Do Repeated Government Infusions Help Financial Stability? Evidence from an Emerging Market

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Abstract

While government led bank capital infusions in US and other developed markets have been usually contingent an external shock or crisis episode, India presents a unique setting where significant capital infusions happen annually to stabilize the weak balance sheets of undercapitalized government owned public sector banks. Such *"repeated"* capital infusions can either better engender financial stability, given the timely government interventions; or create instability arising from possible moral hazard concerns. "*Do such repeated government capital infusions lower banks' financial risks and improve financial stability?*" We shed light on the question through the lens of capital infusions in the Indian market. Based on the exhaustive sample of government capital infusions into public sector banks for the period 2008-18, we find robust evidence that capital infusions are associated with economically significant higher default, capital shortfall and network risks post-infusion, signaling a moral hazard problem, where treated banks may assume more risky investments.

Keywords: government capital infusions; financial stability; systemic risk; default risk; emerging markets.

JEL Classification: G10, G14 G15, G30.

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1. Introduction

The relationship between government guarantees to banks and financial stability has been the subject of intense debate since the global financial crisis - GFC (Allen et al., 2015; Allen and Gu, 2018).[1] The post-GFC (i.e., 2010-2018) period, and more recent Covid epidemic induced global financial compression, have witnessed significant government interventions in the form of explicit or implicit guarantees, recapitalizations, extended subsidies and/or regulatory forbearance in countries around the world. Specifically, three broad types of bank-level measures have been deployed in recent banking crises: (a) government guarantees, (b) government capital injections, and (c) asset restructuring and/or resolution; and such measures were implemented sequentially as crises worsened (Pazarbasioglu et al., 2011). Extant research shows capital infusions from the Capital Purchase Program (CPP) related to the US government sponsored Troubled Assets Relief Program (TARP) during GFC selectively lowered systemic risks in the short run (Berger, Roman and Sedunov, 2021), while causing moral hazard incentives that led to systemic risks in long term (Berger and Sedunov, 2021)[2]; and government interventions in the Eurozone banking sector were associated with subsequent increase in zombie lending and elevated risk in the baking sector (Acharya, Borcher and Jager, 2021).

While government led bank capital infusions in US and other developed markets have been usually contingent an external shock or crisis episode, such as GFC or banking crises, India presents a unique setting where significant capital infusions happen regularly "every year" to stabilize the weak balance sheets of the government owned public sector banks. India witnessed bank capital infusions averaging \$3.4 billion every year, ranging between \$255 million to \$13.5 billion during the period 2008 –2018. Out of 21 total recipients, each public sector bank received on average six (median of seven) infusions during the ten-year window (see Internet Appendix IA,

[1] Financial stability is measured using systemic risk, which refers to quick propagation of illiquidity and insolvency risks, and financial losses across the whole financial system, impacting the connections and interactions among financial stakeholders (Billio, et al., 2012).

[2] Sedunov (2021) finds no relation between Federal Reserve liquidity injections and systemic risk during the COVID-19 crisis.

and Figures IA1, IA2 and IA3). Do such repeated government capital infusions thereby lower the banks' systemic risks and improve the financial stability? Our study addresses this question.

Extant literature finds conflicting evidence on the relationship between government interventions and subsequent bank performance (Allen et al., 2015, Kelley et al., 2016; Acharya, Anginer and Warburton, 2018; Wilcox and Yasuda, 2019; Iyer et al., 2019). On one hand, guarantees/infusions can increase bank value by (a) reducing asymmetric information as better monitoring by governments can improve financing – i.e. more debt issuance, and at better yield, covenant and maturity terms – and in turn help GDP growth; (b) improving credit ratings, lowering funding costs, and increasing franchise value; (c) lowering potential systemic risks if the underlying bank falls into Too Big To Fail (TBTF) category; and (d) providing a downside insurance (or put option) value to banks especially during crises periods. On the other hand, interventions can have unintended adverse consequences: (a) tendency to take on excessive leverage by banks; (b) moral hazard problems arising from increased risk taking by the banks borrowers; (c) unproductive use of capital by the banks' borrowers affecting the industry wide productivity; and (d) counterparty risk to the guarantor arising from system wide shocks (or systemic risks) and potential bail-out costs for the taxpayer (see details in Section 2).

As a result, *repeated* capital infusions can be a double-edged sword. Repeated capital infusions, on one hand, can imply that government has superior information sets and better timing ability to recapitalize the underfunded banks and diffuse a crisis, and hence engender financial stability through periodic bank capital infusions. Government capital infusions are likely to help lower default and systemic risks of the treatment banks by improving (a) the capital cushion and thereby lowering the leverage risk, (b) bank portfolio diversification, (c) growth potential that can offset high distress risk; (d) bank level cash holdings that absorb possible shocks, and (e) effective corporate hedging by banks that would lower any shocks to cash flows (Berger et al., 2021). On the other hand, undercapitalized banks anticipate capital infusion injections from the government and have weakened incentives to implement any risk control mechanisms. Repeated infusions can, hence, increase the moral hazard behavior of banks and their implicit risk taking. The ultimate effect therefore depends upon the relative strength of both forces and hence, is an open empirical question. Focusing on an emerging market that underwent significant policy and regulatory changes, we undertake a comprehensive study of the impact of *repeated* government sponsored bank capital infusions on fostering financial stability.

We consider India as the emerging market of particular interest for several reasons: (a) Non-performing Assets (NPAs) in Indian public sector banks have grown significantly, adversely affecting the solvency of banks, and jeopardizing the onerous bank recapitalization effort by the Indian government (Rajan, 2018); (c) The decade since financial crisis (i.e. 2007 to present) witnessed multiple domestic and foreign exogenous shocks that affected the funding costs and loan quality of Indian banks[3]; (d) The post-crisis period was also marked by mounting corporate debt among emerging market firms, including India, as corporate leverage significantly increased in the post-crisis (2010-2018) period, giving rise to financial stability concerns (Acharya et al., 2015; Elekdag et al., 2015; Dodd, Kalimipalli and Chan, 2021); and finally, (e) India's fiscal dominance, arising from funding of fiscal deficits by the Central bank and managing that debt, may have impacted the financial stability of the banks over time (Acharya, 2020).

We employ data on government capital infusions from the Controller & Auditor General of India (Report No. 28, 2017), augmented by hand collected data for an additional year. This gives us capital infusion data by the Indian government into public sector banks for the period 2008-2018. The capital infusion data in turn is combined with multiple data sets on firm-level default risk and financial variables and aggregate risk proxies (details in Section 3).

We conduct our study by first providing a univariate analysis of the capital infusion effects of treated banks versus several alternate yearly control samples that include unfunded public sector banks (i.e., public sector banks not receiving capital infusion), private banks, public non-banking financial institutions (NBFIs) and private NBFIs. The treated banks receiving capital infusions are found to have significantly larger assets and deposits; however, they are undercapitalized, and have low interest coverage ratios (implying higher interest rate obligations), lower profitability and lower market to book valuations vis a vis control sample financial institution (FIs). Event window plots show that the public banks receiving capital infusions have highest default risk levels that trend up post-infusion after quarter +2 and show no significant decline compared to other control firms. Systemic (i.e., capital shortfall, conditional value at risk or CoVaR, and network) risk

[3] These include (i) domestic (Demonetization, 2016), and foreign (Taper tantrum, 2013-14; Turkish Lira crisis 2018) policy shocks; (ii) regulatory shocks (Basel III capital requirements, 2010; Asset Quality Review, 2015-16; and Insolvency and Bankruptcy Code Implementation, 2016); (iii) global commodity price shocks (2014-15); (iv) domestic banking frauds, (2017-18); (v) Non-banking Financial Institution (NBFI) crisis, (2018-19)) and (vi). Covid-global health shocks amplify macro-financial instability and debt vulnerability for the local firms and hence, increased risk exposure for the funding banks e.g., Covid-19 shock led to $83 billion emerging market outflows in 03/2020 (source: IIF capital flows tracker, April 2020).

measures are significantly higher for treated banks compared to the control samples showing possible TBTF concerns for underlying banks receiving capital infusion. Capital shortfall for the treated public sector banks significantly goes up for up to two quarters compared to other control samples. Univariate DiD analysis indicates that default risk and capital shortfall rise significantly for treated banks versus control FIs for +2 quarters post-infusion. The univariate results, overall, imply escalation of default and capital shortfall risks following government infusion.

We next implement yearly baseline difference in differences (DiD) fixed effects regression, where the last quarter preceding the infusion year is used as the benchmark quarter to form the pooled private bank sample. We find that treated public sector banks experience significant increases in both default and systemic (capital shortfall and network) risks two quarters following capital infusion. In terms of economic significance, treated banks experience 39.81% and 37.16% (22.93% and 42.26%) increases in their capital shortfall and network risks respectively as a percentage of their respective means (standard deviations), following capital infusion.

We alternatively consider a quarterly DiD regression, where we use infusions at quarterly level to construct the treatment and corresponding pooled private bank control samples for each quarter. We once again observe that capital infusion leads to significantly higher default and systemic risks, consistent with the baseline yearly DiD results. Treated banks show economically significant increases in their capital shortfall and network risks (of 52.71% and 34.65%) respectively after infusion with respect to their respective means. In addition, large size (i.e., above median) infusions lead to significantly higher default risk and network risks.

We also consider a matched private bank sample using a propensity score matching (PSM) approach based on a logit model of leverage, total assets, and tier 1 ratio as attributes. The results for yearly and quarterly DiD regressions remain robust. We further subject our findings to a battery of robustness checks. Our baseline line regressions are robust to alternate (a) tail risks, (b) control samples of public and private NBFIs, (c) network risk measures, (d) definitions of post-infusion variable, and (e) measures for size of capital infusion. Dynamic DiD plots also show escalation in default, capital shortfall and network risks post-infusion. We next consider a control sample of public sector banks that receive no government infusion. Given that government infusions are targeting certain undercapitalized public sector banks each year, there is an endogenous choice determining which public sector banks get funded (treated banks) versus those that do not get funded (control banks). Endogeneity can arise from the fact that both bank level risk and capital infusion are driven by common set of risk factors, and only risky public banks would receive government capital infusion. We address underlying endogeneity using two approaches: PSM and two-stage IV. Our earlier results still hold. Collectively, our results are consistent with a possible moral hazard hypothesis causing treated public sector banks to increase their risk exposures thereby aggravating the underlying risks.

We next examine what channels may matter in explaining the effects of capital infusion on default and systemic risks. We first ascertain if the DiD results are driven by stress years that impacted the bank funding. Specifically, we consider three stress years that also witnessed significant increases in capital infusions: 2010-11, 2015-16 and 2017-18. Lax auditing standards led to spike in government infusions in year 2010-11, whereas macro-economic shocks led to surge in infusions during 2015-16 and 2017-18 periods. We find that though stress year funding managed to lower excess credit and network risks among treated banks, the baseline DiD results still hold. We further conduct bank level channel analysis by examining what underlying risk attributes may influence the underlying risks. We find that capital infusions are followed by significant increase in default and systemic risks for *high risk* (i.e., low tier 1, smaller - both low assets and loan to assets, and low market to book) banks. This implies that capital cushion, portfolio diversification and growth channels may explain the amplification of default and systemic risks. Similarly, *low risk* (i.e., low leverage banks, high interest coverage and deposit ratio) banks also experience higher risks following infusion. Our findings together imply risk-taking by treated banks arising from possible moral hazard problems.

Finally, we study the impact of capital infusions on aggregate default and systemic risks. If repeated government capital infusions are meant to sustain undercapitalized banks, we assess if such interventions diminished the aggregate level default and systemic risks. Robust time-series regressions suggest that aggregate default risks for funded public sector banks go down compared to other control FIs following infusions. There is, however, no evidence that there is any attenuation in aggregate systemic risk measures.

Collectively, based on the exhaustive sample of government capital infusions into the public sector government banks for the period 2008-18, we find no unequivocal evidence that capital infusions lower systemic risks for Indian banks. In fact, banks receiving capital infusions have consistently been risky throughout the sample period, and capital infusions are followed by significant increases in the underlying credit and systemic (capital shortfall and network) risks.

Our results also imply that recapitalizing the public sector banks per se may not be bad in times of distress as our stress period infusion results show, but not adequately recapitalizing such banks relative to their true economic losses and yet allowing them to lend may have caused the risks to escalate. The emerging market results stand in contrast to the U.S. market findings about TARP program effects in the short run.[4]

Overall, our study contributes to better understanding of the role of government guarantees in attenuating financial risks and improving the financial stability in emerging markets. To the best of our knowledge, this study contributes to the literature by providing the first study of how government guarantees impact financial stability in the context of emerging markets. The theoretical basis for our findings can be supported by a systemic risk model that combines endogenous default risks with systemic risk evolution. Das, Kim and Ostrov (2019) develop such a dynamic Merton-on-a-network risk model that captures the systemic risk of a financial system. The model includes three important determining elements: (1) connectedness (via banking networks), (2) joint default risk (from an extension of the Merton 1974 model), and (3) size (i.e., the market value of a bank's assets, also implied from the Merton model).

