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Economic impact analysis of Priority Sector Lending

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Executive Summary

The policy on priority sector lending has been in place in India for almost five decades and banks are required to direct at least 40% of their overall credit towards the priority sector. The priority sector encompasses a broad range of economic activities such as the provision of credit to small and marginal farmers, micro enterprises and weaker sections aiming to address systemic equity gaps. Growth considerations are also addressed through this policy as the priority sector includes activities that serve as economic multipliers like exports, medium enterprises and corporate farmers.

Previous research has found that directed lending policies are effective in addressing credit market failures. Priority sector advances (PSAs) have been correlated with a decline in rural poverty and an increase in firm and agricultural investment and firm performance. Studies have also found a possible causal relationship of PSAs with Gross Domestic Product. However, directed lending policies are also associated with significant economic risks. Diversion of credit to potentially inefficient sectors can harm total factor productivity. Directed lending policies are also known to impact bank profitability due to the associated risk of asset default and high asset management costs.

To ascertain the impact of PSA on output growth, this paper examines the status and distribution of priority sector lending in India using district level quarterly data obtained from the RBI for the period 2020 – 2025. District level output during this period was proxied using nighttime luminosity (NTL). A vector error correction model (VECM) was used to study the impact of PSA growth on NTL growth. Results show that an increase in PSA growth rate does not significantly impact a district's output over a two-year horizon. An alternate specification of panel Local Projections was also used for the analysis. Heterogeneity was noted among districts in terms of elasticities of output. The bottom 10 percentile of districts (in terms of outstanding PSAs) had the lowest elasticity as compared to other district tiers. Increasing the allocation of PSAs to these districts using a top-down bank mandate will be inefficient in terms of growth. Instead, targeted interventions that holistically tackle binding development constraints (including access to finance) are likely to give better outcomes.

This paper also examines the use of Priority Sector Lending Certificates (PSLCs) by banks. PSLCs are indirect PSA instruments that were introduced by the Reserve Bank of India (RBI) in 2016. PSLCs help mitigate bank profitability risks from PSAs by allowing banks to trade the fulfilment of priority sector obligations at a market determined rate without trading the underlying asset or risk.

The data shows that PSLCs allow banks to lend as per their expected specialisations without altering regional distribution of PSAs or output growth. Small Finance Banks and Nationalised Banks are net sellers of PSLCs while the State Bank of India is a net purchaser. Indian Private Banks sell PSLCs for micro enterprise PSAs and purchase agricultural PSLCs. The impact of PSLCs on output growth was estimated by modelling them as exogenous shocks to district level PSAs and using Monte Carlo draws, obtained from the VECM impulse response functions, to calculate their impact on output. Results showed that PSLCs did not significantly influence growth. Overall, PSLCs appear to be effective and efficient indirect PSA instruments.

1. Introduction

The supply of credit is known[1] to be an important determinant of economic growth. The relationship has been studied extensively since Schumpeter (1911) where, in his classical work, access to capital through credit was postulated to be fundamental for entrepreneurs.

Levine (2004) and Zhuang *et al.* (2009) have reviewed the literature on this subject. They note that empirical studies have established a causal relation between financial development and economic growth based on the following: first, countries with better functioning banks and markets grow faster (significant differences have not been observed between bank- and market-based financial systems); second, simultaneity bias (between economic growth and financial development that suggests reverse causality) does *not* seem to drive these conclusions; and third, better functioning financial systems ease external financing constraints that impede firm and industrial expansion. Levine's (2004) postulates that growth is facilitated by a reduction of information, enforcement and transaction costs by the financial sector- it produces information, monitors investment, manages risk, mobilises savings and eases exchange of goods and services. The financial sector's stabilization effect on external shocks and output volatility is also important for growth (Beck, Lundberg and Majnoni, 2006; Raddatz, 2006). Further, access to finance is essential for innovation and productivity (Maksimovic, Ayyagari and Demirgüç-Kunt, 2007).

Beyond driving aggregate output, financial sector development and availability of credit are instrumental in mitigating poverty and promoting inclusive growth. Fields (2002) notes that the availability of credit enables the poor to participate in productive ventures. Expansion of small-scale industries expands job creation. The availability of credit also helps in human resource development through education. In a World Bank report on financial sector development, Claessens and Feijen (2007) note that affordable credit enables households to overcome shocks like illness and death and to smooth consumption. Credit also provides an opportunity to invest and increase productivity. Quartey (2008) has shown that financial sector development led to poverty reduction in Ghana. Bittencourt and Manoel (2006) show that broad access to financial and credit markets had a significant and robust effect in reducing inequality. Giné and Townsend (2004) show that financial liberalization in Thailand was associated with considerable income growth, but the associated imperfections were associated with an initial rise in inequality.

Given its critical role in economic development, policy interventions designed to prevent and mitigate credit market failures are frequently employed. These market failures can arise from information asymmetry, institutional lending preferences and structural sub-optimality within the lending architecture. Further, disadvantaged sectors often remain underserved by financial institutions due to higher administrative costs and elevated default risks. Social bias and discrimination also play a role.

Directed lending policies represent one category of credit market interventions. They address the problem of asymmetric allocation of credit by mandating or incentivising financial institutions to dedicate a portion of their credit to marginalised and weaker sections. India's directed lending policy, introduced in the 1970s and in place today, requires all banks operating in the country to advance a percentage of their total credit towards *priority* sectors that include several economic activities like agriculture, small scale industry, weaker sections, export credit etc. Priority sector advances (PSAs) may be extended directly by the bank or through approved indirect mechanisms like interbank transfer of assets, onward lending (on-lending) through microfinance institutions (MFIs) or other non-banking financial companies (NBFCs). From financial year (FY) 2016-17, the Reserve Bank of India (RBI) introduced priority sector lending

[1] Early literature suggests differences of opinion between economists with some advocating that financial sector development is a response to the demand generated from economic growth (Robinson, 1952) or that the causal impact is "over-stressed" (Lucas Jr, 1988) or ignoring the sector altogether in discussion on development (Meier and Seers, 1984).

certificates (PSLCs), instruments that allow banks to trade their priority sector obligations over an electronic platform without trading the underlying asset or associated risk. This market-based approach introduced flexibility for individual banks in meeting priority sector targets without diluting the total volume of priority sector credit at the national level.

Empirical evidence suggests that directed lending policies are effective in diverting credit to underserved areas and communities (Calomiris and Himmelberg, 1993; Eastwood and Kohli, 1999; Barr, 2005). They are associated with socio-economic improvements such as a decline in rural poverty (Burgess, Pande and Wong, 2005; Swamy, 2012), increase in national income (Gaur and Mohapatra, 2020), adoption of higher quality agricultural inputs (Sen and Sana, 2024) and growth in small firms (Banerjee and Duflo, 2014; Kale, 2017). Conversely, some studies show that alteration of credit allocation between economic sectors yields negligible benefits in terms of economic efficiency (Aivazian and Santor, 2008; Uesugi, 2025). Evidence from Belarus suggests that an expansion of directed lending reduced total factor productivity (TFP) with findings suggestive of an unproductive hoarding of capital and diversion of credit to finance of lower-yielding projects (Kruk and Haiduk, 2013).

These seemingly conflicting empirical results reflect a fundamental trade-off between the marginal gains in recipient sectors and marginal declines in other parts of the economy. In the presence of a credit market failure, initial gains in a recipient sector will outweigh the combined decline in other sectors and the inherent efficiency losses of the policy. However, as the volume of diverted credit increases, gains in the recipient sector eventually fall short of aggregated efficiency loss due to diminishing marginal returns. Further credit diversion beyond this threshold becomes economically inefficient, even if it remains warranted from an equity perspective- particularly as policymakers assign a higher social welfare weight to underprivileged and marginalised communities.

Given these conflicting theoretical possibilities, this study analyses the impact of the priority sector lending scheme in India using district level data obtained from the RBI pertaining to the period from April 2020 to December 2025. An analysis of the geographical distribution of PSAs reveals significant concentration, with less than 10% of districts accounting for more than 45% of the overall PSAs. Specifically, the Northeastern states, Eastern parts of the country and Himalayan regions remain particularly underserved.

The data also reveals lending preferences of banks in meeting priority sector obligations. The State Bank of India Group (SBI) and Private - Indian Banks (Private Banks) utilise indirect PSA instruments to meet the overall PSA target as well as various sector-specific sub-targets. On the other hand, Small Finance Banks (SFBs) and Nationalised Banks exceed their targets and sub-targets through the direct lending route and serve as net sellers of indirect instruments.

PSLCs are the most widely used indirect PSA instrument. Observed usage patterns show that PSLCs enable banks to focus on their sector-specific competitive advantages. For example, Private Banks buy agricultural and weaker section PSLCs while selling micro-enterprise ones- a strategy that aligns with their expected operational expertise. However, this flexibility can inadvertently shift credit availability across regions. Empirical analysis shows that PSLCs buyer banks dominate and are negatively correlated with PSLC seller banks in underserved areas, potentially worsening regional inequality. Yet when a marginal allocation key[2] is used to distribute the impact of PSLCs at the district level, the results are heterogenous with no clear trend. Overall, the findings suggest that PSLCs provide flexibility to banks in managing their PSA targets without significantly altering the existing PSA availability in most districts.

[2] An allocation key where the quarterly difference in bank outstanding PSLC balance is allocated to districts based on the incremental PSA in that district to the total incremental PSA by the bank

The study also examines the impact of PSAs on output growth, utilising nighttime luminosity (NTL) as a proxy for district level economic activity. Unit root tests indicated that the series are non-stationery, and stationarity was achieved in most districts only after second differencing. However, as the first differences were found to be cointegrated using the Johansen test, a vector error correction model (VECM) was used to derive district-wise impulse response functions (IRFs). This approach captures both the short-run dynamics and the long-run elasticity of NTL growth in response to a unit shock in PSA growth. Results show that changes in PSA growth do not produce statistically significant shifts in output over a two-year horizon in most districts.

A panel Local Projections (Jordà, 2005) approach was used as an alternate specification. It showed significant district level heterogeneity- poorer districts had lower output elasticity from PSA than richer districts with a one-year horizon. These results indicate that a pure top-down bank mandated diversion of credit to the poorest districts will be inefficient and may fail to serve the social and economic mandate of priority sector lending. Instead, holistic interventions that address binding development constraints, of which finance is one component, may give better outcomes.

Finally, to examine the impact of the PSLC scheme on output growth, PSLCs were modelled as exogenous shocks to district PSAs. Counterfactual NTL growth in the absence of PSLCs was estimated using Monte Carlo simulation draws from the IRFs. Findings indicate that PSLCs had no significant impact on NTL growth during the study period. Given that PSLCs provide flexibility to banks without significantly altering regional PSA distribution, they appear to be effective and efficient indirect PSA instruments.

The paper is structured as follows. Section 2 discusses the mechanisms underlying credit market failures and the factors that lead financial institutions to underserve the priority sector. Section 3 examines the institutional framework of directed lending in India through the priority sector lending scheme. A comprehensive review on the economic impact of directed lending has been provided in Section 4. Section 5 provides a descriptive analysis of PSAs in India followed by an examination of the impact of PSLCs on the regional distribution of PSAs in Section 6. Section 7 utilises and econometric framework to analyse the growth impact of PSAs and PSLCs, with a final discussion of the results and policy implications in Section 8.

2. Credit market failure and sectoral credit under-provision

Information asymmetry

Information asymmetry is one of the most well-studied reasons for credit market failure. Stiglitz and Weiss (1981) and Williamson (1986)[3] show using theoretical models that asymmetric information may lead to credit rationing, an inefficient equilibrium where demand outstrips supply.

Information asymmetry may also lead to adverse selection. Lenders are unable to observe characteristics of potential borrowers' ex-ante. If they solely use interest rate to allocate credit, high risk borrowers will benefit at the expense of others (Jaffee and Russell, 1976; Crawford, Pavanini and Schivardi, 2018). Borrowers facing high interest rates also have the incentive, ex-post, to either default on their loan obligations or to invest in riskier business proposals, leading to moral hazard (Banerjee and Duflo, 2010). Information asymmetry also makes monitoring costly, and lenders are restricted in their ability to observe the effort exerted by borrowers.

[3] While Stiglitz and Weiss (1981) assume that lenders cannot observe the riskiness of different projects or the amount of effort the borrowers need to exert, Williamson (1986) assumes that borrowers do not have the incentive to truthfully reveal the outcome of the project to show that lenders would prefer to restrict credit flow rather than raising the interest rate.

Credit market failures from information asymmetry disproportionately target the priority sector- credit rationing affects informationally opaque borrowers, i.e., those from poor and marginalized backgrounds (Avery, 1981; Jappelli, 1990; Rangarajan, 2008; Brown *et al.*, 2011; Nikaido, Pais and Sarma, 2015). Credit constraints are also binding on the poor as they lack self-owned capital for investment (Banerjee and Newman, 1993; Galor and Zeira, 1993; Aghion and Bolton, 1997).

Larger banks prefer to lend to larger firms

The lending preferences of banks (as the key financial institutions disbursing credit) are also important to understand why the credit market fails to meet credit demands of the priority sector.

Berger *et al.* (2005) extend to banks an organizational model by Stein (2002)[4] and find evidence that larger banks are more likely to lend to larger firms which have more reliable and transparent accounting records. They also find that for a firm, the distance to nearest bank branch increases with the size of the bank, and thus the quality of relationships and intangible indicators worsen with the size of the bank. Smaller banks tend to have stronger- more long- lived relations with borrowers and firms doing business with larger banks communicate more by using impersonal means like mail of phone. Cole, Goldberg and White (2004) provide evidence that large banks tend to employ standard criteria obtained from financial statements in the loan decision process as compared to small banks, which rely to a greater extent on information about the character of the borrower.

Formal credit supply to smaller firms will thus remain inadequate when the market is dominated by large banks, not due to reasons of creditworthiness of these firms but due to the organizational structure prevailing in the market.

Sub-optimal financial institution and lending architecture

Several market-based instruments have been devised to overcome information asymmetry, collectively referred to as the lending architecture. Such instruments include transparent and audited financial accounting records, small business credit scoring, asset- based lending and factoring and trade credit (Berger and Udell, 2006).

These instruments reduce the information opaqueness associated with smaller firms and facilitate credit access from larger financial institutions. Beck, Demirgüç-Kunt and Pería (2011) show that small and medium enterprise (SME) financing need not be based only on relationship-based lending and note that significant differences exist across developed and developing countries, driven by differences in the institutional and legal environments. Berger, Goulding and Rice (2014) demonstrate that the conventional paradigm of small, single-market, local institutions being able to serve informationally opaque small businesses better may not hold and other factors in the lending architecture are important.

The priority sector remains disproportionately vulnerable to any systemic imperfections in a nation's financial institution and lending architecture. Even in environments where the lending architecture functions efficiently, structural barriers may persist. Smaller firms, agricultural producers and weaker sections frequently lack the requisite capacity to use these market-based instruments effectively. Further, even where borrower capacity exists, the actual flow of credit may be constrained by sub-optimal regulatory administration of these instruments.

[4] The model by Stein (2002) proposes that smaller firms have a comparative advantage in the evaluation of projects where the available information is more 'soft' or intangible, while large firms will perform better when the information available can easily be measured or 'hardened' and passed along inside the firm.

Efficiency trade-off

Banks are also constrained by internal policy guidelines that prevent lending to high- risk and costly sectors to ensure solvency, protect the interests of depositors, meet prudential norms and maximise profitability.

Berger and Udell (2006) show that preferences for lending will be governed by the degree of flexibility allowed to lenders while extending credit, state ownership of financial institutions etc. As priority sector accounts have been shown to have high management costs (Jain, Parida and Ghosh, 2015), lending to them has a built in efficiency trade-off.

Studies show that banks are more hesitant to lend to agriculture, small scale industries and weaker sections due to profitability concerns and perceptions about higher risk of lending (Rao, Das and Singh, 2006; Roy, 2006; Uppal, 2009; Raman, 2013).

Social bias and discrimination

Social bias and caste, class, racial, religion and gender-based discrimination are also important factors that govern access to formal credit, possibly by improving relationship- based lending and reducing perceived informational opaqueness. Malapit (2012) shows that women are more likely to be credit constrained than men in the Philippines. Muravyev, Talavera and Schäfer (2009) show that female managed firms are less likely to get a bank loan. Blanchflower, Levine and Zimmerman (2003) find evidence of racial discrimination in the small-business credit market in the United States. Raj SN and Sasidharan (2018) show that firms owned by socially disadvantaged groups have a lower probability of obtaining formal credit and the discrimination extends to the amount of the loan sanctioned. Sangwan and Saha (2026) show that a substantial share of bank lending gaps between general castes and SCs, STs and Other Backward Castes (OBCs) are unexplained by observable characteristics, pointing to potential caste-based discrimination in the access of formal credit. They also show that informal credit sources like moneylenders do not appear to penalize lower-caste borrowers to the same extent. Their findings suggest that formal institutions continue to reinforce caste based social inequalities. Fisman, Paravisini and Vig (2011) present evidence that social proximity between lenders and borrowers in terms or religion and caste improves loan outcomes, increases the intensive and extensive margins of lending, reduces the collateral rate and increases repayment performance.

3. Directed lending policy and priority sector lending in India

Directed lending policies are credit market interventions wherein regulations either incentivise or mandate financial institutions to allocate a specified percentage of their total credit to designated sectors. The broad aim of such policies is to correct credit market failures and facilitate equitable financial access for underserved sectors of the economy. In the Indian context, directed lending has been operationalised through the policy on priority sector lending.

History of priority sector lending in India[5]

Initial years of social persuasion

The regulation of credit flow and its conscious direction by the Government of India (the Government) towards priority sectors traces back to the credit policy of 1967-68 (Murthy, 2005). It had been observed at the time that the bulk of bank advances were directed to large- and medium-scale industries. This credit asymmetry combined with a shortfall in agricultural output and slowdown in industrial production prompted the Government to initiate social control measures over banks in order to better align the

[5] A comprehensive review of priority sector lending in India has been provided in the recommendations made in September 2005 by the Internal Working Group set up in RBI under the chairmanship of Shri C.S. Murthy.

banking system with economic planning. The aim was to enhance the distribution of credit to agriculture and small-scale industries.

The underlying policy stance of prioritising credit to agriculture and industry was explicitly articulated by the then Deputy Prime Minister and Minister of Finance during the budget 1967-68 speech[6]. Emphasising the need to avoid deficit financing, he argued that the Government "*should not appropriate any part of the permissible limit of monetary expansion*" to ensure that the credit needs of agriculture and industry were met. He asserted that this would allow "*a larger expansion of bank credit to agriculture and industry to facilitate higher production."* While making such a statement he underscored a commitment to support "*the immediate programmes for increasing agricultural production that are so vitally important"* and *"ensure that private industry is not inhibited from increasing production by undue limitations on the availability of credit."*

Subsequently, at a meeting of the National Credit Council in July 1968, commercial banks were asked to increase credit flow to agriculture and small-scale industries on an urgent basis. A list of qualifying agricultural advances was prepared and forwarded to banks in March 1969. For small-scale industries, qualifying advances included direct loans given to road-transport operators and loans for setting up industrial estates. These social control measures were formally brought into effect in February 1969. The nationalisation of major commercial banks in July 1969 was also accompanied by a reorientation of bank lending to priority sectors and borrowers of small means (Murthy, 2005).

Issuance of formal targets

An Informal Study Group on Statistics Relating to Advances to the Priority Sectors was constituted by the RBI in May 1971 and its report formed RBIs basis for formalising the definition of 'priority sectors' in 1972. A modified return for reporting PSAs was specified, and guidelines were issued by the RBI in February 1972. In November 1974 RBI formally issued targets when it advised public sector banks to raise their share of PSAs to 1/3rd of total advances by FY 1978-79. A similar direction was given to Private Banks in November 1978, who had to ensure that PSL target of one-third was met by FY 1979-80.

In March 1980 the Government adopted a 20-Point Economic Programme for improving the lot of 'weaker sections.' A Working Group on Priority Sector Lending and 20-Point Economic Programme was established under the Chairmanship of Dr. K. S. Krishnaswamy, the then Director General, RBI to deliberate on implementation modalities (KS Krishnaswamy Committee). It was suggested that a sub-category of weaker sections should be introduced within the main categories of agriculture and small-scale industries. It was also suggested that the scope of priority sector should be broadened bringing within its ambit housing loans advanced to scheduled castes (SCs)/ scheduled tribes (STs) and weaker sections, assistance to any governmental agency for construction of houses for SCs/STs and low-income groups and pure consumption loans granted to the weaker sections under the Consumption Credit Scheme.

RBI issued fresh instructions incorporating suggestions of the KS Krishnaswamy Committee on October 29, 1980. The target for PSAs overall was raised to 40% of aggregate bank advances by FY 1984-85. A sub-target for agriculture was specified as 16% of the net bank credit (NBC), to be achieved by FY 1984-85. A sub-target was also specified for direct advances to weaker sections within agriculture, i.e., advances to small and marginal farmers (SF/ MF) and landless labourers, at 50% of PSAs to agriculture by FY 1982-83. A sub-target for advances to rural artisans, village craftsmen and cottage industries was specified at 12.5% of total PSAs to small-scale industries.

Subsequently, a 'Working Group on the Role of Banks in Implementation of New 20-Point Programme' was constituted under the chairmanship of Shri A. Ghosh in 1982 for reclassification of segments that

[6] Available at: https://www.indiabudget.gov.in/doc/bspeech/bs196768.pdf

comprise priority sectors and the RBI issued fresh instructions based on its report in February 1983. The definition of weaker sections proposed by the working group was accepted and segments classified under priority sector were expanded to include agriculture (direct and indirect finance), small-scale industries, small road and water transport operators, retail trade, small business, professional and self-employed persons, state sponsored schemes for SCs/STs, education, housing and consumption. PSA sub-targets for agriculture were revised, with banks directed to achieve direct agricultural lending of at least 15%, 16%, 17% and 18% of total bank credit by FY 1984-85, 1986-87, 1988-89 and 1989-90 respectively. In October 1993 the agriculture sub-target was bifurcated into a minimum target of 13.5% for direct loans and a maximum of 4.5% for indirect loans.

Extension of targets to cooperative banks, foreign banks and rural banks

Targets for PSAs were extended to primary (urban) cooperative banks (UCBs) and UCBs were required to provide at least 60% of their total advances to priority sectors based on the recommendations of the Standing Advisory Committee for UCBs constituted by the RBI in 1983 under the chairmanship of the then Deputy Governor Dr. M.V. Hate. The target was subsequently brought down to 40%, at par with other domestic banks, in RBIs circular number UBD.PCB.Cir.No.26 /09.09.001/ 2007-08 dated November 20, 2007.

Priority sector targets have also been instituted in a phased manner for foreign banks. The target was 15% of NBC by FY 1991-92, raised to 32% of NBC by FY 1993-94, with sub-targets of 10% of NBC for small-scale industries and 12% of NBC for exports.

Priority sector norms were extended to Local Area Banks (LABs) in August 1996 with a sub-target of 10% of NBC for weaker sections (Murthy, 2005).

Regional Rural Banks (RRBs) initially lent only to their target group comprising SF/ MF, landless labourers, rural artisans and other weaker sections of society. They were subsequently allowed to lend up to 60 per cent of incremental lending during a year to non-target group borrowers. From FY 1997-98, it was stipulated that RRBs will need to have PSAs of at least 40% of outstanding advances, at par with commercial banks, with a sub-target of 25% of PSAs (or 10% of total outstanding advances) to weaker sections. Priority sector lending by RRBs was reviewed in the meeting of the Estimate Committee of Parliament held on August 6, 2002, where it was decided to increase the target of PSAs by RRBs to 60% of their outstanding advances, with at least 25% of PSAs (or 15% of the total advances) to weaker sections by FY 2003-04. The overall PSA target was enhanced to 75% of total outstanding advances in circular number FIDD.CO.Plan.BC.No.14/04.09.01/2015-16 dated December 3, 2015 ('Regional Rural Banks - Priority Sector Lending – Targets and Classification', 2015) with effect from 1st January 2016. Other sub-targets were also prescribed in this circular for agriculture (18%), SF/ MF (8%), micro enterprises (7.5%) and weaker sections (15%).

Salient features of present guidelines

The latest directions for PSAs have been prescribed in RBIs circular number Master Directions-FIDD.CO.PSD.BC.13/04.09.001/2024-25 dated March 24, 2025 ('Master Directions - Reserve Bank of India (Priority Sector Lending – Targets and Classification) Directions, 2025', 2025) and amended in circular number FIDD.CO.PSD.BC.No.11/04.09.001/2025-26 dated January 19, 2026 ('Reserve Bank of India (Priority Sector Lending – Targets and Classification) (Amendment) Directions, 2026', 2026). These directions specify the purpose of priority sector lending, definition of priority sector, the eligible mechanisms for extending PSAs to the priority sector, targets/ sub-targets and reporting requirements.

Aims and objectives of priority sector lending

The main aim of the priority sector lending is to ensure adequate flow of credit to the priority sector. RBIs master directions specify the purpose of the policy as '*…ensuring adequate flow of credit from the banking system to the sectors of the economy which are crucial for their contribution to socio-economic development, with focus on*

specific segments whose credit needs remain underserved despite being credit worthy.' The internal working group on priority sector lending (Murthy, 2005) had also noted that key economic sectors were subject to inadequate credit flows, below their contribution to national income, productivity, export earnings and employment.

Indirect lending mechanisms for extending PSAs

Since its inception, banks have been allowed some flexibility in providing PSAs either directly to the end beneficiary or indirectly through intermediaries, often with a cap on the extent of indirect PSA allowable under the targets. The indirect mechanisms/ instruments by which banks can currently extend PSAs are discussed in further detail below.

On-lending

On-lending is an arrangement by which banks subject to PSA targets lend to eligible intermediaries, which then provide advances to the priority sector. The intermediaries eligible for on-lending can be divided broadly into two types, MFIs and others. MFIs include NBFCs engaged in providing microfinance (NBFC-MFIs) as well as other types of registered entities like Societies and Trusts engaged in microfinance.[7] There is no cap on the use of MFIs for on-lending, however, RRBs, UCBs and LABs are not eligible to lend to MFIs to fulfil their PSA obligations.

Other institutions include, NBFCs (other than MFIs) that provide small loans to individual agriculture (<₹10 lakh) and micro and small enterprise (MSE) (<₹20 lakh) borrowers; housing finance companies (HFCs) that have been approved by the National Housing Bank (NHB) for refinance and who provide small loans (<₹20 lakh) to individual borrowers for the purpose of purchase/ construction/ reconstruction of individual dwelling units or for slum clearance and rehabilitation of slum dwellers; and the National Co-operative Development Corporation (NCDC) for on-lending to co-operative societies for priority sector eligible purposes and activities. On-lending credit provided to these other institutions (i.e., NBFCs, HFCs and NCDC) is subject to an overall cap of 5% of an individual bank's average PSA in the previous FY. Further, RRBs, UCBs[8], Small Finance Banks (SFBs) and LABs are not eligible to lend to these other institutions to fulfil their PSA obligations.

Instruments that transfer risk of a PSA

Banks have been permitted to invest in specific types of financial instruments (associated with a transfer of risks) where the underlying asset would qualify as a PSA. These include Securitization Notes, direct assignment/outright purchase of a pool of assets, inter-bank participation certificates (IBPCs) bought on a risk sharing basis and co-lending arrangements with other banks, NBFCs etc. Specific guardrails have been provided for indirect lending through this route, for example, loans provided to the priority sector by NBFCs against gold jewellery are not eligible and vertically differentiated banks like LABs, RRBs, SFBs[9] and UCBs are not permitted to use these instruments.

PSLCs

The PSLC scheme was introduced from FY 2016-17 '*to enable banks to achieve the priority sector lending target and sub-targets by purchase of these instruments in the event of shortfall and at the same time incentivize the surplus banks; thereby enhancing lending to the categories under priority sector*.' These instruments are issued by banks that exceed their own priority sector obligations (or expect to exceed their priority sector obligations) and bought by banks in lieu of PSAs. PSLC only transfer the fulfilment of priority sector obligations without transferring

[7] Provided that the MFIs adhere to conditions specified in circular number DOR.FIN.REC.290/ 03-10-038/2025-26 dated November 28, 2025 ('Reserve Bank of India (Non-Banking Financial Companies – Microfinance Institution) Directions, 2025', 2025) and banks obtain external auditors' certificates from MFIs confirming that on-lending benefit in respect of these loans has not been claimed from any other bank

[8] UCBs are permitted to lend to HFCs for on-lending

[9] SFBs are not barred from direct assignment/ outright purchase and from IBPCs.

the underlying asset or associated risks. They are of four types, agriculture, SF/ MF, micro enterprises and general, the former three counting towards fulfilment of specific sub-targets and the last counting only towards the overall priority sector target. While measuring a bank's achievement of priority sector targets and sub-targets the net nominal value of PSLCs issued and purchased are included in the sector target/ sub-target achievements.

Aside from issuing PSLCs against underlying assets, banks are also allowed to issue PSLCs in advance (up to 50% of their PSA achievement in the previous year), i.e., without having any underlying asset in their books.

PSLCs are valid for the FY in which they are issued and expire on the last day i.e. March 31. They are traded over RBIs e-*Kuber* portal for a market determined fee where the nominal values of PSLCs represent the traded PSA fulfilment obligation.

Priority sector definition

Agriculture

Lending for agriculture includes farm credit provided to individual farmers for purposes such as crop loans, loans for purchase of agricultural implements, pre- and post- harvest activities, loans to distressed farmers indebted to non-institutional lenders, *Kisan* Credit Card scheme, loans to SF/ MF to purchase agricultural land etc. Farm credit provided to corporate farmers, farmer producer organizations (FPOs)/ farmer producer companies (FPCs) of individual farmers, partnership firms and cooperatives of farmers engaged in agriculture and allied activities also comes within the ambit of agriculture priority sector (subject to lending limits). Similarly, loans for investment in agricultural infrastructure as well as for ancillary activities such as start-ups in agriculture, agro-processing etc. (subject to lending caps) also form part of the agriculture priority sector.

Deposits outstanding with Rural Industrial Development Fund (RIDF) and other eligible funds with National Bank of Agriculture and Rural Development (NABARD) on account of priority sector shortfall in earlier periods are included as agriculture PSAs as is on-lending through MFIs and other NBFCs for agriculture.

SFs/ MFs

Lending to SFs/ MFs constitutes a sub-target under agriculture. MFs are those with landholding of up to 1 hectare while farmers with a landholding of more than 1 hectare and up to 2 hectares are classified as SFs. This category includes lending to landless agricultural labourers, tenant farmers, oral lessees and sharecroppers whose share of landholding is within the limits prescribed for SF/ MF. Loans to groups of SF/MFs such as Self Help Groups (SHGs), Joint Liability Groups (JLGs), FPOs/FPCs and co-operatives are also included within this sub-target.

Micro, Small and Medium Enterprises (MSMEs)

All bank loans to MSMEs form part of PSAs including loans to Khadi and Village Industries. Factoring transactions where MSMEs are assignors including those taking place over the Trade Receivables Discounting System (TReDS) are also eligible. On-lending to MSMEs through MFIs, NBFCs and overdraft to Pradhan Mantri Jan-Dhan Yojna (PMJDY) accounts are considered within this category. Deposits outstanding with Small Industries Development Bank of India (SIDBI) and Micro Units Development and Refinance Agency Limited (MUDRA Ltd) on account of priority sector shortfall are also counted as PSAs to MSMEs.

Export Credit

Pre-shipment and post-shipment export credit is included under the definition of priority sector. Where exports are related to agriculture and MSMEs, PSAs are included in these categories, in other cases

limited amount of export credit (up to 2%) is allowed under the priority sector classification. (For foreign banks with less than 20 branches, the limit is up to 32%.)

Education

Small loans (≤ ₹25 lakh) to individuals for educational purposes, including vocational courses are classified under PSAs.

Housing

Housing PSAs include bank loans to individuals for purchase, construction and repairs of low-cost housing. Loans provided to Government agencies for slum rehabilitation and loans provided for affordable housing projects are also included under the priority sector. Outstanding deposits with NHB on account of priority sector shortall form part of PSAs under the housing segment as well.

Social infrastructure

Bank loans to social infrastructure sector within the specified limits are included under the priority sector. This segment also includes loans extended to MFIs for on-lending to individuals and to members of SHGs/JLGs for water and sanitation facilities.

Renewable energy

Loans extended for renewable energy-based power generators and for renewable energy based public utilities like street lighting systems, remote village electrification etc. fall within the ambit of priority sector.

Others

This is a residual category for priority sector classification and includes microfinance loans provided directly by banks to individuals and individual members of SHGs/JLGs for priority sector activities. Loans to distressed persons (other than distressed farmers) indebted to non-institutional lenders, those sanctioned to state sponsored organisations for SCs/STs, for the specific purpose of purchase and supply of inputs or for marketing of the outputs of their beneficiaries and loans provided to start-ups (engaged in activities other than agriculture or MSME) are also included within this PSA category.

