Quantifying the impact of climate policy uncertainty on banking assets: Novel evidence from the fastest economy

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Abstract

We unravel and quantify a very important channel through which the climate policy uncertainty (CPU) causes systemic risks – that is, loan loss provisions (LLPs) in banks. LLPs are the largest and extremely critical accrual items for banks, as they reflect, ex-ante, the impact of CPU on banking assets. More specifically, this paper examines the influence of CPU on LLPs of Indian banks for the period 2003-2023. Our results show that a 1% increase in CPU results in, on average, (1) about a 66% – 77% increase in LLPs, and in turn, (2) about a 28% – 33% decline in profitability. Moreover, we also document a higher impact of CPU on LLP for banks with low ESG scores, large size, and public sector ownership compared to those with high ESG scores, small size, and non-public sector ownership, respectively. We also show that the impact of CPU on LLP has intensified after the Paris Agreement (2015). Our results are robust to a battery of estimation approaches, including OLS, panel fixed and random effects, system GMM, and instrumental variable (IV) – two-stage least squares (2SLS), subsample analysis, and various LLP specifications. Our findings reveal a new channel linking CPU to macro-financial instability – namely, the impact of CPU on banking sector asset quality and profitability via LLPs.

Keywords: Climate policy uncertainty (CPU); Financial instability; Loan loss provisions (LLPs); Instrument variable (IV) – Two-stage least squares (2SLS); System GMM

JEL classifications: G21; G28; M41; Q5

1. Introduction

The macroeconomic impact of climate change on the financial system has received growing attention in the recent past, with a particular focus on climate policy uncertainty (CPU) (Campiglio et al., 2018; Campiglio & Van Der Ploeg, 2022; Sen & Von Schickfus, 2020). Ambitious climate policies that drive an economy towards the path of low-carbon transition may cause significant disruption in economic activities – often referred to in the literature as "*CPU*" or "*climate transition risk*." More specifically, the market agents (e.g., investors, standard setters, governments, policymakers, and regulators) may not understand and incorporate the impact of these climate policies on different aspects of firm operations and the economy in general. Particularly, those firms that excessively rely on fossil-fuel-driven carbon-intensive business operations may witness the problem of "stranded assets" (Delis et al., 2024; Ploeg & Rezai, 2020). In turn, this may adversely affect the loans offered by banks and financial institutions, and the overall impact on the real economy may be amplified through financial transmission channels (e.g., credit and market risk channels) and significant feedback effects (Ehlers et al., 2022; Letta & Tol, 2019; Ng et al., 2020; Paroussos et al., 2019). This is attributed to the banks' systemic nature and strong linkages within a financial system. The resulting losses, coupled with a high degree of interconnectedness in modern financial systems, may engender financial instability; therefore, since the 2015 Paris Agreement, central banks and financial regulators have become increasingly concerned about CPU as a novel source of systemic financial risk (BIS, 2021a, 2021b; ECB, 2021; ESRB, 2021).

In this backdrop, we highlight that the bank managers' response to CPU and the impact of climate transition risk on banking assets is less well understood (Dafermos et al., 2018; Javadi & Masum, 2021; Nguyen et al., 2022). This is primarily ascribed to the lack of an ex-ante measure capturing the impact of CPU on managerial decision-making in banks, and in turn, the potential repercussions for banking assets. Due to the ex-post nature of CPU, the assessment of a policy initiative is only feasible when it is fully adopted and implemented. Our main research question in this paper is to quantify the impact of CPU on managerial decision-making in banks and banking assets. We argue that (1) banks are at the heart of a financial system due to their systemic nature, and (2) bank managers are at the top of the information hierarchy due to their superior knowledge of various segments of an economy (Bhat et al., 2018; Ng et al., 2020; Nicoletti, 2018). This makes the ex-ante response of bank managers to business and economic conditions an object of close scrutiny by all the market participants. To this end, the classical banking literature guides us towards loan loss provisions (LLPs) – an extremely important discretionary accounting-based measure that captures the response of bank managers to policy uncertainty engendered by climate risk (Ahmed et al., 1999; Beatty et al., 1995; Beatty & Liao, 2011; Bushman & Williams, 2012; Kanagaretnam et al., 2010).

LLPs represent the amount set aside by banks to cover the expected losses in bank loan portfolios (Ahmed et al., 1999). LLPs are the largest discretionary accruals for commercial banks, which makes them particularly useful in examining the impact of policy uncertainty on managerial behavior (Beatty & Liao, 2011; Bushman & Williams, 2012). LLPs play a pivotal role in ensuring that banks are adequately capitalized to handle the financial fallout from probable credit losses, thereby safeguarding depositors' and other stakeholders' interests. Signaling and information hypotheses suggest that the discretionary component of unexpected LLPs reveals bank managers' private information about expected future cash flow prospects, loan losses, and economic activity in general (Elliott et al., 1991; Moyer, 1990; Scholes et al., 1990). Adverse climate changes and associated climate policy related uncertainties can severely affect the critical banking operations related to financial intermediation and lending; in turn, this may affect financial stability and economic growth, particularly for a large economy like India (Campiglio & Van Der Ploeg, 2022; Delis et al., 2024; Diluiso et al., 2021; Ge et al., 2025). In this backdrop, LLPs provide an important source of information about how bank managers perceive the economic impact of CPU. Therefore, it is crucial to understand the linkages between CPU and LLPs to assess the impact of CPU on managerial decision-making in banks, and in turn, the potential repercussions for banking assets.

Next, we discuss our CPU measure obtained from the recent literature on climate change risk. With the rise in computing power, artificial intelligence (AI), machine learning (ML), and recent advances in natural language processing (NLP), it has become feasible to process large volumes of unstructured textual data (available from news & social media and voluminous corpus of research reports in textual form). In this backdrop, leveraging techniques related to big data text-analytics, CPU index has been constructed using scaled frequency of terms related to climate policy uncertainty from eight leading global news media outlets (see, Dai & Zhang, 2023; Gavriilidis, 2021; Liu et al., 2024), namely – Boston Globe, Chicago Tribune, Los Angeles Times, Miami Herald, New York Times, Tampa Bay Times, USA Today, and Wall Street Journal. CPU refers to the lack of predictability and clarity surrounding climate policies and regulations (Gavriilidis, 2021). As firms transition towards a low-carbon economy, they are exposed to the costs and risks associated with the CPU (Liu et al., 2024).[1] However, no study has examined the influence of CPU on banks' loan loss provisioning practices. This is the first study examining the impact of CPU on LLP, employing Indian banking sector data.

[1] A detailed review of the recent literature on CPU is provided in Appendix H.

Our choice of the Indian economy for this empirical examination is motivated by the following important considerations. First, India ranks as the third-largest economy in terms of purchasing power parity (PPP)-adjusted GDP. In 2024, India's GDP (PPP) was approximately USD 14.17 trillion, and it is expected to rise to USD 17.65 trillion in 2025, with the banking sector contributing more than 16% to the country's GDP.[2] Second, according to the IMF Financial Access Survey (2023), outstanding deposits and loans in India account for 64.77% and 48.31% of GDP, respectively. However, these figures are accompanied by significant levels of Non-Performing Assets (NPAs). As per the RBI, NPAs for Indian banks stood at 3.9% of gross advances in 2023. This substantial level of NPAs and the resulting need for high provisioning offer a relevant framework to analyze provisioning behaviors within the Indian banking sector. Lastly, unlike developed nations, where state ownership of banks is relatively uncommon, the Indian banking sector is characterized by diverse ownership structures, with a significant presence of state-controlled banks (Porta et al., 2002). More details on the institutional background of the Indian banking sector and climate initiatives are provided in Section 2.

Our paper makes several important contributions to the extant literature, briefly summarized here. To our knowledge, this is the first and most comprehensive study examining the relationship between CPU and LLP for one of the largest- and fastest-growing economies. We hypothesize that, due to economic uncertainty around heightened CPU levels, bank managers would anticipate an increase in loan defaults, and consequently, set aside more LLP accruals. Using a sample of 56 Indian banks for the period 2003-2023 (630 bank-year observations), we identify a positive and significant relationship between CPU and LLP; more specifically, we show that a 1% increase in

[2] https://www.moneycontrol.com/news/business/economy/the-modern-indian-growth-story-third-largest-economy-by-ppp-and-the-expanding-power-of-the-consumer-12056231.html.

the CPU results in, on average, (1) about a 66% – 77% increase in LLPs, and in turn, (2) about a 28% – 33% decline in profitability. We also study the heterogeneous impact of CPU on LLP across micro (ESG score, size, and ownership) and macro (the Paris Agreement) factors. This impact of CPU on LLP is heterogeneous across banks with *'low versus high ESG (scores),'* '*small versus large (size),'* and '*public versus non-public sector (ownership).'* On average, the impact of a 1% increase in CPU: (1) is higher, for the banks with low ESG scores compared to those with high ESG scores, on LLPs and profitability by about 44% − 55% (of the sample mean LLP) and 19% − 24% (of the sample mean EBPT), respectively; and (2) is lesser, for small/public sector banks compared to large/non-public sector banks, on LLPs and profitability by about 66% − 111% (of the sample mean LLP) and 29% − 48% (of the sample mean EBPT), respectively. Moreover, we also show that, after the Paris Agreement (2015), the impact of CPU on LLP has increased by about 55% (of the sample mean LLP), and it erodes about 24% (of the sample mean EBPT) of the profitability. Our results survive a battery of robustness tests, including multiple LLP specifications, estimation approaches (OLS, panel fixed and random effects, system GMM, and IV-2SLS approaches), and subsample analysis. Overall, our results offer a new channel through which CPU affects financial stability – that is, asset quality and profitability in the banking sector through LLPs. Our results have significant implications for governments, standard setters, policymakers, regulators, banks, investors, academics, and market participants in general, especially those in emerging economies that are substantially exposed to climate change related risks (summarized in the concluding remarks).