Our analysis and discussion proceed as follows. Section 2 summarizes the related literature. Section 3 describes the data and details of the sample construction. Section 4 presents the univariate analysis and baseline DiD results. Section 5 provides additional robustness tests of the regressions. Section 6 studies the channels through which capital infusions may affect the underlying risks. Section 7 examines the effects of capital infusions on aggregate level risks. Section 8 concludes.

2. Background literature

Extant theoretical literature on government guarantees has examined the underlying valuation (Merton, 1977), role of optimal bail-ins versus bailouts (Keister and Mitkov, 2017; Clayton and Scnab, 2020; Bernard, Capponi, and Stiglitz, 2021), and effect of government guarantees on the resolution of underlying firm and aggregate risks (Königa, Anand, and Heinemann, 2014).

Government interventions have been found to have several positive effects. Government capital infusions in banks have a significantly positive impact on borrowing firms' stock returns

[4] Incidentally, a recent compliance audit report of the Controller & Auditor General of India has observed several deficiencies in the recapitalisation of public sector banks (Business Standard, Mar, 27, 2023).

(Norden, Roosenboom, Wang, 2013). Government guarantees help lowers the risks for the financial sector (Kelly et al., 2016), and improve liquidity provision for the banks (Allen et al., 2018); removal of such guarantees can lead to adverse effects on banks credit ratings, funding costs and franchise value (Fischer et al., 2014) and exacerbate wealth inequality (Gete and Zecchetto, 2017). Berger, Roman and Sedunov (2021) show that TARP significantly reduced contributions to systemic risk, particularly for larger and safer banks, and those in better local economies; the effect occurred primarily through a capital cushion channel that reduced market leverage by increasing the value of common equity.

Government interventions can however increase the implicit moral hazard and hence the risk-taking behaviour of the financial institutions; increased moral hazard can create distortions in banks' behavior and/or amplify the likelihood of runs (Dam and Koetter 2012; Allen et al., 2018). Cordella, Dell'Ariccia, and Marquez (2017) show that public guarantees lead unequivocally to an increase in bank leverage and an associated increase in risk taking (and moral hazard) when informed investors hold a sufficiently large fraction of liabilities and bank capital is endogenous. Gropp, Guettler, and Saadi (2017) find that guaranteed banks keep unproductive firms in business for too long and prevent their exit from the market. Ahnert et al. (2019) find that the introduction of deposit insurance or wholesale funding guarantees induces excessive encumbrance and fragility. Brandao-Marques, Correa and Sapriza (2020) use an international sample of rated banks and find that government support through provision of explicit or implicit guarantees is associated with more risk taking by banks, especially prior and during the 2008-2009 financial crisis. Similarly, Borisova et al. (2015) using a cross-country sample show that government equity ownership in publicly traded firms adversely affects the cost of corporate debt. Chava, Ganduri and Yerramilli (2021) find that implicit bailout guarantees of financial institutions can exacerbate moral hazard in bond markets and weaken market discipline.[5]

Recent literature also documents the adverse effects of US (TARP) and European government led bailouts during GFC. Duchin and Sosyura (2014) show that TARP bailed-out banks initiate riskier loans and shift assets toward riskier securities after receiving government

[5] Other papers study the relationships between (a) banks' valuations and government guarantees (Atkeson et al., 2018); (b) cash holdings and state ownership (Chen, et al., 2018); (c) banks earnings management behavior and government guarantees (Dantas et al., 2016); (d) bank complexity and bank risk-taking (Martynova and Vogel, 2022); (e) higher purpose related to banking business decisions, and underlying bank capital and stability (Bunderson and Thakor, 2022); and (f) shadow banking and systemic risk (Pellegrini et al., 2022).

support. Berger, Makaew and Roman (2019) find that riskier borrowers benefitted more from TARP, consistent with moral hazard exploitation; small and unlisted borrowers benefit less, suggesting fewer benefits for financially constrained firms. Berger and Sedunov (2021) show that while TARP bank bailout was effective in reducing the systemic risk contributions of banks during the heart of the GFC, the moral hazard incentives that it created may have increased systemic risks in long term. Lucan Del Viva et al. (2021) find that the TARP bailout increased the likelihood of banks' risk-taking behavior and eventual risk shifting. Further, following TARP bailout there was increased market opacity and crash risk for recipient banks (Bui, Scheulea and Wu, 2020), increased interbank lending activity causing increased risk taking by banks (Behr and Wang, 2020), and no incremental expansion in credit supply by the recipient banks (Helwege and Liu, 2021). In the European setting, Acharya et al. (2021) report that government interventions during Eurozone banking sector during 2008-09 prompted undercapitalized banks to take more risk and led to subsequent increase in systemic risk due to weaker credit supply. Nistor and Ongena (2023) find a significantly positive association of government infusion with systemic risks among European banks that is somewhat mitigated in the long run when the regulator appoints members to the supervisory board.

Previous literature on the effects of government guarantees in the context of emerging markets is however sparse, and has examined (a) the impact of government guarantees on bank deposit growth and performance during the GFC crisis in India (Acharya and Kulkarni, 2017); (b) how the 2009-10 stimulus-driven credit expansion in China disproportionately favored state-owned firms and firms with a lower average product of capital (Cong et al., 2019); (c) impact of implicit Chinese government guarantees on corporate investment and financing policies (Jin et al., 2020); and (d) effect of implicit government guarantees on the Chinese corporate bond market yield spreads of affected and un affected bonds (Walker et.al., 2021).

While government led bank capital infusions in US and other developed markets have been usually contingent an external shock or crisis episode, India presents a unique setting where significant capital infusions happen regularly “every year” to stabilize the weak balance sheets of the public sector banks. The effect of *repeated* government infusions on risk taking by banks is, hence, unclear and an open empirical question. On one hand, repeated capital infusions may help the government to effectively employ the repeated infusions to improve the financial standing of the banks and lower the underlying risks for banks. On the other hand, repeated government infusions can create moral hazard issues, and promote aggressive lending and risk taking by the banks. Drawing on the extant literature, we therefore ask if repeated capital infusions help recipient banks by lowering their default and systemic risks. Overall, we extend the literature on government guarantees studying how *repeated* capital infusions by government can influence the underlying systemic risk, which measures financial stability, and its two components viz., default and network risks (Das et al., 2022).

3. Data and summary statistics

3.1 Capital infusion data

We identify government capital infusions from the Controller & Auditor General of India (Report No. 28, 2017). The data provides capital infusion by the Indian government into public sector banks for the period 2008-2017. We hand collect data from media sources and extend the total sample to 2018. The government capital infusion is based on the expected Tier 1 capital shortfall, macro-credit requirements and maintenance of 52% government stake in the banks[6]. The process for recapitalisation of public sector banks (PSBs), as explained by the federal Department of Financial services (DFS), has the following steps: (1) Every year, the PSBs project their capital requirements for the year to DFS; (2) PSBs consider the credit growth, risk profile of the assets to project the risk-weighted assets of the bank. The internal accruals of the bank and other sources of capital generation are also assessed, and the balance capital requirements are sought; (3) DFS verifies the data submitted by the PSBs and undertakes an assessment of each PSB to arrive at its actual requirement for additional capital. It is possible that having the government funded capital infusion window may induce banks to take excess risks; however, the DFS uses external auditors to evaluate the financial credibility of the banks requisition and scrutinize the Internal Capital Adequacy Assessment Process (ICAAP) standards of the requesting banks.

For each capital infusion, we also search on-line and identify the exact date of capital infusion each year as reported in the financial press (untabulated). We use the announcement date of the capital infusion based on the media reports. Internet Appendix IA, and Figures IA1, IA2 and IA3 present the data breakdown on capital infusions. Internet Appendix IB lists the names of treated banks and various control sample FIs used in our study. The total infusions in our sample

[6] Source: Controller & Auditor General of India, Report No. 28, 2017.

period amounted to $33.80 billion.[7] The average level of capital infusions has trended up over time, while five PSBs viz., State Bank of India, Industrial Development Bank of India (IDBI), Bank of India, Central Bank of India, and Indian Overseas Bank have received largest capital infusions over the sample period and together account for 51% of the total capital infusions.

3.2 Bank level data

The capital infusion data is turn is intersected with multiple databases:

I. Refinitiv/Worldscope Datastream database for data on firm-level financial variables and stock, both firm and index, returns.

We use Datastream to extract a comprehensive list of financial firms publicly listed in the Indian market. We focus on firms whose common equity are traded on a primary exchange (Bombay stock exchange – BSE or National Stock Exchange – NSE). We exclude (a) non-financial firms, (b) inactive (delisted) firms, (c) firms with only preferred stock, (d) foreign firms, and (e) firms trading exclusively in a foreign exchange. We also drop firms with less than 125 active trading days (or six calendar months) of exchange history.

We extract data three types of active financial firms i.e., Banks, Broker-Dealers, and Insurers. For the period 2000-2018, we identify 670 financial firms, consisting of 46 banks (both public and private), 519 NBFIs (public and private) and 105 non-financial institutions (broker-dealers, financial subsidiaries of other non-financial corporations, specialized investment vehicles such as funds and securitized assets). From the sample of 46 banks, our data filters yield 24 public and 16 private banks. Out of the NBFI sample of 519 firms, we have 14 public and 505 private NBFI firms. We extract the largest 25 private NBFI firms out of the sample of 505 firms based on asset size. Large number of private NBFIs are small and hence have illiquid trading or missing data. We drop all 105 non-FI firms. The breakdown is presented in Table 1. We focus on the final sample of 76 financial institutions consisting of 40 banks and 36 NBFIs.

[Insert Table 1 here]

Panel D of Appendix A describes the variables extracted from Datastream. We employ several financial variables such as assets, ROE, loans to assets, tier-1 capital, leverage, interest coverage, market to book and deposit ratio. Additionally, we use market level data on local (India

[7] Monthly USD rupee exchange rates sourced from FRED are used to convert rupee value of infusions to USD.

Nifty 50 index returns) and global (US default spread, term structure level and slope, VIX and TED spreads) market factors, described in Panel E, Appendix A.

II. RMI PD and DTD database

Credit risk is measured using two balance sheet risk measures i.e., one-year ahead distance to default (DTD) and probability of default (PD). The DTD measure, a volatility-adjusted leverage measure based on Merton (1974) and is inversely related to the credit risk. PD is based on forward intensity model.[8] We match the identified 76 financial firms with the Credit Research Initiative database of the Risk Management Institute (RMI) of the National University of Singapore (NUS). From RMI database, we extract company-level monthly data on DTD and measures of PD. PD slope, showing the long-term default risk, is calculated as the difference between 5 year and 1 year PD. Panel B of Appendix A describes the variables sourced from RMI.

3.3 Measures of systemic risks

Systemic risk captures the conditional failure of the economic system at large, conditional on the failure of key financial institutions in an economy. Systemic risk therefore refers to a risk that has (a) large impact, (b) is widespread, i.e., affects many entities or institutions, and (c) has a ripple effect that endangers the existence of the financial system. We use three alternative measures of systemic risk (Panel C of Appendix A presents the details of the computation): marginal expected shortfall (MES), normalized capital shortfall (NSRISK), and conditional value at risk (CoVaR) (Acharya et al., 2012; Brownlees and Engle, 2017; Adrian and Brunnermeier, 2016; and Berger et al. 2019).

MES is obtained as the average FI's equity return on days when the market as a whole is in the lower tail of its return distribution provided year (Acharya et al., 2012). MES measures what happens to a firm's equity returns when the market is in distress. Expected capital shortfall is obtained as the standardized value of *SRISK*. The *SRISK* measure refers to the expected capital shortfall of a FI when the market return is in the lowest 5% bracket each year (Acharya et al.,

[8] Credit Risk Initiative (CRI) at RMI generalizes Merton model DTD by embedding short-term borrowings of banks and FIs and makes suitable modifications to the firm value drift and volatility, thereby allowing negative DTD values possible. Negative DTD shows show high ex ante default risk for a given firm. For PD, CRI uses the forward intensity model based on Duan, Sun and Wang (2012), and Duan, and Fulop (2013); it is a reduced form model in which the PD is computed as a function of firm-specific and systematic factors. (NUS-RMI Credit Research Initiative Technical Report Version: 2016, Global Credit Review, Vol. 6, 2016; 49–132).