Weaker Sections

Weaker sections is an overlapping category that includes loans provided to: SFs/ MFs; artisans, village and cottage industries; National Rural Livelihood Mission (NRLM) and Self Employment Scheme for Rehabilitation of Manual Scavengers (SRMS) beneficiaries; SCs and STs; beneficiaries of Differential Rate of Interest (DRI) scheme; SHGs and JLGs; microfinance provided to individuals and individual members of SHGs/JLGs; individual beneficiaries; distressed farmers and other persons indebted to non-institutional lenders; persons with disabilities; transgenders; and minority communities. PMJDY account overdrafts are also classified under PSAs to Weaker Sections.

Lending targets

Priority sector lending targets are specified as a percentage of the Adjusted Net Bank Credit (ANBC) or Credit Equivalent of Off-Balance Sheet Exposures (CEOBSE), whichever is higher. ANBC is calculated by adjusting the NBC for outstanding deposits with RIDF and other eligible funds with NABARD, NHB, SIDBI and MUDRA Ltd in lieu of non-achievement of targets as well as outstanding PSLCs, securitization notes, IBPCs etc. and other specified assets like recapitalization bonds and amounts eligible for exemptions on issuance of long-term bonds for infrastructure and affordable housing etc. The present targets for extending advances to the priority sector are provided in Table 3-1.

Table 3-1 Targets for PSAs as a percentage of ANBC / CEOBSE (whichever is higher)

	Domestic Commercial Banks (excluding RRBs and SFBs) and Foreign Banks with ≥20 branches	Foreign Banks with <20 branches	RRBs	SFBs	UCBs
Total Priority Sector	40%	40%	75%*	60%	60%
Agriculture	18%	-	18%	18%	
Non-corporate farmers (NCF)	14%	-	14%	14%	
SF/ MF	10%	-	10%	10%	
Micro Enterprises	7.5%	-	7.5%	7.5%	7.5%
Weaker Sections	12%	-	15%	12%	12%
Export Credit	-	32%			
*In RRBs lending to Medium Enterprises, Social Infrastructure and Renewable Energy is considered for priority sector achievement up to 15% of ANBC only.					

Monitoring of PSAs and consequent of non-achievement of targets

Monitoring of PSAs

Compliance of banks with priority sector lending requirements are monitored on a quarterly basis by the RBI (by NABARD in case of RRBs). Banks file reports at the end of every quarter (and annually) in prescribed reporting formats. They are also required to monitor the end usage of PSAs and have in place appropriate internal systems and controls.

While computing the priority sector target/ sub-target achievements, a simple average of all quarters in the FY is considered for computation of overall shortfall/ excess at the end of the year.

Non-achievement of Priority Sector Targets

In case of any shortfall, the RBI allocates amounts (and terms and conditions) for fund contribution by the defaulting bank to the RIDF and other funds with NABARD/ NHB/ SIDBI/ MUDRA Ltd. As a quasi- penal provision, the interest rates payable to banks for such deposits are below the Bank Rate. In case the shortfall is less than 5 percentage points, the deposit rate payable is the Bank Rate minus 2 percentage points, in case the shortfall is 5 percentage points or more but less than 10 percentage points, a 3 percentage point reduction is made and in case the shortfall is 10 percentage points or more, the reduction is of 4 percentage points. When there is shortfall in a sub-target, but the overall target is met, banks receive interest at the Bank Rate minus 2 percentage points.

Non-achievement of priority sector targets and sub-targets are also considered by the RBI while granting regulatory clearances or approvals to banks for other purposes.

4. Economic impact of directed lending policies – a literature review

Benefits from directed lending policies

Directed lending policies have been found effective in diverting credit to underserved areas and communities. Barr (2005) analysed the impact of the US Congress' Community Reinvestment Act of 1977 (CRA)[10] a law aimed to address concerns of credit market failures in low-income communities. He showed that CRA enhanced access to credit for low-income, moderate-income, and minority borrowers at relatively low cost, and helped overcome market failures. Calomiris and Himmelberg (1993) linked Japan's success in directing credit to machine-tool producers with the decision-making process that governs the distribution of credit.

Priority sector lending has been shown to be positively correlated with economic growth and poverty reduction. Burgess, Pande and Wong (2005) have evaluated the impact of Indian governments 1:4 bank branch licence policy applicable between 1977 and 1990 that caused banks to open branches in rural unbanked locations and financially less developed states. Using a 1961-2000 state-level panel data set, they show that the policy was associated with significant reductions in rural poverty. They have also evaluated the impact of the inclusion of weaker sections in the definition of priority sector and show that the program increased access of bank loans for SCs and STs. Combining the two results, they conclude that easier access to bank credit and saving opportunities was associated with a decline in rural poverty. Swamy (2012) also found a strong correlation between priority sector lending and poverty reduction. A positive correlation with Gross Domestic Product (GDP) has been found by Gaur and Mohapatra (2020) who use panel-data collected from a sample of 45 scheduled commercial banks and apply Granger causality tests to show that there exists bidirectional causal relationship between priority sector lending and the GDP. Yadav and Sarma (2021) also provide evidence that priority sector lending has been beneficial to the Indian economy.

Directed lending policies improve access to finance by SMEs. Eastwood and Kohli (1999) use a panel dataset of 788 Indian firms to analyse the linkage between size of firms and their financial environment between 1965–78. They show that large firms were able to obtain external finance at the margin, but small firms could not. Their findings support a conclusion that the priority sector lending policy relaxed a binding constraint on small firms, raising investment. Banerjee and Duflo (2014) analyse the credit behaviour and performance of firms that became eligible for priority sector lending as a result of a policy change in 1998 and lost eligibility as a result of the reversal of this reform in 2000, and compare these with smaller firms that were already eligible for the preferential credit before 1998 and remained eligible in 2000. They find no evidence that directed credit was used as a substitute for other forms of credit and show that the credit was used to finance more production–there was a large acceleration in the rate of growth of sales and profits for these firms in 1998 followed by a corresponding decline in 2000. They conclude that these firms must have been severely credit constrained as their marginal rate of return to capital was very high. Kale (2017) analyses firm investment and sales growth of small firms that became newly eligible for priority sector lending after the criterion was amended in 2006. She notes that, as compared to always eligible firms, the newly eligible firms disproportionately grew their bank credit stock and showed a jump in investment and sales growth. Uesugi (2025) evaluates the impact of the directed credit provided by the Japan Finance Corporation (JFC) to SMEs to find that the financing environment for firms using JFC loans improves without any offset between JFC loans and loans extended by other financial institutions.

[10] The CRA is not exactly a rules-based directed lending policy as it only encourages federally insured banks and thrifts to meet the credit needs of entire communities, including low- and moderate-income areas, consistent with safe and sound banking practices, in a flexible manner.

Sen and Sana (2024) study the impact of priority sector lending on agriculture and show that there is a relation between loan availability under priority sector lending and use of high-quality fertilizers, high-quality seeds and improved irrigation facility in West Bengal.

Risks of directed lending policies

Conversely, alteration of credit allocation between economic sectors has the potential to harm TFP or yield negligible benefits in terms of economic efficiency. Kruk and Haiduk (2013) study the impact of an expansion of directed lending in Belarus and find that it reduced TFP and economic growth. They go on to argue that such negative effects will worsen with time as liquidity constrains restrict overall credit growth in an economy. Their findings suggest that directed lending schemes may cause an unproductive hoarding of capital and financing of lower-yielding projects.

Aivazian and Santor (2008) show that while access to subsidized loans from the World Bank led to higher investment levels by firms, the overall impact on economic efficiency remained inconclusive. Uesugi (2025) also found that while tangible fixed assets increased more in JFC loan user firms, their ex-post-performance does not improve.

5. Descriptive analysis of PSAs

Dataset

Data was obtained from the RBI from the District Quarterly Priority Sector Advances (DQPSA)[11] returns filed by banks, pertaining to 23 quarters from the quarter ended June 2020 to December 2025. 46 banks were covered in the initial dataset- SBI, 11 Nationalised Banks, 21 Private Banks and 13 SFBs.[12] Foreign banks were not present in the dataset. Among these 13 SFBs, Fincare Small Finance Bank Limited merged with AU Small Finance Bank Limited and North East Small Finance Bank Limited merged with Slice to form Slice Small Finance Bank during the period, their figures were aggregated for analysis. Further, Shivalik Bank converted into a UCB during the period, so data became unavailable after conversion; it was removed from the dataset.

The dataset thus includes all public sector and major private sector banks and constitutes >95% of the ANBC of scheduled commercial banks (excluding RRBs)[13] operating in India during the period. Figure 5-1 shows the evolution of ANBC among the different bank groups. Private Banks constitute the largest bank group while SFBs are the smallest.

[11] Details are available at https://www.rbi.org.in/scripts/BS_Listofallreturns.aspx, S. No. 215
[12] Bank classification by the RBI is available at https://rbi.org.in/commonman/english/scripts/banksinindia.aspx
[13] Annual data of priority sector lending is released by RBI in their Database on Indian Economy available at https://data.rbi.org.in/#/dbie/home. The proportion of >95% was calculated by dividing the aggregate ANBC obtained from the dataset with the aggregate ANBC as per the Database on Indian Economy.

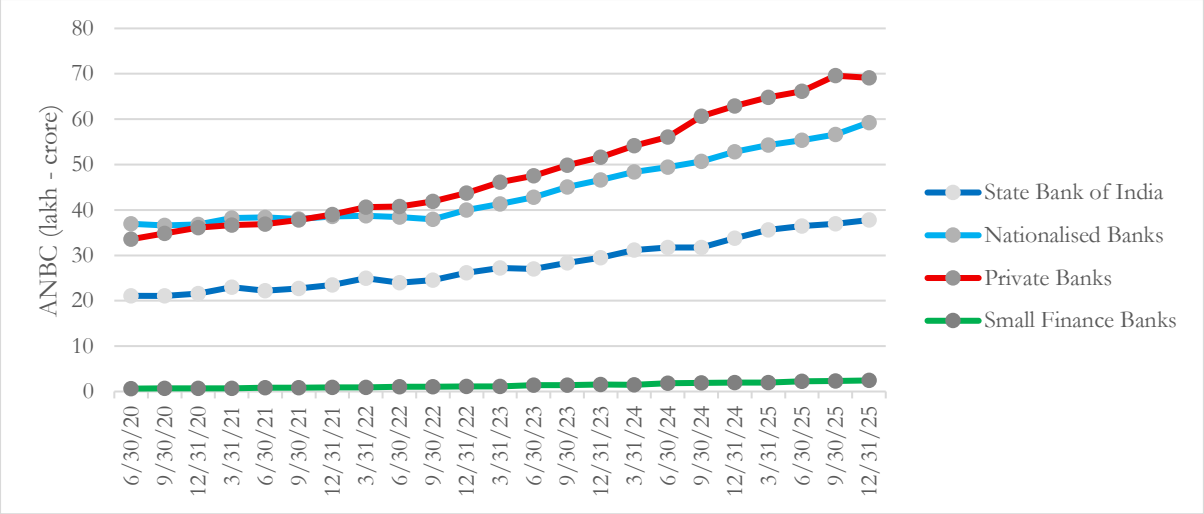

Figure 5-1 Evolution of ANBC among bank groups

Figure 5-2 shows the compounded annual growth rate (CAGR) of ANBC among different bank groups. At quarter ended December 2025, ANBC - CAGR was maximum for SFBs (26.23%), followed by Private Banks (13.38%), SBI (10.68%) and finally Nationalised Banks (8.56%).

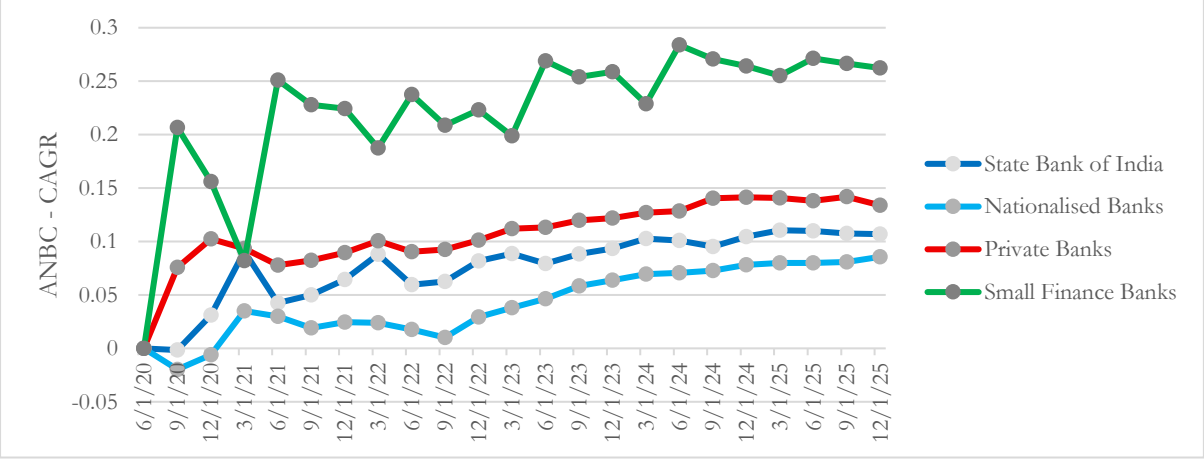

Figure 5-2 CAGR of ANBC among bank groups

Overall PSA

SBI and Private Banks lent less than the overall PSA target of 40% (of ANBC[14]) through the direct route and utilised indirect instruments and deposits to meet their priority sector obligations. In comparison, Nationalised Banks and SFBs exceeded their PSA target (60% for SFBs) through the direct route and served as net sellers of indirect PSA lending instruments.

Direct route

SBI extended an average[15] 26.46% of its ANBC to priority sectors directly during the study period- lowest among all bank types. In comparison, the average PSA extended directly by Private Banks was 37.90%, Nationalised Banks was 44.36% and SFBs was 103.30%. Year wise weighted averages are provided in Table 5-1.

[14] ANBC was higher than CEOBE in all datapoints where CEOBE values were available.
[15] The average has been calculated in a two-step process. The first step being a weighted average for each quarter, weighted by the bank ANBC during the quarter. The second step being a simply average over all quarters.

Table 5-1 Weighted average of PSAs extended directly by different types of banks. *Figures in ₹ crores, percentage of ANBC in parenthesis.*

Financial Year	State Bank of India	Nationalised Banks	Private Banks	Small Finance Banks	Overall
FY 20-21	561322.95 (25.90%)	1616690.79 (43.52%)	1152476.87 (32.63%)	77183.83 (112.55%)	3407674.45 (35.94%)
FY 21-22	630960.73 (27.03%)	1702788.02 (44.32%)	1361970.80 (35.27%)	96182.41 (108.81%)	3791901.96 (37.44%)
FY 22-23	670289.81 (26.35%)	1862988.72 (47.27%)	1642357.05 (38.08%)	119780.28 (112.03%)	4295415.86 (39.39%)
FY 23-24	750055.20 (25.88%)	2053743.95 (44.94%)	2088226.05 (41.05%)	151361.74 (104.84%)	5043386.94 (39.71%)
FY 24-25	851941.94 (25.67%)	2248972.91 (43.44%)	2437572.79 (39.94%)	178674.37 (93.21%)	5717162.01 (38.65%)
FY 25-26*	1052562.59 (28.40%)	2404690.51 (42.09%)	2819380.08 (41.28%)	195753.45 (83.39%)	6472386.62 (39.27%)
Average[15]	739824.80 (26.46%)	1963252.57 (44.36%)	1877763.24 (37.90%)	133912.65 (103.30%)	4714753.25 (38.36%)
*For FY 25-26, average is of the first three quarters.					

Indirect route

Risk transfer instruments

Among indirect mechanisms of extending PSAs, details of credit extended through instruments that are associated with risk transfer, *viz.* Securitization Notes, direct assignment/outright purchase of a pool of assets and IBPCs, are shown in Table 5-2. On an average, Private Banks, SBI and Nationalised Banks extend 1.57%, 0.60% and 0.30% of their ANBC to priority sectors using such instruments respectively. With a net negative balance at an average of -1.52% of their ANBC, SFBs sell such instruments to other banks.

Table 5-2 Weighted average of PSAs extended through instruments that transfer risk including Securitization Notes, direct assignment/ outright purchase of a pool of assets and IBPCs, by different types of banks. *Figures in ₹ crores, percentage of ANBC in parenthesis.*

Financial Year	State Bank of India	Nationalised Banks	Private Banks	Small Finance Banks	Overall
FY 20-21	8516.69 (0.40%)	13651.70 (0.37%)	82657.37 (2.35%)	-766.52 (-1.13%)	104059.24 (1.10%)
FY 21-22	6633.92 (0.28%)	12479.51 (0.33%)	79647.27 (2.07%)	-1425.46 (-1.60%)	97335.24 (0.96%)
FY 22-23	6060.60 (0.23%)	-117.50 (-0.00%)	77412.39 (1.80%)	-3507.25 (-3.29%)	79848.24 (0.73%)
FY 23-24	20599.65 (0.70%)	12686.50 (0.28%)	66609.63 (1.33%)	-3686.55 (-2.56%)	96209.23 (0.76%)
FY 24-25	32998.32 (0.99%)	14888.33 (0.29%)	46028.60 (0.76%)	-320.33 (-0.19%)	93594.92 (0.63%)
FY 25-26*	40323.13 (1.09%)	33140.83 (0.59%)#	66065.49 (0.97%)	95.92 (0.03%)	139625.37 (0.85%)
Average	18269.83 (0.59%)	13642.46 (0.30%)	69896.41 (1.57%)	-1675.51 (-1.52%)	100133.20 (0.84%)
*For FY 25-26, average is of the first three quarters. # There is a single large on-lending entry by a nationalised bank in quarter ended September 2025. In the same quarter, the reported direct PSA of this bank is zero and only indirect PSA is advanced through purchase of securitised assets (5.07% of ANBC), on-lending through NBFCs (other than MFIs and HFCs) (2.13% of ANBC) and HFCs (42.29% of ANBC).					

PSLCs

PSLCs differ from other indirect PSA instruments in three ways. First, they do not transfer credit risk, second, they are applicable only for the FY in which they are issued and third, they can be issued in advance, i.e., before PSAs are extended by the banks (within prescribed limits). The net PSLC balance must square up every quarter by construction. However, the net PSLC balance in the dataset is not zero (even though it approaches zero). The residual balance is likely due to banks which are not present in the dataset, like Foreign Banks (likely to be net purchasers) and UCBs/ RRBs (likely net sellers of PSLCs).

Among banks, SBI is a net purchaser of PSLCs with an average purchase of 4.29% (of its ANBC). Private Banks were net purchasers in the initial years but turned net sellers from FY 2022-23 onwards. Nationalised Banks and SFBs are also net sellers, issuing PSLCs of 1.83% and 15.6% (of ANBCs) on average, respectively. Details of credit extended through PSLCs are provided in Table 5-3.

Table 5-3 Weighted average of PSAs extended through PSLCs by different types of banks. *Figures in ₹ crores, percentage of ANBC in parenthesis.*

Financial Year	State Bank of India	Nationalised Banks	Private Banks	Small Finance Banks	Overall
FY 20-21	53921.94 (2.42%)	-67098.00 (-1.79%)	22024.44 (0.62%)	-17357.50 (-25.08%)	-8509.12 (-0.09%)
FY 21-22	110649.06 (4.70%)	-86033.75 (-2.24%)	21136.88 (0.57%)	-20543.00 (-22.99%)	25209.19 (0.26%)
FY 22-23	127875.00 (4.95%)	-97665.00 (-2.47%)	-23019.19 (-0.51%)	-21185.00 (-19.61%)	-13994.19 (-0.13%)
FY 23-24	160219.25 (5.52%)	-111026.38 (-2.45%)	-41318.69 (-0.78%)	-15201.25 (-10.48%)	-7327.06 (-0.05%)
FY 24-25	168830.75 (5.07%)	-38575.62 (-0.78%)	-117020.01 (-1.86%)	-16471.50 (-8.55%)	-3236.38 (-0.02%)
FY 25-26*	98570.08 (2.64%)	-60611.14 (-1.09%)	-26979.24 (-0.38%)	-9441.62 (-4.00%)	1538.08 (0.00%)
Average	120943.23 (4.29%)	-77540.37 (-1.83%)	-27553.22 (-0.39%)	-17015.56 (-15.60%)	-1165.91 (-0.01%)
*For FY 25-26, average is of the first three quarters.					

On-lending

PSAs (as a percentage of ANBC) extended to MFIs, NBFCs (other than MFIs and HFCs) and HFCs for on-lending does not appear very significant. Lending to MFIs and NBFCs (other than MFIs and HFCs) is mainly used by Private Banks and to a lesser extent by the SBI and Nationalised Banks with an average of 0.39%, 0.13% and 0.07% (of ANBC) extended to MFIs respectively and an average of 0.97%, 0.17%, 0.06% (of ANBC) extended to NBFCs (other than MFIs and HFCs) respectively. Year wise details of on-lending extended to MFIs, NBFCs (other than MFIs and HFCs) and HFCs are provided in Table 5-4, 5-5 and 5-6 respectively.

Table 5-4 Weighted average of PSAs extended to MFIs for on-lending by different types of banks. *Figures in ₹ crores, percentage of ANBC in parenthesis.*

Financial Year	State Bank of India	Nationalised Banks	Private Banks	Small Finance Banks	Overall
FY 20-21	2004.31 (0.09%)	0.00 (0.00%)	11267.01 (0.32%)	0.00 (0.00%)	13271.32 (0.14%)

FY 21-22	2625.08 (0.11%)	273.87 (0.01%)	13383.02 (0.35%)	24.97 (0.03%)	16306.94 (0.16%)
FY 22-23	4510.90 (0.18%)	5306.78 (0.13%)	18362.47 (0.42%)	-66.72# (-0.06%)	28113.42 (0.26%)
FY 23-24	5143.25 (0.18%)	4946.79 (0.11%)	24357.45 (0.48%)	12.80 (0.01%)	34460.30 (0.27%)
FY 24-25	4722.41 (0.14%)	6018.63 (0.12%)	26465.67 (0.44%)	6.94 (0.00%)	37213.64 (0.25%)
FY 25-26*	1993.34 (0.05%)	2548.10 (0.05%)	19067.02 (0.28%)	2.21 (0.00%)	23610.68 (0.14%)
Average	3565.38 (0.13%)	3209.94 (0.07%)	18806.24 (0.39%)	-3.54 (0.00%)	25578.02 (0.21%)

*For FY 25-26, average is of the first three quarters.
There was a single negative entry by one SFB during the quarter ended December 2022. The reason could not be ascertained.

Table 5-5 Weighted average of PSAs extended to NBFCs (other than MFIs and HFCs) for on-lending by different types of banks. *Figures in ₹ crores, percentage of ANBC in parenthesis.*

Financial Year	State Bank of India	Nationalised Banks	Private Banks	Small Finance Banks	Overall
FY 20-21	0.00 (0.00%)	0.00 (0.00%)	17605.35 (0.49%)	0.00 (0.00%)	17605.35 (0.18%)
FY 21-22	3957.32 (0.17%)	0.00 (0.00%)	32656.47 (0.85%)	0.00 (0.00%)	36613.79 (0.36%)
FY 22-23	4539.83 (0.18%)	0.00 (0.00%)	40331.03 (0.93%)	0.00 (0.00%)	44870.85 (0.41%)
FY 23-24	6767.29 (0.23%)	1224.93 (0.03%)	54020.67 (1.06%)	0.00 (0.00%)	62012.90 (0.49%)
FY 24-25	7149.09 (0.22%)	3620.85 (0.07%)	75043.38 (1.23%)	0.00 (0.00%)	85813.32 (0.58%)
FY 25-26*	9039.33 (0.24%)	20010.49 (0.35%)#	92469.85 (1.35%)	0.00 (0.00%)	121519.67 (0.74%)
Average	5077.05 (0.17%)	3452.81 (0.06%)	50262.48 (0.97%)	0.00 (0.00%)	58792.34 (0.45%)

*For FY 25-26, average is of the first three quarters.
There is a single large on-lending entry by a nationalised bank in quarter ended September 2025. In the same quarter, the reported direct PSA of this bank is zero and only indirect PSA is advanced through purchase of securitised assets (5.07% of ANBC), on-lending through NBFCs (other than MFIs and HFCs) (2.13% of ANBC) and HFCs (42.29% of ANBC).

Table 5-6 Weighted average of PSAs extended to HFCs for on-lending by different types of banks. *Figures in ₹ crores, percentage of ANBC in parenthesis.*

Financial Year	State Bank of India	Nationalised Banks	Private Banks	Small Finance Banks	Overall
FY 20-21	0.00 (0.00%)	0.00 (0.00%)	6212.46 (0.18%)	0.00 (0.00%)	6212.46 (0.07%)
FY 21-22	1911.50 (0.08%)	0.00 (0.00%)	3366.54 (0.09%)	0.00 (0.00%)	5278.03 (0.05%)
FY 22-23	1555.44 (0.06%)	0.00 (0.00%)	4006.34 (0.09%)	0.00 (0.00%)	5561.78 (0.05%)
FY 23-24	1704.73 (0.06%)	376.94 (0.01%)	4135.22 (0.08%)	0.00 (0.00%)	6216.90 (0.05%)

FY 24-25	3734.82 (0.11%)	112.58 (0.00%)	2777.78 (0.05%)	0.00 (0.00%)	6625.18 (0.04%)
FY 25-26*	6736.17 (0.18%)	150665.85 (2.66%)#	33154.87 (0.50%)	43.21 (0.02%)	190600.10 (1.16%)
Average	2427.59 (0.08%)	19737.20 (0.35%)	7889.48 (0.15%)	5.64 (0.00%)	30059.90 (0.20%)
*For FY 25-26, average is of the first three quarters. # There is a single large on-lending entry by a nationalised bank in quarter ended September 2025. In the same quarter, the reported direct PSA of this bank is zero and only indirect PSA is advanced through purchase of securitised assets (5.07% of ANBC), on-lending through NBFCs (other than MFIs and HFCs) (2.13% of ANBC) and HFCs (42.29% of ANBC).					

Deposits in RIDF and other funds

Bank wise details of outstanding deposits in RIDF and other specified funds with NABARD/ NHB/ SIDBI/ MUDRA Ltd are available from quarter ended June 2023 onwards. For the entire period and as a percentage of ANBC, outstanding deposits are maximum in SBI at 7.90% followed by Private Banks at 4.33%, Nationalised Banks at 1.77% and minimum in SFBs at 0.29%. Details are provided in Table 5-7.

Table 5-7 Weighted average of deposits in RIDF and other specified funds by different types of banks. *Figures in ₹ crores, percentage of ANBC in parenthesis.*

Financial Year	State Bank of India	Nationalised Banks	Private Banks	Small Finance Banks	Overall
FY 22-23	205479.14 (8.07%)	59010.65 (1.50%)	212761.78 (4.93%)	3.92 (0.00%)	477255.49 (4.37%)
FY 23-24	242588.73 (8.35%)	51220.64 (1.13%)	248923.61 (4.90%)	53.11 (0.04%)	542786.09 (4.27%)
FY 24-25	258836.98 (7.82%)	42352.68 (0.82%)	235881.13 (3.89%)	44.89 (0.02%)	537115.68 (3.64%)
FY 25-26*	266151.43 (7.19%)	250869.32 (4.26%)	230409.91 (3.37%)	3367.58 (1.38%)	750798.23 (4.53%)
Average	241738.25 (7.90%)	90862.92 (1.77%)	232099.72 (4.33%)	700.69 (0.29%)	565401.58 (4.18%)
*For FY 25-26, average is of the first three quarters.					

PSAs to agriculture

SFBs and Nationalised Banks exceed the sub-target of 18% and extend an average of 35.77% and 20.35% of their ANBCs to agriculture directly. In contrast, Private Banks and SBI extend an average of 9.78% and 10.38% of their ANBCs to agriculture through the direct route and use indirect PSA instrument to meet the sub-target. PSLCs are the most common instrument for indirect lending to Agriculture with Private Banks and SBI purchasing agriculture PSLCs worth 3.40% and 2.54% of their ANBCs respectively. SBI also invests an average 4.12% of its ANBC in outstanding deposits with RIDF etc. followed by Private Banks that have an average of 2.23% of their ANBCs in such deposits. Annual details by bank and type of PSA are provided in Table 5-8.

Table 5-8 Annual average of Agricultural PSAs by bank type. *Figures in ₹ crores, percentage of ANBC in parenthesis | Avg- Average; Nat. Banks- Nationalised Banks; Pvt. Banks- Private Banks; SBI- State Bank of India; SFBs- Small Finance Banks*

Bank type	Type of PSA	20-21	21-22	22-23	23-24	24-25	25-26*	Avg
SBI	Direct	232398 (10.73%)	241013 (10.33%)	260295 (10.23%)	300590 (10.38%)	341756 (10.3%)	381247 (10.28%)	292883 (10.38%)

	Risk transfer	0 (0%)	230 (0.01%)	4346 (0.17%)	3833 (0.13%)	7441 (0.23%)	6435 (0.17%)	3714 (0.12%)
	PSLC	42021 (1.9%)	69645 (2.98%)	96673 (3.77%)	100324 (3.47%)	78098 (2.36%)	5237 (0.14%)	65333 (2.44%)
	On-lending	2004 (0.09%)	2861 (0.12%)	4877 (0.19%)	5319 (0.18%)	4775 (0.15%)	2765 (0.07%)	3767 (0.13%)
	Deposits	-	-	109491 (4.3%)	127745 (4.4%)	132881 (4.02%)	135417 (3.65%)	84256 (2.73%)
Nat. Banks	Direct	680006 (18.3%)	747917 (19.47%)	850963 (21.58%)	979020 (21.41%)	1097400 (21.2%)	1147305 (20.08%)	917102 (20.34%)
	Risk transfer	13862 (0.37%)	12865 (0.34%)	5476 (0.14%)	5187 (0.11%)	5728 (0.11%)	19596 (0.35%)	10452 (0.24%)
	PSLC	-36838 (-0.99%)	-40218 (-1.05%)	-87756 (-2.22%)	-119276 (-2.62%)	-116826 (-2.26%)	-73606 (-1.31%)	-79087 (-1.74%)
	On-lending	0 (0%)	762 (0.02%)	1478 (0.04%)	2677 (0.06%)	3576 (0.07%)	71111 (1.26%)	13267 (0.24%)
	Deposits	-	-	38820 (0.98%)	30153 (0.66%)	27100 (0.52%)	118795 (2.02%)	35811 (0.7%)
Pvt. Banks	Direct	330461 (9.36%)	377410 (9.78%)	434433 (10.07%)	527551 (10.38%)	612601 (10.04%)	601116 (8.81%)	480595 (9.74%)
	Risk transfer	20219 (0.57%)	24221 (0.63%)	26651 (0.62%)	34960 (0.69%)	22534 (0.37%)	37894 (0.55%)	27746 (0.57%)
	PSLC	78608 (2.21%)	93483 (2.41%)	137881 (3.19%)	205026 (4.04%)	258975 (4.24%)	316493 (4.63%)	181744 (3.45%)
	On-lending	16381 (0.46%)	32490 (0.84%)	45560 (1.05%)	63345 (1.24%)	83247 (1.36%)	103179 (1.52%)	57367 (1.08%)
	Deposits	-	-	112383 (2.6%)	125103 (2.47%)	116838 (1.92%)	125747 (1.84%)	80012 (1.47%)
SFBs	Direct	27041 (39.4%)	33616 (38.01%)	44589 (41.69%)	53588 (37.12%)	59094 (30.87%)	58246 (24.81%)	46029 (35.32%)
	Risk transfer	-260 (-0.39%)	24 (0.03%)	-1496 (-1.4%)	-2168 (-1.51%)	154 (0.06%)	1659 (0.69%)	-348 (-0.42%)
	PSLC	-7460 (-10.73%)	-11382 (-12.74%)	-13840 (-12.88%)	-12614 (-8.69%)	-12622 (-6.54%)	-9309 (-3.95%)	-11204 (-9.26%)
	On-lending	0 (0%)	5 (0.01%)	24 (0.02%)	47 (0.03%)	13 (0.01%)	24 (0.01%)	19 (0.01%)
	Deposits	-	-	1 (0%)	24 (0.02%)	15 (0.01%)	998 (0.41%)	173 (0.07%)
* For FY 25-26, the average of the first three quarters has been provided.								

SFs/ MFs and non-corporate farmers (NCFs)

Advances provided to SFs/ MFs and NCFs have sub-targets of 10% and 14% respectively. The lending patterns to these sub-sectors are like agriculture PSAs with SBI and Private Banks having less of direct lending and utilizing PSLCs, while Nationalised Banks and SFBs exceeding the targets directly and issuing PSLCs for the balance amount. Annual details by bank and type of PSA are provided in Tables 5-9 and 5-10.