The remaining paper is organized as follows. Section 2 discusses the institutional background of the Indian banking system, followed by the literature review and hypothesis development in Section 3. Section 4 elaborates on data and research methodology, and Section 5 presents empirical findings. Subsequently, Section 6 highlights the robustness tests, and Section 7 concludes with policy implications and future research avenues.

2. Institutional Background of the Indian Banking System

The Reserve Bank of India (RBI) is the central banking authority that oversees and regulates India's banking system under the Banking Regulation Act, 1949 (amended in 2017). Banking operations in India are predominantly concentrated with Scheduled Commercial Banks (SCBs), which include 12 public sector banks (PSBs), 22 private banks (PBs), and 44 foreign banks (FBs).[3] These SCBs collectively account for 95% of the total banking assets in the country.[4] Furthermore, public sector banks (PSBs) are typically subject to more stringent regulatory oversight. These PSBs are mandated to comply with stricter rules and guidelines than PBs and FBs. The PSBs are owned by the Government of India (GoI, more than 50% stake) and comprise 60% of the country's banking industry assets.

2.1. Provisioning norms in the Indian Banking system

Like many other emerging economies, India follows a rule-based system that exercises stronger regulatory oversight and curtails managerial discretion (Pandey et al., 2022). More precisely, banks operating in India follow provisioning practices guided by Indian Generally Accepted Accounting Principles (local GAAP)[5] and the RBI's regulatory and prudential norms, in tandem with Basel-III standards. This starkly contrasts with most advanced economies that utilize principle-based frameworks like the International Financial Reporting Standards (IFRS), which provide more leeway to bank managers in estimating LLP.

[3] As on December 2024: https://rbi.org.in/hindi1/Upload/content/PDFs/APPEH23102021_AP1.pdf
[4] https://rbi.org.in/Scripts/PublicationsView.aspx?id=21083#TC51
[5] https://www.ifrs.org/use-around-the-world/use-of-ifrs-standards-by-jurisdiction/view-jurisdiction/india/

The RBI has issued comprehensive prudential norms on Income Recognition, Asset Classification, and Provisioning (IRACP), leaving little room for subjective judgment. According to these norms, any asset past due for more than 90 days is classified as a Non-Performing Asset (NPA) and attracts mandatory provisioning. NPAs are also further classified into (a) sub-standard, (b) doubtful, and (c) loss assets, each of which attracts a provisioning requirement as per a prescribed matrix.[6] In other words, once a borrower defaults, bank managers have minimal discretion in how they classify or provision for that asset. Moreover, standard assets are also subject to mandatory general provisioning. However, the RBI's norms represent minimum requirements. Bank managers are permitted and often motivated to make specific provisions voluntarily at higher rates than prescribed regulations, depending on their internal risk assessments. This makes the Indian framework more stringent than the Basel guidelines, thereby strengthening the financial position of banks and enhancing overall systemic stability.

2.2. Climate Initiatives by India

The following characteristics make India an ideal country to study the impact of climate risk on an economy and financial system. First, India ranks as the third-largest emitter after China and the United States, with over 2.9 billion tons of carbon dioxide emissions in 2023, accounting for 8% of global CO_2 emissions.[7] Second, the country also faces a wide range of severe climate-related risks, including frequent extreme weather events such as floods, droughts, heat waves, and rising temperatures. In 2024, some regions in India recorded temperatures nearing 50°C, a stark indicator of escalating climate stress. Looking forward, projections indicate a significant rise in the country's

[6] For more detailed information, refer to [Reserve Bank of India - Master Circulars]
[7] https://www.newindianexpress.com/world/2023/Dec/08/global-emissions-of-fossil-carbon-dioxide-hit-record-high-in-2023-india-third-highest-emitter-2639836.html

average temperature, ranging from 1.2–2°C under moderate emission scenarios to as much as 3.5–5.1°C under high emission scenarios, by 2100 (Kumar et al., 2023).[8]

Considering the severe climate-related threats to the Indian population and economy, India joined the global efforts to mitigate climate change by ratifying the Paris Agreement in 2016. As a signatory and ratifying country of the Paris Agreement, India has pledged certain commitments referred to as Nationally Determined Contributions (NDCs). They are as follows: First, India has pledged to lower the emission intensity of GDP by 45% (by 2030) from the 2005 level. Second, like other parties to the Paris Agreement, India also aims to restrict the temperature increase to below 2°C (compared to pre-industrialization levels), ideally at 1.5°C. To this end, India intends to reach around 50% of its cumulative installed electric power capacity from non-fossil fuel sources by 2030, subject to international cooperation in finance and technology.[9] Third, India committed to creating an additional 2.5 to 3.0 billion tonnes of CO_2 equivalent carbon sink through afforestation by 2030. India has also been recognized for making notable progress toward its climate goals, with reports indicating that India is one of the few large economies to have met its Paris Agreement goals early.[10] Furthermore, India has committed to achieving net-zero carbon emissions by 2070, a long-term target set outside the NDC framework, reflecting its proactive stance on climate action.[11] These pledges position India among the leading players in global climate action, reconciling development imperatives and climate responsibility.

[8] https://indianexpress.com/article/cities/kolkata/iit-kgp-study-indias-surface-temperature-may-increase-by-1-1-to-5-1-deg-celsius-by-2100-9012672/
[9] https://unfccc.int/sites/default/files/NDC/2022-08/India%20Updated%20First%20Nationally%20Determined%20Contrib.pdf
[10] https://www.deccanherald.com/india/india-only-g20-nation-to-achieve-climate-targets-under-paris-agreement-ahead-of-schedule-pm-modi-3151376
[11] https://www.energypolicy.columbia.edu/cop28-assessing-indias-progress-against-climate-goals/

In addition, the Indian National Action Plan on Climate Change encourages investment in renewable energy and energy efficiency, which controls carbon emissions. Lastly, according to the Global Climate Risk Index, India ranks among the top 10 countries most vulnerable to climate-related disasters.[12] In 2022, the nation incurred economic losses of around $4.2 billion due to disasters like floods, droughts, and heatwaves, and this trend is likely to continue.[13] India's vulnerability to climate risks is expected to increase. The World Bank has projected that by 2050, climate-related impacts could cost India up to 2.8% of its GDP and depress the living standards of nearly half of its population.[14] This could significantly impact the economic activity across various sectors, including banking.

The total population of India is about 1.4 billion (140 crores), of which 50% earn less than $10 per day, comprising the lower middle class, poor, and those below the poverty line. A substantial proportion of this population is exposed to climate change related risks; this further underscores India's pivotal role in global climate discussions, particularly in addressing climate risk and implementing climate policies effectively. Post the aggressive rolling out of the Jandhan-Aadhar-Mobile (JAM) scheme by GoI, a large section of India's population is now banked with more than 2.52 billion (252 crore) accounts as of December 2024.[15] Most of these accounts are held by economically weaker sections of society that are integrated into the formal economy through these accounts. For example, the government of India runs multiple credit and social welfare schemes

[12] https://timesofindia.indiatimes.com/india/india-among-top-10-worst-hit-countries-due-to-extreme-weather-events-says-a-global-report-on-climate-risk-index/articleshow/80453389.cms

[13] https://www.newindianexpress.com/nation/2023/Jul/27/climate-change-induced-substantial-economic-losses-for-india-in-2022-2599138.html#:~:text=NEW%20DELHI%3A%20India%20faced%20significant,followed%20by%20drought%20and%20heatwaves.

[14] https://www.worldbank.org/en/news/press-release/2018/06/28/climate-change-depress-living-standards-india-says-new-world-bank-report#:~:text=NEW%20DELHI%2C%20June%2028%2C%202018,a%20World%20Bank%20report%20says.

[15] https://www.pmindia.gov.in/en/government_tr_rec/leveraging-the-power-of-jam-jan-dhan-aadhar-and-mobile/

for poorer sections of the economy that are operationalized through these accounts.[16] It is precisely this stratum of Indian population that is most vulnerable to extreme weather events and climate change related catastrophes (e.g., floods, droughts, heatwaves, and rising temperatures that cause disruptions in economic activity). Most of the Indian industrial and manufacturing growth is labor-intensive and depends on this stratum for the workforce's supply. Moreover, to safeguard against such climate change related crises, the government is expected come up with ambitious policy responses that may cause transition risks for banks' carbon-intensive assets, especially those in industrial and manufacturing segments.[17] In this backdrop, it is of utmost importance to understand the impact of climate policy uncertainty on the asset profile and profitability of Indian banks, more specifically, the loan loss provisioning practices; this may provide important insights into the behavior of bank managers with respect to the perceived impact of CPU on the Indian economy.