2012) – compared to *MES*, *SRISK* incorporates information on a FI's size and leverage. We standardize SRSIK cap by bank market capitalization, and refer to it as *NSRISK*, which captures the proportional capital shortfall in the event of a crisis. NSRISK builds on the MES measure by incorporating information on firm size and leverage, and hence addresses the too-big-to-fail dimension of systemic risk. *CoVaR* refers to the excess of value at risk (VaR) of the financial system conditional on a FI being in distress over the VaR of the financial system conditional on the bank being in a normal state. CoVaR complements MES by measuring the incremental value at risk of the financial system when the firm is in distress (Adrian and Brunnermeier, 2016; Benoit et al., 2017; Anginer et al., 2018). MES, NSRISK and CoVaR are reported at both 5% and 1% levels, where 1% level captures the extreme tail risk exposure of the underlying financial institution or the overall market.

Finally, we also use a network risk-based measure, *Score*, which is additively decomposable and attributable to each FI, and further can be partitioned into credit and network risks (Das, 2016; Das, Kalimipalli and Nayak, 2022). *Score* is obtained as a function of number of banks in the system, adjacency matrix and size weighted credit scores of the banks, and then decomposed into a specific bank level contribution. Network analysis is built from data on direct interconnections between firms and allows regulators to estimate how the distress of a given firm would directly affect the other firms in the network (Billio et al., 2012, 2013; Diebold and Yimaz, 2014).

3.4 Treatment and Pooled Control samples

To conduct our empirical analysis, we form yearly treatment and control samples. For the banks receiving capital infusion in year *t*, we use the last quarter preceding each infusion year (i.e., quarter 4 of year *t-1*) as the benchmark quarter and obtain the corresponding pooled control samples. Specifically, government owned public sector banks that receive capital infusions are denoted as Treatment firms (sample A). Those public banks not receiving capital injection that year are categorized as control firms (control sample B). Control sample C consists of 16 private sector banks that receive no infusions.

In addition, we consider two NBFI control samples: Government owned public sector NBFIs (control sample D); and Private sector NBFIs (control sample E). The public NBFIs are also referred to as shadow banks as they primarily fund their assets through loan and debt borrowings, rather than public deposits. There exists active bank-NBFI nexus in Indian markets, and public NBFIs are regarded by the Reserve Bank of India as being systemically important (Acharya et al., 2013). Control sample D has 14 public NBFIs. Control Sample E has 25 largest private NBFIs by asset size. In summary, while for public sector banks pooled control sample banks are constructed on a yearly basis, for private banks and NBFIs the pooled control firms remain the same throughout the sample period.

Table 2 reports the pairwise sample comparisons of averages of annual financial variables across the sample period. We consider four pairwise comparisons between the treatment sample (A. Government bank-with Infusion), and each of four pooled control samples (B, C, D and E) described above. We observe that the treatment sample banks have significantly higher assets and deposit to asset ratio compared to control sample institutions. In addition, treated banks have much lower market capitalization (market to book), profitability, interest coverage, loan to asset, and Tier-1 ratios (differences are significant at 5% level or below) compared to control firms. Treated banks have high leverage (i.e., debt to equity or debt to capital) ratios compared to control sample B and C. In summary, treated banks receiving capital infusions though have significantly larger assets and deposits, are undercapitalized, and have higher interest cost obligations, lower profitability, and market to book valuations vis a vis control sample FIs.

[Insert Table 2 here]

4. Effect of capital infusion on default and systematic risks

4.1 Univariate event study tests

4.1.1 Credit risks

We first consider the evolution of different credit risk variables around the [-1 to +3] quarter window of each capital infusion date averaged across all the sample-period capital infusions. Figure 3 presents the event window effects on 12-month or 1-year PD and PD slope (i.e., 5-year PD minus 1-year PD) for the treatment and four different control samples for the sample period. To better discern the event study effects, we also present scaled PD and PD slope values, where we normalize the starting values at the pre-event -1 quarter at 100 and compare joint evolution of treated banks in comparison to control samples.

We observe that treatment sample has the highest default risk levels compared to all control samples. The capital infusion seems to have no clear long-term reduction on the credit risk for treatment banks. Interestingly, the 1-year PD measure declines one quarter prior to the capital infusion date, implying an anticipation by the market of a possible infusion. The 1-year PD then remains relatively stable for two quarters following infusion and trends up gradually for next two quarter. The control sample banks PDs all experience a minor drop in their risk one quarter prior to the capital infusion event and trend up after two quarters post-infusion. The normalized plots show that public NBFIs experience marked increase in their PDs post bank capital infusions far exceeding PDs of all other control FIs. PD slope displays a similar evolution signifying long-term market expectations of implicit default post-infusion.

[Insert Figure 1 here]

To better evaluate the capital infusion effect, we examine univariate pairwise comparisons of post- and pre- event differences in PD measures. Table 3 reports the results for -1 to +2 quarter window. Each panel presents post- versus pre- infusion comparison for each sample and then compares such differences between treatment-control pairs. The univariate difference-in-differences (DiD) are positive and significant for two of the four controls implying that treatment banks experience significantly higher PDs post-capital infusions in comparison to control samples. PD slope shows similar results. DiD values for PD slope are significant when compared to private control banks, implying increase in long term default risk for treated banks post-infusion.

[Insert Table 3 here]

4.1.2 Systemic and network risks

We next evaluate the systemic risk evolution following capital infusions. NSRISK, CoVaR and network (Figure 2) measures shows that systemic risks for treated banks are significantly higher in the event window compared to control firms showing possible too-big-to-fail concerns for underlying banks receiving capital infusion. There is an increase in NSRISK two quarters following capital infusion. Scaled NRISK plots show that there is a steady increase in capital shortfall for control sample firm until +2 quarters. Capital infusion leads to increase in CoVaR levels of treatment firms for 1-quarter post-infusion followed by a drop in quarter 2 and then stabilizing thereafter. No increases in network risk post-infusion are found.

[Insert Figure 2 here]

Furthermore, univariate DiD tests (Table 3) show significant increase in capital shortfall risk (both 5% and 1% levels) implying that treated banks significantly worsen post-infusion. However, no significant DiD values are found for CoVaR and network measures.[9]

4.2 Baseline Difference-in-Differences (DiD) regressions

Yearly DiD Regressions

To better understand the effects of capital infusions, we implement the following DiD specification to examine the hypothesis:

$$\begin{aligned}(\textit{risk measure})_{i,t} = \alpha_0 + \alpha_1\, (\textit{treatment})_i + \alpha_2\, (\textit{post-infusion})_t + \beta_0\, (\textit{treatment} \times \textit{post-infusion})_{i,,t} \\ + \gamma_0\, (\textit{controls})_t + \gamma_1\, \textit{firm fixed effects}_i + \gamma_2\, \textit{time fixed effects}_t + \textit{error}_{i,t} \qquad (1)\end{aligned}$$

where the dependent variable is a quarterly default or systemic risk measure. Coefficient α_1 captures the treatment effect on each risk metric. Treatment dummy refers to the public sector banks receiving the government capital infusion, while control firms refer to the pooled private banks, or control sample C, described in Section 4.1. For the public sector banks receiving capital infusion in year *k*, the last quarter preceding year *k* (i.e., quarter 4 of year *k-1*) is used as the benchmark quarter to form the pooled private bank sample. We consider bank infusions made each year to construct the treatment and control samples for that year. Coefficient α_2 helps in assessing the post- infusion effect across all the FIs. $\textit{Post-infusion}_{i,t}$ refers to dummy set equal to 1 for the infusion quarter and 2 subsequent quarters after infusion and is defined at the firm-quarter level.[10] Coefficient β_0 measures the DiD interaction effect of treatment post-infusion and forms the basis for assessing post- infusion effects. We consider two types of fixed effects: (1) year and firm fixed effects, and (2) quarter and firm fixed effects. The quarter fixed effects subsume the time-period consequences of capital infusion, while the firm fixed effects subsume the firm level treatment outcomes. All regressions include local (India Nifty 50 index returns) and US (default spread, level, and slope of term structure, VIX and TED spreads) market factors, and firm and year or quarter specific fixed effects and adjustments for heteroscedasticity using Huber/White robust standard errors, and clustered by bank level.

[9] We conduct additional robustness tests using other risk variables DTD and MES – results are reported in Figures IA4 and IA5 and Tables IA1 and IA2 in the Internet Appendix. Overall, DTD and MES results mirror findings for PD and NSRISK respectively.

[10] We exclude infusion quarter as a robustness check and our results still hold (see Section 5.4).

Table 4 presents the baseline DiD regression results for model (1) – i.e., regressions 1, 2, 5, 6, 9 and 10 - that employ default risk (12-month PD, PD slope and DTD) measures in Panel A and systemic risk (NSRISK, CoVaR and network) measures in Panel B, using private banks as the control. The dependent risk variables are scaled by 100 so that coefficients refer to percentage effects. NSRISK and CoVaR measures are presented using five percentile threshold levels. We find that the capital infusions are associated with significant decreases in default and systemic risk (α_2 coefficient) – this implies positive network effects among both treated and control banks as they experience improvement in risks following infusion. Moreover, the DiD or β_0 coefficient is significantly positive indicating that capital infusions are associated with higher credit, capital shortfall, and network risks for the treated banks. CoVaR measure shows no signs of risk attenuation.

[Insert Table 4 here]

We further explore the possible effect of large capital infusions on underlying risks. We define the large infusion dummy to classify each infusion into high or low bins based on the median value of all the capital infusions for a given year. We extend model (1) by considering two additional regression terms: *treatment* $\times$ *large-infusion dummy* (to test if size of infusion matters for risks of treatment banks), and the triple interaction *treatment* $\times$ *post-infusion* $\times$ *large-infusion dummy* (to check the overall DiD interaction effect for large infusion). The *large infusion* variable is absorbed by the firm fixed effects, and *treatment* $\times$ *post-infusion* interaction effect is absorbed by the triple interaction *treatment* $\times$ *post-infusion* $\times$ *large infusion*. Table 4 shows that the treated banks receiving large infusion have significantly higher default (i.e., PD and PD slope) risks; large infusions lower such default risks for the treated firms but have no incremental effects on the systemic risks.

For economic significance, we present both mean (DiD coefficient ÷ mean of the risk variable) and sigma (DiD coefficient ÷ standard deviation of the risk variable) shock values. Mean (sigma) shock value shows the effect of capital infusion on each risk variable relative to mean (standard deviation) of each variable. We report the analysis based on the baseline regressions with both firm and quarter fixed effects in Table 4. The treated banks post-infusion experience an increase (decrease) in their PD and PD slope (DTD) values by 30.76% and 30.27% (24.33%) respectively as percentage of their respective means. Similarly, treated banks register 28.34%, 31.46% and 12.55% increases in their PD, PD slope and DTD respectively as percentage of their respective standard deviations. In terms of systemic risks, post-infusion, treated banks display 39.81% and 37.16% (22.93% and 42.26%) increases in their NSRISK and network risks respectively with respect to their respective means (standard deviations). [11] Our results overall show that (a) effect of government infusions is economically significant and (b) impact on systematic risks has greater economic significance compared to the default risk variables.

Quarterly DiD Regressions

Table 4 specification uses infusions to construct yearly treatment and control samples. We consider alternative DiD specification based on infusion effects at a quarterly level; here we use infusions at quarterly level to construct the treatment and control samples for each quarter. Specifically, we consider the following baseline quarterly specification.

$$\textit{(risk measure)}_{i,t} = \alpha_0 + \beta_0 \textit{ (quarter specific post-infusion)}_t + \gamma_0 \textit{ (controls)}_t + \gamma_1 \textit{ firm fixed effects}_i + \gamma_2 \textit{ time fixed effects}_t + \textit{error}_{i,t} \qquad (2)$$

where public sector banks receiving capital infusion in each quarter constitute the treatment sample and those control banks not receiving infusions *in that quarter t* form the pooled controls. The β_0 coefficient can be interpreted as the average effect of infusion on treated banks in the 3 quarters after infusion. We also implement model (2) for large capital infusions, where banks receiving large capital infusion in each quarter constitute the treatment sample. We consider three alternate definitions of large infusion dummy: (a) *8-Quarter Median Large Infusion dummy*: if the current quarter infusion of a bank is greater than the median of previous 8 quarters of infusions for all banks; (b) *Current Quarter Median Large Infusion dummy*: if the current quarter infusion of a bank is greater than the median of all current quarter infusions; and finally, (c) *Modified 8-Quarter Median Large Infusion dummy*: if the infusion of a bank in the last 8 quarters is greater than the median of previous 8 quarters of infusions for all banks. Table 5 presents regressions that include both quarter and firm fixed effects. We observe that capital infusion leads to significantly higher default (Panel A) and systemic – i.e., NSRISK and network (Panel B) - risks (β_0 coefficient),

[11] In terms of mean shocks. based on regressions with year and firm fixed effects in Table 4, treated banks experience increase (decrease) in PD and PD slope (DTD) of 23.67% and 22.33% (18.03%) respectively compared to their respective means; treated banks also see increases of 36.25% and 33.38% respectively in NSRISK and network risks compared to their respective means.

consistent with the baseline Table 4 results. In addition, large infusions lead to significantly higher default risk and network risks. Overall, capital infusions are associated with escalation in default and systemic risks for the treated banks.