Table 5-9 Annual average of PSAs provided to SFs/ MFs by bank type. *Figures in ₹ crores, percentage of ANBC in parenthesis | Avg- Average; Nat. Banks- Nationalised Banks; Pvt. Banks- Private Banks; SBI- State Bank of India; SFBs- Small Finance Banks*

Bank type	Type of PSA	20-21	21-22	22-23	23-24	24-25	25-26*	Avg
SBI	Direct	131333 (6.06%)	144688 (6.2%)	167337 (6.57%)	193328 (6.67%)	248413 (7.49%)	271765 (7.33%)	192811 (6.72%)
	Risk transfer	0 (0%)	0 (0%)	0 (0%)	108 (0%)	21 (0%)	267 (0.01%)	66 (0%)

	PSLC	35168 (1.6%)	59660 (2.55%)	75822 (2.96%)	95542 (3.29%)	89098 (2.69%)	2487 (0.07%)	59630 (2.19%)
	On-lending	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Nat. Banks	Direct	419653 (11.29%)	477033 (12.42%)	585616 (14.85%)	682611 (14.93%)	753568 (14.56%)	761543 (13.33%)	613337 (13.56%)
	Risk transfer	-5741 (-0.15%)	-4914 (-0.13%)	-5476 (-0.14%)	0 (0%)	5244 (0.1%)	14900 (0.26%)	669 (-0.01%)
	PSLC	-49862 (-1.34%)	-41374 (-1.08%)	-85680 (-2.16%)	-131314 (-2.88%)	-148864 (-2.87%)	-76845 (-1.37%)	-88990 (-1.95%)
	On-lending	150 (0%)	0 (0%)	0 (0%)	770 (0.02%)	1206 (0.02%)	39876 (0.7%)	7000 (0.12%)
Pvt. Banks	Direct	154755 (4.38%)	181860 (4.72%)	198716 (4.61%)	243800 (4.79%)	284188 (4.66%)	245837 (3.6%)	218193 (4.46%)
	Risk transfer	3056 (0.09%)	1512 (0.04%)	1935 (0.04%)	5055 (0.1%)	1997 (0.03%)	12126 (0.18%)	4280 (0.08%)
	PSLC	70359 (1.98%)	80305 (2.07%)	127481 (2.94%)	196776 (3.88%)	249030 (4.07%)	286947 (4.2%)	168483 (3.19%)
	On-lending	5947 (0.17%)	14149 (0.37%)	20947 (0.48%)	37495 (0.73%)	59225 (0.97%)	75517 (1.11%)	35547 (0.64%)
SFBs	Direct	20922 (30.5%)	25884 (29.27%)	32378 (30.28%)	40268 (27.89%)	43943 (22.96%)	37715 (16.06%)	33518 (26.16%)
	Risk transfer	219 (0.32%)	22 (0.03%)	14 (0.01%)	41 (0.03%)	22 (0.01%)	421 (0.17%)	123 (0.1%)
	PSLC	-3979 (-5.71%)	-8588 (-9.59%)	-9945 (-9.24%)	-11691 (-8.06%)	-12064 (-6.25%)	-8601 (-3.65%)	-9145 (-7.08%)
	On-lending	0 (0%)	5 (0.01%)	9 (0.01%)	2 (0%)	0 (0%)	0 (0%)	3 (0%)
* For FY 25-26, the average of the first three quarters has been provided								

Table 5-10 Annual average of PSAs provided to NCFs by bank type. *Figures in ₹ crores, percentage of ANBC in parenthesis | Avg- Average; Nat. Banks- Nationalised Banks; Pvt. Banks- Private Banks; SBI- State Bank of India; SFBs- Small Finance Banks*

Bank type	Type of PSA	20-21	21-22	22-23	23-24	24-25	25-26*	Avg
SBI	Direct	208228 (9.61%)	216267 (9.27%)	235615 (9.25%)	271650 (9.37%)	318461 (9.6%)	352247 (9.5%)	267078 (9.43%)
	Risk transfer	0 (0%)	0 (0%)	0 (0%)	108 (0%)	21 (0%)	267 (0.01%)	66 (0%)
	PSLC	35168 (1.6%)	59660 (2.55%)	75822 (2.96%)	95542 (3.29%)	89098 (2.69%)	2487 (0.07%)	59630 (2.19%)
	On-lending	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Nat. Banks	Direct	573421 (15.43%)	676138 (17.6%)	764675 (19.4%)	876959 (19.18%)	999811 (19.31%)	1048570 (18.36%)	823262 (18.21%)
	Risk transfer	9391 (0.25%)	9203 (0.24%)	4489 (0.11%)	-250 (-0.01%)	5367 (0.1%)	15388 (0.28%)	7265 (0.16%)
	PSLC	-33238 (-0.89%)	-35918 (-0.93%)	-75217 (-1.9%)	-131314 (-2.88%)	-148864 (-2.87%)	-83195 (-1.48%)	-84624 (-1.82%)
	On-lending	0 (0%)	0 (0%)	0 (0%)	1755 (0.04%)	1447 (0.03%)	51493 (0.91%)	9116 (0.16%)
Pvt. Banks	Direct	273548 (7.75%)	317689 (8.24%)	360720 (8.36%)	432438 (8.51%)	497176 (8.15%)	467657 (6.85%)	391538 (7.98%)
	Risk transfer	40854 (1.16%)	50585 (1.31%)	23507 (0.54%)	32316 (0.64%)	21831 (0.36%)	35152 (0.51%)	34041 (0.75%)
	PSLC	42994 (1.21%)	41672 (1.07%)	137517 (3.17%)	196776 (3.88%)	248880 (4.07%)	284811 (4.17%)	158775 (2.93%)
	On-lending	7948 (0.22%)	23906 (0.62%)	33535 (0.78%)	50195 (0.98%)	74916 (1.23%)	94840 (1.39%)	47557 (0.87%)

SFBs	Direct	26244 (38.24%)	32281 (36.5%)	41143 (38.48%)	50619 (35.07%)	56202 (29.36%)	54810 (23.35%)	43550 (33.5%)
	Risk transfer	-183 (-0.27%)	23 (0.03%)	-1496 (-1.4%)	-2161 (-1.5%)	-54 (-0.04%)	1659 (0.69%)	-369 (-0.42%)
	PSLC	-3541 (-5.08%)	-4685 (-5.26%)	-11370 (-10.57%)	-11541 (-7.95%)	-12064 (-6.25%)	-9304 (-3.94%)	-8751 (-6.51%)
	On-lending	0 (0%)	0 (0%)	24 (0.02%)	2 (0%)	0 (0%)	0 (0%)	4 (0%)
* For FY 25-26, the average of the first three quarters has been provided								

PSAs to MSMEs

Year wise details of lending to MSMEs by bank type are provided in Tables 5-11, 5-12 and 5-13. With only 4.08% (of its ANBC) advanced on average to micro enterprises through the direct route, SBI meets the sub-target of 7.5% by utilizing indirect routes like PSLCs. Private Banks and SFBs are net sellers of micro enterprise PSLCs, while SFBs are also net sellers of risk transferring instruments.

SBI extends the least amount of credit as a percentage of its ANBC to SMEs directly as compared to other bank groups. As lending to SMEs does not have a separate sub-target, indirect routes of extending PSAs are not common.

Table 5-11 Annual average of PSAs provided to micro enterprises by bank type. *Figures in ₹ crores, percentage of ANBC in parenthesis | Avg- Average; Nat. Banks- Nationalised Banks; Pvt. Banks- Private Banks; SBI- State Bank of India; SFBs- Small Finance Banks*

Bank type	Type of PSA	20-21	21-22	22-23	23-24	24-25	25-26*	Avg
SBI	Direct	77609 (3.58%)	90204 (3.86%)	88090 (3.46%)	116800 (4.02%)	154144 (4.64%)	193232 (5.21%)	120013 (4.13%)
	Risk transfer	770 (0.04%)	797 (0.03%)	727 (0.03%)	6338 (0.22%)	13322 (0.4%)	16854 (0.45%)	6468 (0.2%)
	PSLC	9376 (0.41%)	3586 (0.15%)	23763 (0.89%)	12750 (0.42%)	81982 (2.47%)	66667 (1.78%)	33021 (1.02%)
	On-lending	0 (0%)	1777 (0.08%)	2203 (0.09%)	4048 (0.14%)	4425 (0.13%)	3287 (0.09%)	2623 (0.09%)
Nat. Banks	Direct	333632 (8.98%)	351626 (9.15%)	396891 (10.07%)	446809 (9.77%)	493546 (9.53%)	530603 (9.29%)	425518 (9.46%)
	Risk transfer	1803 (0.05%)	1747 (0.05%)	-552 (-0.01%)	6024 (0.13%)	8072 (0.15%)	7267 (0.13%)	4060 (0.08%)
	PSLC	-3782 (-0.1%)	-9000 (-0.23%)	-4804 (-0.12%)	8250 (0.17%)	10250 (0.19%)	7535 (0.13%)	1408 (0.01%)
	On-lending	0 (0%)	166 (0%)	474 (0.01%)	241 (0.01%)	2437 (0.05%)	36207 (0.64%)	6588 (0.12%)
Pvt. Banks	Direct	286663 (8.13%)	295678 (7.65%)	396358 (9.18%)	537115 (10.56%)	641104 (10.5%)	827429 (12.11%)	497391 (9.69%)
	Risk transfer	13194 (0.37%)	9778 (0.25%)	10119 (0.24%)	10705 (0.21%)	11166 (0.18%)	13242 (0.19%)	11367 (0.24%)
	PSLC	-13277 (-0.37%)	6536 (0.17%)	-24851 (-0.55%)	-30466 (-0.57%)	-135208 (-2.21%)	-153268 (-2.22%)	-58422 (-0.96%)
	On-lending	7727 (0.22%)	7165 (0.19%)	8078 (0.19%)	11927 (0.23%)	16150 (0.26%)	26545 (0.39%)	12932 (0.25%)
SFBs	Direct	25409 (37.17%)	31273 (35.39%)	38519 (36.02%)	50457 (34.93%)	69041 (35.95%)	86389 (36.79%)	50181 (36.04%)
	Risk transfer	67 (0.1%)	-34 (-0.04%)	-496 (-0.47%)	23 (0.01%)	165 (0.09%)	-765 (-0.32%)	-173 (-0.1%)
	PSLC	-8885 (-12.9%)	-7222 (-8.08%)	-6981 (-6.39%)	-2588 (-1.79%)	-3850 (-2.01%)	-467 (-0.2%)	-4999 (-5.23%)

	On-lending	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
* For FY 25-26, the average of the first three quarters has been provided								

Table 5-12 Annual average of PSAs provided to small enterprises by bank type. *Figures in ₹ crores, percentage of ANBC in parenthesis | Avg- Average; Nat. Banks- Nationalised Banks; Pvt. Banks- Private Banks; SBI- State Bank of India; SFBs- Small Finance Banks*

Bank type	Type of PSA	20-21	21-22	22-23	23-24	24-25	25-26*	Avg
SBI	Direct	78770 (3.64%)	82831 (3.55%)	73492 (2.9%)	73123 (2.53%)	76465 (2.31%)	81360 (2.2%)	77674 (2.86%)
	Risk transfer	0 (0%)	0 (0%)	0 (0%)	2393 (0.08%)	5459 (0.16%)	10897 (0.29%)	3125 (0.09%)
	PSLC	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	On-lending	0 (0%)	1945 (0.08%)	1971 (0.08%)	2543 (0.09%)	2671 (0.08%)	4980 (0.13%)	2352 (0.08%)
Nat. Banks	Direct	253005 (6.81%)	237982 (6.19%)	239471 (6.08%)	253857 (5.56%)	269048 (5.19%)	269411 (4.72%)	253796 (5.76%)
	Risk transfer	-6408 (-0.17%)	-5914 (-0.15%)	-5476 (-0.14%)	868 (0.02%)	887 (0.02%)	169 (0%)	-2646 (-0.07%)
	PSLC	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	453 (0.01%)	76 (0%)
	On-lending	0 (0%)	79 (0%)	3008 (0.08%)	2808 (0.06%)	3301 (0.06%)	21716 (0.38%)	5152 (0.1%)
Pvt. Banks	Direct	276370 (7.83%)	326965 (8.47%)	386640 (8.97%)	445357 (8.77%)	528015 (8.64%)	653484 (9.57%)	436138 (8.71%)
	Risk transfer	9995 (0.29%)	3872 (0.1%)	886 (0.02%)	906 (0.02%)	-367 (-0.01%)	4105 (0.06%)	3233 (0.08%)
	PSLC	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	37 (0%)	6 (0%)
	On-lending	3048 (0.09%)	4532 (0.12%)	2013 (0.05%)	1286 (0.03%)	917 (0.02%)	6588 (0.1%)	3064 (0.07%)
SFBs	Direct	6095 (8.9%)	4604 (5.23%)	5286 (4.94%)	8479 (5.87%)	10968 (5.71%)	11480 (4.89%)	7819 (5.92%)
	Risk transfer	22 (0.03%)	-8 (-0.01%)	-6 (-0.01%)	3 (0%)	-4 (0%)	-108 (-0.05%)	-17 (-0.01%)
	PSLC	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	On-lending	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
* For FY 25-26, the average of the first three quarters has been provided								

Table 5-13 Annual average of PSAs provided to medium enterprises by bank type. *Figures in ₹ crores, percentage of ANBC in parenthesis | Avg- Average; Nat. Banks- Nationalised Banks; Pvt. Banks- Private Banks; SBI- State Bank of India; SFBs- Small Finance Banks*

Bank type	Type of PSA	20-21	21-22	22-23	23-24	24-25	25-26*	Avg
SBI	Direct	18146 (0.84%)	41045 (1.75%)	53037 (2.08%)	58235 (2.01%)	68436 (2.06%)	97503 (2.63%)	56067 (1.9%)
	Risk transfer	0 (0%)	0 (0%)	0 (0%)	826 (0.03%)	709 (0.02%)	751 (0.02%)	381 (0.01%)
	PSLC	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	On-lending	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Nat. Banks	Direct	93097 (2.5%)	105206 (2.74%)	113036 (2.87%)	118697 (2.6%)	143686 (2.77%)	153558 (2.68%)	121213 (2.69%)

	Risk transfer	394 (0.01%)	510 (0.01%)	0 (0%)	18 (0%)	280 (0.01%)	95 (0%)	216 (0%)
	PSLC	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	7 (0%)	1 (0%)
	On-lending	0 (0%)	15 (0%)	346 (0.01%)	444 (0.01%)	546 (0.01%)	11352 (0.2%)	2117 (0.04%)
Pvt. Banks	Direct	121555 (3.42%)	191105 (4.94%)	236882 (5.49%)	281192 (5.53%)	336566 (5.51%)	344002 (5.04%)	251884 (4.99%)
	Risk transfer	2114 (0.06%)	1011 (0.03%)	940 (0.02%)	1488 (0.03%)	1992 (0.03%)	817 (0.01%)	1394 (0.03%)
	PSLC	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	On-lending	44 (0%)	88 (0%)	1 (0%)	1 (0%)	1 (0%)	963 (0.01%)	183 (0%)
SFBs	Direct	381 (0.56%)	616 (0.69%)	1329 (1.24%)	2525 (1.75%)	3125 (1.63%)	2756 (1.18%)	1789 (1.18%)
	Risk transfer	0 (0%)	0 (0%)	-1 (0%)	0 (0%)	0 (0%)	-8 (0%)	-2 (0%)
	PSLC	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
	On-lending	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
* For FY 25-26, the average of the first three quarters has been provided								

PSAs to weaker sections

The overlapping category of weaker sections has a sub-target of 12%, which was met by Nationalised Banks and SFBs through the direct route. SBI and Private Banks utilized indirect lending instruments, primarily PSLCs, to meet this sub-target as their direct lending fell short at 8.40% and 7.10% (of their ANBC) respectively. Year wise details are provided in Table 5-14.

Table 5-14 Annual average of PSAs provided to weaker sections by bank type. *Figures in ₹ crores, percentage of ANBC in parenthesis | Avg- Average; Nat. Banks- Nationalised Banks; Pvt. Banks- Private Banks; SBI- State Bank of India; SFBs- Small Finance Banks*

Bank type	Type of PSA	20-21	21-22	22-23	23-24	24-25	25-26*	Avg
SBI	Direct	168095 (7.76%)	186081 (7.97%)	212104 (8.33%)	250372 (8.64%)	294088 (8.86%)	333933 (9.01%)	240779 (8.43%)
	Risk transfer	0 (0%)	0 (0%)	0 (0%)	108 (0%)	21 (0%)	267 (0.01%)	66 (0%)
	PSLC	35168 (1.6%)	59660 (2.55%)	75822 (2.96%)	95542 (3.29%)	89098 (2.69%)	2487 (0.07%)	59630 (2.19%)
	On-lending	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Nat. Banks	Direct	553873 (14.91%)	609540 (15.86%)	728814 (18.48%)	847944 (18.55%)	928604 (17.94%)	947186 (16.58%)	769327 (17.05%)
	Risk transfer	2016 (0.06%)	6629 (0.17%)	4489 (0.11%)	-125 (0%)	5989 (0.12%)	19246 (0.34%)	6374 (0.13%)
	PSLC	-43237 (-1.16%)	-35918 (-0.93%)	-79080 (-2%)	-131314 (-2.88%)	-148864 (-2.87%)	-78012 (-1.39%)	-86071 (-1.87%)
	On-lending	0 (0%)	0 (0%)	0 (0%)	393 (0.01%)	545 (0.01%)	51529 (0.91%)	8744 (0.16%)
Pvt. Banks	Direct	257454 (7.29%)	274869 (7.13%)	312543 (7.25%)	371725 (7.31%)	432806 (7.09%)	435531 (6.38%)	347488 (7.08%)
	Risk transfer	14723 (0.42%)	14543 (0.38%)	23153 (0.53%)	32932 (0.65%)	21522 (0.36%)	31897 (0.47%)	23128 (0.47%)
	PSLC	72646 (2.05%)	80199 (2.07%)	137659 (3.18%)	195084 (3.84%)	248880 (4.07%)	284477 (4.16%)	169824 (3.23%)
	On-lending	9756 (0.28%)	17996 (0.46%)	24394 (0.56%)	39811 (0.78%)	60365 (0.99%)	77639 (1.14%)	38327 (0.7%)

SFBs	Direct	40262 (58.74%)	44385 (50.2%)	56227 (52.66%)	67316 (46.64%)	69477 (36.32%)	65587 (27.95%)	57209 (45.42%)
	Risk transfer	-256 (-0.39%)	23 (0.03%)	-2446 (-2.28%)	-3656 (-2.53%)	-1281 (-0.69%)	-284 (-0.13%)	-1317 (-1%)
	PSLC	-3629 (-5.21%)	-5725 (-6.37%)	-6762 (-6.28%)	-11691 (-8.06%)	-14564 (-7.56%)	-8601 (-3.65%)	-8495 (-6.19%)
	On-lending	0 (0%)	0 (0%)	-100 (-0.09%)	0 (0%)	0 (0%)	0 (0%)	-17 (-0.01%)
* For FY 25-26, the average of the first three quarters has been provided								

Geographical distribution of PSAs lent directly by banks

Overall PSA

Among the PSAs lent directly and mapped to a district, the median outstanding PSAs per district (averaged over the study period) is ~₹2,635 crores with an interquartile range (IQR) of ~₹6,095 crores. 63 Districts were outliers[16] and outstanding PSAs in such districts total ~₹22,46,407 crores- over 45% of total PSAs mapped to specific districts. Key distribution statistics for each type of PSA is provided in Table 5-15 and details of PSAs for agriculture, SFs/ MFs, micro enterprises and weaker sections are described in further detail below.[17]

Figure 5-3 shows the geographical distribution of overall PSA. Outlier districts are highlighted and labelled. On expected lines, most of advances to the priority sector have been extended in State capitals or important industrial districts. Underserved regions include Himalayan states, Northeastern states, eastern Uttar Pradesh, Bihar, Jharkhand, Odisha, parts of Madhya Pradesh (Eastern region) and part of Rajasthan. Figure 5-4 shows the distribution of CAGR of overall PSA. The scale has been curtailed to +/- 50% to increase the contrast among other districts. An absolute convergence analysis reveals evidence of convergence, with a significant negative slope (-1.5165, standard error 0.1432) in the correlation between CAGR and log of initial outstanding PSA in a district. The CAGR of overall PSA during the period was 14.93%. However, there is significant heterogeneity between districts with many districts in the Northeastern states showing degrowth.

Table 5-15 District level distribution of quarter-average outstanding PSAs. *Outliers were calculated based on 75th percentile + 1.5 * Interquartile range. Agri- Agricultural; SF/ MF- Small and Marginal Farmers; NCF- Non Corporate Farmers; Agri – NCF- Corporate Farm credit calculated as the difference between the credit provided to Agriculture and Non-corporate Farmers; MSME- Micro, Small and Medium Enterprises; Weaker- Weaker sections*

Type of PSA	Median (₹ crore)	IQR (₹ crore)	Outlier cutoff (₹ crore)	No. of outlier districts	PSA in outlier districts		CAGR (%)
					(₹ crore)	(%)	
Overall	2634.58	6095.43	16085.36	63	2246407.92	45.78	14.93
Agri	1208.11	2797.58	7338.19	64	663608.32	36.32	12.84
SF/ MF	749.63	1557.97	4098.15	68	461439.87	41.09	14.09
NCF	1058.97	2432.02	6373.64	60	576004.56	35.75	13.55
Agri - NCF	87.70	267.91	688.82	77	120840.17	56.04	8.44
MSME	871.12	1918.18	5066.88	92	1559971.02	67.32	17.26

[16] Defined as 75th Percentile + 1.5*IQR

[17] The distributions show minor statistically significant differences in all comparisons except for the distribution between PSA to small and medium enterprises using the non-parametric Syrjala (1996) test, which is based on a generalization of the two-sample Cramer-von Mises test for a difference between two univariate probability distributions.

Micro	580.53	1061.95	2865.76	81	615376.91	55.80	18.51
Small	212.92	600.12	1554.30	108	587266.98	75.04	11.57
Medium	42.79	223.36	563.03	123	381238.17	88.28	27.53
Weaker	1053.45	1990.22	5339.98	69	576340.49	38.75	13.06

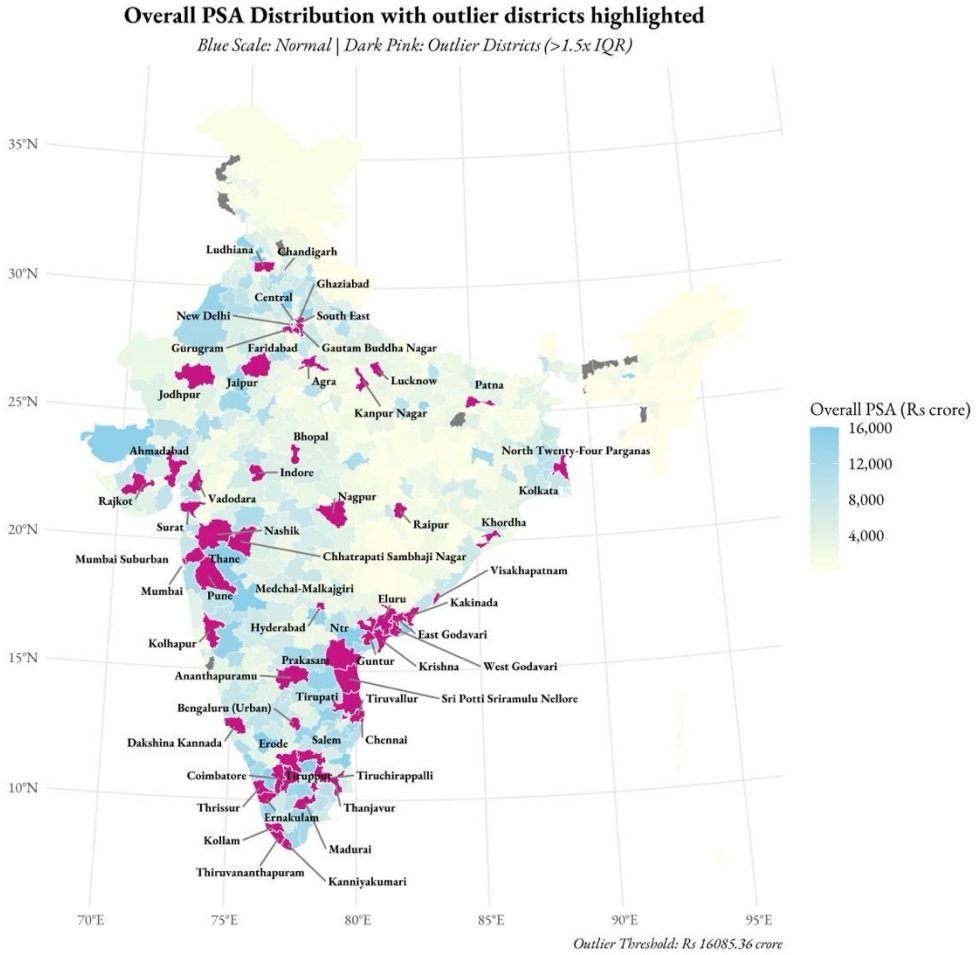

Figure 5-3 Geographical distribution of overall PSAs

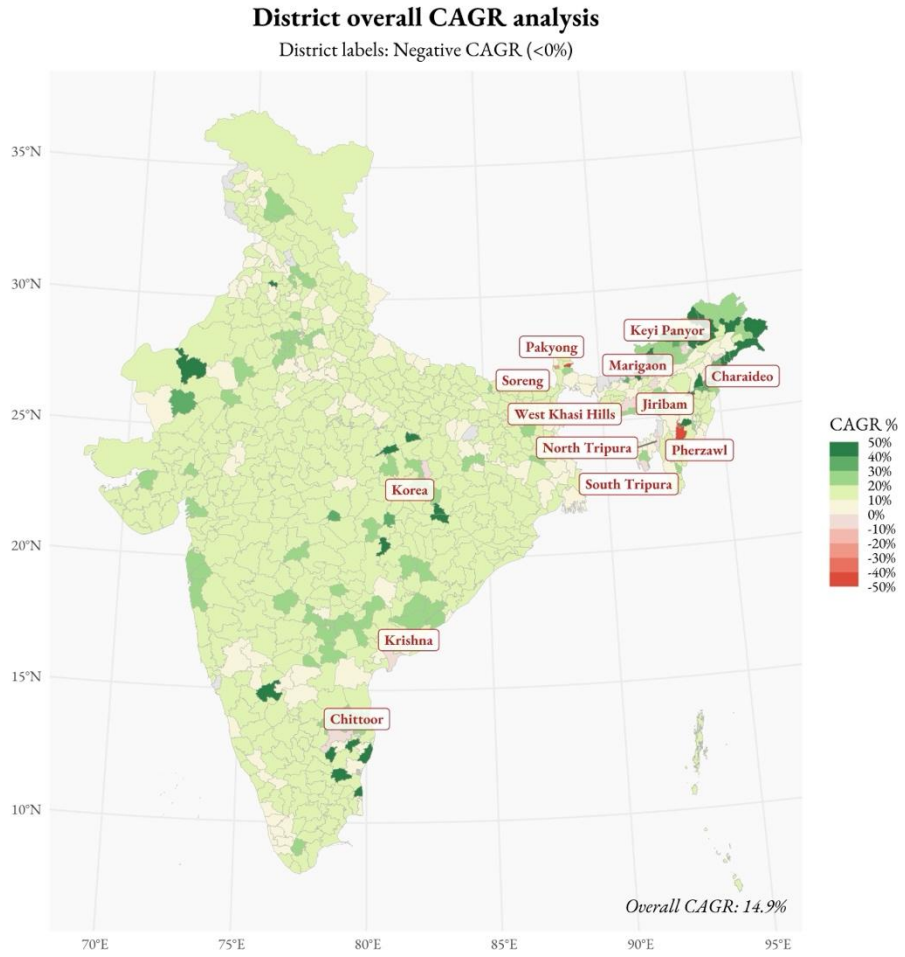

Figure 5-4 Geographical distribution of overall PSA CAGR. *Scale has been curtailed to +/- 50% to aid visualisation. District labels represent districts with negative CAGR.*

Agriculture

The median outstanding agriculture PSA per district is ~ ₹1208 crore with an IQR of ~₹2798 crore. 63 Districts are outliers, concentrated in the southern and western parts of the country. Outlier districts constitute 36.32% of the total agriculture PSA. The regional distribution is shown in Figure 5-5. Agricultural PSAs are growing at a CAGR of 12.8%. However, there is significant heterogeneity between districts with many districts in the northeast reporting degrowth. Details are shown in Figure 5-6.

The distribution of NCF PSAs is like agriculture PSAs. The median NCF PSA outstanding is ~1058 crore per district with an IQR of ~ 2432 crore. 60 Districts are outliers and corner 35.75% of the total NCF PSA available.

SF/ MF PSAs

SF/ MF PSAs, a sub-type of agricultural PSA, is also concentrated in the southern and western part of the country as shown in Figure 5-7. The district- median outstanding PSA to SF/ MF is ~₹750 crore with an IQR of ~₹1558 crore. 68 districts are outliers and constitute 41.09% of the total PSA to SF/ MF. While the overall CAGR for SF/ MF PSAs is ~14.1%, there is significant geographical variation with many districts reporting degrowth. Details are shown in Figure 5-8.