3. Literature Review and Hypothesis Development

Our paper contributes to a novel and unexplored strand of literature examining the impact of climate policy uncertainty (CPU) on managerial decision-making in banks and banking assets. More specifically, we examine the relationship between CPU and discretionary LLPs. Considerable literature has emerged in the last five years examining the CPU's broad macroeconomic and firm-level implications. The major notable strands of this literature include: (a) impact of CPU on asset pricing and valuation (Barnett et al., 2020; Engle et al., 2020; Hsu et al., 2023; Ilhan et al., 2021); (b) CPU and the problem of stranded assets (Delis et al., 2024; Ploeg

[16] https://www.india.gov.in/my-government/schemes-0

[17] For example, various government initiatives such as low-interest or interest-free loans to support transition from high- to low-carbon economy are often implemented through scheduled commercial banks (SCBs), especially public banks. Examples of such initiatives include the Pradhan Mantri Kisan Urja Suraksha evam Utthan Mahabhiyan (PM-KUSUM) scheme, SBI Surya Ghar Loan for Solar Rooftop, SBI Green Car Loan, PNB Green Car Loan, and the Bank of Maharashtra's Maha Super Green Car Loan Scheme. These programs aim to promote sustainable practices like installing solar panels, adopting energy-efficient appliances, and purchasing electric vehicles.

& Rezai, 2020; Sen & Von Schickfus, 2020); (c) implications of CPU for firm-level total factor productivity (Letta & Tol, 2019; Ren et al., 2022); (d) role of CPU in macroeconomic stability and financial development (Battiston et al., 2021; Campiglio & Van Der Ploeg, 2022; Carattini et al., 2023; Diluiso et al., 2021); and (e) implications of CPU for employment, job creation, and investment in research and development (Dietz & Stern, 2015; Martin et al., 2014; Yamazaki, 2017). We briefly summarize this literature from the CPU perspective as follows.

The last 40 years have witnessed carbon-intensive global economic growth driven by fossil fuels (Dietz & Stern, 2015; Diluiso et al., 2021; Yamazaki, 2017). However, this has resulted in substantial climate changes and catastrophic events (e.g., extreme temperatures, rising sea levels, severe droughts, floods, and heat waves). This has motivated governments and policymakers to develop regulatory climate policies and innovative climate change mitigation instruments (such as carbon taxes, cap-and-trade schemes, and emission limits, among others) to transition the economy from a high-carbon to a low-carbon path (Carattini et al., 2023; Paroussos et al., 2019; Ren et al., 2022). One of the major unanticipated consequences of these policy measures is the "*climate transition risk;*" that is, the uncertainty in the business and economic environment, which is further amplified due to the ambitious and accelerated pace of climate change mitigation targets ("Carbon Pricing," Financial Times, 2019).[18] The consequences are much more relevant and adverse for carbon-intensive firms (e.g., stranded assets, high cost of doing business, and financing constraints) (Delis et al., 2024; Sen & Von Schickfus, 2020).

However, one of the major challenges with the CPU and the associated transition risk is that all the stakeholders see and learn the consequences of an anticipated policy action only when

[18] For example, the 2015 Paris Agreement stipulates keeping the global temperatures well below 2^0C compared to pre-industrial levels by the end of this century.

it is fully adopted and implemented (Carattini et al., 2023; Ilhan et al., 2021). The loss of firm value and economic activity associated with a future climate regulation is quantifiable only ex-post, not ex-ante (Barnett et al., 2020; Carattini et al., 2023; Ge et al., 2025). For academics, regulators, investors, policymakers, and stakeholders in general, analyzing the contemporaneous managerial response to climate policy uncertainty is extremely important to assess the climate transition risk (from high-carbon to low-carbon). There is a wide consensus that this climate transition risk is a potential systemic risk, engendered by the abrupt and unpredictable implementation of stringent climate policies (Campiglio & Van Der Ploeg, 2022; Ge et al., 2025; Ginglinger & Moreau, 2023). Furthermore, this risk directly impacts various aspects of firm operations (e.g., risk premium on capital raising, contractual transactions along the various levels of the supply chain). This motivates us to search for ex-ante quantifiable measures of the impact of CPU on firm operations and economic activity. In this backdrop, we refer to the classical literature on earnings management in banking, which considers banks as systemic entities at the center of a financial system, with bank managers at the top of the information hierarchy in an economy (Beatty & Liao, 2011; Bushman & Williams, 2012; Collins et al., 1995; Wahlen, 1994). This literature identifies loan loss provisions (LLPs) as the most significant accruals, especially the discretionary component of LLPs (Ahmed et al., 1999; Kim & Kross, 1998; Moyer, 1990). The classical literature argues that the discretionary component of LLPs reflects bank managers' view of expected future losses in the bank's loan portfolio. Bank managers typically peruse discretionary LLPs for three key purposes: (a) earnings' management, (b) managing regulatory capital, and (c) as a signal to communicate their private information to various stakeholders (Bushman & Williams, 2012; Elliott et al., 1991; Moyer, 1990; Scholes et al., 1990). Given the cardinal position of bank managers in the informational hierarchy of a financial system, we argue that their estimate of the loss of economic activity and firm value on account of CPU is extremely important. Moreover, a directly quantifiable forward-looking estimate of this loss is available contemporaneously in the form of discretionary LLPs. To that extent, we hypothesize that the contemporaneous relationship between CPU and LLP, after controlling for the well-established determinants of LLP (control variables for extracting the expected non-discretionary component of LLP), captures the bank managers' estimate of the impact of CPU on economic activity and firm value in an aggregate manner.[19] To the best of our knowledge, this is the first study that examines the relationship between CPU and LLP.

Our paper also contributes to a novel and growing strand of literature examining the macroeconomic adverse effects of climate change on the stability of a financial system, and banks in particular (Battiston et al., 2017; Ge et al., 2025; Nguyen et al., 2022; Sen & Von Schickfus, 2020; Wu et al., 2024). For example, Xu et al. (2024) stress test the Chinese banking system using a network-based climate risk model. They show that the Chinese policy target of peaking carbon in 2030 and CO_2 concentration of 500 ppm by 2100 may result in equity losses for Chinese banks of about 1.93% – 14.03%. In another influential work, Wu et al. (2024) study the systemic risk engendered by climate change in 1,570 banks from 120 countries, spanning 2007-2020, with total assets exceeding \$1 billion. They document a significant increase in the banks' systemic risk due to climate change, driven by deteriorating credit quality. In a similar vein, Ge et al. (2025) examine the impact of extreme temperatures on syndicated bank loan pricing for 35 countries. They find that banks charge a higher interest rate for borrowers with a higher climate risk. Ginglinger & Moreau (2023) also find that post-2015 (after the Paris Agreement), banks charge higher spreads

[19] While the estimate of one bank manager may be subject to noise and error of estimate, in the aggregate, on average, the relationship between CPU and LLP may give us a reasonably accurate estimate of the impact of CPU on the economy.

to climate-sensitive firms, resulting in lower credit availability. Similar findings are reported by many important contributions (Ehlers et al., 2022; Javadi & Masum, 2021; Kleimeier & Viehs, 2021; Li & Pan, 2022; Nguyen et al., 2022) – that is, lenders do price climate risk in their assets to account for potential future losses due to climate risk. However, there are no studies quantifying this relationship of CPU with potential future loan losses. We briefly summarize this literature as follows. The two broad channels through which climate change engenders systemic financial risk include: (a) climate transition risk from low-carbon to high-carbon economy (e.g., stranded assets), and (b) the physical risk driven by the direct losses from chronic (e.g., rising sea levels and temperatures) and catastrophic (e.g., earthquakes, severe floods and draughts, hurricanes) climate events (Pagliari, 2023; Wu et al., 2024; Xu et al., 2024). This literature suggests that banks recognize the climate risk by reducing the loan amount and maturity, and increasing the interest rates for climate-sensitive sectors, and vice-versa for companies with better environmental performance (Battiston et al., 2017; Delis et al., 2024; Diluiso et al., 2021). The extant literature predominantly focuses on stress-testing of banking assets against physical risks (e.g., floods, extreme temperatures), and to an extent, on the impact of ex-post implementation of climate policies (e.g., carbon taxes and carbon pricing) on bank performance. However, the literature remains silent on the ex-ante impact of CPU (or climate transition risk) on banking assets and bank managers' response to the same. This is primarily attributed to the difficulty in measuring the climate transition risk. We contribute to this literature by quantifying the impact of CPU on banking assets by investigating the relationship between CPU and LLP.

3.1. Hypothesis development

For the banking sector, we hypothesize that the transition risk may directly originate from the asset side through two key channels: (a) The credit risk channel (lending operations): due to the uncertainty associated with CPU, banks may tighten credit to climate-sensitive and emission-intensive sectors. For example, the advent of new renewable energy technologies may cause old resources and technologies to become obsolete, and the firms using them may lose their market share. Moreover, market-oriented measures such as carbon trading and emission limits may significantly affect the production and operations of emission-intensive firms, leading to constrained margins and, in turn, deteriorating credit profile and debt repayment capacity; (b) The market risk channel (pricing of assets): the market risk channel may put a substantial haircut on carbon-intensive assets, and may even result in a "fire-sale" of these assets at significantly discounted prices. This is attributed to the stringent and ambitious implementation of climate policies, which may result in some of these banking assets turning into "stranded assets." Based on the aforementioned discussion, we develop our research questions (RQs) and the corresponding hypotheses as follows.