[Insert Table 5 here]

In terms of economic significance, based on baseline Table 5 regression values, PD and PD slope values increase post- infusion for treated banks by 42.97% and 41.13% (39.59% and 42.76%) respectively with respect to their respective means (standard deviations). Similarly, treated banks experience 52.71% and 34.65% (30.35% and 39.40%) increases in their NSRISK and network risks respectively with respect to their respective means (standard deviations).

In summary, the baseline DiD regressions results show that treated public sector banks experience statistically and economically significant increases in both default and systemic (capital shortfall and network) risks following capital infusion. Our results are consistent with a possible moral hazard problem causing treatment banks to assume risky investments thereby increasing the underlying risks. Collectively, our DiD results find no evidence that repeated capital infusions help lower risks of the underlying banks. We next subject our findings to a battery of robustness checks.

5. Additional robustness tests

5.1 Effect of Tail risk

We next examine how capital infusions impact the tail measures of systematic risk. Table 4 uses 5% level threshold for NSRSIK and CoVaR risk measures. We redo Table 4 DiD regressions using 1% level for both the systemic risk measures.[12] Accordingly, NSRSIK at 1% level refers to the expected capital shortfall of a FI when the market return is in the lowest 1% performance each year, and hence captures the proportional capital shortfall when the market experiences extreme downside performance. Similarly, CoVaR at 1% level refers to the excess value at risk of the banking system when a single FI's return is at the lowest 1st percentile - and hence that FI is undergoing severe distress - minus the value at risk of the system when the institution' return is at the 50% percentile. We implement DiD specification (1), and tabulate models from Table 4 (Internet Appendix, Table IA4, Panel A). We observe that the DiD regression coefficients are significant for capital shortfall risk. We next implement Quarterly DiD specification (2) (in Panel

[12] Event window plots for NSRISK and CoVaR at 1% level are presented in Internet Appendix, Figure IA6.

B) and find that once again capital shortfall is highly significant post-infusion. Overall, Section 4.2 baseline results remain robust to tail measures of systemic risk.

5.2 Matched control sample

To alleviate the concerns that we might be using a pooled control sample, we examine the effect of capital infusion using a matched private bank sample. We implement the annual DiD specification (1) based on PSM based control sample of private banks. For the banks receiving capital infusion in year *k*, we use the final quarter preceding each infusion year (quarter 4 of year *k-1*) as the matching quarter and obtain the propensity scores for that quarter using a logit model based on debt to total asset ratio, total assets, and tier-1 ratio as attributes. For each treated public sector bank, we obtain private bank with the closest propensity score in the same matching quarter. Results are presented in Table 6, Panel A. We find that the DiD coefficients are strongly positive and significant for capital shortfall (measured at both 5% and 1% levels) and network risks showing that capital infusions are followed by significant increase in systemic and network risks for the public sector banks. We also consider Quarterly DiD specification (2) and employ PSM control sample for the quarter preceding the infusion quarter. Panel B shows that capital infusions are followed by increases in PD, capital shortfall and network risks, and a drop in CoVar. Overall, our results are consistent with baseline results in Section 4.2.

[Insert Table 6 here]

5.3 Endogeneity and the effect of capital infusion on default and systemic risks - public bank control sample

We next consider the control sample of public sector banks that receive no government infusion (control B). Endogeneity can arise from the fact that the risk measure and capital infusion are driven by a common set of risk factors, and only risky banks are likely to receive capital infusion. Given that government infusions are targeting certain public sector banks each year, there is an endogenous choice determining which banks get funded (treated banks) versus those that do not get funded (control banks). Given that the funded public sector banks change every year, we use quarterly regressions to better pin down the unfunded public sector control sample. We consider two sets of endogeneity tests below.

5.3.1 Propensity Score Matching (PSM) Approach

We first consider an endogeneity test using PSM approach. We implement the quarterly DiD specification (2) using PSM control sample of unfunded public banks. As described in Section 5.1, for the banks receiving capital infusion in each quarter, we use the quarter preceding each infusion quarter as the matching period and obtain the propensity scores using a logit model based on debt to total asset ratio, total assets, and tier-1 ratio as attributes. For each treated public sector bank, we obtain the non-treated public bank with the closest propensity score in the same matching quarter. Results are presented in Table 7. We find that the DiD coefficients are strongly positive and significant for default risk, capital shortfall (measured at both 5% and 1% levels) and network risks showing that capital infusions are followed by significant increases in risks for the public sector banks; overall, the baseline results in Section 4.2 still hold.

[Insert Table 7 here]

5.3.2 Two- Stage Least Squares (SLS) IV approach

We next implement a quarterly two-stage least squares regression using instrumental variables in the first stage probit regression and then employ the probit estimate as the infusion proxy in the second stage DiD regression. The following first-stage probit model is used to determine the probability of capital infusion for a public sector bank.

$$Prob\ (capital\ infusion)_{i,,t} = \alpha_0 + \alpha_1\ (financial\ variables)_{t-1} + \gamma_1\ (controls)_{t-1} + \gamma_2\ firm\ fixed\ effects_{i-1} + \gamma_3\ time\ fixed\ effects_{t-1} + error_{i,,t} \quad (3)$$

where the dependent variable is the dummy variable that identifies for a bank receiving capital infusion. The covariates consist of lagged financial variables as of the quarter preceding the infusion quarter, and include total debt to total capital, total assets, interest coverage, and tier 1 ratio, in addition to US and Local market factors, firm, and time fixed effects. Additionally, we use two lagged instrumental variables. The Finance Ministry, according to the Controller and Auditor General Report (Source: Controller & Auditor General of India, Report No. 28, 2017), reviews annual bank capital infusion requests from the public banks and gets such requests vetted through external auditors. To the extent that the recipient banks have challenges in funding deficits in their Tier 1 capital, capital infusions may play a greater role. The Tier 1 capital funding depends upon the capital market conditions and level of retained earnings. The access to equity markets in turn depends upon the existing capital market conditions. Hence, the probability of capital infusion critically depends on the effects of prevailing capital market conditions that are proxied by the responsiveness of individual firm's returns to (a) aggregate net capital flows into the financial markets, and (b) macro-policy uncertainty. Accordingly, we use two additional instrumental variables: (a) Cash flow Beta, which is obtained as the quarterly stock return betas of the banks with respect to aggregate net foreign capital flows, which refer to macro-level dollar capital inflows net of capital outflows into the country other than foreign direct investment (source: Oxford Economics, Datastream); and (b) policy uncertainty beta, obtained as the quarterly stock return betas of the banks with respect to aggregate policy economic uncertainty (described in Appendix A) . The policy uncertainty is constructed as a textual index based on news coverage (Baker, Bloom and Davis, 2016). Both firm specific betas are calculated using a moving 3- year window.

We implement 2-SLS regressions by first fitting treatment dummy from first-stage probit model and then using the fitted value as input into the second-stage baseline quarterly DiD specification (2). Results are presented in Table 8. Panel A presents the probit models that show that lagged tier 1 ratio and policy beta are significantly related to current period infusion even after inclusion of both time and firm level fixed effects. Banks with lower tier 1 ratios and higher covariance as well as policy uncertainty previous quarter are more likely to receive current quarter infusion. Cash flow beta plays a significant role when year fixed effects are included. We use the fitted values from the probit model 5 that includes both firm and quarter fixed effects as inputs into the second stage quarterly DiD specification in Panel B.[13] We find significant increases in default risk, capital shortfall and network risks following infusion, consistent with Table 5 results.[14] The Kleibergen-Paap rk Wald F statistic measures weak instruments, and exceeds the Stock-Yogo (2005) critical value of 10, suggesting that the regressions with both firm and quarter fixed effects do not suffer from a weak instrument problem and are valid.

[Insert Table 8 here]

[13] Our results are qualitatively similar when Probit model 4 is used.

[14] The high IV estimates compared to Model 5 are consistent with similar findings in the literature (see Berger et al., 2020).

5.4 Additional checks

Alternate control samples – private and public NBFIs

We consider two additional control samples consisting of private (control D) and public (control E) NBFIs. The private NBFIs are not eligible for capital infusion. Public NBFIs received no government infusions during our sample period. We present the annual (Table IA5) and quarterly (Table IA6) DiD regressions comparing the treatment sample with each of the two alternate control samples. We find that capital infusions are followed by significant increases in default, capital shortfall and network risks for the treated banks compared to both sets of NBFIs. Our baseline results from Section 4.2 are hence robust.[15]

Alternate network risk variables

We examine two additional network variables i.e., *degree* and *between centrality* (Das, Kalimipalli and Nayak, 2022). Degree measures the number of connections of each node, which characterizes how interconnected the network is. Higher magnitude of degree implies fewer nodes with stronger connections and hence, a concentrated network. Betweenness centrality measures how central a bank's position in the network is; when a large proportion of shortest paths in the network pass through a particular node, that node is deemed to be ''between'' other nodes. DiD coefficients based on yearly specification (1) show that capital infusions lead to significant increase in the degree - or number of connections for each node - for the treated banks post infusion (Internet Appendix, Table IA7). Hence Section 4.2 results are robust to Degree measure of network risk. Betweenness centrality goes up significantly for all the firms post infusion but has no incremental effect for treated banks.

Alternate definition of Post variable

We next consider alternate definitions of Post infusion variable. Post infusion variable in Table 4 is set as a 2-quarter window following the capital infusion date. We consider two alternate definitions (a) where Post Infusion dummy as equal to 1 for the infusion quarter and 3 subsequent quarters after infusion; and (b) similar to Panel A, except that the infusion quarter – i.e., quarter 0 - is dropped in the sample. Definition (a) extends the window size and definition (b) drops information effects arising from including the infusion quarter (Internet Appendix, Table IA8,

[15] We also implement PSM matched NBFIs as control samples (untabulated) and find that our results hold.

panels A and B respectively present the results tied to definitions (a) and (b)). We once again find that the post infusions are marked by significant increases in default and systemic (NSRISK and network) risks for traded banks, and baseline Table 4 results hold.

Alternate definition of Large capital infusion

We check the robustness of our results using alternate measures for size of capital infusion. The capital infusion size dummy in Table 4 is based on the median value of all the capital infusions for each year. We consider alternate definitions of size in relation to the underlying size of the bank. Accordingly, we categorize capital infusions as large (or otherwise) using three alternate standardized infusion measures: ratio of capital infusion to total assets, ratio of capital infusion to total deposits and ratio of capital infusion to tier-1 capital. This enables us to better control for recipient banks' size in terms of assets, deposits, or tier-l capital, while comparing across banks and over time. In each year, we use the distribution of each infusion ratio to determine the median for the year, and based on the median, we create a dummy variable equal to 1 if the ratio for a bank is greater than the median. We only present 5 regressions from Table 4 that include quarter and firm fixed effects (tabulated in Internet Appendix, Table IA9). We find that baseline Table 4 results with respect to post-infusion effects on treatment banks still hold. In addition, we observe that large capital infusions lower default risks for treated firms in the post-infusion period, consistent with Table 4.

5.5 Dynamic effects of capital infusion on risks

Finally, to better understand the dynamic effects of capital infusions on the underlying risks we implement, two tests. First, we employ the following dynamic specification based on firm and quarter fixed effects, where we interact the dummy variable for treatment banks (TREAT) with dummy variables indicating each of the quarters for the -1 to +2 quarter window:

$$\begin{aligned}(\textit{risk measure})_{i,t} = {} & \alpha_0 + \beta_{-1}[\mathbb{1}(t = -1) \times TREAT_i] + \sum_{n=1}^{2} \beta_n[\mathbb{1}(t = n) \times TREAT_i + \\ & + \gamma_0\, (\textit{controls})_t + \gamma_1\, \textit{firm fixed effects}_i + \gamma_2\ \textit{time fixed effects}_t + \textit{error}_{i,t}\end{aligned} \tag{4}$$

where n is the specific quarter in the pre- and post-capital infusion window. The coefficient estimates of the interaction terms can be interpreted as the effect of treatment relative to control sample in each quarter. The coefficient estimates are presented in Figure 3. We find that the coefficients for treated banks increase over two quarters after infusion for default risk, capital shortfall, and network risk measures and are significantly different from zero. The treatment coefficients are close to zero pre one quarter. Our findings confirm Table 4 baseline results that after infusions banks experience significantly higher default, capital shortfall and network risks.

[Insert Figure 3 here]

Second, we study how the dynamic effect of capital infusions over time. We estimate the yearly DiD specification (1) from Table 5 with both firm and quarter fixed effects using only a four-year moving window and plot the DiD coefficient (β_1). Figure 4 presents the results. We observe that the β_1 coefficients for default risk, capital shortfall and network measures increase until year 2013, dropping in year 2014 and then trending up for next two years, and trending up again post-2017. The CoVar risk follows a similar path decreasing until 2014, remaining stable until 2016 and thereafter trending up. The effect of capital infusions on default and shortfall risks of treated banks have trended up over time while the effect on CoVar and network seem to have stabilized. Overall, the results based on rolling DiD regressions show that the effect on capital infusions on treated banks is time varying and show enhanced effect on risks during post-2014 (taper tantrum) period.