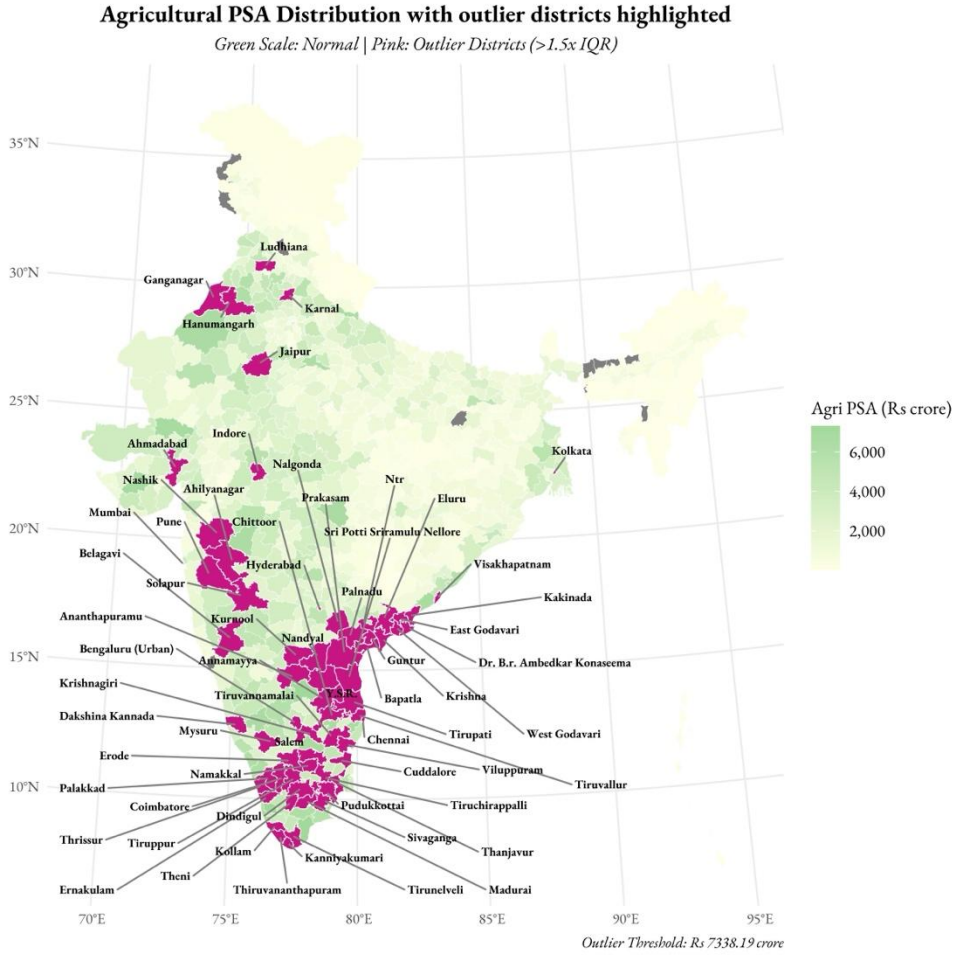

Figure 5-5 Geographical distribution of agricultural PSAs

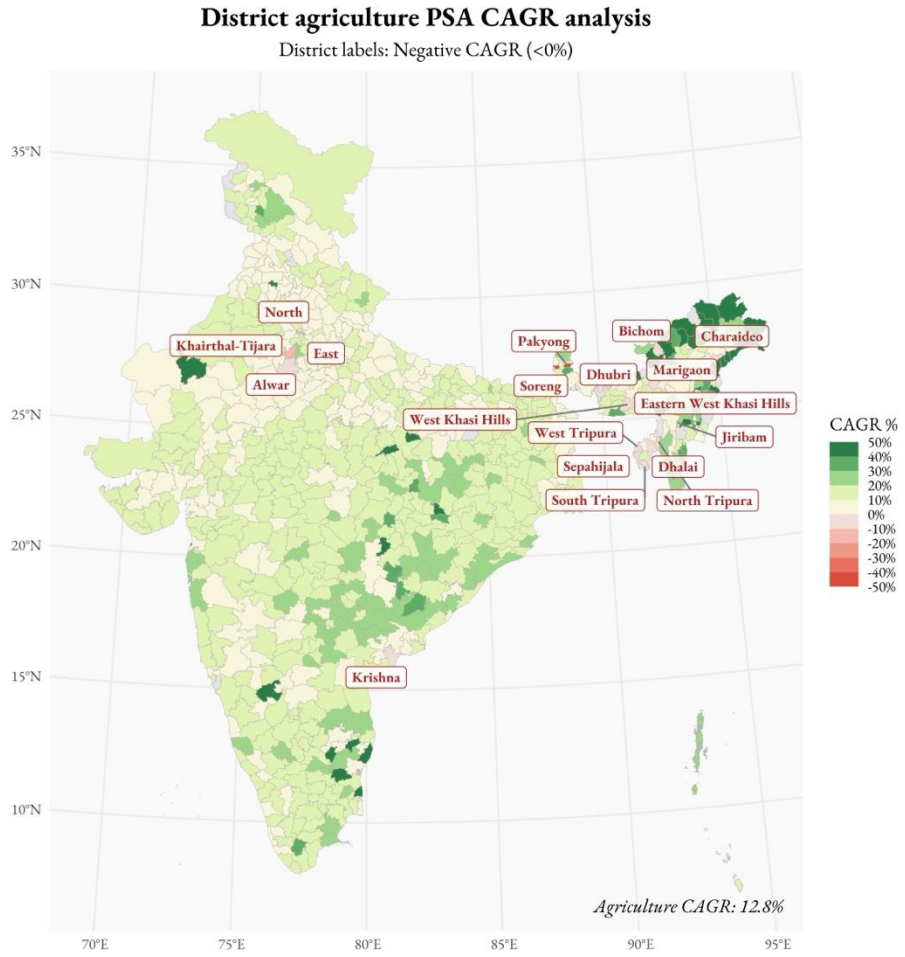

Figure 5-6 Geographical distribution of agriculture PSAs CAGR. *Scale has been curtailed to +/- 50% to aid visualisation. District labels represent districts with negative CAGR.*

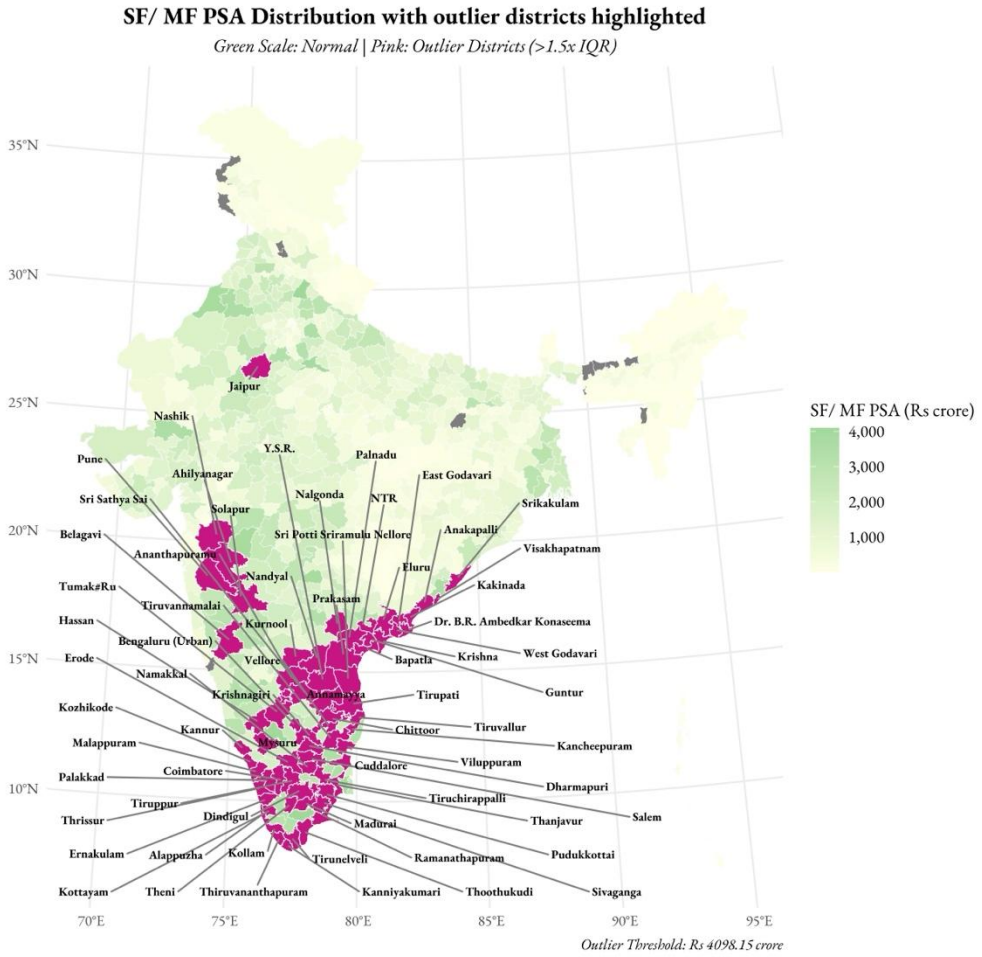

Figure 5-7 Geographical distribution of PSAs to SFs/ MFs

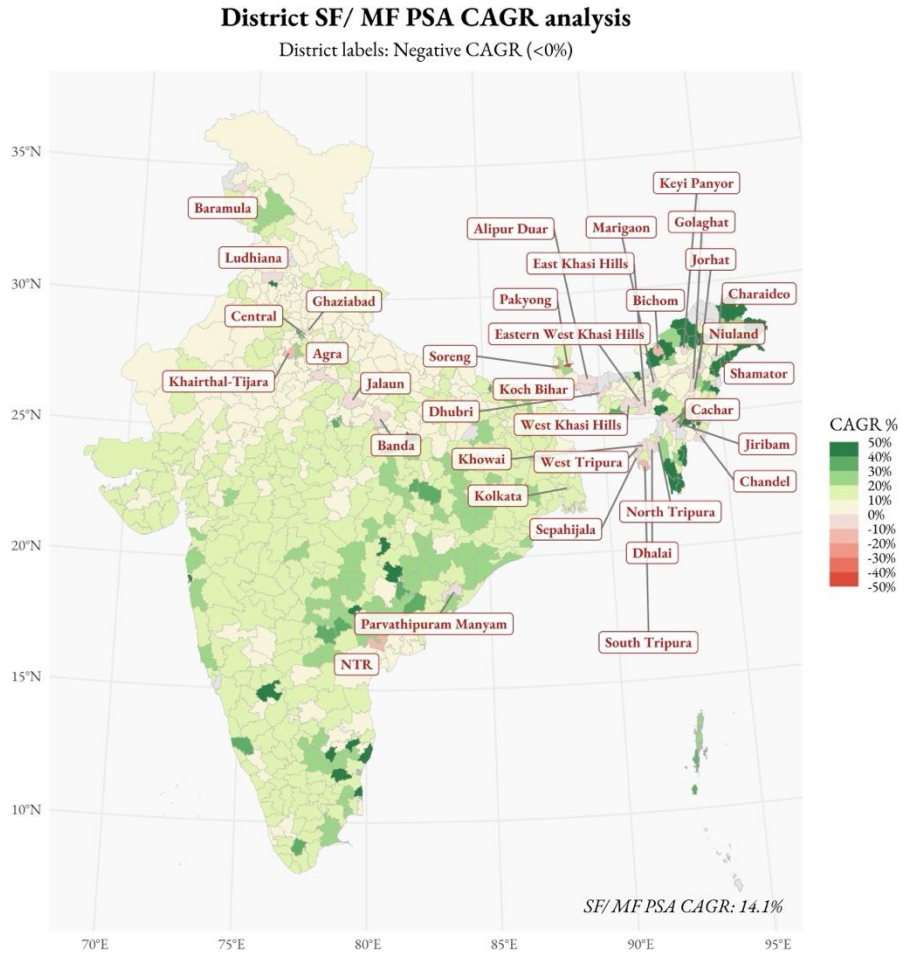

Figure 5-8 Geographical distribution of SF/ MF PSAs CAGR. *Scale has been curtailed to +/- 50% to aid visualisation. District labels represent districts with negative CAGR.*

Micro PSAs

The district- median of Micro enterprise PSA (Micro PSA) is ~₹580.53 crore per district with an IQR of ₹1061.95 crore. 81 Districts were outliers and cornered nearly 55.8% of the PSAs available for micro enterprises. The geographical distribution of Micro PSAs is provided in Figure 5-9. Outlier districts are highlighted and labelled. While the distribution appears more geographically dispersed in comparison to agricultural PSAs, the underserved areas remain similar. Micro PSAs are growing at a healthy CAGR of 18.5% overall. The geographical distribution is shown in Figure 5-10. Districts showing negative CAGR are labelled.

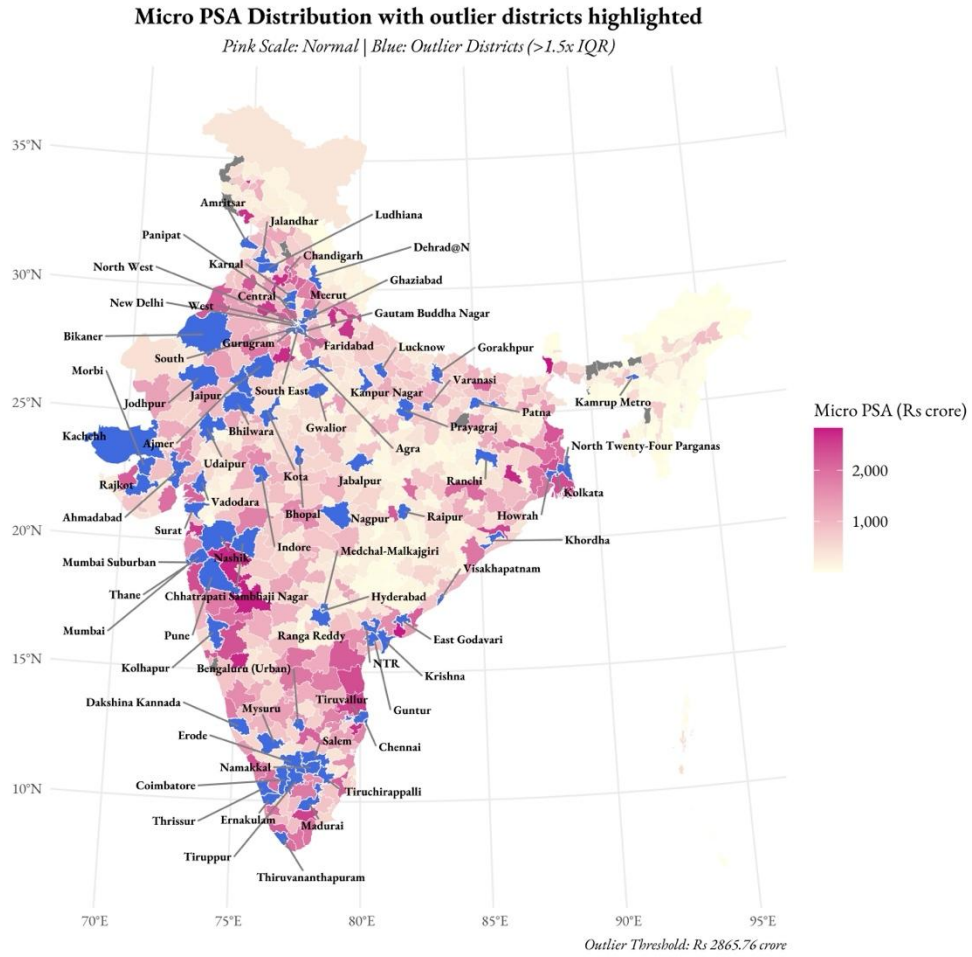

Figure 5-9 Geographical distribution of PSAs to micro enterprises

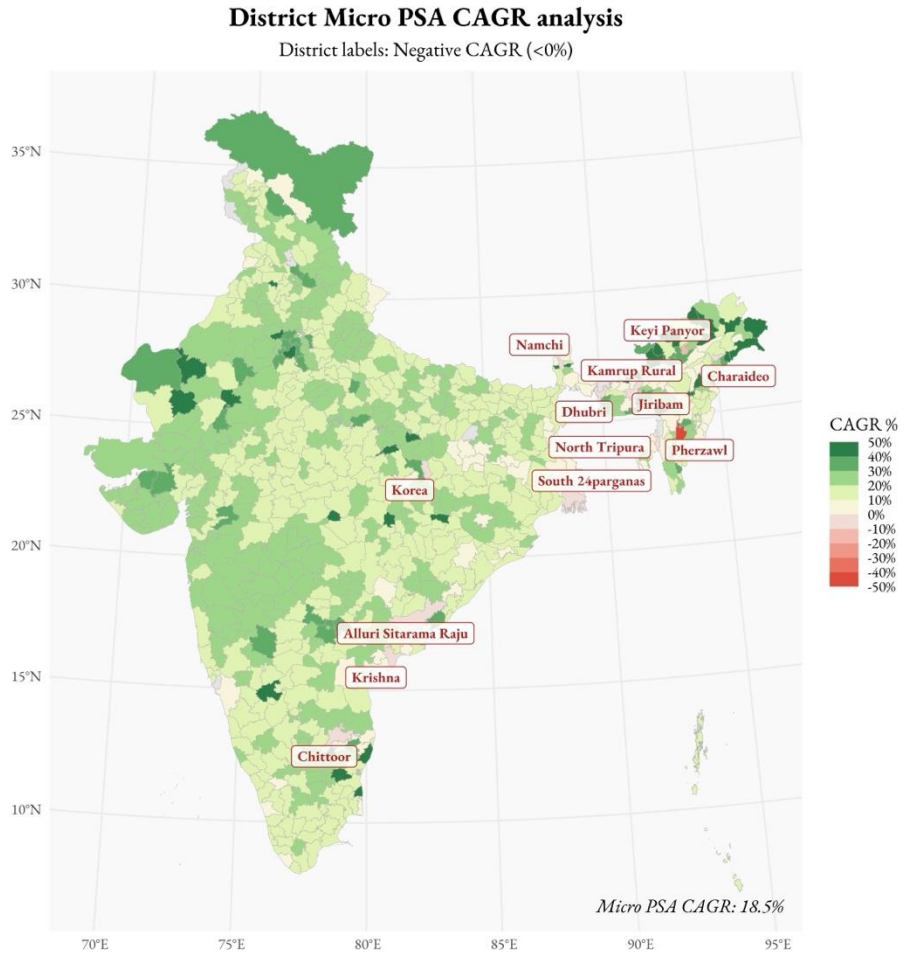

Figure 5-10 Geographical distribution of SF/ MF PSAs CAGR. *Scale has been curtailed to +/- 50% to aid visualisation. District labels represent districts with negative CAGR.*

Weaker sections

The median PSA in the overlapping category of weaker sections is ~₹1053 crores per district with an IQR of ~₹1990 crores. 69 Districts that cornered 38.75% of the total PSA to Weaker Sections were identified as outliers. As shown in Figure 5-11, these outlier districts are skewed towards the southern and western parts of the country. Weaker sections PSAs are growing at a CAGR of 13.1%. As seen from Figure 5-12, many districts have reported a degrowth in their weaker section PSAs, primarily located in the northeast.

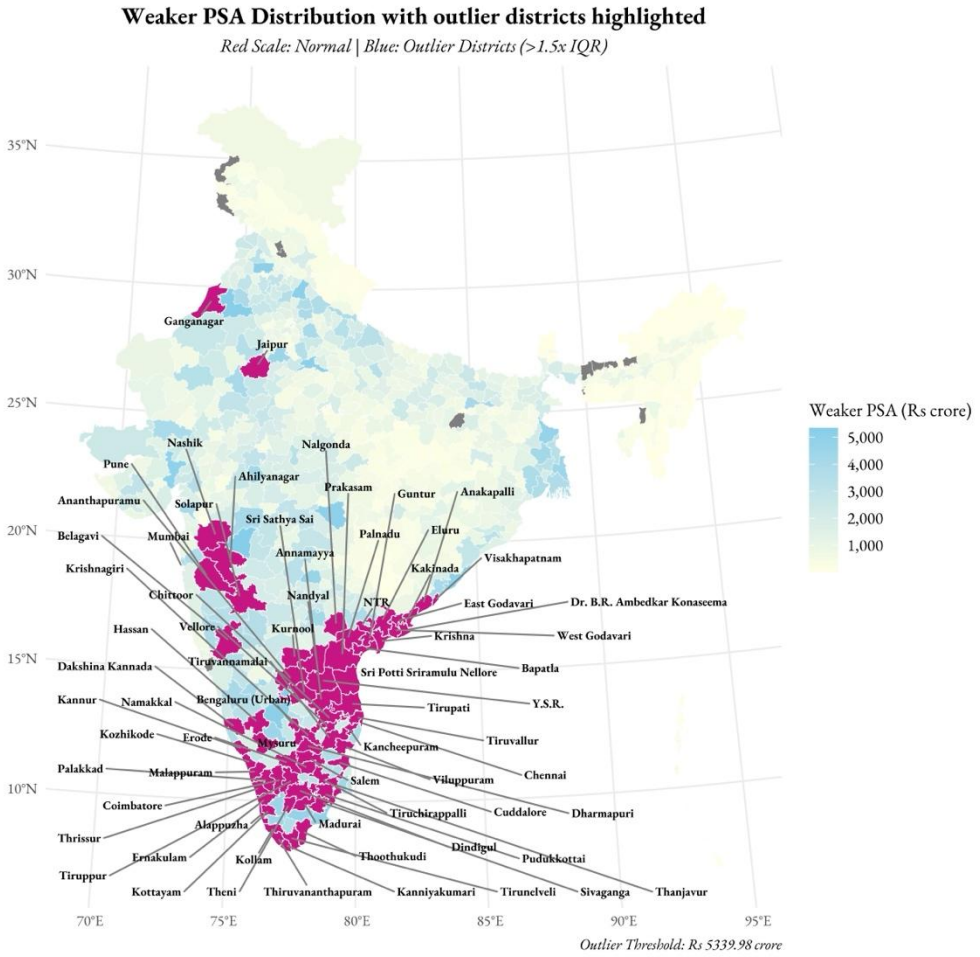

Figure 5-11 Geographical distribution of PSAs to Weaker Sections

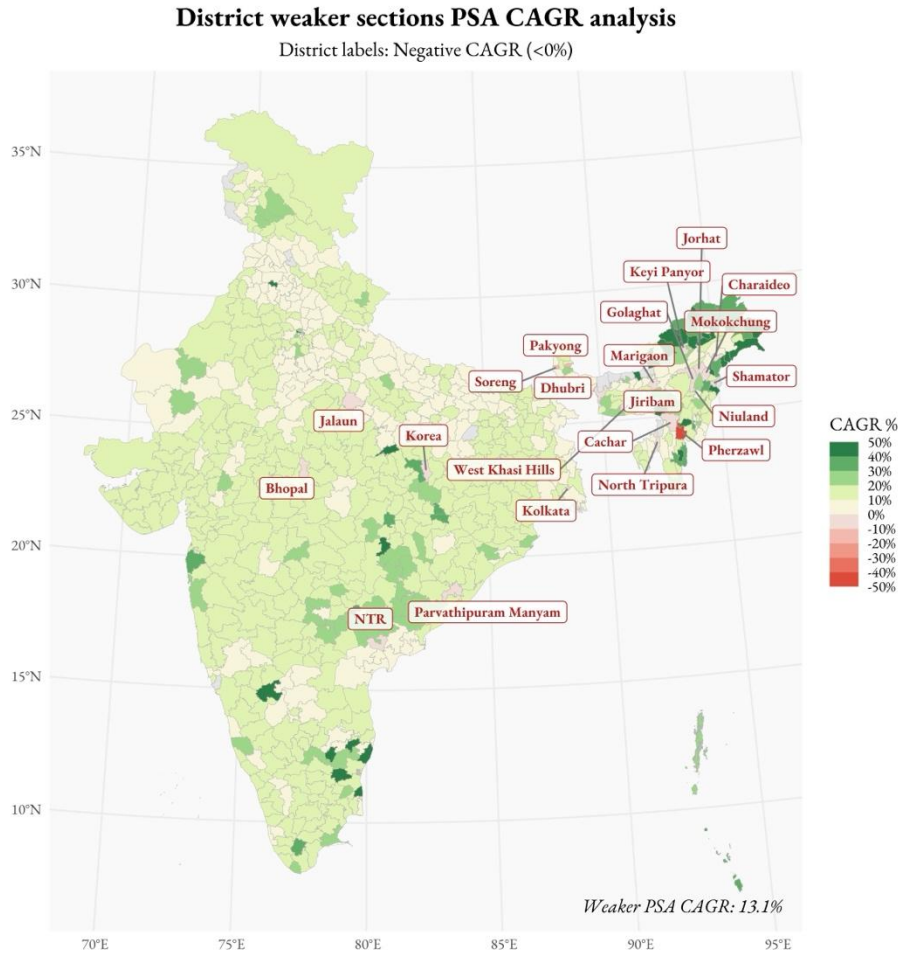

Figure 5-12 Geographical distribution of CAGR of weaker sections PSAs. *Scale has been curtailed to +/- 50% to aid visualisation. District labels represent districts with negative CAGR.*

Per capita distribution of PSA

The distributions of PSA were also normalised between districts in per capita terms. For this calculation, the district population was estimated using the Periodic Labour Force Survey (PLFS). The districts reported in PLFS were mapped to the latest districts as per data available on mergers, renaming etc. wherever possible. While the primary objective of PLFS (conducted by the National Sample Survey of India and sponsored by the Ministry of Statistics and Programme Implementation) is to estimate key employment and unemployment indicators (including worker population ratio, labour force participation rate, unemployment rate etc.)[18] it also provides district level worker and population data. To mitigate the shortcomings of the limited sample survey methodology used in PLFS, this study does not use the district wise population results (which have wide quarter to quarter variation) like a panel dataset, rather the district wise figures obtained from the last two calendar years of survey (2023 and 2024) were averaged between all quarters, and the estimates have been applied to average PSA in each district only for the purpose of normalisation.

The resulting average PSA per capita distributions are particularly useful in identifying districts where PSAs are low in per capita terms. As before, the upper outliers have been identified as districts receiving a per capita PSA allocation that is more than an upper fence defined by the 75th percentile + 1.5 times the IQR. The IQR methodology is not useful for identifying lower outliers as the distribution is skewed on

[18] and not for estimating population statistics *per se*.

the right. Accordingly, the lower outliers have been defined as districts receiving an allocation below the 10th percentile of per capita allocation.

Figure 5-13 shows the distribution of overall PSA per capita, which has been calculated as the ratio of average overall PSA and average total population in the district. The figure shows that lower outliers are clustered in the northeast and are also found in the eastern regions of the country.

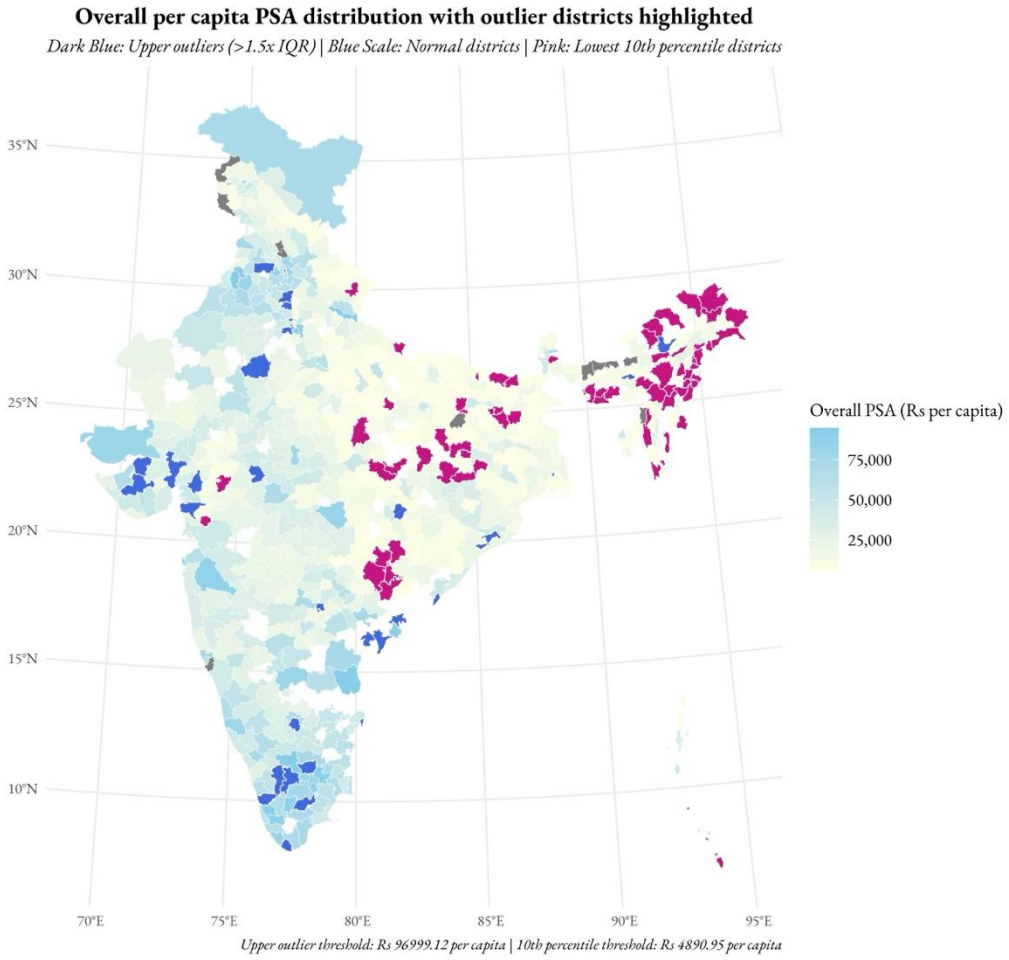

Figure 5-13 Geographical distribution of overall PSA per capita (average)

Figure 5-14 shows the distribution of agriculture PSA per capita, which has been calculated as the ratio of average agriculture PSA and average number of workers engaged in agriculture (or allied activities)[19] in the district. The figure shows that clustering of lower outlier districts is very similar to overall PSA, however, the distribution of upper outliers is different.

[19] Using two digit NIC codes 01, 02, 03, 10, 11 & 12.

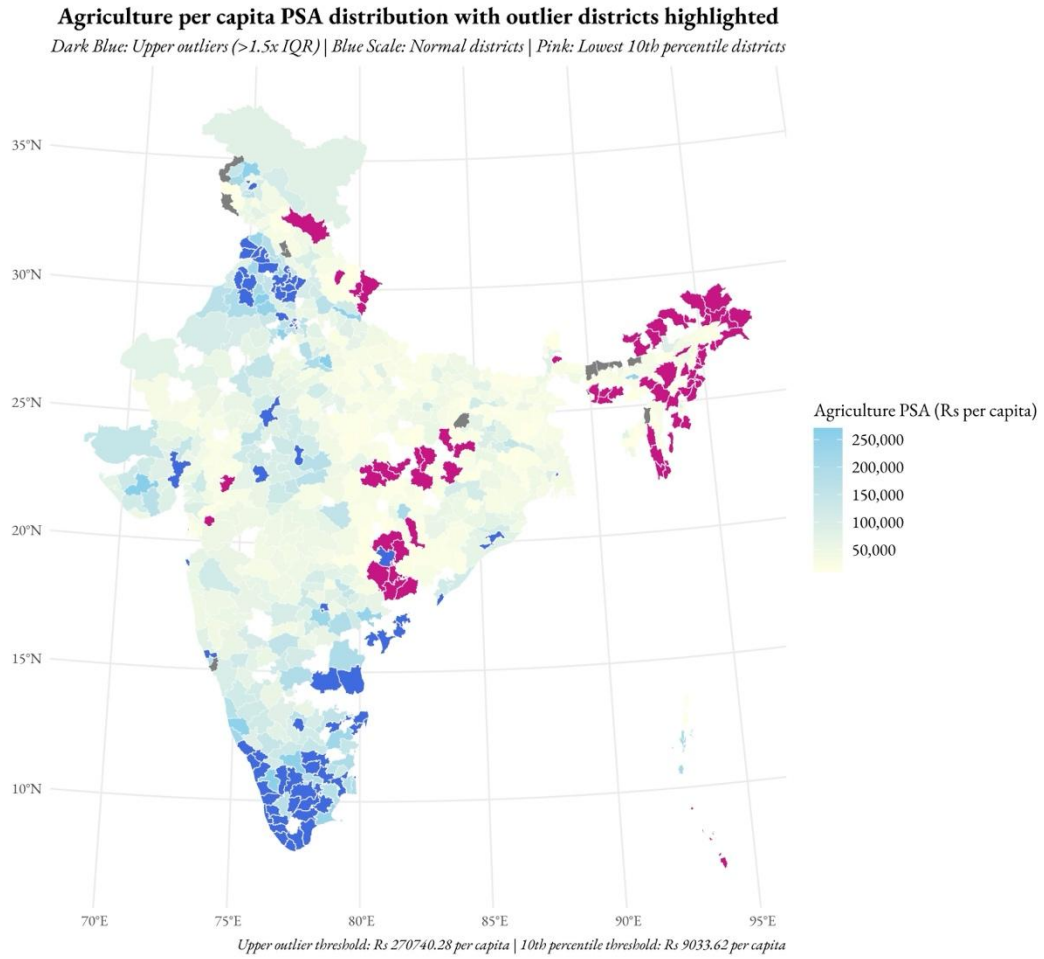

Figure 5-14 Geographical distribution of agriculture PSA per capita (average)

The distributions of MSME and Micro PSA per capita are shown in Figures 5-15 and 5-16 respectively. The population denominator used while calculating MSME PSA per capita is the average number of non-farm labour[20] in the district, while for Micro PSA it is the average number of workers involved in enterprises employing less than 20 workers.[21] These figures show that the clustering of lower outlier districts is very similar to overall PSA.

[20] Estimate of the total number of workers except those involved in NIC codes 01, 02 and 03

[21] While the definition of MSME in India is not based on capital employed and annual revenue, these figures are not available in the PLFS data, which does provide the number of workers engaged by the employer's enterprises. The figure of <20 workers has been used as a proxy for micro enterprises. The total number of workers used is more than international definitions for micro enterprises (which generally have <5 workers) to account for the more labour-intensive nature of Indian industry.