RQ 1: Adverse climate changes and the resulting climate policies implemented by the government may affect LLPs in Indian banks in the following manner. First, India is exposed to adverse climate changes, causing events such as rising temperatures, floods, and other economic catastrophes. In response, the government's swift implementation of drastic climate policies may adversely affect the financial position of individuals and businesses, consequently increasing the risk of loan defaults (Delis et al., 2024; Ploeg & Rezai, 2020). Second, CPU may lead to information asymmetry and motivate risk-averse economic agents to respond conservatively. For example, evidence from the literature at both macro and firm levels suggests that CPU negatively impacts financial stability (Nakhli et al., 2024), employment (Yamazaki, 2017), corporate investment (Krueger et al., 2020), productivity (Letta & Tol, 2019; Ren et al., 2022), and firm value (Dafermos et al., 2018; Sen & Von Schickfus, 2020). Anticipating these repercussions, banks may increase their LLPs as a precautionary measure to safeguard against climate-engendered risks. Consequently, we argue that CPU is expected to be positively associated with LLPs.

H1a: ***Climate policy uncertainty positively influences banks' loan loss provisions (LLPs).***

RQ2: More recently, there has been a considerable impetus to incorporate ESG parameters – namely, environmental (E), social (S), and governance (G) – into investment philosophy. Arguably, a bank that incorporates ESG parameters in its investment decision-making would be less exposed to the CPU-related uncertainties (e.g., stranded asset problems, difficulty in raising capital, disruption in supply chains, and higher regulatory capital requirements for carbon-intensive assets). A higher ESG score, therefore, reflects lower vulnerability and exposure to the adverse effects of CPU. Ceteris paribus, we hypothesize that a higher ESG score would be related to lower bank LLPs.

H2a: ***Banks with lower ESG scores tend to have (incrementally) more LLPs during CPU than those with higher scores.***

RQ3: The Paris Agreement (2015, COP21)[20] is a watershed climate change event requiring significant commitments from the signatories, such as India. In particular, the agreement includes ambitious targets such as keeping global warming below 2^0C compared to the pre-industrial levels and net-zero emissions by 2050. Emerging economies like India have witnessed fossil-fuel-driven growth over the last three decades. Being a signatory to the Paris Agreement requires a significant policy shift and may expose the Indian economy to considerable transition risks. In emerging market economies like India, the banking sector plays a major role in providing credit and facilitating economic growth (e.g., infrastructure development and priority sector lending).

[20]UN Climate Change Conference (COP21): https://unfccc.int/process-and-meetings/the-paris-agreement

Therefore, unexpected changes in climate policies, regulations, and technological shifts may affect the banking industry primarily through the market and credit risk channels. Overall, we hypothesize that the threat of transition risk on account of CPU has significantly increased post the Paris Agreement (2015, COP21).

H3a: ***The impact of CPU on bank LLPs is greater after the Paris Agreement (2015) than before.***

RQ 4: Next, we propose to conduct a heterogeneity analysis based on bank size. We argue that large banks are systemic in nature ("too big to fail") – for example, the top-5 and the top-10 banks in India hold about 50% and 75% of the total deposits, respectively. Therefore, these large banks are heavily scrutinized and monitored for their adherence to prudential norms and regulatory standards by authorities and market participants (such as analysts, investors, and academics), especially during times of uncertainty (Anginer et al., 2024; Hirtle et al., 2020). Hence, we hypothesize that large banks, compared to small banks, may adopt a more proactive and conservative LLP approach, particularly during times of heightened CPU. Following this, we propose our next hypothesis.

H4a: ***Large banks tend to have (incrementally) more LLPs during CPU than small banks.***

RQ 5: Finally, we investigate the role of ownership (public versus non-public) in the CPU-LLP relationship. We argue that the government ownership of public sector banks makes them fundamentally different from non-public sector (private and foreign) banks. Indian public sector banks are often characterized by (a) a bureaucratic leadership that is dependent on the approval of political bosses for survival, (b) less concern for bank profitability and more for social welfare, running government schemes, and populist measures to create a good image of the government, and (c) riskier lending practices influenced by political considerations with less concern for credit profile of the borrower (Carvalho, 2014). For example, one crucial mandate of public sector banks is to provide banking services to the poor living in the extremely remote corners of the country and integrate them into the formal economy; for private and foreign banks, this may not be considered a worthwhile proposition due to profitability concerns. Similarly, facilitating social welfare schemes (e.g., zero balance accounts), giving loans to priority sectors at subsidized rates, and creating employment are central to public banks' lending practices. However, these issues may not be relevant to the private and foreign bank objectives, as these banks are primarily profit-oriented and less concerned with these social welfare related aspects. Finally, given the control and influence of the government, public sector banks are expected to implement any climate-related initiatives promoted by the government, whether prudential or regulatory, with much more vigor and urgency than non-public sector banks. In this backdrop, we hypothesize that the impact of climate policy uncertainty may affect public sector banks more severely due to (1) the government ownership and control and (2) their close linkages with the low-income strata, particularly the lower middle class of the Indian economy (Jin et al., 2019). Following this, we propose our fifth hypothesis.

H5a: ***Public sector banks tend to have (incrementally) more LLPs during CPU than their non-public sector peers.***

4. Data and Methodology

4.1. Data

We collect bank information and financial data from the CMIE Prowess database. Our Climate Policy Uncertainty (CPU) index aims to proxy global climate change related risks (Dai & Zhang, 2023; Gavriilidis, 2021; Tedeschi et al., 2024). To make the CPU measure suitable for our annual frequency empirical investigation, we transform it by taking the natural log of 12 monthly average values for each year: $CPU_{annual} = ln\left(\frac{\Sigma_{monthly=1}^{12} CPU_{monthly}}{12}\right)$. The time-series movement of CPU_{annual} is shown in Figure 1.

[Kindly insert figure 1 about here]

Moreover, the data related to Oil Volatility Index (OVX)[21] and GDP are obtained from Bloomberg and World Development Economic Indicators Database, respectively. For ESG ranking, we peruse Crisil ESG ratings registered with SEBI as a 'Category 1' ESG rating provider.[22] The final sample consists of 630 bank-year observations for 56 Indian banks, including 12 public sector, 20 private sector, and 24 foreign banks, from 2003 to 2023.

4.2. Methodology

To examine the relationship between CPU and LLP, we employ OLS, the panel fixed effects model, the IV-2SLS approach, and the system GMM approach. In line with Bushman & Williams (2012), we propose the following baseline model [Eq.(1)] to test our main hypothesis.[23]

[Kindly insert Table 1 about here]

[Kindly insert Table 2 about here]

$$LLP_{it} = \beta_o + \beta_1 CPU_t + \beta_2 \Delta NPL_{it} + \beta_3 \Delta NPL_{it+1} + \beta_4 \Delta NPL_{it-1} + \beta_5 \Delta NPL_{it-2} + \beta_6 \Delta GDP_t + \beta_7 \Delta LOAN_{it} + e_{it} \quad (1)$$

[21] Data for the Oil Volatility Index (OVX) is available from 2007, limiting any analysis involving OVX to start from this year.
[22] These are performance ratings based on ESG parameters. The parameters include actual outcomes, such as funding to green projects, reducing carbon emission, minimizing energy consumption, ensuring fair labor practices, fostering gender diversity and inclusion, among others (https://www.crisilesg.com/).
[23] We also employ other important LLP specifications; the corresponding results are presented in Appendix D.

Where subscripts (i,t) stand for bank 'i' and time 't', respectively. Loan loss provisions (LLP_{it}) and Climate Policy Uncertainty (CPU_t) are the main variables of interest. Detailed definitions of the variables [Eq.(1)] are provided in Table 1. All the variables are deflated by total assets, except CPU and GDP. Descriptive statistics are provided in Table 2. To control for the expected non-discretionary component of LLP, we include well-established determinants of LLP as control variables in the model (Bushman & Williams, 2012; Kanagaretnam et al., 2004; Pandey et al., 2022). Furthermore, we also conduct a battery of robustness tests, including multiple estimation approaches (OLS, panel fixed and random effects, system GMM, IV-2SLS), subsample analysis, and different LLP specifications. These are discussed in Section 6 on robustness tests. Correlation matrix and VIF values are provided in Tables 3 and 4. Most of the correlations are economically low. In fact, the VIF values are much less than 2.0, indicating that multicollinearity issues would not vitiate the model estimation.

[Kindly insert Table 3 about here]

[Kindly insert Table 4 about here]

5. Empirical results

Table 5 presents our baseline results [for Eq.(1)], with columns (1) and (2) showing estimates from the OLS and panel fixed effects method, respectively.[24] We find a positive and significant relationship between CPU and LLP. More specifically, a 1% increase in CPU is associated with 0.6% – 0.7% of assets being provisioned to account for loan losses – that is, an increase in LLP. To understand the economic significance of this relationship, we compare it with the magnitude

[24]We employ Hausman test for comparing fixed and random effects for different model specifications. However, no one particular panel approach dominates over the other; the Hausman test results are provided in Appendix F. So we estimate both fixed and random effects. The results corresponding to random effects are presented in the respective Appendices.

of: (a) LLP (mean, minimum, and maximum LLP amounting to 0.9%, 0.1%, and 2.8% of the corresponding assets, respectively) and (b) EBPT (mean, minimum, and maximum EBPT amounting to 2.1%, 0.7%, and 4.1% of the corresponding assets, respectively) in our sample, as provided in the descriptive statistics (Table 1). These figures suggest that a 1% increase in CPU, on average (or mean), results in an increase in LLP of about 66% – 77%, and in turn, accounts for approximately 28% – 33% (of EBTP) erosion of profitability.

