author's calculations using National Credit Bureau (NCB) and night-time lights data.

Notes: Each figure plots coefficient estimates and 95% confidence intervals from the borrower fixed-effects specification. All paths are relative to the cohort's initial period $t = -1$ (2019 Q4). Vertical dashed lines mark the end of Debt Relief 1–2 and Debt Relief 3. Standard errors are clustered at the postal-code level.

The indicator variable for Have Agri Pre-COVID is one if a borrower held an active agricultural loan at some point in the two years before COVID (2018 and 2019). This was the case for 35.43% of borrowers in the sample. Panel (a) shows the period-specific association between NTL exposure and $\ln D_{iq}$ for the reference group. Panel (b) shows the differential time path of $\ln D_{iq}$ for borrowers with agricultural loans pre-COVID. Panel (c) shows the additional differential effect of NTL exposure for borrower with agricultural loans pre-COVID relative to the reference group.

Figure C.4: Event-Study Estimates of Delinquency with Pre-COVID Agricultural Heterogeneity



Source: Author's calculations using National Credit Bureau (NCB) and night-time lights data.

Notes: Each figure plots coefficient estimates and 95% confidence intervals from the borrower fixed-effects specification. All paths are relative to the cohort's initial period $t = -1$ (2019 Q4). Vertical dashed lines mark the end of Debt Relief 1-2 and Debt Relief 3. Standard errors are clustered at the postal-code level.

The indicator variable for Have Agri Pre-COVID is one if a borrower held an active agricultural loan at some point in the two years before COVID (2018 and 2019). This was the case for 35.43% of borrowers in the sample. Panel (a) shows the period-specific association between NTL exposure and $Delin_{iq}$ for the reference group. Panel (b) shows the differential time path of $Delin_{iq}$ for borrowers with agricultural loans pre-COVID. Panel (c) shows the additional differential effect of NTL exposure for borrower with agricultural loans pre-COVID relative to the reference group.

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