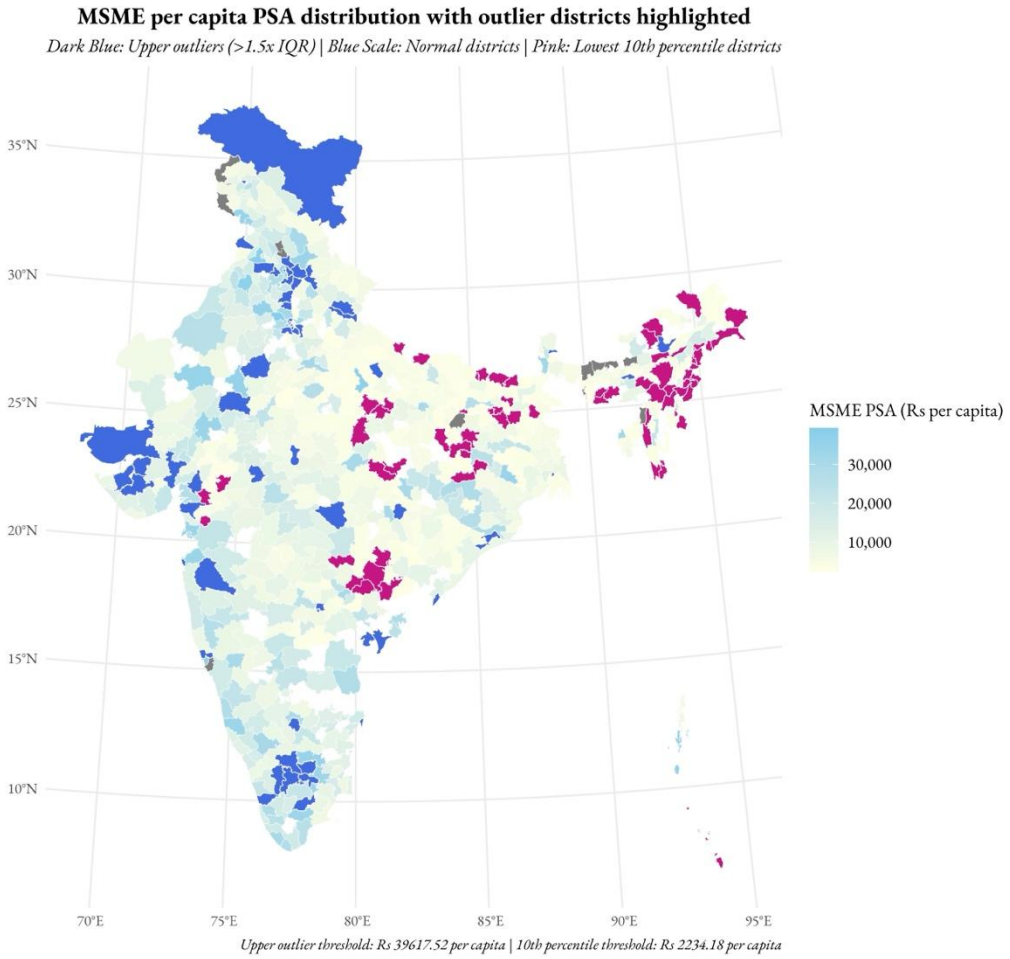

Figure 5-15 Geographical distribution of MSME PSA per capita (average)

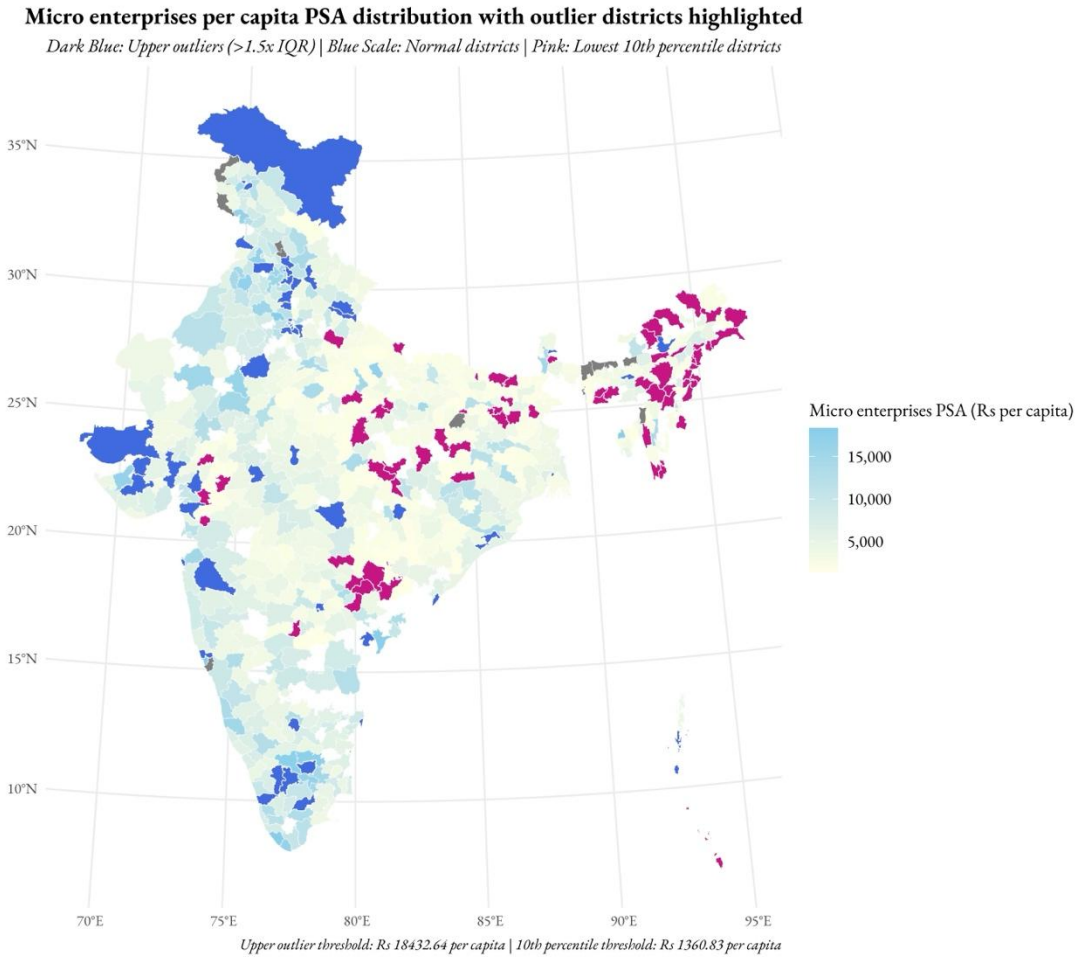

Figure 5-16 Geographical distribution of micro enterprises PSA per capita (average)

The distribution of weaker sections PSA per capita is shown in Figures 5-17. The population denominator used is the average of total district population.[22] The figure shows a concentration of weaker section PSA in the southern states and a dearth of the weaker sections PSA in the northeast, eastern regions and certain Himalayan regions of the country.

[22] A specific proxy for the RBI definition of weaker sections could not be obtained from the PLFS data.

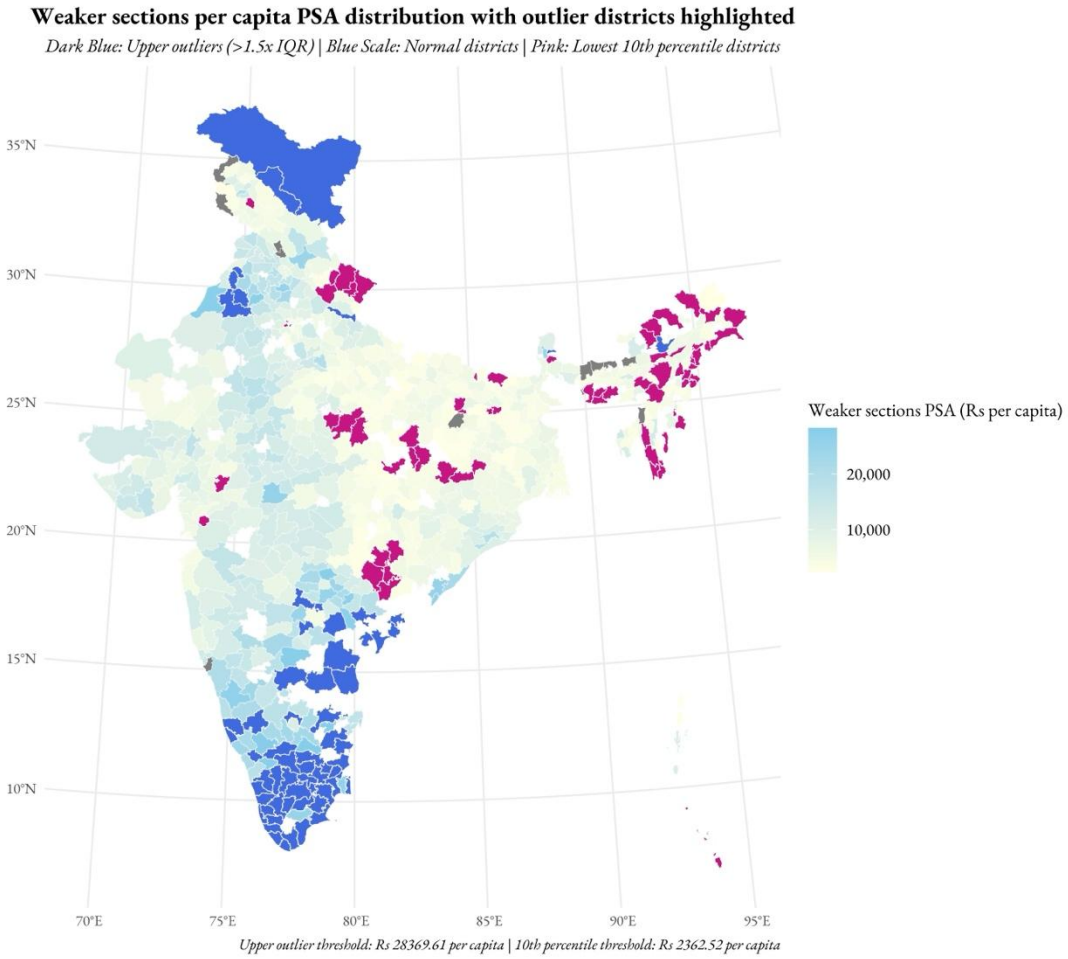

Figure 5-17 Geographical distribution of weaker sections PSA per capita (average)

Geographical distribution of PSA by bank type

Figure 5-13 shows the distribution of overall PSA (%) by bank type. An easily discernible feature is that many districts in the south that are prominent for SBI and Nationalized Banks are less so for Private Banks and SFBs. The distribution of PSAs for SFBs appears to be wider, but the underserved areas remain similar. The distribution is also similar for other types of PSAs as seen in Figures 5-14, 5-15 and 5-16 that show the distribution of agriculture, Micro and weaker sections PSAs respectively.

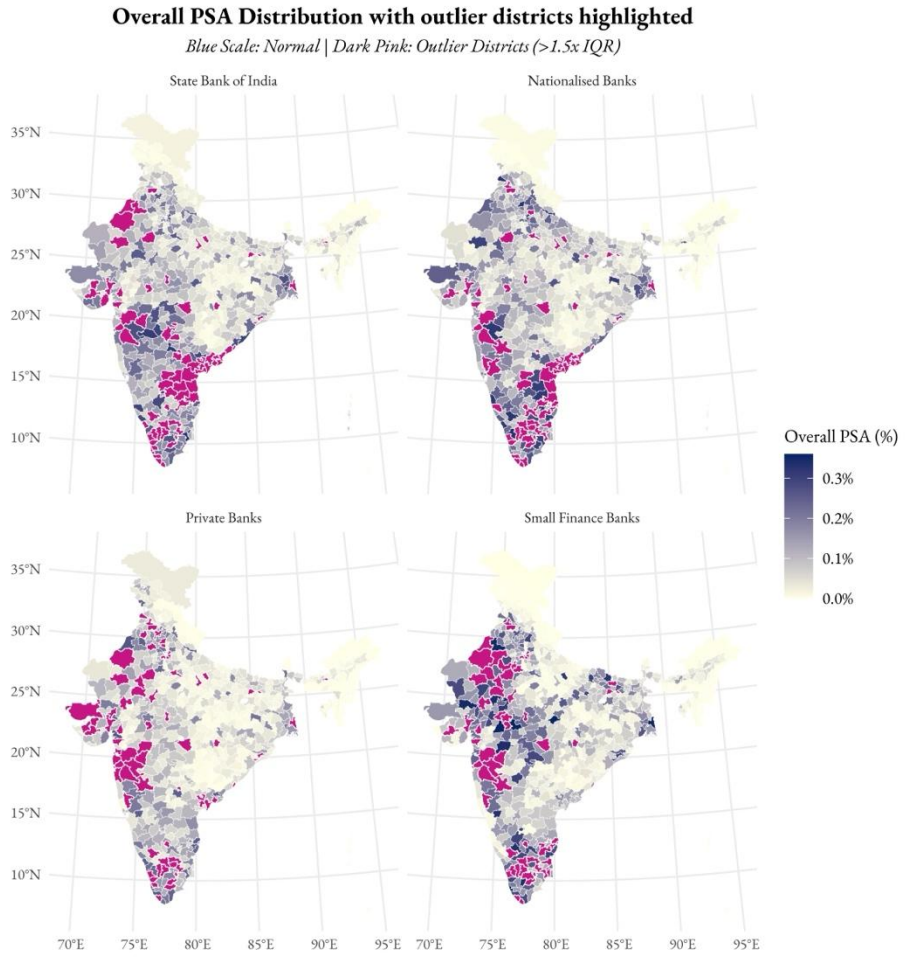

Figure 5-18 Distribution of overall PSA by bank type

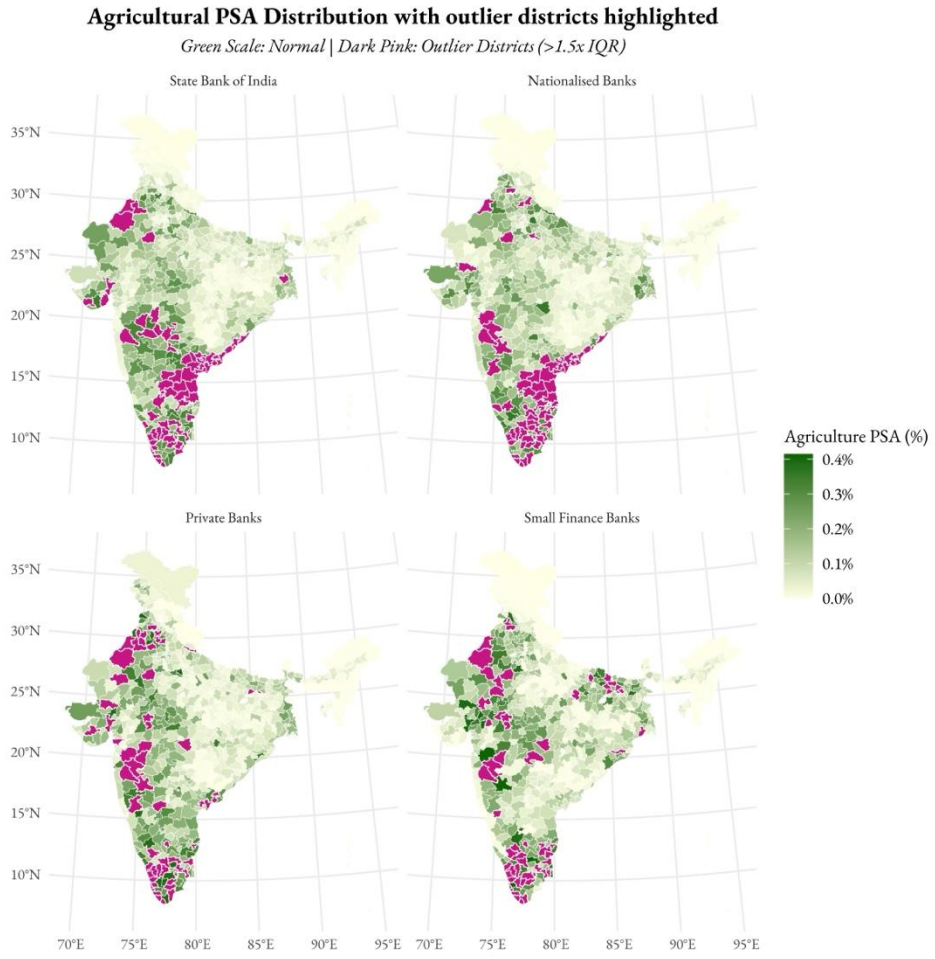

Figure 5-19 Distribution of agricultural PSA by bank type

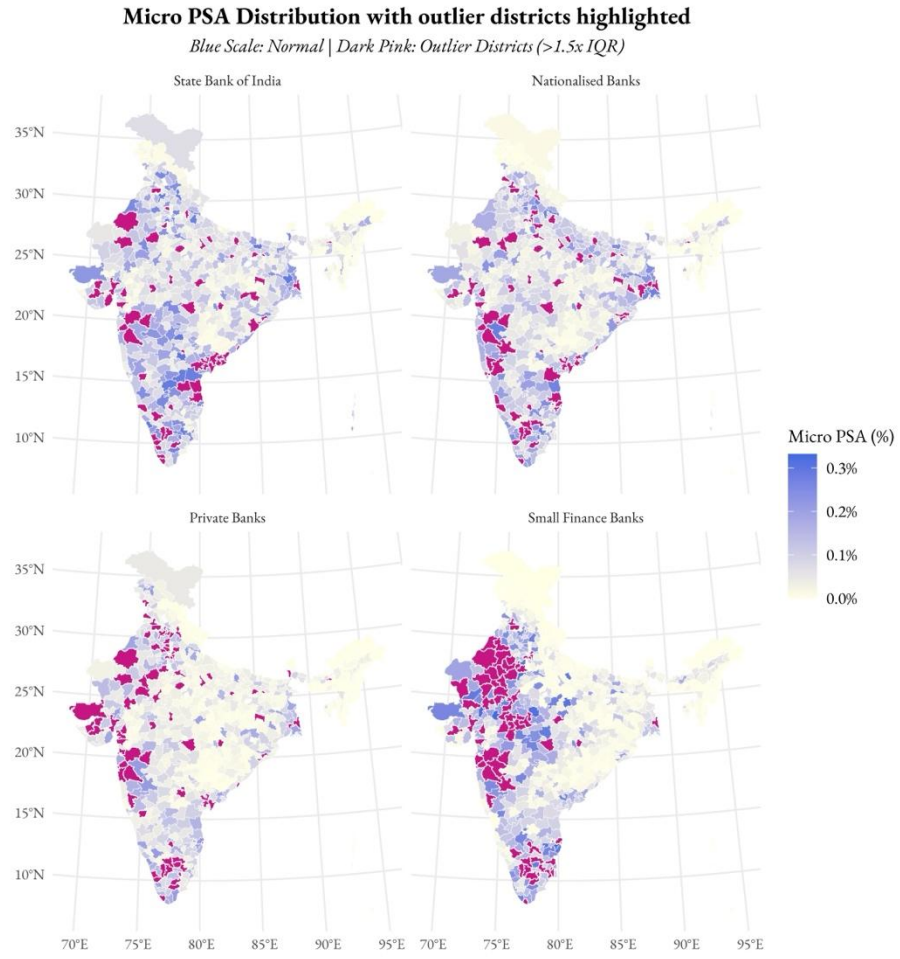

Figure 5-20 Distribution of Micro PSA by bank type

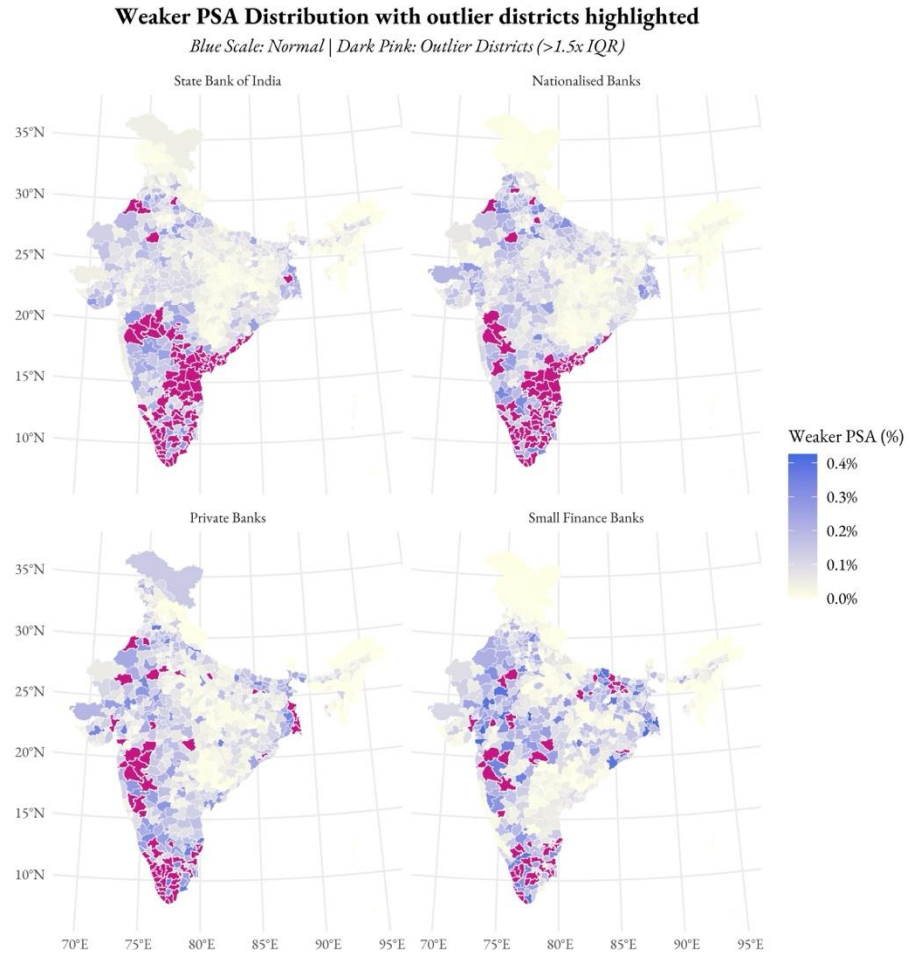

Figure 5-21 Distribution of weaker sections PSA by bank type

6. Impact of PSLC on PSA distribution

Purchase and sale of PSLCs are one of the most popular indirect mechanisms for extending PSAs. They are particularly relevant for agriculture, including the sub-component of lending to SFs/ MFs. They are also important for the overlapping category of weaker sections PSA and to a lesser extent, for Micro PSAs. This section examines the impact of PSLC on PSA distribution for these sectors.

Distribution of PSLC buyers and sellers

Banks can be divided into PSLC non-traders, PSLC buyers and PLSC sellers for each quarter based on their net outstanding PSLC balance at the end of each quarter. Bank category and quarter wise details of direct PSAs are provided in Table 6-1. On an average, outstanding PSAs (direct route) of PSLC non-traders is ₹5,61,493 crore, PSLC buyers is ₹21,50,401 crore and PSLC sellers is ₹21,50,401 crore.

Table 6-1 Number and outstanding direct PSA balance of PSLC non-traders, PSLC buyers and PSLC sellers in each quarter. *The definition of non-traders, buyers and sellers is based on the outstanding PSLC balance at the end of the quarter*

Quarter ended	PSLC non-traders		PSLC buyers		PSLC sellers	
	No	Direct PSA Rs Crore (%)	No	Direct PSA Rs Crore (%)	No	Direct PSA Rs Crore (%)
30/06/20	20	632583 (19.60%)	11	1823204 (56.48%)	11	772468 (23.93%)
30/09/20	16	574323 (17.20%)	11	1925098 (57.66%)	15	839191 (25.14%)
31/12/20	13	541204 (15.56%)	9	1681972 (48.36%)	20	1254603 (36.07%)

31/03/21	11	231314 (6.44%)	9	1498752 (41.73%)	22	1861820 (51.83%)
30/06/21	17	643739 (18.04%)	9	1977353 (55.42%)	16	946571 (26.53%)
30/09/21	15	317249 (8.63%)	8	1956471 (53.22%)	19	1402454 (38.15%)
31/12/21	9	159894 (4.15%)	8	1880857 (48.87%)	26	1807635 (46.97%)
31/03/22	3	7410 (0.18%)	11	1850211 (45.33%)	29	2224182 (54.49%)
30/06/22	13	700437 (17.03%)	8	1666984 (40.53%)	22	1745866 (42.44%)
30/09/22	11	415301 (9.88%)	9	1775056 (42.22%)	23	2014381 (47.91%)
31/12/22	11	324473 (7.49%)	11	1889629 (43.64%)	21	2116340 (48.87%)
31/03/23	8	240149 (5.29%)	9	1631431 (35.93%)	26	2668862 (58.78%)
30/06/23	13	619177 (13.44%)	12	2062427 (44.77%)	18	1925431 (41.79%)
30/09/23	12	549224 (11.00%)	12	2325779 (46.57%)	19	2119605 (42.44%)
31/12/23	11	535415 (10.32%)	13	2472455 (47.64%)	19	2182401 (42.05%)
31/03/24	7	426524 (7.92%)	15	1935765 (35.94%)	21	3024445 (56.15%)
30/06/24	17	1017786 (18.67%)	10	2140297 (39.26%)	16	2293319 (42.07%)
30/09/24	12	646373 (11.41%)	14	2597112 (45.83%)	17	2423270 (42.76%)
31/12/24	10	594226 (10.23%)	15	3051750 (52.54%)	18	2162757 (37.23%)
31/03/25	8	408953 (6.88%)	18	2781015 (46.79%)	17	2754008 (46.33%)
30/06/25	13	1349818 (21.62%)	17	3276378 (52.48%)	13	1617243 (25.90%)
30/09/25	8	616748 (9.89%)	15	2385426 (38.24%)	20	3236355 (51.88%)
31/12/25	9	1362015 (19.64%)	18	2873813 (41.43%)	16	2700835 (38.94%)
Average		**561493 (11.91%)**		**2150401 (45.60%)**		**2004089 (42.50%)**

PSLCs alter geographical distribution of PSAs

As PSLCs square up every quarter, they do not change the total PSAs extended at the national level. However, as the geographic areas of bank operations are different, PSLCs can affect the geographic distribution of PSAs- they divert PSAs from the areas of operation of PSLC buyers to the areas of operations of PSLC sellers.

If we divide banks based on the outstanding PSLC balance at the end of the FY, i.e., the final PSLC position of each bank[23], we can study the geographical distribution of average outstanding PSAs during a FY. Figure 6-1 shows the geographical distribution of average overall PSAs by PSLC buyers and sellers in each FY. The plot shows that while many of the districts of operations are common, PSA intensity of PSLC seller banks is higher in districts in the southern part of the country, particularly in years prior to 2025-26.

[23] Such a categorization makes logical sense, as each PSLC certificate is valid for the duration of the FY

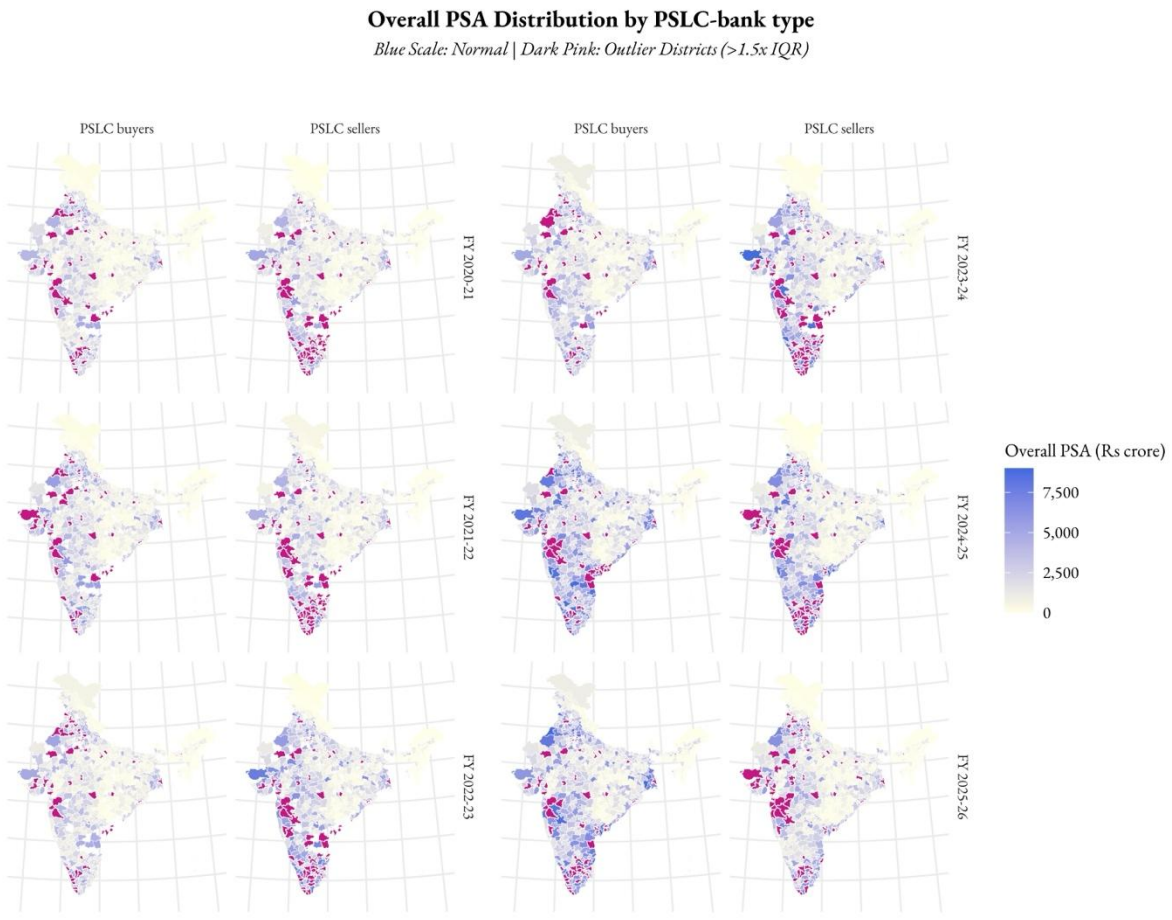

Figure 6-1 Distribution of overall PSA by PSLC bank type

The difference is more distinct when agricultural PSAs are considered as shown in Figure 6-2. PSLC buyer banks have a more widespread area of disbursement of agricultural PSAs, with fewer number of districts as outliers, while PSLC seller banks are highly concentrated in certain districts clustered towards the southern and western regions. Similar differences in distribution are also seen between PSLC buyer and seller banks in SF/ MF PSAs.

The distribution of PSAs to micro enterprises and weaker section by PSLC buyer and seller banks is shown is Figures 6-3 and 6-4 respectively. No obvious patterns emerge in PSAs for micro enterprises, however, for weaker sections a distributional pattern similar to agricultural PSAs is seen.