[Kindly insert Table 5 about here]

5.1. Instrumental Variable approach

Next, we employ an instrumental variable (IV) approach to mitigate potential endogeneity issues. Following Dai & Zhang (2023), we utilize the IV-2SLS estimation procedure with the OVX measure as an instrumental variable for CPU. Volatility in oil prices often prompts governments to accelerate climate policies to reduce dependency on fossil fuels. These policy variations puzzle economic agents because they lack clarity and predictability, thereby contributing to CPU. Hence, OVX is relevant to CPU, as a higher level of OVX is expected to increase uncertainty related to climate policymaking. On the other hand, we expect OVX to be an exogenous variable in our LLP specification, thus satisfying the exclusion restriction condition as a suitable instrumental variable. Table 6 provides the results of first- and second-stage regressions, respectively. First, we verify the appropriateness of our instrumental variable (IV) approach in the following manner. In the first stage IV regression, the instrumental variable OVX carries a positive and significant coefficient and a significant F-value for the overall regression. The Weak Instrument test statistic (Stock & Yogo, 2002)[25] examining the correlation of the instrumental variable with the endogenous variable

[25] For implementation of "Weak Instrument" and "Wu-Hausman" tests, we employ 'ivreg' function from AER package in R.

(CPU) is also significant, suggesting the appropriateness of the instrument. Lastly, the Wu-Hausman statistic (Greene, 2003) shows the significance of endogeneity in the original model, and therefore, the appropriateness of the IV-2SLS approach. Overall, these results are consistent with our baseline results (shown in Table 5). These results suggest that, on average, a 1% increase in CPU is associated with: (a) 1.3% of assets being provisioned to account for loan losses; (b) 144% increase in LLP; and (c) 62% (of EBTP) erosion of the profitability. The results pertaining to different estimation approaches (OLS, panel fixed and random effects, system GMM, and IV-2SLS), subsample analysis, and other LLP specifications are provided in online Appendices A and G. These results are qualitatively similar to our baseline results.

[Kindly insert Table 6 about here]

5.2. Heterogeneity analysis based on 'ESG scores' and the impact of the Paris Agreement

To test our second hypothesis (H2a), we create an 'ESG' indicator variable equal to '1' for higher ESG scores (above the median score) and '0' otherwise. Further, we interact CPU with ESG and include the interaction term 'CPU×ESG' in our model, as shown in Table 7 (OLS, panel fixed effects, and IV-2SLS approaches). The negative coefficient of the interaction term suggests that banks with higher ESG scores provision 0.4% − 0.5% (LLPs as a percentage of assets) less than those with lower ESG scores;[26] that is, on average, the impact of CPU on LLPs is lower for banks with higher ESG scores. To understand the economic significance of this figure, (a) it is about 44% − 55% of the sample mean LLP, and (b) it erodes about 19% − 24% (of the sample mean EBPT) of the profitability. This means that while CPU generally increases LLP, this increase is less for

[26] Across multiple configurations some of the estimates are not as significant. However, the sign remains consistent.

banks with a higher ESG score. This confirms our second hypothesis. The results pertaining to different model specifications (estimated using OLS, panel fixed and random effects, system GMM, and IV approaches) and subsample analysis are provided in online Appendix B. Moreover, we also estimate our results using only environmental (E) scores. These results are qualitatively similar to our baseline results.

[Kindly insert Table 7 about here]

Next, to test our third hypothesis (H3a), we create a 'Paris' indicator variable ('1' for the period 2016-2023 and '0' otherwise) and include 'CPU×Paris' as the interaction term in our model. The corresponding results are shown in Table 8 (OLS, panel fixed effects, and IV-2SLS approaches). The interaction term exhibits a positive coefficient, suggesting a higher influence of CPU on bank LLPs after the Paris Agreement.[27] More specifically, on average, the impact of CPU on LLPs (as a percentage of assets) is 0.5% higher after the Paris Agreement than before. To understand the economic significance of this figure, (a) it is about 55% of the sample mean LLP, and (b) it erodes about 24% (of the sample mean EBPT) of the profitability. The results pertaining to different model specifications (estimated using OLS, panel fixed and random effects, system GMM, and IV approaches) and subsample analysis are provided in online Appendix C. These results are qualitatively similar to our baseline results.

[Kindly insert Table 8 about here]

[27] Across multiple configuations some of the estimates are not as significant. However, the sign remains consistent.

5.3. Heterogeneity analysis based on 'Size' and 'Ownership'

To test our fourth hypothesis (H4a), we create a 'size' indicator variable equal to '1' for small banks and '0' otherwise.[28] We include the interaction term 'CPU×size' in our model, as shown in Table 9 (OLS, panel fixed effects, and IV-2SLS approaches). The negative and significant coefficient of the interaction term 'CPU×size' indicates that, on average, the impact of CPU on LLPs (as a percentage of assets) of small banks is 0.6% − 1.0% less than that of large banks. To understand the economic significance of this figure, (a) it is about 66% − 111% of the sample mean LLP, and (b) it erodes about 29% − 48% (of the sample mean EBPT) of the profitability. This means that while CPU generally increases LLP, this increase is less for small banks. This confirms our fourth hypothesis. The results pertaining to different model specifications (estimated using OLS, panel fixed and random effects, system GMM, and IV approaches) and sample-split across large and small sizes are provided in online Appendix D. These results are qualitatively similar to our baseline results.

[Kindly insert Table 9 about here]

Similarly, to test our fifth hypothesis (H5a), we create a 'public' indicator variable ('1' for public and '0' otherwise) and include 'CPU×public' as the interaction term in our model. The positive and significant coefficient of the interaction term 'CPU×public' (as shown in Table 10) shows that, on average, the impact of CPU on LLPs (as a percentage of assets) of public sector banks is 0.6% − 1.0% higher than that of private banks.[29] This confirms our fifth hypothesis. The

[28] We classify the banks as large or small based on the median value of size, which is calculated as the natural logarithm of total assets. Banks with observations below the median are categorized as small, while those above the median are classified as large.

[29] The coefficient of the interaction term 'CPU×public' is similar in terms of magnitude as that of 'CPU×size' in different configurations.

results pertaining to different model specifications (estimated using OLS, panel fixed and random effects, system GMM, and IV approaches) and sample-split across public and non-public sector banks are provided in online Appendix E. These results are qualitatively similar to our baseline results.

[Kindly insert Table 10 about here]

6. Robustness analysis

We briefly discuss the robustness tests conducted in the study (Appendices A-H). First, we employ the different variations of our main LLP specification [Eq. (1)] as provided below.

$$LLP_{it} = \beta_o + \beta_1 CPU_t + e_{it} \quad \text{(a)}$$

$$LLP_{it} = \beta_o + \beta_1 CPU_t + \beta_2 \Delta NPL_{it} + \beta_3 \Delta NPL_{it+1} + \beta_4 \Delta NPL_{it-1} + \beta_5 \Delta NPL_{it-2} + \beta_6 \Delta LOAN_{it} + e_{it} \quad \text{(b)}$$

$$LLP_{it} = \beta_o + \beta_1 CPU_t + \beta_2 \Delta NPL_{it} + \beta_3 \Delta NPL_{it+1} + \beta_4 \Delta NPL_{it-1} + \beta_5 \Delta NPL_{it-2} + \beta_6 \Delta LOAN_{it} + \beta_7 \Delta GDP_t + e_{it} \quad \text{(c)}$$

$$LLP_{it} = \beta_o + \beta_1 CPU_t + \beta_2 \Delta NPL_{it} + \beta_3 \Delta NPL_{it+1} + \beta_4 \Delta NPL_{it-1} + \beta_5 \Delta NPL_{it-2} + \beta_6 \Delta LOAN_{it} + \beta_7 \Delta GDP_t + \beta_8 CAP_{it} + \beta_9 EBPT_{it} + e_{it} \quad \text{(d)}$$

Here, specification (a) excludes all the control variables, (b) includes only non-discretionary controls, (c) is the same as Eq. (1), which includes non-discretionary and macro control variables, and (d) further augments the LLP specification [Eq. (1)] with discretionary control variables. All the variable definitions are provided in Table 1. All the additional specifications [(a), (b), and (d)] are estimated with the OLS, panel fixed and random effects, system GMM, and IV-2SLS approaches. The corresponding results are provided in Appendix A. We employ the system GMM (SGMM) method to estimate the dynamic model containing the lagged dependent variable. The validity of our GMM estimations is verified by the results corresponding to AR(1), AR(2), and the Sargan test for the overall instrument validity. Moreover, we use a two-step GMM estimator (instead of a one-step estimator) because of its efficiency property.

We also employ these specifications [(a), (b), and (d)] to conduct heterogeneity analysis based on ESG scores (H2a), the impact of the Paris Agreement (H3a), size (H4a), and ownership (H5a). We peruse the OLS, panel fixed and random effects, system GMM, and IV-2SLS estimation approaches for the heterogeneity analysis. Moreover, we also conduct a subsample analysis based on these heterogeneities (i.e., ESG scores, the Paris Agreement, size, and ownership). We also reestimate our models [(a), (b), (c), and (d)] with the environmental scores provided by Crisil ESG ratings, using all the estimation methods as earlier. The corresponding results are presented in Appendices B-E. We also perform data winsorization and truncation at 1% levels; the corresponding results remain qualitatively similar and are not reported for brevity. These results are available upon reasonable request from the authors.