[Insert Figure 4 here]

6. Examining channels of capital infusion effects

We continue the analysis by determining what economic channels may matter in explaining the effects of capital infusion on default and systemic risks. We consider both time-series and cross-sectional channels.

6.1 Time-series channels of capital Infusion - Impact of macro-stress periods

We first examine how stress periods influence the effect of infusions and check if the earlier results are primarily driven by stress period capital infusions. Our sample is characterized by three critical periods that may have influenced the amount of government capital infusions: (a) Year 2010-11: According to the Controller and Auditor General Report (Source: Controller & Auditor General of India, Report No. 28, 2017), year 2010-11 witnessed lax regulatory standards enforced by Ministry of Finance where infusions were approved without subjecting to external auditor scrutiny; hence the initial (often inflated) requisitions by banks were sanctioned as requested without whetting by the auditors. (b) Year 2015-16: this period witnessed multiple macro-stress events including: domestic policy shock (Demonetization, 2016), and regulatory shocks (Asset Quality Review, 2015-16; and Insolvency and Bankruptcy Code Implementation, 2016). (c) Finally, year 2017-18, experienced domestic banking frauds; and onset of Non-Banking Financial company (NBFI) crisis, 2018-19). In 09/2018, Infrastructure Leasing & Financial Services Limited (IL&FS), a prominent NBFI, defaulted on its debt obligations, precipitating a crisis that engulfed the entire NBFI sector (Sengupta et al., 2021). To understand how these events may have influenced the aggregate capital infusions, we extract the annual capital infusion values from the Internet Appendix table IA.

	2008-09	2009-10	2010-11	2011-12	2012-13	2013-14	2014-15	2015-16	2016-17	2017-18
Capital infusion $mi	$414.31	$255.37	$4,362.41	$2,401.14	$2,237.39	$2,342.90	$1,117.48	$1,117.48	$3,809.10	$3,781.49
Year to year change		-38.36%	*1608.30%*	-44.96%	-6.82%	4.72%	-52.30%	*240.86%*	-0.72%	*256.72%*

The above table shows that the three critical periods, identified earlier, witnessed significant spikes in capital infusions i.e., 2010-11 (1608%), 2015-16 (241%) and 2017-18 (257%), where the percentage numbers capture the respective year-to-year increase in capital infusion amounts. Therefore, while lax auditing contributed to surge in infusions in year 2010-11, macro-economic shocks led to significant increases in infusions for 2015-16 and 2017-18.

Accordingly, we define a new dummy *StressYears* capturing three stress years i.e., 2010-11, 2015-16, and 2017-18. We consider the augmented version of DiD specification (1) with interaction terms involving the stress-year dummy. Results are reported in Table 9. We find that treated banks experience high default risks during stress years (*Teatment* × *StressYears Dummy*). Capital infusions during the stress years, captured by *Post Infusion* × *StressYears Dummy*, show significant decreases in credit and CoVar risks for all banks. Additionally, treated firms experience significant decrease in default and network risks post-infusion during the stress years (*Treatment* × *Post Infusion* × *StressYears Dummy*). Moreover, the DiD term (*Treatment* × *Post Infusion Dummy*) shows that our key finding - that capital infusions on average are followed by significantly higher default, capital shortfall and network risks – is still valid. In summary, though stress year funding managed to lower excess credit and systemic risks among treated banks, the baseline Table 4 results still hold.

[Insert Table 9 here]

6.2 Cross-sectional channels of capital infusion effects – Bank-level risk variables

We next examine the different bank level channels through which capital infusions may have influenced the systemic risks. Government capital infusions are likely to help lower default and systemic risks of the treatment banks through improved capital cushion, bank portfolio diversification, growth potential, cash holdings and effective hedging (Berger et al., 2020). Accordingly, we examine how each of the channels may have influenced the effect of capital infusions. Capital infusions can reduce the risks for low capital cushion (low tier 1) banks by increasing their equity capital buffer; however, such infusions can amplify bank risk taking if such banks resort to moral hazard behavior. Similarly, smaller size banks. i.e., banks with lower asset size and loan portfolio, are less likely to diversify, and if so, the capital infusions can help them lower their risks by increasing their charter value. However, such banks can use extra capital to act more aggressively and increase their supplies of risky credit, raising portfolio risks. Banks characterized by low growth potential (measured by low market to book) and low cash reserves (based on low interest coverage and deposit ratio) have higher implicit market risks. Capital infusions can help lower such risks by providing additional funding for investments and/or operating expenses; moral hazard led actions by such banks, however, can aggravate their risks. Less profitable (low ROE and high leverage[16]) banks are less likely to undertake active corporate hedging activities. Capital infusions can improve their hedging activities by augmenting their cash reserves. However, such banks can use extra capital to undertake risky initiatives and decrease their hedging exposures. Hence the evidence on what specific channel(s) hold is subject to empirical scrutiny.

We accordingly consider financial proxies for each of the channels and implement the annual DiD specification (1) using high-low bins formed by the median value of each financial variable in the last quarter preceding each infusion year. Results are presented in Table 10. For brevity, we only present coefficient and significance of the DiD interaction term: β_0 (or treatment x post-infusion effect).

[Insert Table 10 here]

[16] High leverage implies onerous interest commitments and restrictive covenant restrictions and increased risk for shareholders.

We summarize below different channels, respective financial proxies and key findings on default and systemic risks from Table 10.

		Evidence of higher default risk for banks characterized by following		Evidence of higher systemic risks for banks characterized by following	
channels	*Proxies for each channel*	*high risk attributes*	*low risk attributes*	*high risk attributes*	*low risk attributes*
• Capital cushion	− Tier 1	− low tier 1		− low tier 1 (NSRSIK & network risk)	
• Bank portfolio diversification channel	− size: total assets − loan to assets	− small firms − low loan to asset ratio		− small firms: (NSRISK & network risk) − low loan to asset ratio (NSRISK & network risk)	
• Growth potential channel	− market to book	− low market to book		− low market to book (NSRISK & network risk)	
• Cash holdings channel	− interest coverage − deposit to assets		− high interest coverage − high deposit to asset ratio	− low deposit to asset ratio (CoVar & network risk)	− high interest coverage (NSRISK & network risk) − high deposit to asset ratio (NSRISK)
• Corporate hedging channel	− profitability (ROE) − leverage	− less profitable	− more profitable − low leverage	− less profitable (NSRISK) − high leverage (network risk)	− more profitable (network risk) − low leverage (network risk)

As summarized in the above table, capital infusions significantly increase default and systemic risks for low Tier 1 capital, smaller (i.e., both low assets and loan to assets), and low valuation (or market to book) banks in our sample. These findings imply that *high risk* Indian public sector banks characterized by low levels of capital cushion, portfolio diversification and growth potential seem to experience higher risks post-infusion. Our evidence is consistent with capital cushion, portfolio diversification and growth channels explaining the amplification of default and systemic risks. High risk banks experiencing higher risks after government infusions indicates possible moral hazard behavior. We also observe that *low risk* (i.e., high deposit ratio, interest coverage, and low leverage) banks exhibit higher risks following infusions. No clear trends emerge on the profitability channel. Collectively, our findings taken together imply that treated banks are likely to engage in additional risk-taking arising from possible implicit moral hazard issues.

7. Effect of capital infusions on aggregate default and systemic risks

Finally, we study the impact of capital infusions on aggregate default and systemic risks. Earlier studies how that government guarantees can engender sovereign's default risk (Zhao, 2017), and induce interconnections between sovereign risk and risk of banks and underlying borrowers (Bedendo and Colla, 2015; Leonello, 2018; Mäkinen, Sarno and Zinna, 2020). Sovereign credit rating downgrades adversely affect returns for those banks that are expected to receive stronger support from their governments (Correa et al., 2014), and risk spillovers occur from sovereign to corporate credit risk for firms that are bank or government dependent (Augustin et al., 2018).

If periodic capital infusions are chosen government's funding mechanisms for weaker public sector banks, do they help in controlling the aggregate default and systemic risks? The analyses in the pervious sections focused on bank level risks. In this section, we examine the overall impact of capital infusions on aggregate level default and systemic risks across different types of FIs. Widespread bank vulnerabilities may lead to expectations of rising defaults, enhanced financial vulnerability of the economy, increase in government capital infusions and bailouts, rise in expected future government subsidies and deficits, and hence an increased aggregate risk.

We first plot the time-series of aggregate default and systemic risks, averaged across all the individual bank level risks, for the full sample period. We consider raw and scaled time series plots respectively for default (Figure 5) and systemic risk (Figure 6) measures over time for different treatment and control sample FIs. Figure 5 shows that PD and PD slope measures are significantly higher for treatment banks consistently over time. We also see that the treatment bank credit risks spike significantly during several crisis episodes: year 2008 (i.e., the Global financial crisis), year 2011 (coinciding with Greek bailout crisis), year 2013-14 (taper tantrum) and 2015-16 (rupee currency crisis and Demonetization). Scaled plots show that public NBFIs exhibit elevated default risks far higher than treatment banks since 04/2017. Figure 6 shows that capital shortfall (NSRISK), CoVaR and network risk levels are significantly higher for treatment banks compared to control banks, and experience large spikes during the 2008 GFC and 2015-16 crises; raw and scaled plots for NSRISK and network risks show that public NBFIs experience high capital shortfall towards the end of sample from 04/2017. CoVaR levels - showing the exposures of the market VaR to the tail risk of individual FIs –trend down over time and cluster together for all the FIs for the second part of the sample.[17]

[Insert Figures 5 and 6 here]

We next implement the following time-series specification to evaluate how the capital infusions impact the aggregate default and systemic risks.

$$(aggregate\ risk\ spread)_t = \alpha_0 + \alpha_2\ Post \times infusion\_index_t + \gamma_0\ (controls)_t + \gamma_1\ time\ fixed\ effects_t + error_t \quad (5)$$

where aggregate risk spreads refer to *difference* between aggregate spreads of (a) treated public sector banks and (b) control private sample banks; therefore, aggregate risk spread reflects the excess risk in treated versus private sector banks at the aggregate level. The aggregate spreads are obtained as cross-sectional averages of default or systemic risks of underlying banks over time. We consider five risk measures PD, PD slope, NSRISK, CoVaR and Network risks; the mean risks are obtained as the cross-sectional averages for each risk variable. Post refers to two-quarters post window following infusion. The key explanatory variable, infusion index, is measured in three different ways i.e., Infusion index 1 is the infusion dummy that refers to the quarters where capital infusions occur; Infusion index 2 is the large number infusion dummy that reflects the quarters where large number (or above median number) of infusions take place. Infusion index 3 is the large dollar value infusion dummy that reflects the quarters where large dollar value (or above median dollar value) of infusions happen. Hence, while Infusion Index 1 captures the infusion quarters, Indices 2 and 3 reflect quarters with large number and dollar value of infusions respectively. All regressions include local and US market factors, year specific fixed effects and Huber/White robust standard errors.

Table 11 presents the results for regression using the spread between public and private banks control sample. Capital infusions lead to lower aggregate default risk (PD and PD slope) measures for treated banks versus private control sample for Infusion indices 1 and 2 while showing no discernable effects on aggregate systemic risks. Aggregate default spreads go down post-infusion implying that aggregate default risk of the treatment banks decreases compared to the control sample. There is, however, no evidence to show that aggregate systemic risk measures

[17] Additionally, find that time-series plots of DTD, MES and 1 percentile – NSRISK and CoVaR reveal similar trends (Internet Appendix, and figures A7, A8 and A9 respectively).

decrease following infusion. Additional robustness tests using the spreads between public banks and private or public NBFI control samples show the results are robust (Internet Appendix, Table A10).

[Insert Table 11 here]

8. Summary and conclusions

In this paper, we study the possible effect of "repeated" government infusions on financial stability. While government led bank capital infusions in US and other developed markets have been usually contingent an external shock or crisis episode, India presents a unique setting where significant capital infusions happen regularly to stabilize the weak balance sheets of the public sector banks. Such repeated capital infusions can either better engender financial stability, given the timely government interventions; or create instability arising from possible moral hazard concerns. Based on the exhaustive sample of government capital infusion into the public sector government banks for the period 2008-18, and several robustness tests, we find that capital infusions are followed by economically significant escalation in default, capital shortfall and network risks for the government owned public sector banks. These results still hold after controlling for three critical period (i.e., 2010-11, 2015-16, and 2017-18) infusions, which led to lower credit and systemic risks among treated banks. While capital infusion during stress times can lower risks and improve financial stability, not adequately recapitalizing such banks relative to their implicit economic losses and letting them issue risky loans may have escalated the post infusion risks. Further evidence shows that multiple economic channels may explain the additional risk-taking by the banks. While aggregate default spreads go down post-infusion, we find no evidence of reduction in aggregate systemic risk measures. Taken together our results imply that treated banks are likely to engage in additional risk-taking arising from possible implicit moral hazard issues.