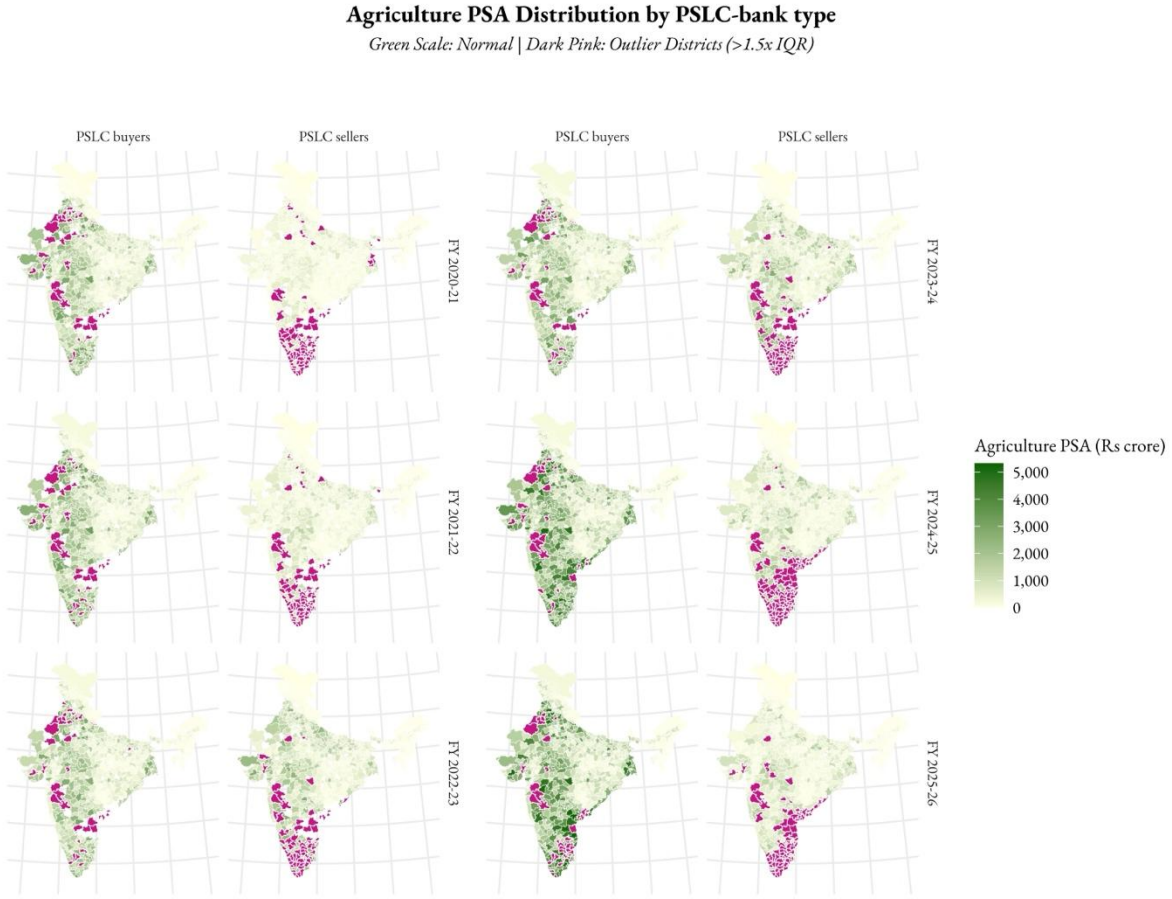

Figure 6-2 Distribution of agricultural PSA by PSLC bank type

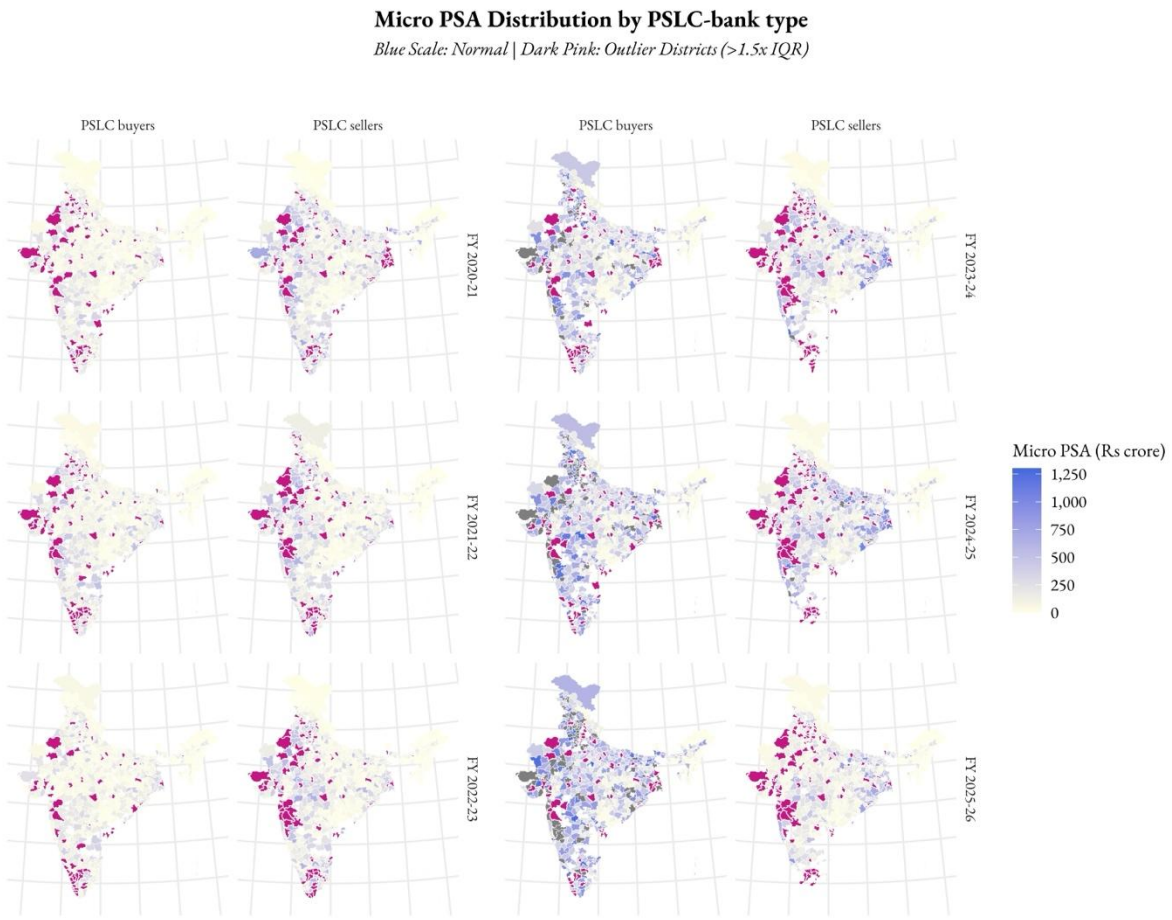

Figure 6-3 Distribution of micro enterprises PSA by PSLC bank type

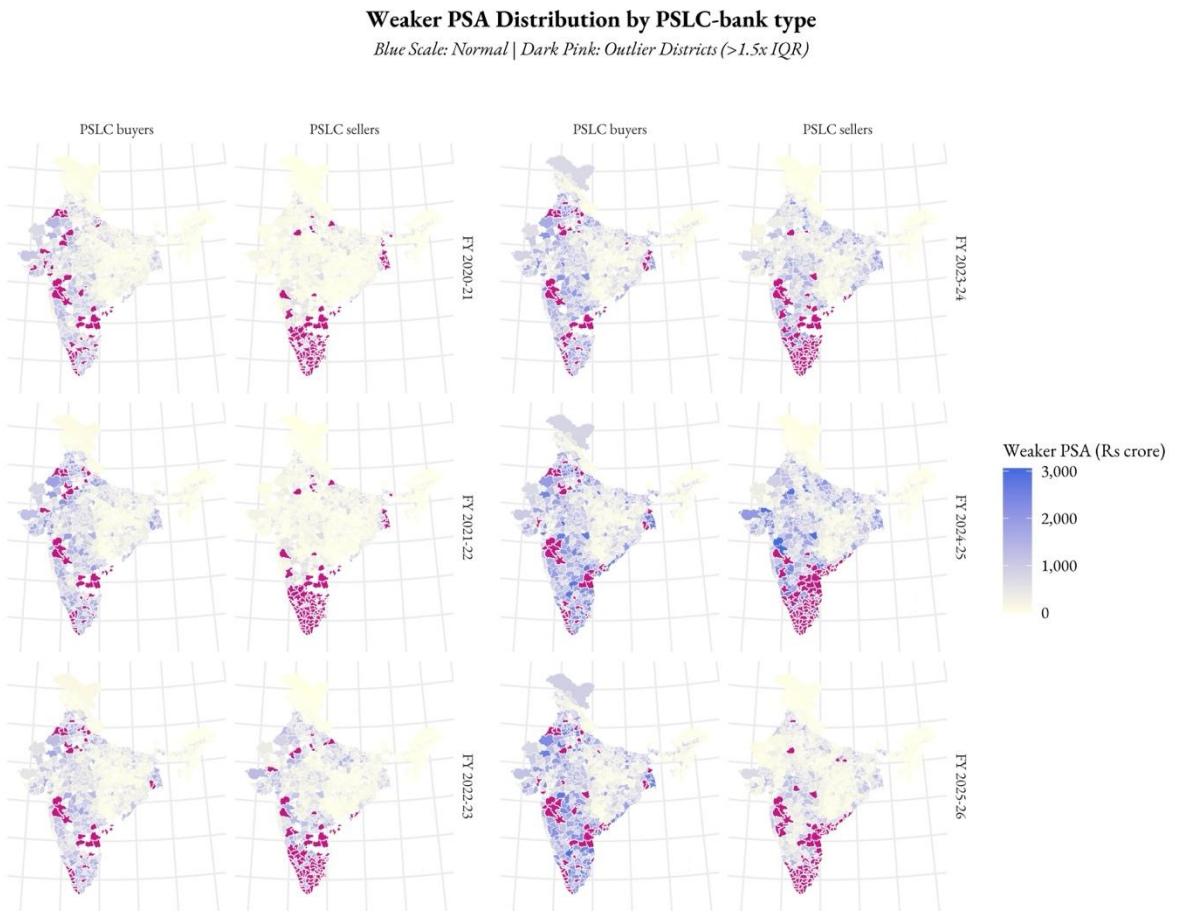

Figure 6-4 Distribution of weaker sections PSA by PSLC bank type

Negative correlation between PSLC buyer and seller banks PSA

To ascertain whether the district wise distributions of PSAs were correlated, Pearson correlation coefficients were calculated in each district between the PSAs provided by PSLC buyer and seller banks at the end of each quarter. A positive correlation indicates whether the decrease in district PSA from PSLC buyer banks will be offset by an increase in district PSA from PSLC seller banks. Negative correlation, however, is a cause for concern as the outstanding PSA balance in these districts will be affected by PSLCs, either positively- when the PSLC seller banks dominate or negatively- when PSLC buyer banks dominate in the district.

District showing statistically significant negative correlations have been plotted in Figure 6-5. Districts in blue (red) represent those where PSAs provided by PSLC selling banks are higher (lower) than those provided by PSLC buyer banks, i.e., these districts are those where PSLCs may have led to an increase (decrease) in the outstanding PSAs.

However, this negative correlation is only indicative of the possibility that PSLCs may be altering regional distribution of PSAs and the exact impact of PSLCs on district level PSA balance needs to be ascertained before conclusive statements can be made.

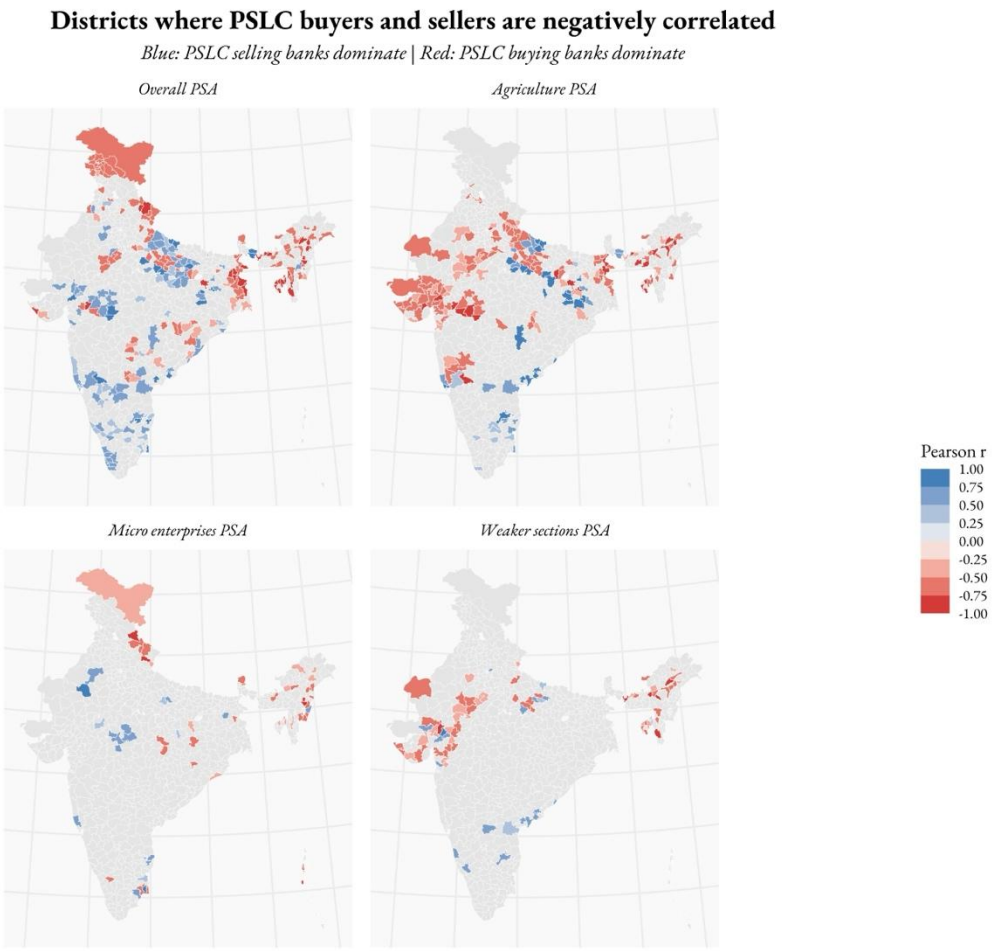

Figure 6-5 Districts where PSAs between PSLC buyer and seller banks are negatively correlated

Quantitative impact of PSLCs on geographical distribution of PSAs

To understand how PSLCs will alter the geographical distribution of PSAs by an individual bank, consider a simple model of PSLC purchase/ sale decisions by a representative bank. The model assumes a fixed cost of capital, i.e., it does not consider the liabilities side and focusses only on the asset side. It also assumes that banks take decisions independent of each other, i.e., there is no competition nor any impact of advances of one bank on the returns of others.

Assuming that there are two types of bank agents, district level managers (district managers) located in the district and supervisors located at the headquarter level (Bank Hq). The bank operates in $d \in \{1, \dots, n\}$ districts.

In a sequential game, district managers collect information $\mathcal{I}$ for district d at time $t-1$, i.e., $\mathcal{I}_{d,t-1}$ at the first step and arrive at rational expectations of how the baseline returns i change with advances a (in nominal terms) extended by the bank to sector θ (where θ comprises of either the priority sector p or other sectors o, i.e., $\theta \in \{p, o\}$) during the period t. The expectations of these functions have been designated as $\widehat{\mathbb{E}}[i_{d,\theta,t}(a_\theta) | \mathcal{I}_{d,t-1}]$.

District managers send signals $\mathcal{S}_d$ to the Bank Hq about the returns expected in their district in the next period. The Bank Hq only has access to $\mathcal{S}_d$ and does not have access to $\mathcal{I}_{d,t-1}$. It needs to arrive at

expected return functions considering $\mathcal{S}_d$ and use these functions to assign district level priority sector targets, $a_{d,p}^{\mathcal{T}}$ with an aim to maximise national level returns.

The district managers then allocate assets to the priority sector such that the allocation is weakly greater than the assigned target.

At the end of the period, the performance of district managers is evaluated based on two independent assessment criteria- one criterion is meeting priority sector target, and the other one is the realized return of the bank in the district.

Full information case: Bank Hq has access to $\mathcal{I}_{d,t-1}$

District manager's problem

The district manager aims to optimise district level returns in line with their assessment criteria. The manager will ascertain information to maximise the probability that the expected return function, $\widehat{\mathbb{E}}[.]$ approximates the true return function, $i_{d,\theta,t}(a_{d,\theta,t})$:

$$\mathcal{I}_{d,t-1} = \underset{\mathcal{I}_{d,t-1}}{\operatorname{argmax}} P\left(\widehat{\mathbb{E}}\left[i_{d,\theta,t}(a_{d,\theta,t})|\, \mathcal{I}_{d,t-1}\right] \sim i_{d,\theta,t}(a_{d,\theta,t})\right) \quad \textbf{(1)}$$

In the full information case the Bank Hq is assumed to have access to $\mathcal{I}_{d,t-1}$ and this prevents the district manager from sending any signal other than the true estimate of $\widehat{\mathbb{E}}[i_{d,\theta,t}(a_\theta)|\, \mathcal{I}_{d,t-1}]$, i.e.,

$$\mathcal{S}_d = \widehat{\mathbb{E}}[i_{d,\theta,t}(a_\theta)|\, \mathcal{I}_{d,t-1}] \quad \textbf{(2)}$$

Bank Hq's problem

The Bank Hq uses $\mathcal{S}_d = \widehat{\mathbb{E}}[i_{d,p,t}(a_\theta)|\, \mathcal{I}_{d,t-1}]$ to maximise the bank's overall (national level) return.

Assuming PSLCs are not available

In the absence of PSLCs, Bank Hq will decide on priority sector targets $a_{d,p}^{\mathcal{T}}$ as per the following maximisation problem:

$$a_{d,p,t}^{\mathcal{T}} = \underset{a_{d,p,t}}{\operatorname{argmax}} \sum_{d=1}^{n} \sum_{\theta} a_{d,\theta,t} \widehat{\mathbb{E}}[i_{d,\theta,t}(a_{d,\theta,t})|\, \mathcal{I}_{d,t-1}] \quad \textbf{(3)}$$

(Note: the marginal costs of extending loans to different sectors are subsumed within the expected returns for each type of assets)

The bank HQ's problem will be subject to the following two constraints:

First, total assets equal exogenously determined ANBC (*total asset constraint*):

$$\sum_{d=1}^{n} \sum_{\theta} a_{d,\theta,t} = ANBC_t \quad \textbf{(4)}$$

Second, the total assets allocated to the priority sector should meet the bank's PSA targets at the national level *(priority sector target constraint)* [24]:

$$\sum_{d=1}^{n} a_{d,p,t} \geq 0.4(ANBC_t)$$

(5)

Setting up the Lagrangian and finding the first order conditions (FOCs) reveals that when the priority sector target constraint is not binding, i.e., when the bank's profits are maximised at a solution that exceeds the priority sector targets, Bank Hq's optimization solution is same as the district managers optimization solution, i.e.,

$$\widehat{\mathbb{E}}[i_{d,o,t}(a_{d,o,t})|\,\mathcal{I}_{d,t-1}] + a_{d,o,t}\,\partial\widehat{\mathbb{E}}\big[i_{d,o,t}(a_{d,o,t})|\,\mathcal{I}_{d,t-1}\big]\Big/_{\partial a_{d,o,t}}$$
$$= \hat{E}[i_{d,p,t}(a_{d,p,t})|\,\mathcal{I}_{d,t-1}] + a_{d,p,t}\,\partial\widehat{\mathbb{E}}\big[i_{d,p,t}(a_{d,p,t})|\,\mathcal{I}_{d,t-1}\big]\Big/_{\partial a_{d,p,t}}\Big|_{a^{\mathcal{I}}_{d,p,t},a^{\mathcal{I}}_{e,p,t}}$$

(6)

The term $\widehat{\mathbb{E}}[i_{d,\theta,t}(a_{d,\theta,t})|\,\mathcal{I}_{d,t-1}] + a_{d,\theta,t}\,\partial\widehat{\mathbb{E}}\big[i_{d,\theta,t}(a_{d,\theta,t})|\,\mathcal{I}_{d,t-1}\big]\Big/_{\partial a_{d,\theta,t}}$ is the difference between the expected return from a particular asset type in a district *less* the expected decrease in absolute return when an additional unit of advance is provided to the same asset type in the district (as the differential is negative), and represents the *marginal return* in a district from the particular asset type. For notational purposes it is being shortened to $\mathbb{E}[\hat{\theta}_{d,t}|\,\mathcal{I}_{d,t-1}]$. Thus, the maximisation solution becomes:

$$\mathbb{E}[\hat{o}_{d,t}|\,\mathcal{I}_{d,t-1}] = \mathbb{E}[\hat{p}_{d,t}|\,\mathcal{I}_{d,t-1}]$$

(7)

The Bank Hq and the district manager both aim to equate the marginal returns to the bank from the priority and other sectors advances. This is because any additional asset allocation to either type at the expense of the other will reduce the total return given that i is a diminishing function of advances a.

The priority sector target assigned to the district will thus be equal to the district's return maximising priority sector allocation $a^{*}_{d,p,t}$.

Further, the following solutions holds irrespective of whether the priority sector target constraint is binding or not:

$$\mathbb{E}[\hat{o}_{d,t}|\,\mathcal{I}_{d,t-1}] - \mathbb{E}[\hat{p}_{d,t}\big|\,\mathcal{I}_{d,t-1}] = \delta_t$$

(8)

where δ_t is the Lagrange constant of the priority sector target constraint.

(8) implies that at the maximum, the difference between marginal returns from different sectors between districts will be the same and will equal the Lagrange constant for the priority sector target constraint, i.e., the marginal value of diluting the priority sector target for the Bank Hq.

[24] For simplicity, it is assumed that banks meet their priority sector obligations and that the penal returns act as sufficient deterrence from under investing in PSAs.

The targets for two districts d and e will be specified as under:

$$a_{d,p,t} = -\frac{\widehat{\mathbb{E}}[i_{d,p,t}(a_{d,p,t})|\,\mathcal{I}_{d,t-1}] - \widehat{\mathbb{E}}[i_{e,p,t}(a_{e,p,t})|\,\mathcal{I}_{e,t-1}]}{\widehat{\mathbb{E}}\left[\partial i_{d,p,t}(a_{d,p,t})|\,\mathcal{I}_{d,t-1}\big/\partial a_{d,p,t}\right]} + a_{e,p,t}\left.\frac{\partial\widehat{\mathbb{E}}\left[i_{e,p,t}(a_{e,p,t})|\,\mathcal{I}_{e,t-1}\right]\big/\partial a_{e,p,t}}{\partial\widehat{\mathbb{E}}\left[i_{d,p,t}(a_{d,p,t})|\,\mathcal{I}_{d,t-1}\right]\big/\partial a_{d,p,t}}\right|_{a^{\mathcal{T}}_{d,p,t},a^{\mathcal{T}}_{e,p,t}}$$

(9)

Considering that i is a diminishing function of advances a, and assuming that the returns are diminishing at an increasing rate, i.e. $\partial i/\partial a < 0$ and $\partial^2 i/\partial a^2 < 0$, the following relationship will hold:

$$a^{\mathcal{T}}_{d,p,t} > a^{\mathcal{T}}_{e,p,t} \Leftarrow \left\{\begin{array}{c}\hat{\hat{\mathbb{E}}}[i_{d,p,t}(a_{d,p,t})|\,\mathcal{I}_{d,t-1}] > \hat{\hat{\mathbb{E}}}[i_{e,p,t}(a_{e,p,t})|\,\mathcal{I}_{e,t-1}] \\ + \\ \left|\partial\widehat{\mathbb{E}}\left[i_{e,p,t}(a_{e,p,t})|\,\mathcal{I}_{e,t-1}\right]\big/\partial a_{e,p,t}\right| > \left|\partial\widehat{\mathbb{E}}\left[i_{d,p,t}(a_{d,p,t})|\,\mathcal{I}_{d,t-1}\right]\big/\partial a_{d,p,t}\right|\end{array}\right|_{a^{\mathcal{T}}_{d,p,t},a^{\mathcal{T}}_{e,p,t}}$$

(10)

From (10) we can infer that the priority sector target for district d will exceed priority sector target for district e when the expectation of the return is higher and the decrease in return with increase in assets is smaller in d.

As the Bank Hq is only constrained to meet the priority sector targets at the national level, the district level priority sector target $a^{\mathcal{T}}_{d,p,t}$ could be below 40% of the district advances depending on the district level heterogeneity in returns. Further, the target assigned to the district may be above or below the district's return maximising priority sector allocation $a^{*}_{d,p,t}$. After the target is assigned, bank managers will advance $a_{d,p,t}$ to the priority sector as per the following:

$$a_{k,p,t} = \begin{cases} a^{*}_{k,p,t} & ;\, a^{\mathcal{T}}_{k,p,t} < a^{*}_{k,p,t} \\ a^{\mathcal{T}}_{k,p,t} & ;\, a^{\mathcal{T}}_{k,p,t} \geq a^{*}_{k,p,t} \end{cases}$$

(11)

It follows from (9), (10) and (11) that there will be endogeneity in the observed $a_{d,p,t}$ when compared with district economic parameters like growth, provided $\widehat{\mathbb{E}}[i_{d,p,t}(a_{d,p,t})|\,\mathcal{I}_{d,t-1}] \sim i_{d,p,t}(a_{d,p,t})$.

With PSLCs but excluding other indirect PSA mechanisms

The availability of indirect PSA mechanisms modifies the analysis. If we assume that PSLCs are the only indirect PSA instrument available to the Bank, and that the Bank Hq can purchase $j \in \{1, \ldots, m\}$ tranches of PSLCs with each tranche costing c_j at time t, the maximisation problem becomes:

$$a^{\mathcal{T}}_{d,p,t} = \underset{a_{d,p,t}}{\operatorname{argmax}} \sum_{d=1}^{n} \sum_{\theta} a_{d,\theta,t} \widehat{\mathbb{E}}[i_{d,\theta,t}(a_{d,\theta,t}) | \mathcal{I}_{d,t-1}] - \sum_{j=1}^{m} c_{j,t} PSLC_{j,t}$$

(12)

(For seller banks, the cost c_j is negative, and they increase their returns from sale of PSLCs)

The new maximisation problem remains subject to the total asset constraint:

$$\sum_{d=1}^{n} \sum_{\theta} a_{d,\theta,t} = ANBC_t$$

(13)

however, the priority sector target constraint gets modified. The total assets allocated to the priority sector *plus* PSLCs balance will now *exactly* meet the PSA targets at the national level:

$$\sum_{d=1}^{n} a_{d,p,t} + \sum_{j=1}^{m} PSLC_{j,t} = 0.4(ANBC_t)$$

(14)

FOCs reveal that the Bank Hq's optimization solution is no longer the same as the district managers optimization solution. Bank Hq's will now set the weighted average of cost of all tranches of PSLC, $\overline{c_t}$ as follows:

$$\mathbb{E}[\hat{o}_{d,t} | \mathcal{I}_{k,t-1}] - \mathbb{E}[\hat{p}_{d,t} | \mathcal{I}_{d,t-1}] = \delta_t = \overline{c_t}$$

(15)

The Bank Hq thus purchases PSLCs at a weighted average cost that equals its marginal value from diluting the priority sector target constraint. The intuition being that when the difference in marginal returns is higher, the bank will want to invest in other assets over the priority sector and will be willing to purchase PSLCs at a higher cost in order to maximise profits.

An evaluation of (15) provides the following conclusions:

First, as the district's return maximising problem requires that the left side of (15) be zero, $a^{\mathcal{T}}_{d,p,t} \neq a^{*}_{d,p,t}$.

Proposition 1: The district manager does not have an incentive to report an accurate signal to Bank Hq in the presence of PSLCs

Second, the quantum of net PSLCs will impact $a^{\mathcal{T}}_{d,p,t}$, and as the district manager provides PSAs as per (11) above, the quantum of PSLCs will correlate with the $a_{d,p,t}$ in the district.

Proposition 2: Quantum of the bank's net PSLC balance will influence the observed PSAs at the district level

And third, if we assume that the price of PSLCs is exogenously determined on the exchange, the quantum of PSLCs purchased by the bank at the national level will not be endogenous to a district's economic parameters like growth.

Proposition 3: Net PSLC balance of the bank is exogenous to district economic parameters

Asymmetric information case

District manager's problem

In the asymmetric information case, the district manager continues to collect $\mathcal{I}_{d,t-1}$ and set $\widehat{\mathbb{E}}[i_{d,\theta,t}(a_{d,\theta,t})|\,\mathcal{I}_{d,t-1}]$ at the level that optimises district level returns, however, the manager can now send any $\mathcal{S}_d = \dot{\mathbb{E}}[.]$ to the Bank Hq within reasonable bounds.

From the model assumptions, it can be shown that district managers will set $\mathcal{S}_d$ to ensure that the Bank Hq sets $a^{\mathcal{T}}_{d,p,t} \leq a^{*}_{d,p,t}$. Using backward induction, there are only two scenarios where the district manager has any incentive to set $\mathcal{S}_d = \widehat{\mathbb{E}}[i_{d,p,t}(a_\theta)|\,\mathcal{I}_{d,t-1}]$. The first is when PSLCs are not available and the profit maximisation solution of the bank lies at a point where the PSA target of the bank are achieved. The second is when PSLCs are available and the PSA target is expected to be met exactly, i.e., with no PSLC purchase. In both these scenarios $a^{\mathcal{T}}_{d,p,t} = a^{*}_{d,p,t}$. While the former is purely theoretical, the latter is unlikely and the weakly dominant strategy will be to minimise $a^{\mathcal{T}}_{d,p,t}$.

Taking the returns in all other district as given, the district manager will set $\mathcal{S}_d$ to maximise purchase of PSLCs and minimise their priority sector target:

$$\mathcal{S}_d = \underset{i_{d,p,t}}{\operatorname{argmax}}\, \mathbb{E}[\hat{o}_{d,t}|\,\mathcal{I}_{d,t-1}] - \mathbb{E}[\hat{p}_{d,t}|\,\mathcal{I}_{d,t-1}]$$

(16)

Accordingly, the expected returns on priority sector (other) assets will be under (over[25]) projected and their decrease with an increase in allocation is over (under) projected, i.e.,

$$\mathcal{S}_d = \begin{cases} \dot{E}[\hat{o}_{d,t}|\,\mathcal{I}_{d,t-1}] \geq E[\hat{o}_{d,t}|\,\mathcal{I}_{d,t-1}] \\ \dot{E}[\hat{p}_{d,t}|\,\mathcal{I}_{d,t-1}] \leq E[\hat{p}_{d,t}|\,\mathcal{I}_{d,t-1}] \end{cases}$$

(17)

The bounds for this under projections will be the district managers *expectation* of the minimum value the Bank Hq will accept without questioning the integrity of the signal. Such an expectation can be based on many factors that includes prior period marginal returns, any reported major economic events etc.

Bank Hq's problem

Bank Hq will form its own expectations $\tilde{E}[.]$ of the asset return functions based on the signal. Being aware of the district manager's incentives, the Bank Hq will set them as following:

$$\tilde{E}[\hat{p}_{d,t}|\,\mathcal{S}_{d,t-1}] > \mathcal{S}_d = \dot{E}[\hat{p}_{d,t}|\,\mathcal{I}_{d,t-1}]$$

$$\tilde{E}[\hat{o}_{d,t}|\,\mathcal{S}_{d,t-1}] \approx \mathcal{S}_d = \dot{E}[\hat{o}_{d,t}|\,\mathcal{I}_{d,t-1}]$$

(18)

and use these expectations to set targets as with the full information case. The main difference in the results from the full information case will be that the endogeneity in the observed $a_{d,p,t}$ when compared with district economic parameters like growth will reduce as the accuracy of $\tilde{E}[i_{d,p,t}(a_{d,p,t})|\,\mathcal{S}_{d,t-1}]$ reduces.

[25] While under projection of priority sector return and over projection of other asset returns are theoretically possible, loss aversion will imply that under projection in priority sector returns is much more likely

Application to the empirical dataset

One of the key insights from the above discussion was that an increase or decrease in the direct PSA by a bank on account of sale or purchase of PSLCs will impact all districts where the bank is in operation. The most appropriate allocation key for this change would ideally be the difference between the marginal returns from other assets and priority sector assets in the district. While this is not available, from the model we know profit maximising allocation of PSAs between districts ensures that the difference between the marginal returns from other assets and priority sector assets are equal. If we assume that returns from other assets are similar across the country (which is a strong assumption), the ratio of marginal allocation of PSAs between districts, i.e., the ratio of the increase in priority sector assets in a district by the bank to the total increase in priority sector assets by the bank during the quarter, can be used as a proxy for the returns on priority sector assets and for the allocation of PSLCs. For notational purposes, this is being referred to as the marginal allocation key.

The allocation of PSLC to a district d at time t is thus given by the following:

$$PSLC_{d,t} = \sum_{b} \Delta PSLC_{d,t,b} \times \left(\frac{\Delta PSA_{d,t,b}}{\sum_{d} \Delta PSA_{d,t,b}} \right)$$

(19)

Such an allocation also assumes that PSLCs have been bought by banks against extending PSAs directly and not in competition with other indirect PSA mechanisms.

The geographical distribution of overall PSAs based on the marginal allocation key on account of PSLCs can be observed from Figure 6-6. No clear district wise pattern emerges from the allocation, with the same district showing an increase and decrease in average PSAs during consecutive FYs. It may reflect the utility of the PSLC scheme for bank, allowing it to reallocate assets based on returns varying between time and districts. Similarly, there is also no obvious pattern in the impact of PSLCs on the geographical distribution of specific types of PSAs. The impact on PSAs towards Agriculture, SFs/ MFs, Micro enterprises and weaker sections is shown in Figures 6-7, 6-8, 6-9 and 6-10 respectively.