6.1. Different model specifications

Following the extant literature, we further employ three different LLP specifications (Ahmed et al., 1999; Beatty & Liao, 2011; Ng et al., 2020) as an additional robustness check (provided below).

$$LLP_{it} = \beta_o + \beta_1 CPU_t + \beta_2 \Delta NPL_{it} + \beta_3 \Delta NPL_{it+1} + \beta_4 \Delta NPL_{it-1} + \beta_5 \Delta NPL_{it-2} + \beta_6 \Delta GDP_t + \beta_7 \Delta Loan_{it} + \beta_8 Allow_{it} + e_{it} \quad (2)$$

$$LLP_{it} = \beta_o + \beta_1 CPU_t + \beta_2 \Delta NPL_{it} + \beta_3 \Delta Loan_{it} + \beta_4 \Delta GDP_t + \beta_5 Allow + e_{it} \quad (3)$$

$$LLP_{it} = \beta_o + \beta_1 CPU_t + \beta_2 \Delta NPL_{it} + \beta_3 \Delta NPL_{it+1} + \beta_4 Loan_{it} + \beta_5 \Delta GDP_t + \beta_6 Allow_{it} + \beta_7 size_{it} + e_{it} \quad (4)$$

The detailed results pertaining to these three LLP specifications [(2), (3), and (4)] are presented in Appendix G. These results again validate our baseline findings, indicating that any particular model specification does not influence our results.

7. Conclusion and policy implications

In this study, we unravel and quantify the impact of CPU on bank LLPs, which is a very important source of systemic risk and macro-financial instability. In an economic environment characterized by information asymmetry between bank managers and other economic agents, LLPs provide a very important assessment of banks' asset quality by the managers. We find that CPU adversely affects the quality of banking assets via climate transition risk. This impact of CPU is heterogeneous across the banks' ESG scores, size, and ownership. We show that the impact of CPU on LLPs is higher for banks with low ESG scores, large size, and public sector ownership, as compared to those with high ESG scores, small size, and non-public sector ownership. First, we argue that higher ESG scores reflect lower exposure and vulnerability to climate transition risk (e.g., risk of stranded assets and distress sales, a higher regulatory capital requirement for carbon-intensive assets, ability to raise funds, and disruption in supply chains during heightened CPU environments); this, in turn, may require higher provisioning by banks with lower ESG scores anticipating deterioration in asset quality. Next, we posit that large banks are systemic in nature, and therefore, heavily regulated and monitored. Thus, compared to small banks, they need to be more cautious and proactive regarding their LLPs. As regards the public sector banks, we argue that, due to government ownership and control, they are expected to implement climate-related policies in a stringent and swift manner. Moreover, it is also their mandate to integrate the poor sections of society that are most vulnerable to climate-related changes. Thus, public sector banks are more exposed to CPU than their non-public sector counterparts. Finally, we also find evidence to suggest that the Paris Agreement has put a significant onus and time-bound commitment on signatories like India, thus requiring a substantial shift in the economics of climate policy (e.g., potential change in asset mix from brown to green, less stringent regulatory capital requirements for green assets, accelerated investment in renewable energy technologies); this has increased the impact of CPU on bank LLPs, especially those with carbon-intensive asset portfolio. Our results are both statistically and economically significant, and robust to different estimation approaches, including the OLS, panel fixed and random effects, system GMM, IV-2SLS, subsample analysis, and different LLP specifications.

This is the first study documenting that banks consider the information content of CPU while accounting for LLPs. Higher LLPs indicate future potential deterioration in the banking sector's asset quality and profitability. This creates a ripple effect, causing issues related to capital adequacy, exacerbating banks' ability to create credit, and curtailing economic growth, ultimately destabilizing the financial system. All in all, we find a novel channel through which CPU may cause financial instability – that is, through LLPs affecting the asset quality and profitability of the banking sector.

Our results have important implications for bank managers, regulators and policymakers, investors, academics, and market participants in general. First, investors need to carefully examine the climate risk related sensitivity of not only individual assets but markets in general; as our results suggest that CPU may result in systemic risk through the banking channel and erode the benefits of portfolio diversification when they are needed the most. Investors need to devise optimal portfolio strategies that carefully consider climate risks explicitly. Second, regulators and policymakers need to incorporate climate risk in macroprudential and regulatory frameworks by identifying the potential vulnerabilities and systemic risks engendered by climate change related risk factors. In addition, unplanned implementation of climate risk mitigating policies such as carbon taxes, emission trading systems, etc., can create policy uncertainty and may destabilize the economy. Therefore, governments and regulators need to implement any such policy measures in a stable, transparent, predictable, and long-term manner [e.g., providing regular forward guidance and conducting a pilot testing phase (e.g., EU-ETS phase 1)[30] before full-fledged implementation] through clear and concise communications. Besides, banks need to strengthen their internal risk management and supervision mechanisms by incorporating CPU as an important risk indicator in existing systems. For example, our results show that CPU affects banks heterogeneously (e.g., ESG scores, size, ownership). Therefore, efficient pricing of assets would involve testing their resilience against the occurrence of climate-related risk events. This, in turn, may require creating robust climate risk metrics with scenario analysis to stress test the loan portfolios. Climate change disproportionately affects a large population of an emerging market economy like India; therefore, the traditional risk management models are not well suited to address the impact of climate change on banks' asset quality. Moreover, any potential lack of coordination among diverse climate policies may further exacerbate the situation and have a spiralling effect on the macro-financial stability.

Lastly, the study opens future research avenues for academics in other emerging and developed economies. These results are especially important for and may provide guidance to emerging market economies striving to advance climate risk governance in banking, since they face similar challenges related to economic, political, and climate related uncertainty, high credit concentration in a few carbon-intensive sectors, lower levels of financial inclusion, and a heavy reliance on banks for liquidity creation, especially in priority sectors such as agriculture. For

[30] https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets/development-eu-ets-2005-2020_en

example, our results suggest that higher transparency and information dissemination levels may facilitate early detection of climate-related losses and potential adverse developments in banks' books. Moreover, our results also indicate that capital requirement regulations (e.g., Basel norms) cannot be devised in isolation and that a systemic risk buffer pertaining to environmental parameters in alignment with the global sustainability objectives needs to be built. Future research could explore the discretionary behaviors of bank managers, including capital management, earnings management, and signaling behaviors around CPU. The researchers may also explore the effectiveness of various green instruments in mitigating the climate-related risk and the response of emerging market economies to these instruments.

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Figures

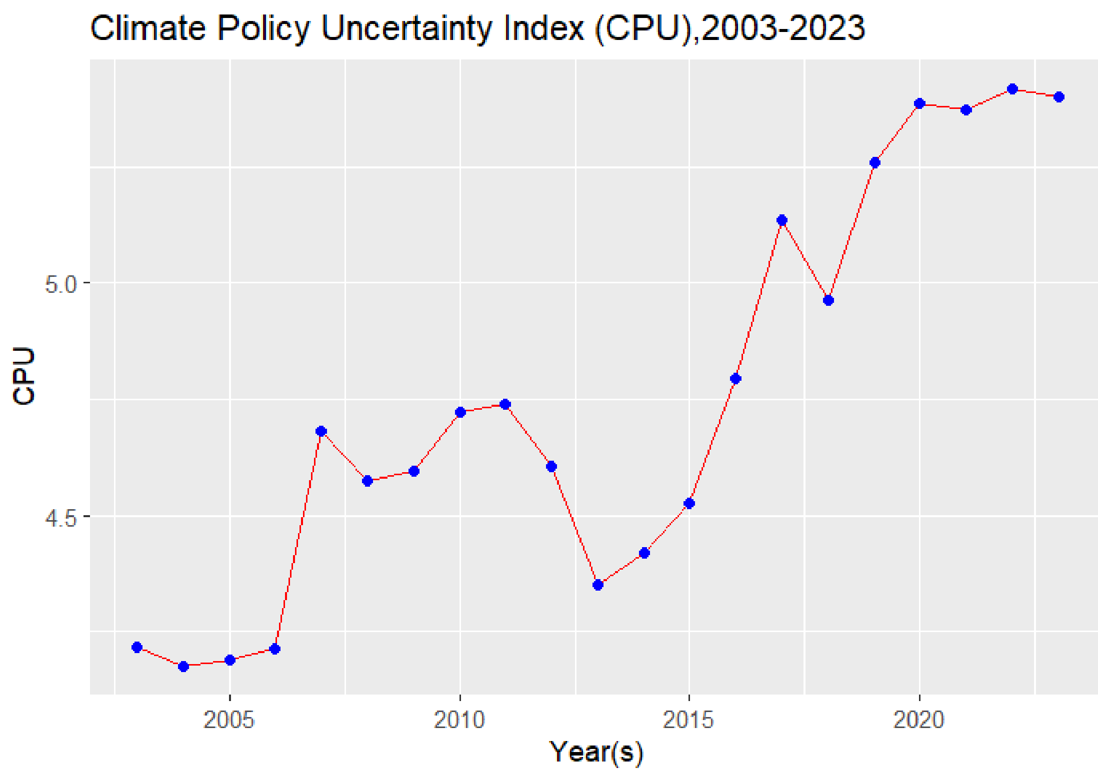

Figure 1: Natural log of the annual CPU measure for the period 2003-2023.