Governments often employ prudential regulatory tools to ensure financial stability. Governments support ailing banks in many ways including (preferred) equity capital injections, liquidity infusions, financial guarantees, and large-scale nationalization. The question of how governmental support through repeated capital infusions to banks affects the financial stability has a wider policy interest. It is also likely tricky because we do not observe the counterfactual of what the condition of the financial system would have been in the absence of government assistance.

To the best of our knowledge, this study contributes to the literature by providing the first study of how “repeated” government guarantees impact financial stability in the context of emerging markets.

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References

Acharya, V. V., Khandwala, H., & Sabri Öncü, T. (2013). The growth of a shadow banking system in emerging markets: Evidence from India. Journal of International Money and Finance, 39, 207-230.

Acharya, V. V., Anginer, D., & Warburton, A. J. (2018). The end of market discipline? Investor expectations of implicit government guarantees. SSRN Working paper.

Acharya, V. V., Cecchetti, S. G., De Gregorio, J., Kalemli-Özcan, Ş., Lane, P. R., & Panizza, U. (2015). Corporate debt in emerging economies: A threat to financial stability? The Brookings Institution and the Centre for International Governance Innovation.

Acharya, V. V., Engle, R., & Richardson, M. (2012). Capital shortfall: A new approach to ranking and regulating systemic risks. American Economic Review, 102(3), 59-64.

Acharya, V. V., & Kulkarni, N. (2019). Government Guarantees and Bank Vulnerability during a Crisis: Evidence from an Emerging Market. NBER Working Paper, (w26564).

Acharya, V. V., Borchert, L., Jager, M., & Steffen, S. (2021). Kicking the Can Down the Road: Government Interventions in the European Banking Sector. The Review of Financial Studies, 34(9), 4090–4131.

Acharya, V. V., (2020). "Quest for Restoring Financial Stability in India" SAGE Publications India Pvt Ltd.

Adrian, T., & Brunnermeier, M. K. (2016). CoVaR. American Economic Review, 106(7), 1705-1741.

Ahnert, T., Anand, K., Gai, P., & Chapman, J. (2019). Asset encumbrance, bank funding, and fragility. The Review of Financial Studies, 32(6), 2422-2455.

Allen, F., Carletti, E., Goldstein, I., & Leonello, A. (2015). Moral hazard and government guarantees in the banking industry. Journal of Financial Regulation, 1(1), 30-50.

Allen, F., Carletti, E., Goldstein, I., & Leonello, A. (2018). Government guarantees and financial stability. Journal of Economic Theory, 177, 518-557.

Allen, F., & Gu, X. (2018). The interplay between regulations and financial stability. Journal of Financial Services Research, 53(2-3), 233-248.

Atkeson, A. G., d'Avernas, A., Eisfeldt, A. L., & Weill, P. O. (2019). Government guarantees and the valuation of American banks. NBER Macroeconomics Annual, 33(1), 81-145.

Augustin, P., Boustanifar, H., Breckenfelder, J., & Schnitzler, J. (2018). Sovereign to corporate risk spillovers. Journal of Money, Credit and Banking, 50(5), 857-891.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring Economic Policy Uncertainty, The Quarterly Journal of Economics, 131(4), 1593–1636.

Bedendo, M., & Colla, P. (2015). Sovereign and corporate credit risk: Evidence from the Eurozone. Journal of Corporate Finance, 33, 34-52.

Behr, P., & Wang, W. (2020). The (un)intended effects of government bailouts: The impact of TARP on the interbank market and bank risk-taking. Journal of Banking & Finance, 116.

Benoit, S., Colliard, J. E., Hurlin, C., & Pérignon, C. (2017). Where the risks lie: A survey on systemic risk. Review of Finance, 21(1), 109-152.

Berger, A. N., Makaew, T., & Roman, R. A. (2019). Do Business Borrowers Benefit from Bank Bailouts? The Effects of TARP on Loan Contract Terms. Financial Management, 48(2), 575–639.

Berger, Allen N. & Sedunov, John (2021). The Life Cycle of Systemic Risk. SSRN. Retrieved from https://ssrn.com/abstract=3988373.

Berger, Allen N., Raluca A. Roman, John Sedunov (2020). Did TARP reduce or increase systemic risk? The effects of government aid on financial system stability, Journal of Financial Intermediation, Volume 43. 1042-9573.

Berger, Allen N., Himmelberg, Charles P., Roman, Raluca A., & Tsyplakov, Sergey (2022). Bank Bailouts, Bail-Ins, or No Regulatory Intervention? A Dynamic Model and Empirical Tests of Optimal Regulation and Implications for Future Crises. Financial Management, Forthcoming. Retrieved from https://ssrn.com/abstract=3179226.

Billio, M., Getmansky, M., Gray, D., Lo, A., Merton, R., & Pelizzon, L., (2013). Sovereign, Bank, and Insurance Credit Spreads: Connectedness and System Networks. Working Paper, IMF.

Billio, M., Getmansky, M., Lo, A.W., & Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. Journal of Financial Economics 104 (3), 535–559.

Bernard, B., Capponi, A., & Stiglitz, J. E. (2017). Bail-ins and Bail-outs: Incentives, Connectivity, and Systemic Stability. National Bureau of Economic Research Working Paper Series, No. 23747.

Borisova, G., Fotak, V., Holland, K., & Megginson, W. L. (2015). Government ownership and the cost of debt: Evidence from government investments in publicly traded firms. Journal of Financial Economics, 118(1), 168-191.

Brandao-Marques, L., Correa, R., & Sapriza, H. (2020). Government support, regulation, and risk-taking in the banking sector. Journal of Banking and Finance, 112, 10, 52-84.

Brownlees, C. T., & Engle, R. F. (2017). SRISK: A Conditional Capital Shortfall Measure of Systemic Risk. The Review of Financial Studies, 30, 48-79.

Bunderson, S., & Thakor, Anjan V., (2022). Higher purpose, banking and stability, Journal of Banking and Finance, Volume 140, 106138.

Chava, S., Ganduri, R., & Yerramilli, V. (2021). Do Bond Investors Price Tail Risk Exposures of Financial Institutions? Quarterly Journal of Finance, 11, 1.

Chen, R. R., El Ghoul, S., Guedhami, O., & Nash, R. (2018). State ownership and corporate cash holdings. Journal of Financial and Quantitative Analysis, 53(5), 2293-2334.

Clayton, C., & Schaab, A. (2020). Bail-Ins, Optimal Regulation, and Crisis Resolution. SSRN.

Cong, L. W., Gao, H., Ponticelli, J., & Yang, X. (2019). Credit allocation under economic stimulus: Evidence from China. The Review of Financial Studies, 32(9), 3412-3460.

Cordella, T., Dell'Ariccia, G., & Marquez, R. (2017). Government guarantees, transparency, and bank risk-taking. World Bank Policy Research Working Paper No. 7971.

Correa, R., Lee, K. H., Sapriza, H., & Suarez, G. A. (2014). Sovereign credit risk, banks' government support, and bank stock returns around the world. Journal of Money, Credit and Banking, 46(s1), 93-121.

Bui, C., Scheule, H., & Wu, E. (2020). A cautionary tale of two extremes: The provision of government liquidity support in the banking sector. Journal of Financial Stability, 51.

Dantas, M., Merkley, K. J., & Silva, F. B. G. (2019). Government Guarantees and Banks' Earnings Management. SSRN.

Dam, L., & Koette, M.(2012). Bank bailouts and moral hazard: Evidence from Germany. Review of Financial Studies, 25:2343–80

Das, S. R. (2016). Matrix metrics: Network-based systemic risk scoring. The Journal of Alternative Investments, 18(4), 33-51.

Das, S. R., Kalimipalli, M., & Nayak, S. (2022). Banking Networks, Systemic Risk, and the Credit Cycle in Emerging Markets. Journal of International Financial Markets, Institutions and Money, Volume 80.

Das, S. R., Kim, S., & Ostrov, D. N. (2019). Dynamic Systemic Risk: Networks in Data Science. The Journal of Financial Data Science, 1(1), 141-158.

Diebold, Francis X. & Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. Journal of Econometrics, Volume 182, Issue 1, 119-134.

Dodd, O., Kalimipalli, M., & Chan, W. H. (2021). Evaluating the Impact of Post-Crisis Growth in Emerging Market Corporate Debt. International Review of Financial Analysis, 73, 101610.

Duan, J. C., J. Sun, & Wang, T. (2012). Multiperiod Corporate Default Prediction — A Forward Intensity Approach. Journal of Econometrics, 170, 191–209.

Duan, J. C., & Fulop, A. (2013). Multiperiod Corporate Default Prediction with the Partially-Conditioned Forward Intensity. National University of Singapore Working Paper.

Duchin, R., & Sosyura, D. (2014). Safer ratios, riskier portfolios: Banks' response to government aid. Journal of Financial Economics, 113:1–28.

Elekdag, S., Alter, A., Arregui, N., Ichiue, H., Khadarina, O., Kikkawa, A. K., ... & Zhang, J. (2015). Corporate leverage in emerging markets - a concern? IMF Global Financial Stability Report.

Fischer, M., Hainz, C., Rocholl, J., & Steffen, S. (2014). Government guarantees and bank risk-taking incentives. SSRN Working paper.

Gete, P., & Zecchetto, F. (2018). Distributional implications of government guarantees in mortgage markets. The Review of Financial Studies, 31(3), 1064-1097.

Gropp, R., Guettler, A., & Saadi, V. (2019). Public bank guarantees and allocative efficiency. Journal of Monetary Economics.

Helwege, J., & Liu, X. (2021). TARP from the Banks' Perspective: Evidence from Conference Calls. SSRN.

Iyer R, Jensen TL, Johannesen N, Sheridan Aet al., (2019), The distortive effects of too-big-to-fail: evidence from the Danish market for retail deposits, The Review of Financial Studies, Vol: 32, Pages: 4653-4695, ISSN: 0893-9454

Jin, S., Wang, W., & Zhang, Z. (2018). The Value and Real Effects of Implicit Government Guarantees. Working paper.

Keister, T., & Mitkov, Y. (2016). Bailouts, bail-ins, and banking crises. Memo, presented at the Board of Governors of the Federal Reserve System.

Kelly, B., Lustig, H., & Van Nieuwerburgh, S. (2016). Too-systemic-to-fail: What option markets imply about sector-wide government guarantees. American Economic Review, 106(6), 1278-1319.

König, P., Anand, K., & Heinemann, F. (2014). Guarantees, transparency and the interdependency between sovereign and bank default risk. Journal of Banking and Finance, 45, 321-337.

Leonello, A. (2018). Government guarantees and the two-way feedback between banking and sovereign debt crises. Journal of Financial Economics, 130(3), 592-619.

Mäkinen, T., Sarno, L., & Zinna, G. (2020). Risky bank guarantees. Journal of Financial Economics, 136(2), 490-522.

Martynova,N. & Vogel, U., (2022). Banks' complexity-risk nexus and the role of regulation, Journal of Banking and Finance, Volume 134.

Merton, R. C. (1977). An analytic derivation of the cost of deposit insurance and loan guarantees an application of modern option pricing theory. Journal of Banking & Finance, 1(1), 3-11.

Nistor, S., & Ongena, S. (2023). The Impact of Policy Interventions on Systemic Risk across Banks. Journal of Financial Services Research. https://doi.org/10.1007/s10693-023-00404-8.

Norden, L., Roosenboom, P., & Wang, T. (2013). The impact of government intervention in banks on corporate borrowers' stock returns. Journal of Financial and Quantitative Analysis, 1635-1662.

Pazarbasioglu, C., L. Laeven, O. M. Nedelescu, S. Claessens, F. Valencia, M. Dobler, & Seal,K. (2011). Crisis management and resolution: Early lessons from the financial crisis. Report, International Monetary Fund, Washington, DC.

Pellegrini, Carlo B., Cincinelli, P., Meoli, M., & Urga, G. (2022). The role of shadow banking in systemic risk in the European financial system, Journal of Banking and Finance, Volume 138, 106422.

Rajan, R. (2018). "Note to Parliamentary Estimates Committee on Bank NPAs", (Sept 6). Source: The Hindu Business Online.

Sengupta, R., Song, L. L., & Vardhan, H., (2021). A study of nonbanking companies in India, ADB South Asia Working papers series, No.83. R. (2018). Note to Parliamentary Estimates Committee on Bank NPAs.

Sedunov, J., (2021). Federal reserve intervention and systemic risk during financial crises, Journal of Banking and Finance, Volume 133. 106210

Walker, T., Zhang, X., Zhang, A., & Wang, Y. (2021). Fact or fiction: Implicit government guarantees in China's corporate bond market. Journal of International Money and Finance, 116, 10.