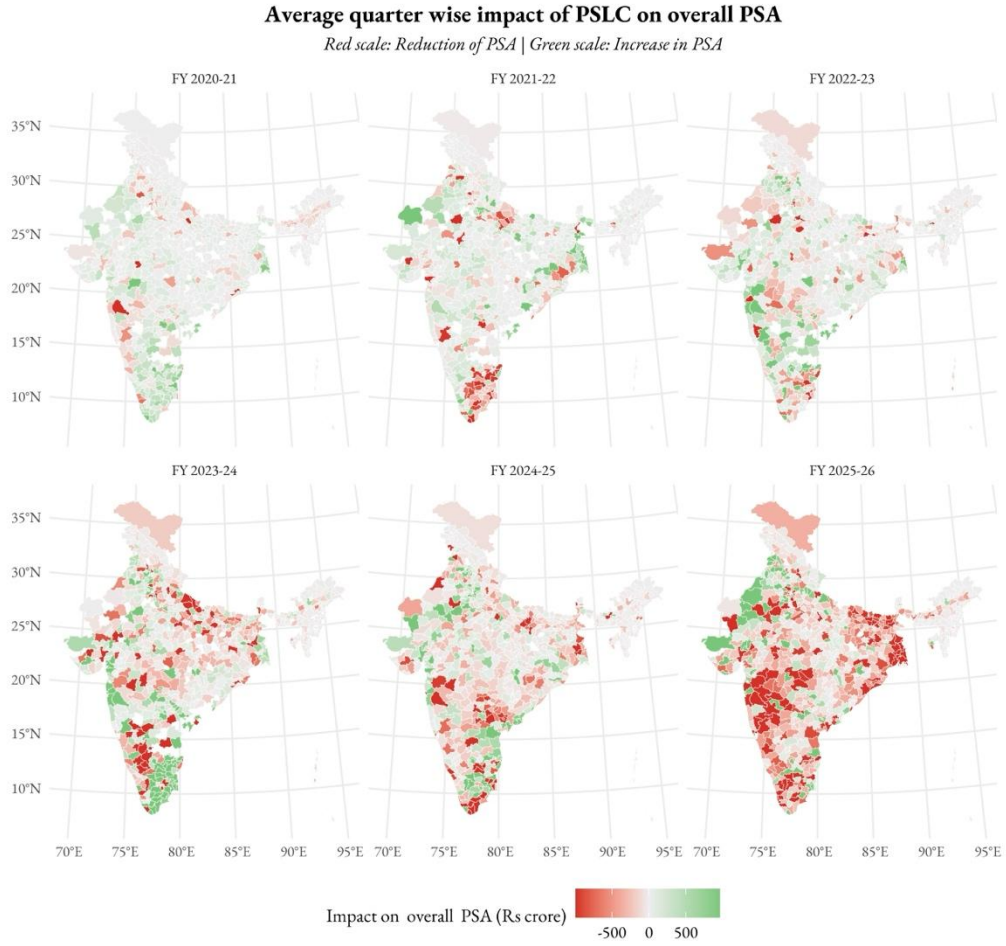

Figure 6-6 Geographical distribution of the PSLC impact on overall PSAs

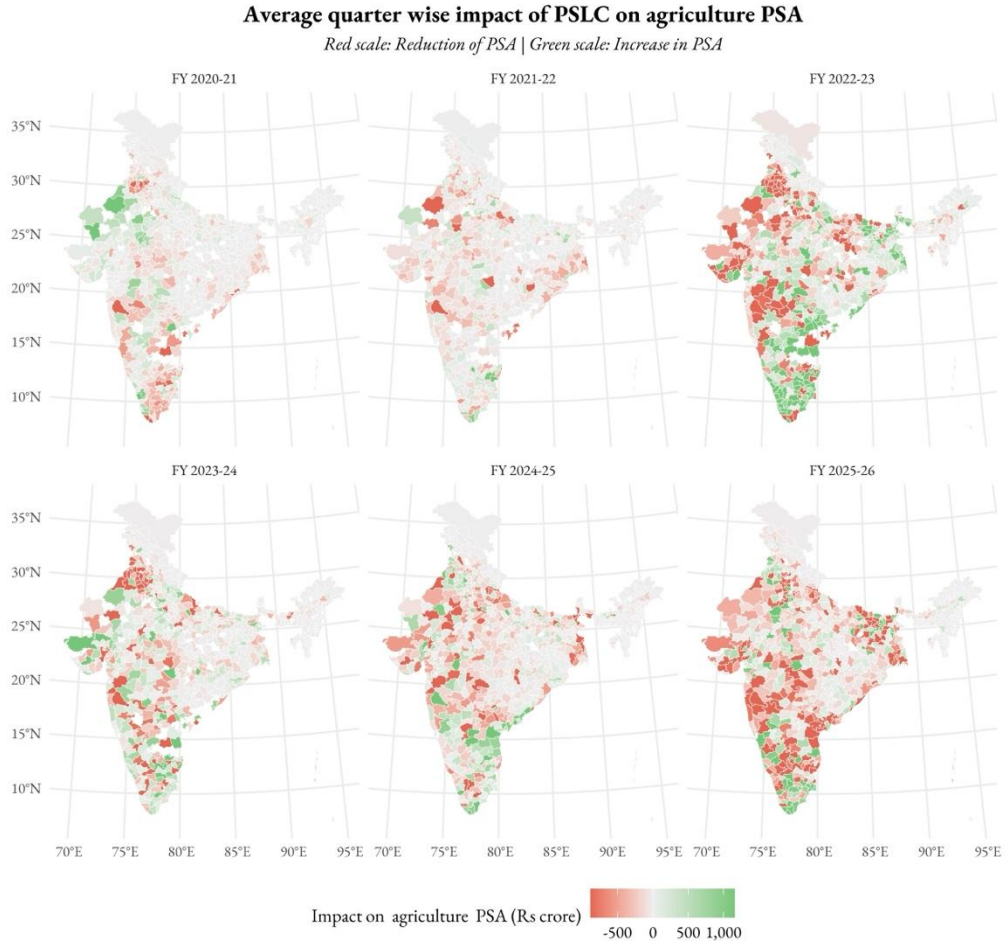

Figure 6-7 Geographical distribution of the PSLC impact on agriculture PSAs

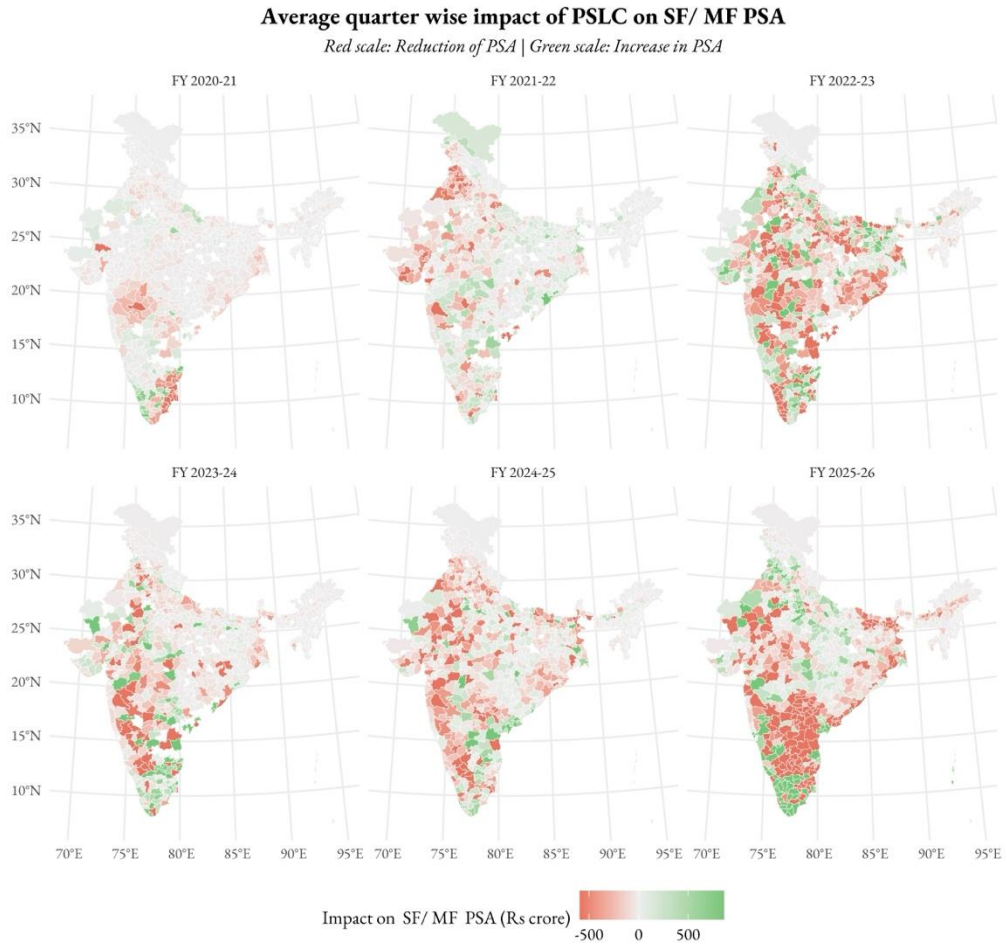

Figure 6-8 Geographical distribution of the PSLC impact on SF/ MF PSAs

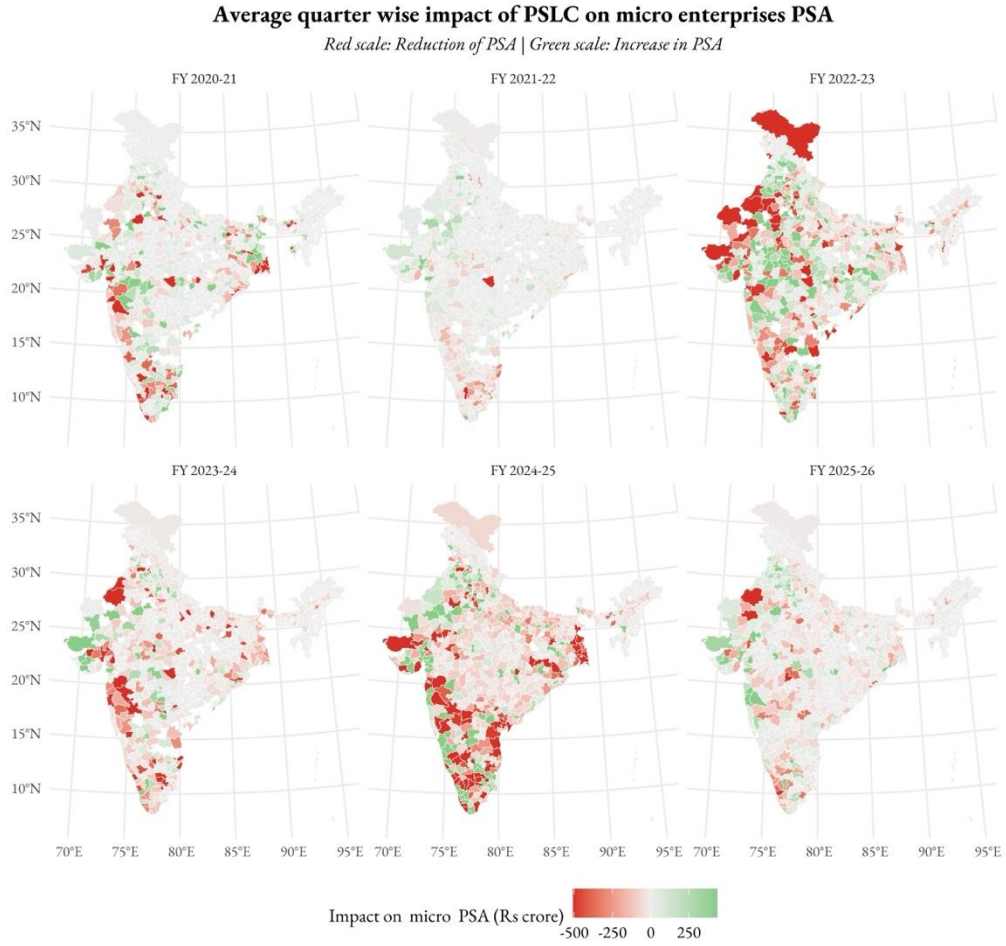

Figure 6-9 Geographical distribution of the PSLC impact on micro enterprises PSAs

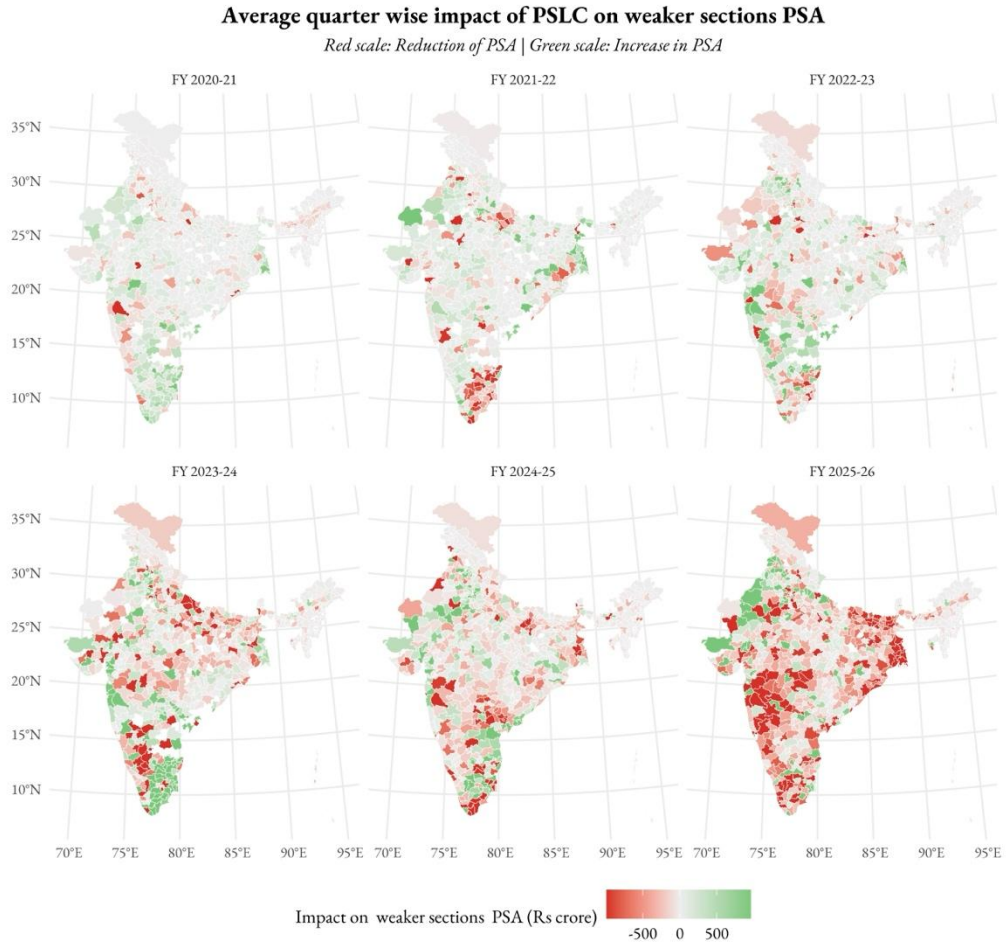

Figure 6-10 Geographical distribution of the PSLC impact on weaker sections PSAs

The distribution of the impact of PSLC as a percentage of district-level PSA on average is provided in Figure 6-11. In most of the districts the impact is limited to +/- 10%, though outliers are also present.

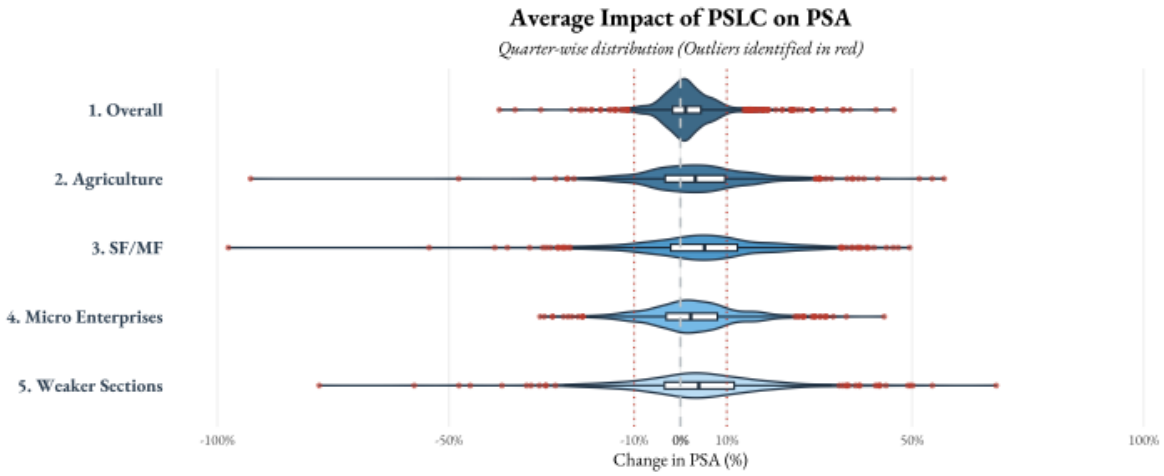

Figure 6-11 Distribution of the quarter wise average impact of PSLC on PSA

7. Economic impact of PSAs

District level estimation of output

To estimate the impact of PSAs on economic growth at the district level, NTL was used as a proxy for the economic performance of regions as administrative data at this level of granularity was not available. NTL is captured using satellite imagery and has been proven to be a reliable proxy of human activities (Rybnikova, 2022). It indicates the presence of either residential, industrial, commercial or entertainment areas and is frequently used as a broad measure of population concentrations and the economic performance of regions.

NTL at a district level granularity was extracted from the Earth Observation Group's (EOG) Visible and Infrared Imaging Suite (VIIRS) Day Night Band (DNB) on board of the United States' National Oceanic and Atmospheric Administration's (NOAA) Joint Polar-orbiting Satellite System (JPSS) satellites as distributed by the Google Earth Engine. The district boundaries used to extract the data were obtained from the Administrative Boundary Database of the Survey of India, Ministry of Science and Technology.[26] Version 1 of the data was used, that includes a procedure whereby raw data is corrected for stray light. However, this version does not apply a filter to screen out lights from fires, boats, and other temporal lights etc. (Earth Observation Group and NOAA National Centers for Environmental Information (NCEI), 2014)

Figure 7.1 shows the evolution of NTL in districts between FY 2019-20 and FY 2024-25. On expected lines, major cities and surrounding districts are bright points, while mountainous regions, the north-east, remote regions of Rajasthan and some districts in the south-east part of the country are particularly dark.

[26] OVSF/1M/7 shapefile available at https://onlinemaps.surveyofindia.gov.in/Product_NewSpecification.aspx

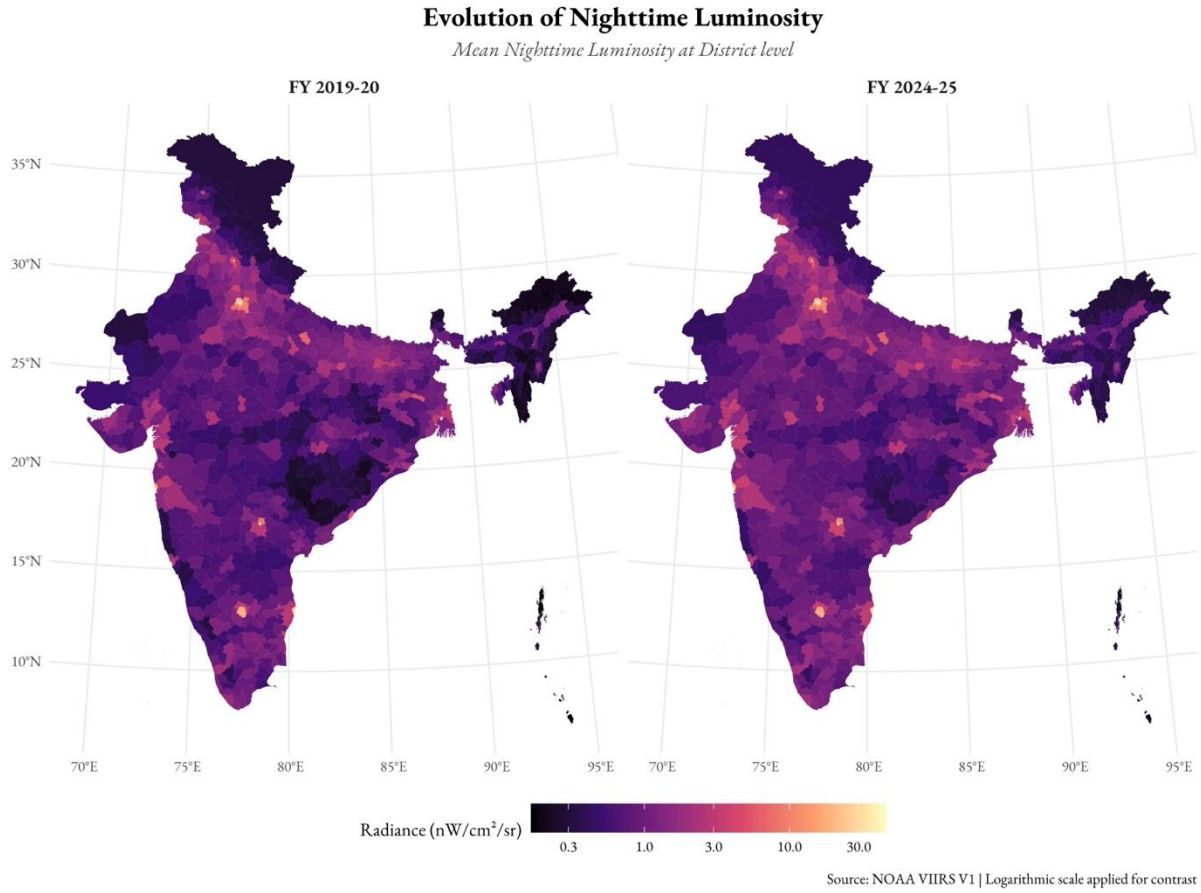

Figure 7-1 Evolution of Nighttime Luminosity between FY 2019-20 and FY 2024-25

NTL is not a perfect approximation of economic output and its main utility lies in making comparisons over time. The CAGR of NTL was calculated from 01/04/2020 to 31/03/2025 and is shown in Figure 7-2. On an average, NTL CAGR has grown over the country. Regions in eastern Uttar Pradesh, Kerala and some industrial districts were stand-outs. Districts where CAGR was more than 18.2% were outliers (75th percentile + 1.5xIQR) and have been labelled in the figure. Certain districts have also shown a negative CAGR, many of them are located in the Northeastern states while some are located in Andhra Pradesh, Madhya Pradesh and Rajasthan.

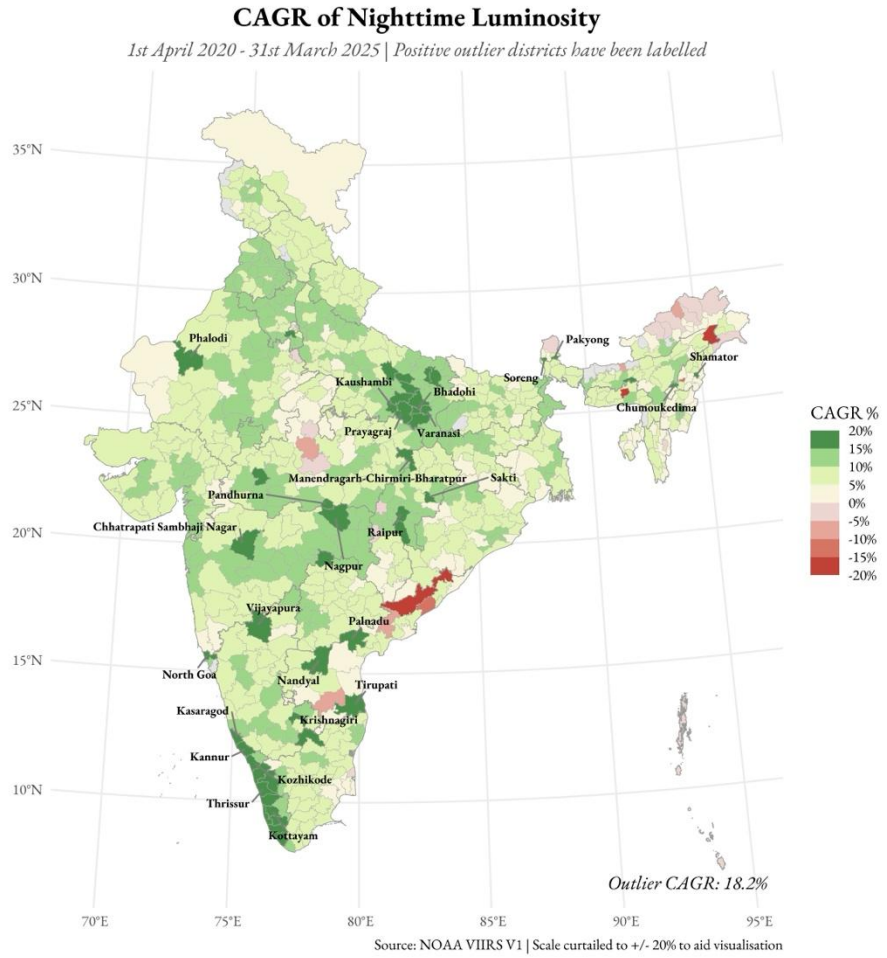

Figure 7-2 CAGR analysis of Nighttime Luminosity

Empirical specification

To estimate the impact of overall PSA extended directly by banks on district level output as proxied by NTL in the panel data, a VECM was used as explained below. PSLCs were then modelled as exogenous shocks on district overall PSA and through it on district level output.

Given the short panel, Local Projections (Jordà, 2005) were also estimated as an alternate methodology. Districts were sub-set into tiers for Local Projection.

Removing the effect of seasonality in output and PSA

Both the study variables, NTL and overall PSA are expected to show seasonality. Seasonality in NTL is on account of varying climactic conditions and associated increase/ decrease in artificial light requirements and atmospheric penetration of artificial light. Seasonality in overall PSA will be on account of loco-regional agricultural and economic cycles, and on account of the business cycles of banks. This seasonality is not relevant for studying the relationship between NTL and overall PSA and was removed by accounting for fixed effects and extracting ordinary least squares (OLS) residuals as per the following specification:

$$\mathbf{Z}_{s,d,t,q} = \boldsymbol{\delta}_{s\times q} + \tilde{\mathbf{z}}_{d,t} \quad \textbf{(20)}$$

Where $\mathbf{Z}_{s,d,t,q}$ represents the vector of natural log of NTL $(lnNTL_{s,d,t,q})$ and overall PSA $(lnPSA_{d,t,q})$ of state s and district d at time t and quarter q, i.e., $\mathbf{Z}_{s,d,t,q} = [lnNTL_{s,d,t,q}, lnPSA_{s,d,t,q}]'$. $\boldsymbol{\delta}_{s\times q}$ is the

vector of state x quarter wise fixed effects, i.e., $\boldsymbol{\delta_{s\times q}} = [\delta_{s\times q}, \delta_{s\times q}]'$. $\tilde{\mathbf{z}}_{d,t}$ is the vector of residuals, $\tilde{\mathbf{z}}_{d,t} = [ntl\_resid_{d,t}, psa\_resid_{d,t}]'$.[27]

Structural modelling and cointegration

$\tilde{\mathbf{z}}_{d,t,q}$ was found to be non-stationary and most districts[28] were following an integrated process of order 2 $I(2)$ or below. The avoid spurious regression, first differences of the variables were obtained, denoted as $\mathbf{z}_{d,t} = [\Delta ntl\_resid_{d,t}, \Delta psa\_resid_{d,t}]'$. In every district d where the null of no cointegration was rejected $(r \neq 0)$ using the Johansen Trace Test, the relationship between the first differences was represented using a VECM[29] with the following specification:

$$\Delta \mathbf{z}_{d,t} = \alpha_d\left(\beta_d' \mathbf{z}_{d,t-1}\right) + \sum_{i=1}^{k-1} \Gamma_{d,i} \Delta \mathbf{z}_{d,t-i} + \mathbf{u}_{d,t}$$

(21)

Where α_d being the coefficient of the error correction term $(\beta_d' \mathbf{z}_{d,t-1})$ represents the speed of adjustment while β_d' the cointegrating vector represents the long run equilibrium.

In ~26% of districts the Johansen Trace Test failed to reject the null of no cointegration $(r = 0)$ and a Vector Auto-Regression model in first differences (VAR) was employed in place of VECM with the following specification:

$$\Delta \mathbf{z}_{d,t} = \sum_{i=1}^{k-1} \Gamma_{d,i} \Delta \mathbf{z}_{d,t-i} + \mathbf{u}_{d,t}$$

(22)

The lag order k in each specification was identified by minimizing the Akaike Information Criterion (AIC). The AIC provides an appropriate balance between model fit, particularly in a dataset where the panel is relatively short. To preserve degrees of freedom in the analysis while allowing for sufficient dynamics, the search space for lags, was restricted between 1 and 4 quarters for each district.

IRFs

The dynamic response of change in overall PSA on a change in NTL was quantified using Orthogonalized IRFs via Cholesky decomposition. Variables were ordered as $\mathbf{z}_{d,t} = [\Delta ntl\_resid_{d,t}, \Delta psa\_resid_{d,t}]'$ thereby assuming a recursive structure where overall PSA adjusts contemporaneously in response to a change in district output (proxied by NTL), however the overall PSA can only affect the NTL after one quarter lag. This is reasonable as banks are expected to respond to demand in real time, while any output growth from capital will be visible after a lag.

The IRF for district d after h quarters is denoted by $\phi_{d,h}$ and represents the marginal change in $\Delta ntl\_resid_{d,t+h}$ to a unit impulse in $\Delta psa\_resid_{d,t}$, i.e.

[27] Such a specification has been used assuming that the seasonal impact on NTL and overall PSA would be similar for all districts in a particular state.

[28] >90% districts out of a total of 733 districts for which contiguous data was available were stationary after second differencing.

[29] to account for the remaining non-stationarity, $I(1)$,

$$\phi_{d,h} = \frac{\partial \Delta ntl\_resid_{d,t+h}}{\partial \Delta psa\_resid_{d,t}}$$

(23)

Uncertainty in the estimation was captured using 100 runs of non-parametric bootstrapping for each district that provided a distribution of $\tilde{\phi}_{d,h}$ in each district. The final estimates reported in the IRF plots is the mean of the simulated distributions, with 95% Confidence Intervals derived from the 2.5th and 97.5th percentiles of the Monte Carlo draws.

PSLC shocks on overall PSA

Shock $\mu_{d,t}$ to a district d at time t was calculated as the impact of PSLC on overall PSA, i.e.,

$$\mu_{d,t} = \ln\left(PSA_{d,t} + PSLC_{d,t}\right) - \ln\left(PSA_{d,t}\right)$$ [30]

(24)

As per the Proposition 3, the change in PSA due to PSLC should be exogenous to other economic factors prevailing in a district as well as to the target PSA. To confirm this result, district-level Granger Causality tests were conducted within a VAR framework with a null hypothesis that the endogenous system (of NTL change and PSA change) does not predict the shock sequence (i.e. sequence of $\Delta s_{d,t}$). With a median p-value of 0.245 and 75.6% of districts failing to reject to the null, empirical results support the treatment of PSLC shocks as exogenous. Figure 7-3 provides a distribution of the p-values from the district-level causality tests.

[30] While calculating $\ln\left(PSA_{d,t} + PSLC_{d,t}\right)$, the function used was $sign\left(PSA_{d,t} + PSLC_{d,t}\right) * \ln\left|PSA_{d,t} + PSLC_{d,t}\right|$ as it was found that in a few districts, the impact of the shock was leading to a negative value for overall PSA i.e. in the absence of PSLC, there would not have been any incentive for banks to extend PSAs in that district.

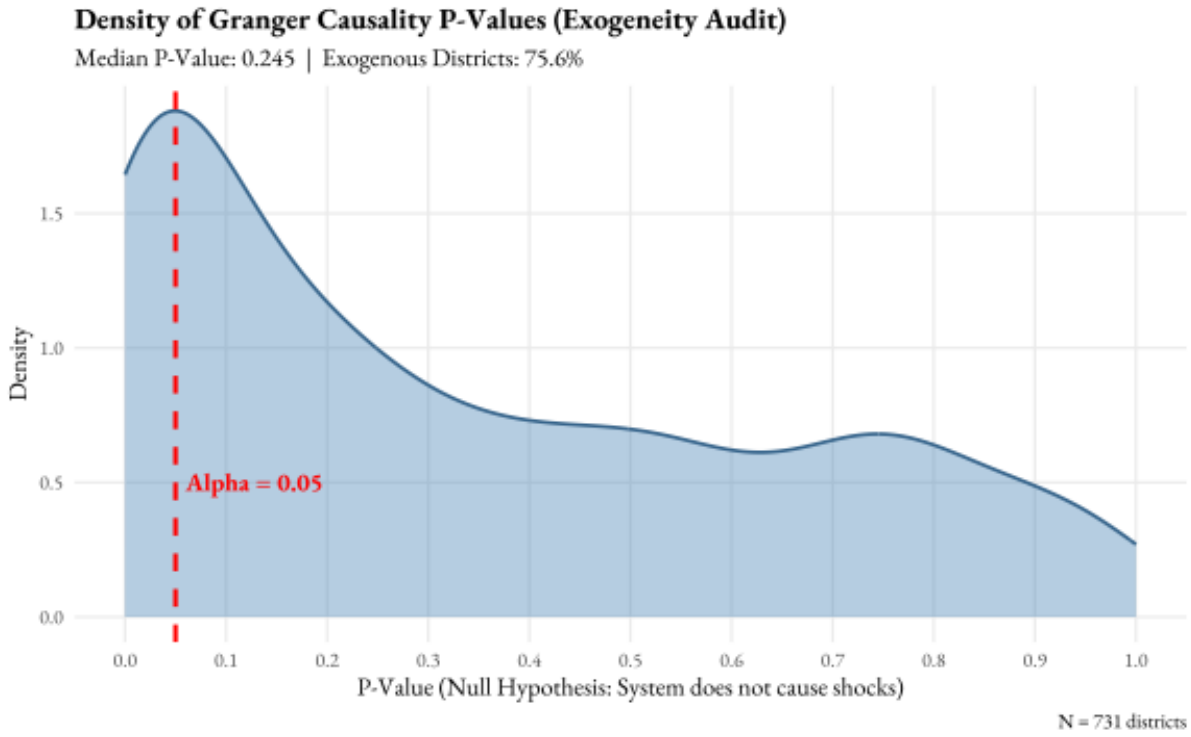

Figure 7-3 Distribution of p-values for district wise Granger Causality tests with the null that the PSLC shocks are exogenous.