Tables

Table 1

Variable definitions

The table provides the definitions of all the important variables used in the study. Subscripts (i,t) stand for bank 'i' and time 't', respectively. All the variables are deflated by total assets, except CPU and GDP.

Variable	Definition
CPU_t	Climate policy uncertainty (CPU)
LLP_{it}	Loan loss provisions
ΔNPL_{it}	Changes in the non-performing loans between time (t-1) and (t)
ΔNPL_{it+1}	Changes in the non-performing loans between time (t) and (t+1)
ΔNPL_{it-1}	Changes in the non-performing loans between time (t-2) and (t-1)
ΔNPL_{it-2}	Changes in the non-performing loans between time (t-3) and (t-2)
ΔGDP_t	Changes in GDP growth rate
$\Delta LOAN_{it}$	Changes in total loans and advances
CAP_{it}	Total Equity divided by total assets
$EBPT_{it}$	Earnings before provisions and taxes
$Size_{it}$	Natural log of total assets
OVX_t	Oil Volatility Index
$public$	An indicator variable taking a value of '1' for Public-sector banks and '0' otherwise
ESG	An indicator variable taking a value of '1' for observations above the median of ESG score and '0' otherwise
$Paris$	An indicator which takes a value of '1' if the observation belongs to the period 2016-2023 and '0' otherwise
$size$	An indicator variable taking a value of '1' for observations below the median of $Size_{it}$ (Natural log of total assets) in a particular year and '0' otherwise
$Allow_{it}$	Beginning value of loan loss allowance

Table 2

Descriptive statistics

The table shows the descriptive statistics of the important variables used in the study, namely, the mean, median, standard deviation (Std. Dev.), minimum, and maximum. Variable definitions are provided in Table 1. All the variables, except GDP and CPU, are deflated by total assets.

Statistic	N	Mean	Std. Dev.	Min.	Median	Max.
LLP	630	0.009	0.008	0.001	0.006	0.028
CPU	630	4.824	0.359	4.351	4.724	5.418
$\Delta LOAN$	630	0.002	0.036	-0.071	0.003	0.072
ΔNPL	630	0.001	0.009	-0.018	-0.00001	0.024
ΔGDP	630	-0.001	0.049	-0.096	0.001	0.155
CAP	630	0.024	0.043	0.001	0.005	0.166
EBPT	630	0.021	0.009	0.007	0.019	0.041

Table 3

Correlation Matrix

The table presents the Pearson correlations for the key variables used in the study. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	LLP	CPU	$\Delta LOAN$	ΔNPL	ΔGDP	CAP	$EBPT$
LLP	1						
CPU	0.430***	1					
$\Delta LOAN$	-0.220***	-0.191***	1				
ΔNPL	0.384***	0.108**	-0.114**	1			
ΔGDP	-0.027	-0.047	-0.053	-0.017	1		
CAP	0.084*	-0.046	-0.067	-0.076	-0.017	1	
$EBPT$	-0.040	0.023	-0.011	-0.048	0.027	0.306***	1

Table 4

Variance Inflation Factor (VIF)

Variables	VIF
CPU_t	1.171
ΔNPL_{it}	1.173
ΔNPL_{it+1}	1.167
ΔNPL_{it-1}	1.283
ΔNPL_{it-2}	1.237
$\Delta LOAN_{it}$	1.104
ΔGDP_t	1.044

Table 5

CPU and loan loss provisions (H1a): OLS and Fixed Effects estimation of Eq. (1)

The table presents the results of Eq. (1) estimated through OLS and fixed effects methods. The coefficient and t-statistics (below) are reported for each variable, along with the Adjusted R^2 and F-statistics from the estimated model. Robust standard errors are employed for the calculation of t-statistics. The standard errors are clustered at the bank level for the fixed effects estimation. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels.

	Dependent variable: LLP_{it}	
	OLS	*Fixed effects*
CPU_t	0.006^{***}	0.007^{***}
	(8.967)	(11.643)
ΔNPL_{it}	0.161^{***}	0.159^{***}
	(4.252)	(6.415)
ΔNPL_{it+1}	0.135^{***}	0.147^{***}
	(3.295)	(5.839)
ΔNPL_{it-1}	0.178^{***}	0.199^{***}
	(4.403)	(7.196)
ΔNPL_{it-2}	0.211^{***}	0.178^{***}
	(5.957)	(6.085)
$\Delta LOAN_{it}$	-0.007	-0.008
	(-0.914)	(-1.288)
ΔGDP_t	0.001	0.001
	(0.132)	(0.233)
Constant	-0.023^{***}	
	(-6.697)	
Observations	630	630
Adjusted R^2 (%)	44.4%	48.5%
F Statistic	72.685^{***}	92.618^{***}

Table 6

CPU and loan loss provisions (H1a): Instrumental variable (IV) – Two-stage Least Squares (2SLS) approach [Eq. (1)]

The table presents the results of Eq. (1) estimated through the IV-2SLS approach. Oil volatility index (OVX) is employed as the instrument variable (IV) for CPU. The implementation includes two stages. In the first stage, CPU is regressed on OVX and other control variables. The fitted values of CPU are extracted from the first-stage and used to proxy CPU in the second-stage, along with other control variables, and LLP as the dependent variable. The coefficient and t-statistics (below) are reported for each variable, along with the Adjusted R^2 and F-statistics from the estimated model. Robust standard errors are employed for the calculation of t-statistics. The table also reports Weak Instruments test statistics (Stock & Yogo, 2002) related to the correlation of the instrument with the endogenous regressor, and Wu-Hausman test statistics (Greene, 2003) related to endogeneity. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels.

	Instrument Variable Approach	
	CPU	LLP
	First-stage	Second-stage
OVX_t	0.309***	
	(8.038)	
CPU_t		0.013***
		(5.496)
ΔNPL_{it}	1.639	0.214***
	(0.990)	(6.936)
ΔNPL_{it+1}	-8.057***	0.211***
	(-5.004)	(5.787)
ΔNPL_{it-1}	0.311	0.229***
	(0.160)	(6.262)
ΔNPL_{it-2}	8.471***	0.204***
	(4.442)	(4.902)
$\Delta LOAN_{it}$	-1.348***	-0.009
	(-3.017)	(-1.024)
ΔGDP_t	-0.745**	0.003
	(-2.563)	(0.638)
Constant	2.503***	-0.055***

	Instrument Variable Approach	
	CPU	LLP
	First-stage	Second-stage
	(8.471)	(-4.813)
Observations	502	502
Adjusted R^2 (%)	22.4%	45.1%
F-value	21.681^{***}	58.4^{***}
Weak instruments	-	64.614^{***}
Wu-Hausman	-	6.888^{**}

Table 7

Heterogeneity analyses based on ESG scores (H2a): OLS, Fixed Effects, and IV-2SLS approach

$$LLP_{it} = \beta_o + \beta_1 CPU_t + \beta_2 \Delta NPL_{it} + \beta_3 \Delta NPL_{it+1} + \beta_4 \Delta NPL_{it-1} + \beta_5 \Delta NPL_{it-2} + \beta_6 \Delta LOAN_{it} + \beta_7 \Delta GDP_t + \beta_8\, ESG + \beta_9\, ESG * CPU_t + e_{it} \quad \text{(H2a)}$$

Eq. (1) is augmented with 'ESG' as a dummy control variable ('1' for higher ESG scores and '0' for lower ESG scores) and the interaction term '$ESG * CPU_t$'. The model is estimated using (1) OLS, (2) Fixed Effects, and (3) the IV-2SLS approaches. Oil volatility index (OVX) is employed as the instrument variable (IV) for CPU. For the IV approach, only the final second-stage results are shown. The coefficient and t-statistics (below) are reported for each variable, along with the Adjusted R^2 and F-statistics from the estimated model. Robust standard errors are employed for the calculation of t-statistics. The table also reports Weak Instruments test statistics (Stock & Yogo, 2002) related to the correlation of the instrument with the endogenous regressors, and Wu-Hausman test statistics (Greene, 2003) related to endogeneity. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels.