Wilcox, James A. & Yasuda, Yukihiro, (2019). Government guarantees of loans to small businesses: Effects on banks’ risk-taking and non-guaranteed lending, Journal of Financial Intermediation, Elsevier, vol. 37(C), pages 45-57.

Zhao, L. (2018). Market-based estimates of implicit government guarantees in European financial institutions. European Financial Management, 24(1), 79-112.

Appendix A. Variable Definitions

VARIABLE	DEFINITION
Panel A: Capital infusion variables (Sources: Source: Controller & Auditor General of India, Report No. 28, 2017).	
Treatment dummy	Public sector banks receiving capital infusion
Post Infusion dummy	Two-quarter period post-capital infusion
Large infusion dummy	Capital infusion size dummy variable in yearly regressions to indicate if the capital infusion for a given bank is above (=1) or below (=0) the median value of all the capital infusions in a given year.
8-Quarter Median Large Infusion dummy	Capital infusion size dummy variable in quarterly regressions to indicate if the current quarter infusion of a bank is greater than the median of previous 8 quarters of infusions for all banks
Current Quarter Median Large Infusion dummy	Capital infusion size dummy variable in quarterly regressions to indicate if the current quarter infusion of a bank is greater than the median of all current quarter infusions
Modified 8-Quarter Median Large Infusion dummy	Capital infusion size dummy variable in quarterly regressions to indicate if the infusion of a bank in the last 8 quarters is greater than the median of previous 8 quarters of infusions for all banks
Infusion index 1	Aggregate Infusion dummy that refers to the quarters where capital infusions occur
Infusion index 2	Aggregate large number infusion dummy that reflects the quarters where large number (or above median number) of infusions take place
Infusion index 3	Aggregate large dollar value infusion dummy that reflects the quarters where large dollar value (or above median dollar value) of infusions happen
Panel B: Credit risk variables (Sources: DTD and PD data: Risk Management Institute (RMI) at the National University of Singapore (NUS); Equity market risk data: Refinitiv Datastream-Worldscope)	
PD	12-month probability of default at the quarterly level
PD slope	The difference between 60-month and 12-month probabilities of default at the quarterly level
DTD	Monthly distance-to-default measure, which is a volatility-adjusted leverage measure based on Merton (1974)., aggregated at the quarterly level
Panel C: Systemic risk variables (Sources: Equity market data: CMIE, Datastream - Worldscope)	
MES	Marginal expected shortfall (*MES) is* obtained as the average financial institution (FI)'s equity return on days when the market as a whole is in the lower tail of its return distribution provided year (Acharya et al., 2012). It is calculated as $MES_{i,t} = E(R_{i,t} \mid R_{m,t} < C)$, where R_{it} is firm i 's equity return on

	day t, $R_{m,t}$ is the aggregate market index return, and C is the 5th or 1st percentile value of the market index returns over the past 12 months. We compute *MES* on a quarterly basis using daily stock market information from CMIE for Indian firms. For the aggregate market index, we use the NIFTY stock index. We impose the filter that a given stock should have 125 days in any given year. We multiply MES numbers by a negative sign. Therefore, a higher *MES* indicates that a firm experiences lower returns during market distress, and hence implies a higher systemic risk.
NSRISK	A financial institution (FI)'s expected capital shortfall is obtained as standardized value of *SRISK*. The *SRISK* measure refers to *the* expected capital shortfall of a FI when the market return is in the lowest 5% bracket in a given year (Acharya et al., 2012). Compared to *MES*, *SRISK* incorporates information on a FI's size and leverage. *SRISK* measures capital shortfall with respect to a prudential capital ratio and is computed as $SRISK = E[k(Debt + Equity) - Equity \mid crisis]$. *SRISK* is for each firm i in year t as follows: $SRISK_{i,t} = k \,.\, Debt_{i,t} - (1-k).(1 - LRMES_{i,t}).Equity_{i,t}$, where *Debt* is the book value of debt, *Equity* is the market value of equity, and k is the prudential capital ratio set to 9% for Indian setting; *LRMES* is the long-run marginal expected short- fall computed as $\text{LRMES}_{\text{i,t}} = 1 - \exp(18 \times MES_{i,t})$. For *MES* calculations, we impose the filter that a given stock should have 125 days in any given year. A higher *SRISK* variable indicates a FI's expected capital shortfall and greater systemic risk. We calculate *SRISK* using both 5% and 1% thresholds. We then standardize SRSIK cap by bank market capitalization, and refer to it as NSRISK, which captures the proportional capital shortfall in the event of a crisis.
CoVaR	Here we obtain the conditional value at risk, *CoVaR*, and refers to the value art risk (VaR) of the financial system conditional on a financial institution (FI) being in distress minus the VaR of the financial system conditional on the bank being in a normal state (Adrian and Brunnermeier, 2016). We compute the CoVaR measure for each firm using quantile regressions and a set of macro state variables. In particular, we run the following two quantile regressions.: $R_{i,t} = \alpha_i + \gamma_i M_{t-1} + \varepsilon_{i,t}$ and $R_{m,t} = \alpha_{system\mid i} + \beta_{system\mid i} R_{i,t} + \beta_{system\mid t} M_{t-1} + \varepsilon_{i,t}$ in which $R_{i,t}$ is the equity return for firm i in week t , and $R_{m,t}$ is the weekly return of country m's stock index. M_{t-1} are lagged state variables: the change in the term spread (i.e. 10 years - 2-year GVT BMK YLD), the weekly country stock index (Nifty 50) return, and the volatility of the Nifty 50 index return over the past four weeks. For individual firms return, sourced from CMIE, we impose the filter that a given stock should have 125 days in any given year. Data on T-yield rates are obtained from Datasream. We use weekly stock market information from CMIE. The two quantile regressions are estimated at the end of each quarter using data from a rolling five-year window. The CoVaR variable is computed as $CoVar_t^k = \hat{\beta}^k_{system\mid i}\left(\hat{R}^k_{i,t} - \hat{R}^{50\%}_{i,t}\right)$, and denotes the change in the value at risk of the system when the institution's return is at the k^{th} i.e. 5th or 1st percentile (or when the institution is in distress) minus the value at risk of the system when the institution' return is at the 50% percentile. We multiply CoVaR numbers by a negative sign. Therefore, a higher *CoVaR* indicates a higher contribution to the systemic risk.
Score	*Score* is a network based systemic risk measure of a financial institution following Das, Kalimipalli and Nayak (2022). The network score (S), defined below, is described as a function of number of banks in the system (n), Adjacency matrix (A) and n-vector of size-weighted credit risk scores of each bank (C). $$S = \frac{1}{n}\sqrt{C^T.A.C \geq 0}$$ The vector C obtained as $C = a \cdot \lambda$, where a = log($Total\ Assets$) and λ is a credit quality measure. We require that λ be increasing in credit risk.

	The score S summarizes the level of systemic risk of all banks, which in turn is decomposed into a specific bank level contribution, applying Euler's homogeneous function theorem. $$S = \frac{\partial S}{\partial C_1} C_1 + \frac{\partial S}{\partial C_2} C_2 + \cdots + \frac{\partial S}{\partial C_n} C_n = \sum_{i=1}^{n} \frac{\partial S}{\partial C_i} C_i$$ where each component $\frac{\partial S}{\partial C_i}$ of this equation comprises the ''risk contribution'' of bank i to total systemic risk. This allows a regulator to apportion systemic risk to each bank such that it is additive across all banks.
Degree	The number of connections of each node, which characterizes how interconnected the network is. The degree of distribution also reveals how concentrated the network connections may be in a few nodes, as often occurs in hub and spoke networks.
Betweenness centrality	A measure of how central a bank's position in the network is. A node is said to be ''between'' other nodes when a large proportion of shortest paths in the network pass through that particular node.
Panel D: Firm-level variables Annual data at the end of each financial year (i.e. April to March). (Source: Refinitiv Datastream - Worldscope)	
Total assets	TOTAL ASSETS represent the sum of cash & due from banks, total investments, net loans, customer liability on acceptances (if included in total assets), investment in unconsolidated subsidiaries, real estate assets, net property, plant and equipment and other assets.
Loans	Loans refers to long term loans and advances refers long term loans and advances given by the company with a maturity period of more than 12 months.
Deposits	Deposits refers to the sum of the outstanding values of a company's long term and short term deposits.
Debt / market value of equity	Ratio of Debt to Market value of equity
Debt / Total assets	Ratio of Debt to Total assets
Debt/market value of equity	Ratio of Total Debt to Market value of Equity
Total Debt/ total capital	(Long Term Debt + Short Term Debt & Current Portion of Long Term Debt) / (Total Capital + Short Term Debt & Current Portion of Long Term Debt) * 100
Leverage	Leverage is calculated by dividing the company's total debt divided by shareholder's equity. Shareholder's equity or equity shareholders' funds or net worth is arrived at by adding up equity capital and reserves.
Interest coverage	Interest coverage refers to the ratio of EBIT to Total interest expense
Deposit ratio	Ratio of Deposits to Total Assets
Loans/assets	Ratio of Loans to total assets
Return on Equity (ROE)	(Net Income – Bottom Line - Preferred Dividend Requirement) / Average of Last Year's and Current Year's Common Equity * 100
Market value of equity	Market value of equity refers to the product of number of shares outstanding multiplied by adjusted closing price of the share at the end of the year
Market to book ratio	Ratio of Market value of equity to Book value of equity

Q ratio	Ratio of market-value of assets to book-value of assets arrived as [(Total Assets - Book value of equity + Market value of equity)/Total Assets]
Tier 1 Capital Ratio	Ratio of Equity capital to Total Assets
Panel E: Local and Global market variables (Source: Refinitiv Datstream - Worldscope)	
Market returns	India Nifty (50) stock market index returns
SP500	U.S. Market returns using the S&P 500 index.
VIX	U.S. aggregate Risk Aversion factor obtained as VIX index.
Default factor	U.S. default factor, sourced as Moody's BAA yield minus 10-year swap rate.
Level rates	U.S. term-structure level factor obtained as 3-month T-Bill rate.
Slope rates	U.S. term-structure slope factor, obtained as 10-year rate minus 2-year Treasury rates.
TED	U.S. aggregate liquidity factor referred to as TED spread, obtained as 30-day LIBOR rate minus 3-month Treasury-Bill rate.
Cap flows	Capital flows is captured using "non-foreign direct investment net capital" which measures the monetary value of capital inflow net of capital outflow other than foreign direct investment. (source: Oxford Economics, Datastream).
Policy uncertainty	Baker, Bloom and Davis (2016) measure of economic policy uncertainty (EPU) based on newspaper coverage frequency. (Source: Author Website).

Figure 1: Event window plots of Probability of default (PD) around capital infusion

We present quarterly mean plots (both raw and scaled) of 1-year PD and PD slope - measured as 5-year PD minus 1-year PD - for the treatment and four different control samples for the sample period. We present [-1 to +3] quarters around the infusion event (period zero), which denotes the capital infusion quarter. All the variables are defined in Appendix A.

Figure 2: Event window plots of the systemic risk measures around capital infusion

We present quarterly mean plots (both raw and scaled) of Expected capital shortfall (NSRISK), Covariance risk (CoVar) and network risk score at five-percentile level for the treatment and four different control samples for the sample period. We present [-1 to +3] quarters around the infusion event (period zero), which denotes the capital infusion quarter. All the variables are defined in Appendix A.