Impact of PSLC shocks on district level output and growth

To estimate the overall impact of PSLC shocks at any time t, a convolution of the district level PSLC shocks available (from time $t - H$) and the estimated IRF was performed. The impact $I_{d,t}$ of PSLC shocks is the product of the estimated IRF with the shock level. By definition, it approximates the difference in expected value of $\Delta ntl_{d,t}$[31] in the shocked (no PSLC) and unshocked states of the world:

$$I_{d,t} = \sum_{h=0}^{H} \mu_{d,t-h} \cdot \tilde{\phi}_{d,h} \approx \mathbb{E}[\Delta ntl_{d,t} | noPSLC_d] - \mathbb{E}[\Delta ntl_{d,t} | PSLC_d] \quad \textbf{(25)}$$

This approach incorporates data of all past shocks and estimates their impact as per district-level IRFs.

District level counterfactuals were estimated with an assumption that PSLC related deviation starts from the beginning of the study period, i.e., baseline NTL is same with or without PSLC, i.e., $\mathbb{E}[ntl_{d,t}|PSLC_d] = \mathbb{E}[ntl_{d,t}|noPSLC_d]$ when $t = 0$. $\mathbb{E}[ntl_{d,t}|noPSLC_d]$ in each subsequent period was calculated as follows:

[31] Log differences

$$\mathbb{E}\left[ntl_{d,t}|noPSLC_d\right] \approx \mathbb{E}\left[ntl_{d,t}|PSLC_d\right] + \sum_{i=0}^{t-1} I_{d,t-i}$$ [32]

(26)

$g^c_{d,t}$, the district level year-on-year growth in the counterfactual, was estimated using a log-linear approximation as follows:

$$\mathbb{E}\left[g^c_{d,t}\right] \approx \mathbb{E}\left[ntl_{d,t}|noPSLC_d\right] - \mathbb{E}\left[ntl_{d,t-4}|noPSLC_d\right]$$

(27)

For consistency, calculation of actual year-on-year growth $g^a_{d,t}$ was also performed using a log-linear approximation.

Aggregation of impact of PSLC shocks at the state and national level

Finally, the impact of PSLC shocks on state level growth $g^c_{s,t}$ and national level growth g^c_t was estimated by calculating a average of the district level counterfactual growth weighted by the absolute level of luminosity in a district.

$$g^c_{s,t} = \frac{\sum_{d\in s}\left(NTL_{d,t}.\,\mathbb{E}\left[g^c_{d,t}\right]\right)}{\sum_{d\in s} NTL_{d,t}}$$

(28)

$$g^c_t = \frac{\sum_{d}\left(NTL_{d,t}.\,\mathbb{E}\left[g^c_{d,t}\right]\right)}{\sum_{d} NTL_{d,t}}$$

(29)

The final estimates reported in the PSLC impact plots is the mean of the simulated distributions, with 95% Confidence Intervals derived from the 2.5th and 97.5th percentiles of the Monte Carlo draws.

All estimations were implemented in R using the *urca* framework for the Johansen Trace Test, *tsDyn* framework for VECM and VAR.

Alternate specification – Local Projections by District Tiers

Given the short duration of the panel data, an alternate specification of Local Projections (Jordà, 2005) was also used to increase robustness of the results. While Local Projections have been shown to provide IRFs similar to traditional autoregressive inference frameworks (Plagborg-Møller and Wolf, 2021), they offer an advantage of being more robust to model misspecifications and are also simpler to implement (Montiel Olea and Plagborg-Møller, 2021).

[32] The derivation as by iteration of the following:

$$\mathbb{E}[\Delta ntl_{d,1}|noPSLC_d] \approx \mathbb{E}[\Delta ntl_{d,1}|PSLC_d] - I_{d,1}$$
$$\mathbb{E}\left[ntl_{d,1}|noPSLC_d\right] - \mathbb{E}\left[ntl_{d,0}\right] \approx \mathbb{E}\left[ntl_{d,1}|PSLC_d\right] - \mathbb{E}[ntl_{d,0}] - I_{d,1}$$
$$\mathbb{E}\left[ntl_{d,1}|noPSLC_d\right] \approx \mathbb{E}\left[ntl_{d,1}|PSLC_d\right] - I_{d,1}$$

For Local Projection, districts were divided into 10 tiers based on the percentile of overall PSA (period average) outstanding in the district. For each tier, the following specification was estimated:

$$ntl\_resid_{d,t+h} - ntl\_resid_{d,t-1} = \alpha_{d,h} + \beta_h psa\_resid_{d,t} + \sum_{j=1}^{4} \gamma_{d,j} z_{d,t-j} + \varepsilon_{d,t+h}$$

Where, $ntl\_resid_{d,t+h} - ntl\_resid_{d,t-1}$ represents the cumulative change in log NTL, $\alpha_{d,h}$ are district specific fixed effects at horizon h, β_h is the coefficient of interest representing the impulse response of the district log NTL at horizon h at time t to a unit shock in log PSA at time t. j represent the lags in $z_{d,t-j}$ that comprises of $ntl\_resid_{d,t-j}$ and $psa\_resid_{d,t-j}$.

The panel Local Framework estimation was performed using *lpirfs* framework in R. Potential heteroskedasticity and within-unit autocorrelation was addressed using robust standard errors using the HC1 variance-covariance estimator, with errors clustered at the district level. This approach ensured that the 95% confidence intervals remain conservative.

Results

District level IRFs – VECM/ VAR

District wise plots of IRFs show that the elasticity of ΔNTL with ΔPSA, i.e., the percentage change in output growth with a unit shock to PSA growth acceleration in the district, is not significant in most districts over a two year horizon.[33] Absolute impact plots show the change in NTL from the unit PSA acceleration shock as compared to the baseline (i.e. without shock).

The plots reveal significant heterogeneity even within districts located in the same state. Most districts do not show a sustained or long-term trend in output with a change in PSA and output growth generally fluctuates around the mean. While most districts show a transient positive response on expected theoretical lines, many districts also show a transient initial negative response, possibly indicating inefficiencies in capital allocation and utilization.

The absolute impact plots show that the impact on NTL from a shock to PSA growth is not statistically significant. The trends are positive in most districts, while some districts also show a negative trend. A negative trend may be indicative of inefficient allocation of capital. Such a trend can also arise on account of PSA induced emigration. Further, as output growth was measured using NTL, an increase in non-light producing activities like agriculture and allied activities at the expense of light producing ones, can also explain such negative trends.

Impact of PSLC shocks

The impact of PSLC shocks on district level and state level output growth over time show that they do not significantly impact output growth in most districts- the imputed median counterfactual growth closely follows the actual growth during this period.[34] Extreme values and artifacts were noted in smaller districts[35] and the median of the counterfactual was analysed to prevent few outlier observations from influencing the results.

At the state level, PSLCs appear to have helped reduce growth volatility in Andhra Pradesh post FY 2023-24, supported output growth in Tripura in FY 2022-23 and 2023-24. However, these findings are primarily on account of severe counterfactual volatilities seen in one or two districts in each state and may

[33] Districts level IRFs and absolute impact on district NTL from the shock are available in the online Appendix 1.
[34] District and State-level plots are provided in online Appendices II and III respectively. The plots show the actual growth trend and the counterfactual (along with confidence intervals) in the hypothetical scenario without PSLC.
[35] possibly due to the very low NTL base, as even small variations will be magnified.

be due to statistical artifacts induced by bootstrapping of IRFs. The analysis was repeated after winsorizing impact values at +/- 50%, which confirmed that outliers were responsible for these observations.

The national level actual and counterfactual growth aggregates are provided in Figure 7-4. As seen in the figure, the implementation of PSLC has not led to any significant impact in national growth.

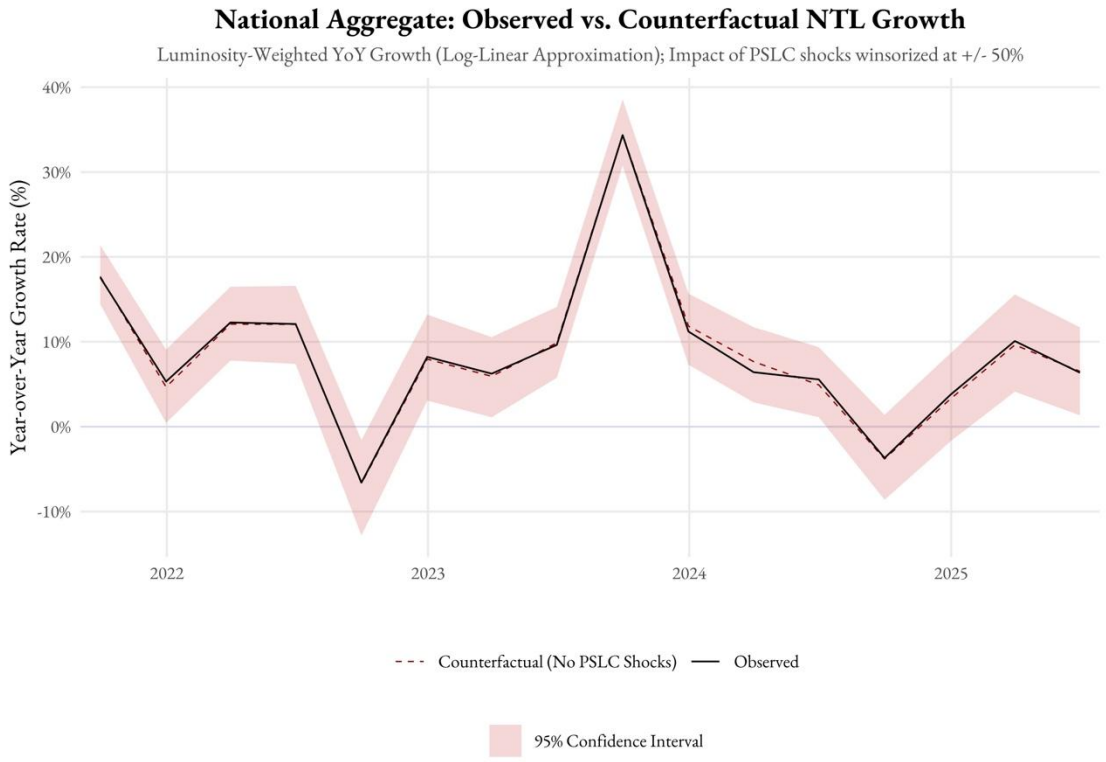

Figure 7-4 Observed and counterfactual year over year growth rates of NTL luminosity in each quarter. Shaded region represents the 95% confidence interval of counterfactual growth while the dashed line represents the median value. Impact of PSLC shocks has been winsorized at +/-50% while calculating the counterfactuals.

Local Projection Results

Tier wise local projection results are shown in Figure 7-5. While the impulse response is initially not significant, district tiers show a statistically significant positive NTL elasticity from a unit shock in district level PSA after 1 year. Heterogeneity between district tiers is clearly observable, with elasticity being minimum in the least served districts (lowers outstanding PSA balance). Elasticity increases and is maximum in the districts located in the middle of the distribution while it again reduces in the richest districts (but the level is still above the poorer districts).

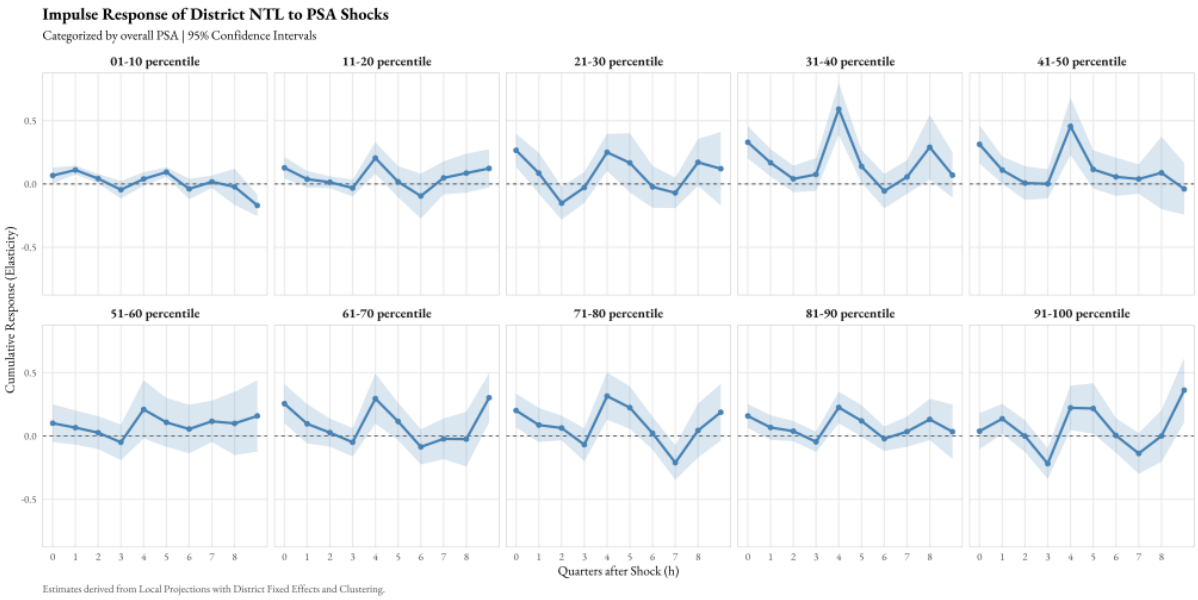

Figure 7-5 Impulse Response of District NTL to PSA Shocks derived using local projections by district tier

If we combine all districts, an NTL elasticity of ~0.2 is observed after one year of PSA shock as shown in Figure 7-6.

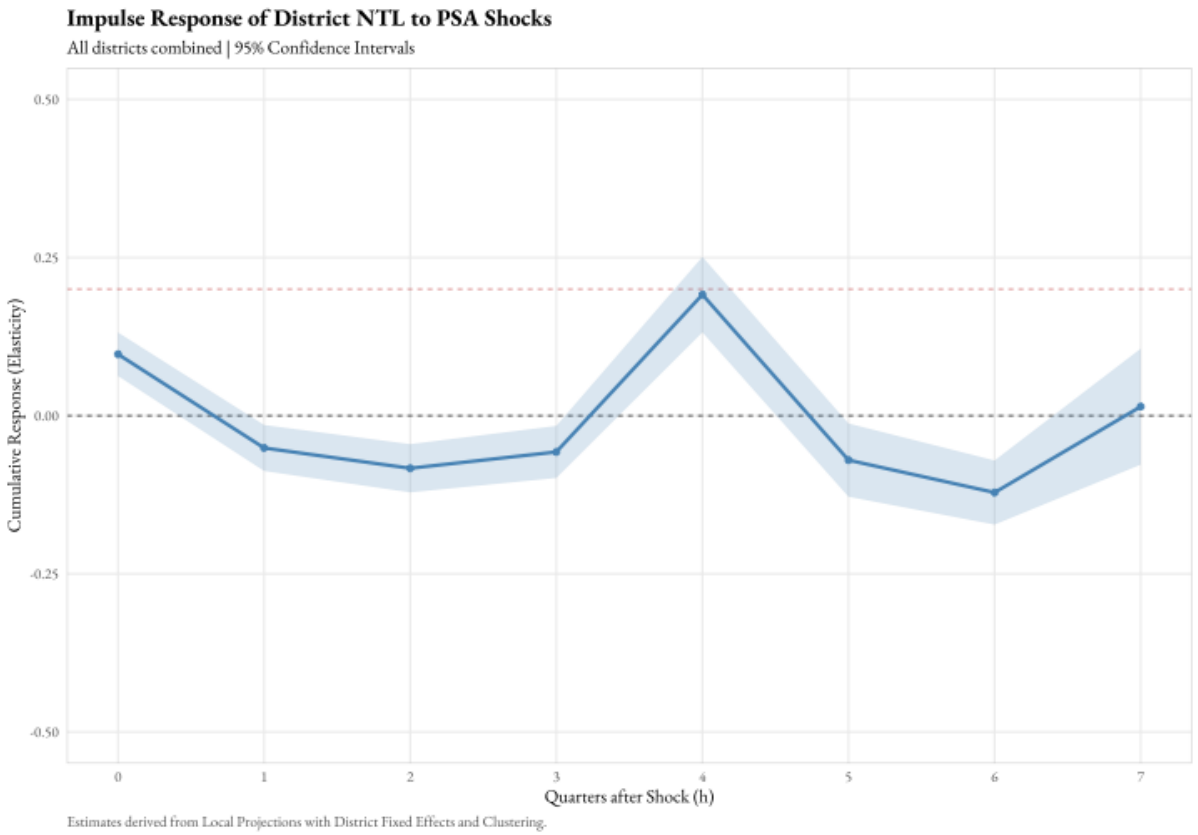

Figure 7-6 Impulse Response of District NTL to PSA Shocks derived using local projections – all districts combined

One year elasticities are extracted from the panel Local Projections are shown in Table 7-1.

Table 7-1 NTL elasticity from PSA at one year horizon extracted from panel Local Projection

	Tier	Elasticity	P Value	N Obs.	R^2	Adj. R^2
1	1-10	0.05	0.204	537	0.543	0.488
2	11-20	0.19	0.001	754	0.527	0.472
3	21-30	0.20	0.020	754	0.579	0.531
4	31-40	0.46	0.000	790	0.673	0.636
5	41-50	0.46	0.000	789	0.622	0.579
6	51-60	0.24	0.043	787	0.603	0.557
7	61-70	0.34	0.000	774	0.608	0.563
8	71-80	0.31	0.007	788	0.614	0.570
9	81-90	0.26	0.003	797	0.595	0.549
10	91-100	0.41	0.000	786	0.600	0.554
11	All Districts	0.19	0.000	7523	0.576	0.533

8. Discussion

Skewed distribution of PSAs

On an average, the distribution of priority sector credit in India is heavily skewed. 63 out of the 809 districts (7.8%) account for ~46% of overall PSAs. Among different types of PSAs, 92 districts (11.4%) account for ~67.3% of MSME credit, while 123 districts (15.2%) account for ~88.3% of the medium enterprise credit. Northeastern states, Himalayan states and Eastern parts of the country are particularly underserved. Figure 8-1 shows a Lorenz style curve for the distribution of overall PSA per capita (average of the study period), with a Gini coefficient of ~0.6 it shows that there is significant inequality between districts.

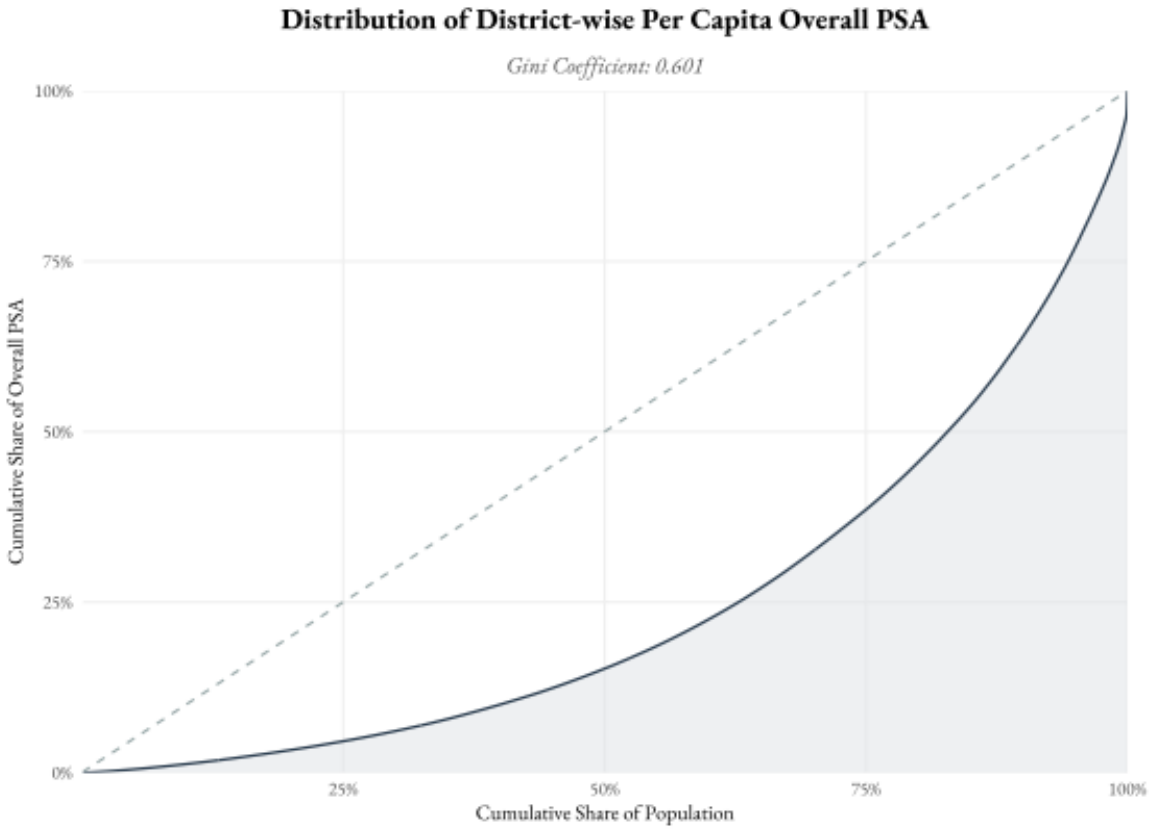

Figure 8-1 A Lorenz style curve for district-wise per capita overall PSA distribution

While the primary reason for regional disparity is underlying geographically uneven economic development, distribution of PSAs may also be influenced by indirect PSA instruments like PSLCs. Imbalanced regional growth is known to severely impact overall development. It can cause excessive pressures on the more developed areas on the one hand while curtailing economic opportunities to populations living in less developed areas. It also leads to distress migration.

To address the issue of skewed PSA distribution, the RBI has created a disincentive framework from FY 2021-22 onwards ('Master Directions - Reserve Bank of India (Priority Sector Lending – Targets and Classification) Directions, 2025', 2025) where a higher weight of 125% is provided to banks on their incremental PSAs in underserved districts while a lower weight of 90% is provided for extending incremental PSAs in districts that already have significant outstanding PSAs.

While no causative implications can be made with this disincentive framework policy (as pre-policy data was available for limited periods only) there is evidence of convergence in PSAs- the growth rate of PSAs in underserved areas is higher. However, any policy that uses a top down approach to incentivise diversion of capital from currently served to underserved district can impact productivity growth. Manaresi and Pierri (2024) show that while credit contractions harm TFP growth in firms, the impact of positive shocks in stimulating TFP growth is limited. Diversion of credit may thus reduce TFP growth in districts that see an outflow of PSAs without a commensurate increase in beneficiary districts.

Instead of a pure top-down mandate, targeted fiscal policy interventions that are closely linked with credit policy will be better suited to support economic growth. Interventions need to target all binding constraints for development like infrastructure adequacy, human resources, supply and market linkages

and a favourable regulatory environment. The aim should be for sustainable development, led by either cooperative or private entrepreneurship and ably supported and assisted by the government.

Output considerations of PSAs

This study found that a PSA growth shock did not have a significant impact on NTL growth, however, the lack of significance may be on account of the short panel.

In the more robust specification of Local Projections, district level heterogeneity was noted- the poorest districts being likely to show only a very modest growth impact from an increase in PSAs. This finding also supports the argument of linking development interventions with credit policy. Without such linkages, a pure top-down bank mandated diversion of credit to the poorest districts will not only be inefficient for growth but will also be unsustainable and will fail to serve the social mandate of priority sector lending.

The increase in output elasticity from PSAs found in districts towards the middle of the distribution is also important. Credit constraints are likely to be binding in these districts, and they may benefit from an increase in PSA brought about through a bank mandate.

The study findings differ from an earlier study by Gaur and Mohapatra (2020), who show a bidirectional causal (Granger) relationship between PSAs and GDP. One reason for the results may be due to the difference in study periods- this study uses data post 2020 and it is likely that with recent expansion of credit other developmental constraints are more important. Another reason is the district level heterogeneity observed in this study. Earlier studies examine the impact at the National level, and the underlying heterogeneity will be lost with State- and National- level aggregation. Richer districts, which have higher elasticities, will mask the impact seen on poorer districts and overall results will seem better than expected.

Re-orientation of the priority sector lending policy

The national level elasticity was ~0.19 (seen one year after a PSA shock). It is lower than the long run output elasticity from budgetary capital estimated at ~0.29 (Pradhan, 2020)- indicating that the PSAs may be less economically efficient even when compared to public funds.

Given this economic inefficiency, the focus of PSAs should be changed from economic to social equity. Emphasis should be placed on its original goals of making credit available to SFs/ MFs, small scale industries and weaker sections. Legacy inclusions in the definition of priority sector that are no longer relevant can be removed. Targets can be adjusted commensurately. For example, while retaining sub-targets for SFs/ MFs and non-corporate farmers, the separate target on agriculture (which constitutes lending towards corporate farmers) can be removed. Similarly, while retaining the sub-target for micro enterprises and weaker sections, others can be removed from the definition of priority sector, and the overall target can be lowered. With these changes, banks will have more flexibility in allocating capital while restoring emphasis on the social goals of PSAs.

Efficiency consideration of PSLCs

This paper also studied the efficiency considerations of PSLCs. PSLCs are commonly used by banks for meeting both the overall PSA target as well as for meeting the sub-targets of agriculture, SFs/MFs, micro enterprises and weaker sections. They are unique as instruments in that they do not transfer risk of the underlying asset, which remains with the bank that originated the loan, and only securitise the achievement of the PSA targets. PSLCs are successful as they collectivise the priority sector obligations at the national level, i.e., priority sector lending remains as per the prescribed targets as a percentage of total ANBC in the country, however, individual banks get flexibility while lending to the priority sector.

The data shows that larger banks like SBI are net purchasers of PSLCs. SFBs, which can lend more efficiently to the priority sector, are regularly exceeding their targets and selling the excess as PSLCs. The highly versatile nature of PSLCs is best reflected in the lending patterns of Private Banks. Private Banks are net buyers of agriculture PSLCs, an area where they have traditionally performed sub-optimally, and act as net sellers of micro enterprise PSLCs, reflecting their expertise in lending to enterprises. Overall, the purchase and sale pattern of PSLCs by banks clearly shows that PSLCs are likely to improve operational efficiency of the banking sector.

However, PSLCs have distributional implications for PSAs. Geographical areas of operations of banks are different and banks providing PSAs in underserved regions appear to be net purchasers while those operating in already well served district are net sellers, indicating that PSLC may be worsening regional disparity. At the same time, the marginal allocation key shows that PSLCs may impact the same district differently every period. The theoretical model also predicts that this allocation may not reflect the underlying district economic performance, i.e., they may not necessarily be allocating PSAs to the most efficient districts.

Empirically, PSLC shocks to PSAs were found to be exogenous to both district economic growth as well as PSA lent directly in each district, as was predicted by the theoretical model. Further, these exogenous shocks did not significantly alter output growth in the long term.

Overall, PSLCs appear to increase efficiency of the banking sector, without significantly impacting output growth.

Caveats

The results of the impact of PSA on output growth must be seen along-with important caveats inherent in the study design.

Use of NTL as a proxy for output

Output growth has been proxied using growth in NTL. While NTL has shown to be a good proxy for human activity overall, it is not perfect and is associated with some limitations.

Firstly, NTL is significantly affected by atmospheric clarity and is impacted by the level of dust in the air. An increase in human activity is likely to be correlated with atmospheric dust and pollution, and NTL may underestimate actual growth. Secondly, NTL is also significantly associated with prevailing weather conditions and shows seasonality. The seasonal variation in NTL has been addressed to some extent in the econometric specification- seasonal effects from both PSA and NTL were removed by regressing these variables on quarter dummies and extracting the residuals (Frisch-Waugh-Lovell theorem). However, year to year changes in weather for the same quarter may still impact estimations. For example, significant differences in local monsoon levels between consecutive years may introduce errors in the estimations. Thirdly, NTL is also biased against agriculture which is a non-light producing activity. Growth in agriculture will reveal itself only indirectly- when higher agricultural incomes increase NTL through increased consumption. Other sectors like manufacturing impact NTL both directly, through production of industrial light as well as indirectly, via income growth. Finally, NTL growth is also influenced by change in lighting technology. Adoption of newer LED lights and use of shielded lights that face downwards can reduce NTL despite economic growth. However, given the relatively short panel of 5 years, change in lighting technology is unlikely to be a major confounding variable.

To validate the efficacy of NTL as a proxy for output, state-level NTL aggregates were compared with Gross State Value Added (GSVA) at constant prices[36]. Results, shown in Figure 8-2, demonstrate a

[36] Source: RBI Handbook of Statistics on Indian States 2024-25; available at: https://www.rbi.org.in/scripts/AnnualPublications.aspx?head=Handbook+of+Statistics+on+Indian+States

robust log-linear relationship. The national level correlation coefficient of 0.914 indicates that NTL changes are consistent with the official national accounts data. Further, at the State/UT-level aggregation, correlation coefficients exceed 0.7 in most cases. Weaker correlations were observed in the UTs of Puducherry (0.59) and Andaman and Nicobar Islands (0.07), as well as in the states of Nagaland (0.56) and Arunachal Pradesh (0.41), likely attributable to geographical reasons.

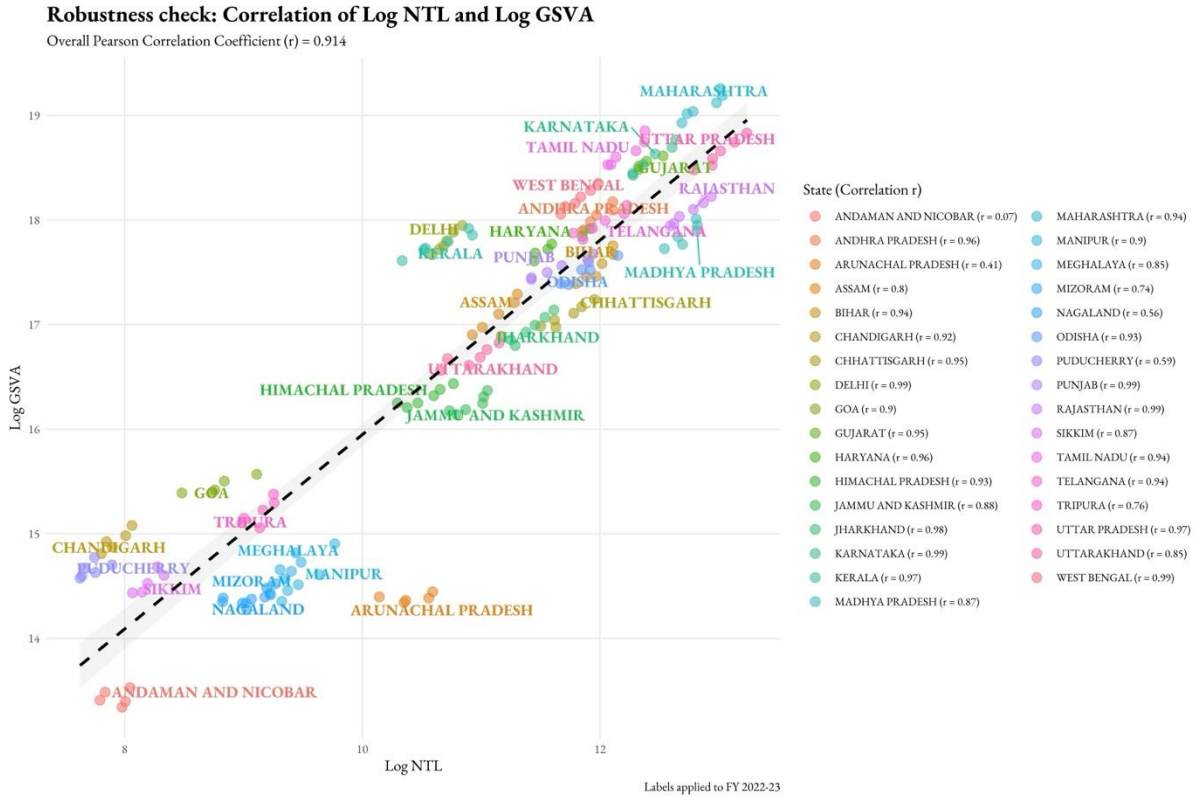

Figure 8-2 Correlation of Log NTL and Log GSVA

Allocation of PSLCs to district

Examination of economic efficiency of PSLCs required the use of the marginal allocation key. The key assumes that returns on non-priority sector assets are similar across districts. This is a strong assumption and may not necessarily hold. However, as the output impact of PSAs was not found to be very large- the errors in PSLC allocation to districts are unlikely to impact the conclusions drawn from this study. The econometric specification used where the impact was winsorized should also take care of any outliers arising from this assumption.

Panel duration

Data was available for a short panel only. Many of the asymptotic assumptions inherent in the econometric specifications will not hold with such a finite panel and the power of the study may not be sufficient to capture individual district level impacts. Accordingly, policy recommendations are not being made for individual districts or regions. Instead, the policy recommendations are based on the more robust results of the study design only.

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