	Dependent variable: LLP_{it}		
	OLS	Fixed effects	IV-2SLS
CPU_t	0.010***	0.010***	0.016***
	(9.229)	(11.703)	(4.919)
ΔNPL_{it}	0.191***	0.185***	0.188***
	(4.576)	(6.991)	(5.785)
ΔNPL_{it+1}	0.201***	0.193***	0.256***
	(4.888)	(7.468)	(6.530)
ΔNPL_{it-1}	0.234***	0.229***	0.200***
	(5.130)	(7.867)	(5.136)
ΔNPL_{it-2}	0.298***	0.261***	0.220***
	(6.606)	(8.261)	(4.375)
ΔGDP_t	0.0002	-0.001	0.002
	(0.029)	(-0.293)	(0.348)
$\Delta LOAN_{it}$	-0.019*	-0.019**	-0.011
	(-1.731)	(-2.156)	(-0.949)
ESG	0.019***		0.022
	(3.056)		(0.998)
$CPU_t \times ESG$	-0.004***	-0.005***	-0.005

	Dependent variable: LLP_{it}		
	OLS	Fixed effects	IV-2SLS
	(-3.028)	(-4.953)	(-1.050)
Constant	-0.040^{***}		-0.072^{***}
	(-8.031)		(-4.426)
Observations	373	373	373
Adjusted R^2(%)	63.3%	64.2%	55.9%
F statistics	72.314^{***}	88.303^{***}	53.05^{***}
Weak instruments (CPU_t)	-	-	24.626^{***}
Weak instruments ($CPU_t \times ESG$)			28.841^{***}
Wu-Hausman	-	-	5.035^{**}

Table 8

Paris agreement (H3a): OLS, Fixed Effects, and IV-2SLS approach

$$LLP_{it} = \beta_o + \beta_1 CPU_t + \beta_2 \Delta NPL_{it} + \beta_3 \Delta NPL_{it+1} + \beta_4 \Delta NPL_{it-1} + \beta_5 \Delta NPL_{it-2} + \beta_6 \Delta LOAN_{it} + \beta_7 \Delta GDP_t + \beta_8\, Paris + \beta_9\, Paris * CPU_t + e_{it} \quad \text{(H3a)}$$

Eq. (1) is augmented with 'Paris' as a dummy control variable ('1' for the period 2016-2023 and '0' otherwise) and the interaction term '$Paris * CPU_t$'. The model is estimated using (1) OLS, (2) Fixed Effects, and (3) the IV-2SLS approaches. Oil volatility index (OVX) is employed as the instrument variable (IV) for CPU. For the IV approach, only the final second-stage results are shown. The coefficient and t-statistics (below) are reported for each variable, along with the Adjusted R^2 and F-statistics from the estimated model. Robust standard errors are employed for the calculation of t-statistics. The table also reports Weak Instruments test statistics (Stock & Yogo, 2002) related to the correlation of the instrument with the endogenous regressors, and Wu-Hausman test statistics (Greene, 2003) related to endogeneity. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels.

	Dependent variable: LLP_{it}		
	OLS	Fixed effects	IV-2SLS
CPU_t	0.0002	0.0004	0.021
	(0.092)	(0.415)	(0.406)
ΔNPL_{it}	0.153***	0.150***	0.253***
	(3.995)	(5.058)	(4.965)
ΔNPL_{it+1}	0.125***	0.133***	0.339***
	(2.945)	(4.849)	(3.420)
ΔNPL_{it-1}	0.169***	0.188***	0.277***
	(4.196)	(5.204)	(6.291)
ΔNPL_{it-2}	0.195***	0.159***	0.268***
	(5.363)	(6.163)	(4.428)
$\Delta LOAN_{it}$	-0.007	-0.008	-0.006
	(-0.888)	(-1.038)	(-0.332)
ΔGDP_t	-0.0003	-0.0002	0.005
	(-0.062)	(-0.058)	(0.372)
$Paris$	-0.021	-0.020**	-0.064
	(-1.590)	(-2.203)	(-0.298)
$CPU_t \times Paris$	0.005*	0.005***	0.011
	(1.845)	(2.616)	(0.226)

	Dependent variable: LLP_{it}		
Constant	0.005		-0.090
	(0.674)		(-0.385)
Observations	630	630	502
Adjusted R^2(%)	45.07%	49.51%	26.9%
F statistics	58.35^{***}	74.9976^{***}	39.48^{***}
Weak instruments (CPU_t)	-	-	12.514^{***}
Weak instruments ($CPU_t \times paris$)	-	-	19.866^{***}
Wu-Hausman	-	-	7.604^{***}

Table 9

Heterogeneity analyses based on bank size (H4a): OLS, Fixed Effects, and IV-2SLS approach

$$LLP_{it} = \beta_o + \beta_1 CPU_t + \beta_2 \Delta NPL_{it} + \beta_3 \Delta NPL_{it+1} + \beta_4 \Delta NPL_{it-1} + \beta_5 \Delta NPL_{it-2} + \beta_6 \Delta LOAN_{it} + \beta_7 \Delta GDP_t + \beta_8\, size + \beta_9\, size * CPU_t + e_{it} \qquad \text{(H4a)}$$

Eq. (1) is augmented with 'size' as a dummy control variable ('1' for small and '0' for large) and the interaction term '$size * CPU_t$'. The model is estimated using (1) OLS, (2) Fixed Effects, and (3) the IV-2SLS approaches. Oil volatility index (OVX) is employed as the instrument variable (IV) for CPU. For the IV approach, only the final second-stage results are shown. The coefficient and t-statistics (below) are reported for each variable, along with the Adjusted R^2 and F-statistics from the estimated model. Robust standard errors are employed for the calculation of t-statistics. The table also reports Weak Instruments test statistics (Stock & Yogo, 2002) related to the correlation of the instrument with the endogenous regressors, and Wu-Hausman test statistics (Greene, 2003) related to endogeneity. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels**.**

	Dependent variable: LLP_{it}		
	OLS	Fixed effects	IV-2SLS
CPU_t	0.009***	0.009***	0.016***
	(10.283)	(13.106)	(5.835)
ΔNPL_{it}	0.169***	0.165***	0.228***
	(4.646)	(6.796)	(7.198)
ΔNPL_{it+1}	0.141***	0.157***	0.221***
	(3.550)	(6.317)	(5.966)
ΔNPL_{it-1}	0.181***	0.201***	0.232***
	(4.645)	(7.423)	(6.294)
ΔNPL_{it-2}	0.204***	0.174***	0.197***
	(6.117)	(6.059)	(4.721)
ΔGDP_t	0.001	0.001	0.003
	(0.109)	(0.246)	(0.598)
$\Delta LOAN_{it}$	-0.005	-0.006	-0.006
	(-0.675)	(-0.883)	(-0.617)
$size$	0.028***	0.029***	0.049**
	(4.045)	(4.859)	(2.235)
$CPU_t \times size$	-0.006***	-0.006***	-0.010**

	Dependent variable: LLP_{it}		
	OLS	Fixed effects	IV-2SLS
	(-4.059)	(-4.784)	(-2.281)
Constant	-0.033***		-0.072***
	(-8.453)		(-5.243)
Observations	630	630	502
Adjusted R^2(%)	46%	50.5%	45.1%
F statistic	60.53***	77.688***	46.3***
Weak instruments (CPU_t)	-	-	32.16***
Weak instruments ($CPU_t \times size$)	-	-	33.14***
Wu-Hausman	-	-	4.43*

Table 10
Heterogeneity analysis based on different ownership (H5a: public versus non-public): OLS, Fixed Effects, and IV-2SLS approach

$$LLP_{it} = \beta_o + \beta_1 CPU_t + \beta_2 \Delta NPL_{it} + \beta_3 \Delta NPL_{it+1} + \beta_4 \Delta NPL_{it-1} + \beta_5 \Delta NPL_{it-2} + \beta_6 \Delta LOAN_{it} + \beta_7 \Delta GDP_t + \beta_8\, public + \beta_9\, public * CPU_t + e_{it} \quad \text{(H5a)}$$

Eq. (1) is augmented with 'public' as a dummy control variable ('1' for public and '0' otherwise) and the interaction term '$public * CPU_t$'. The model is estimated using (1) OLS, (2) Fixed Effects, and (3) the IV-2SLS approaches. Oil volatility index (OVX) is employed as the instrument variable (IV) for CPU. For the IV approach, only the final second-stage results are shown. The coefficient and t-statistics (below) are reported for each variable, along with the Adjusted R^2 and F-statistics from the estimated model. Robust standard errors are employed for the calculation of t-statistics. The table also reports Weak Instruments test statistics (Stock & Yogo, 2002) related to the correlation of the instrument with the endogenous regressors, and Wu-Hausman test statistics (Greene, 2003) related to endogeneity. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels.

	Dependent variable: LLP_{it}		
	OLS	Fixed effects	IV-2SLS
CPU_t	0.005***	0.005***	0.010***
	(5.580)	(7.045)	(3.794)
ΔNPL_{it}	0.164***	0.161***	0.224***
	(4.254)	(6.586)	(7.213)
ΔNPL_{it+1}	0.147***	0.165***	0.242***
	(3.509)	(6.529)	(6.152)
ΔNPL_{it-1}	0.170***	0.195***	0.215***
	(4.138)	(7.152)	(5.943)
ΔNPL_{it-2}	0.190***	0.164***	0.171***
	(5.367)	(5.666)	(4.110)
ΔGDP_t	0.001	0.001	0.003
	(0.106)	(0.210)	(0.629)
$\Delta LOAN_{it}$	-0.006	-0.006	-0.008
	(-0.773)	(-0.918)	(-0.924)
$public$	-0.027***		-0.049**
	(-4.174)		(-2.185)
$CPU_t \times public$	0.006***	0.007***	0.010**

	Dependent variable: LLP_{it}		
	OLS	Fixed effects	IV-2SLS
	(4.380)	(5.946)	(2.279)
Constant	-0.015***		-0.042***
	(-3.753)		(-3.233)
Observations	630	630	502
Adjusted R^2(%)	47.4%	51.2%	47.2%
F statistic	63.940***	89.519***	49.05***
Weak instruments (CPU_t)	-	-	32.11***
Weak instruments ($CPU_t \times public$)	-	-	36.26***
Wu-Hausman	-	-	4.23*