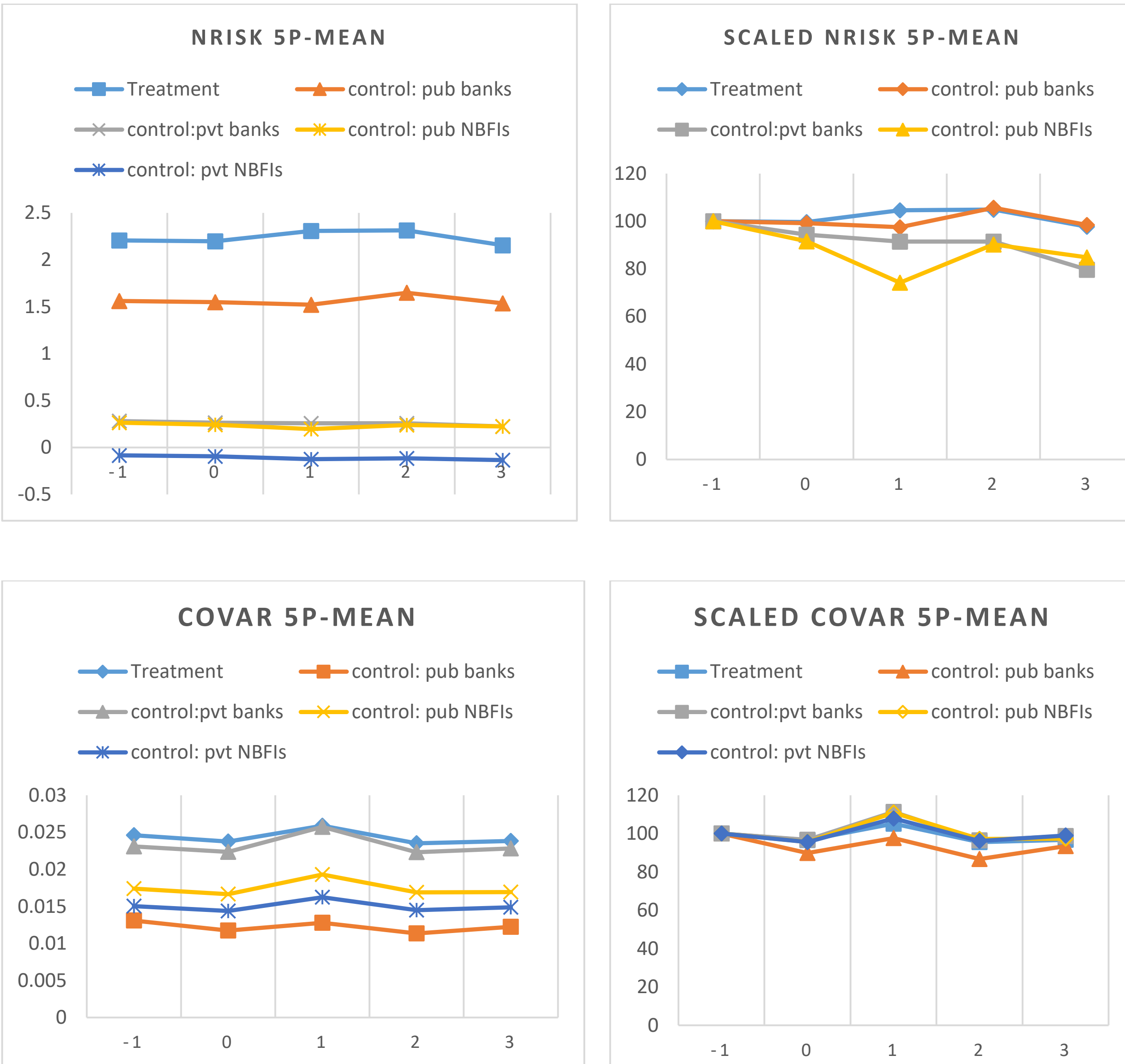
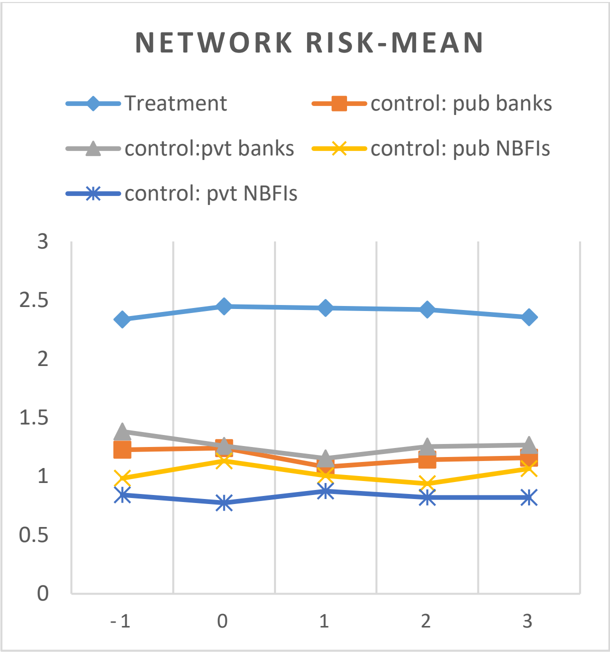


Figure 2: contd.



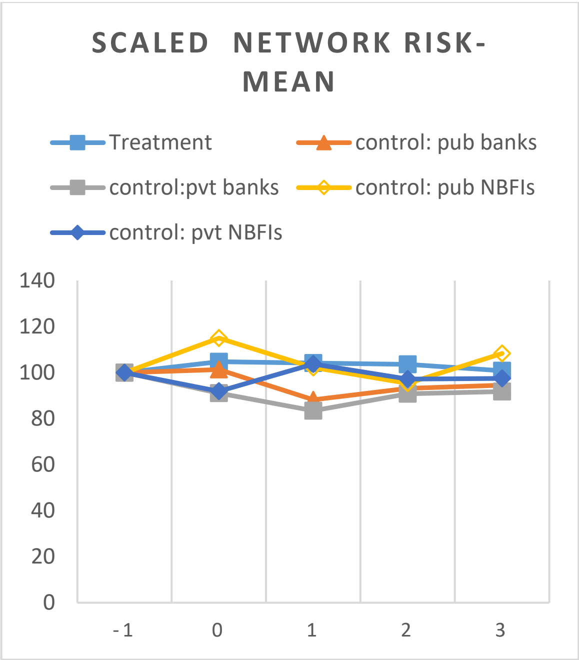


Figure 3: DiD coefficient plots of default and systemic risk measures over the sample period 2008-2018

We present time series plots of DiD coefficients with respective 95% confidence intervals from specification (4) with firm and quarter fixed effects estimated each quarter using the treatment versus private bank control sample. The capital infusion quarter is denoted period zero. All the variables are defined in Appendix A.

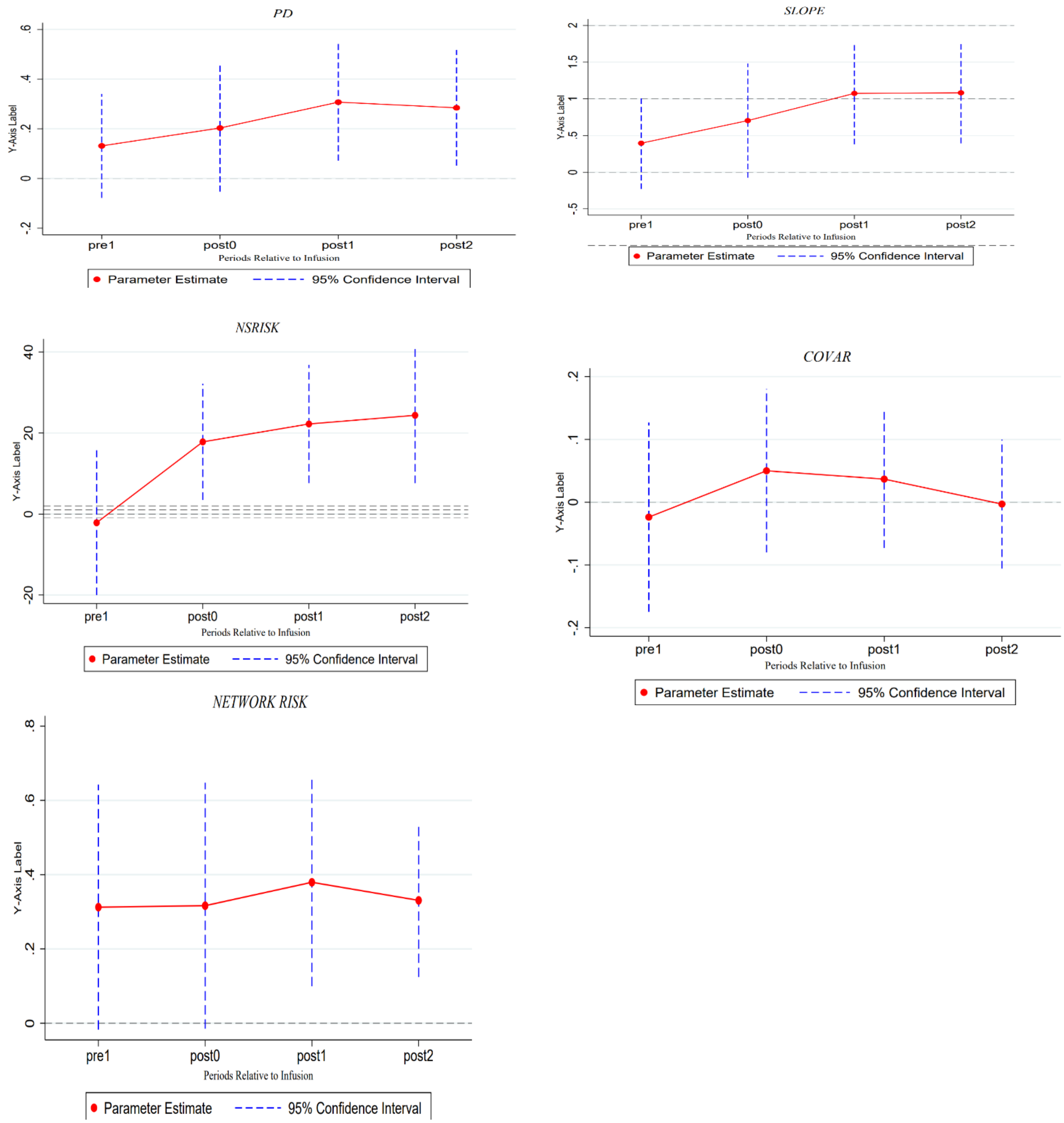
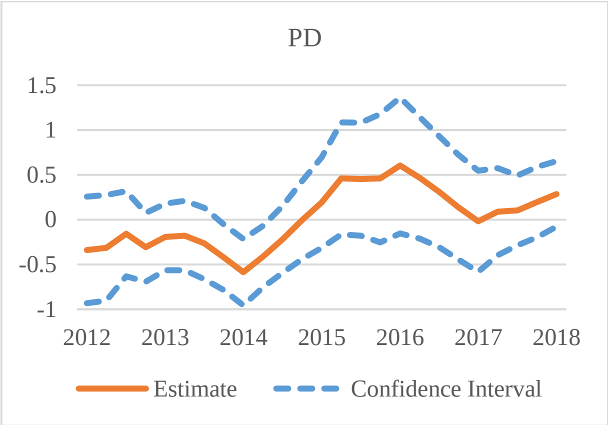
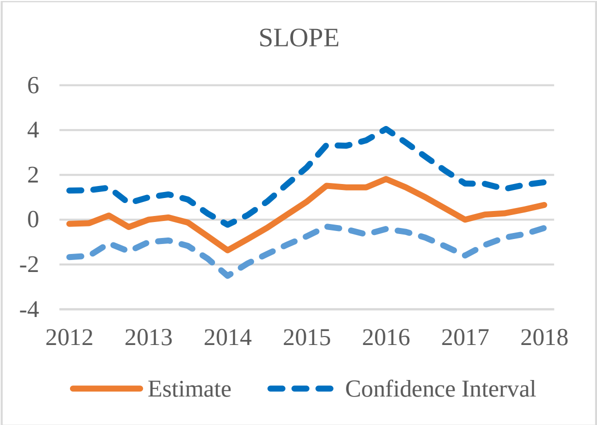
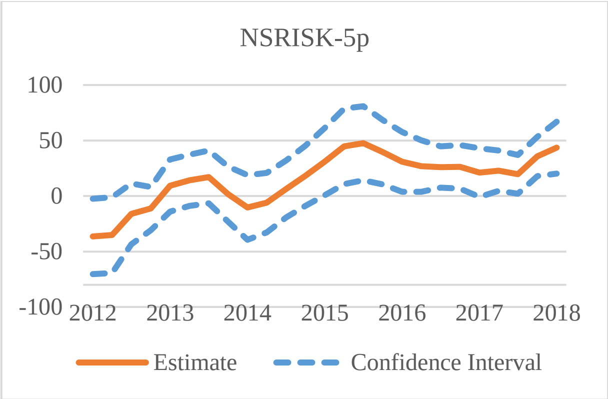


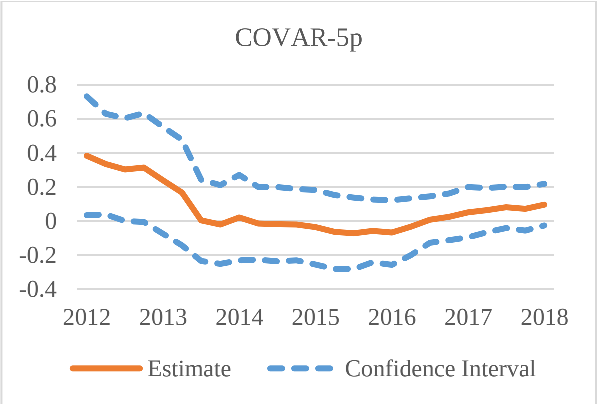
Figure 4: Rolling DiD regression coefficient plots of default and systemic risk measures over the sample period 2008-2018

We present time series plots of rolling DiD regression coefficients of model (1) for various default and systemic risk measures estimated with four year moving window using the treatment versus private bank control sample. All the variables are defined in Appendix A.









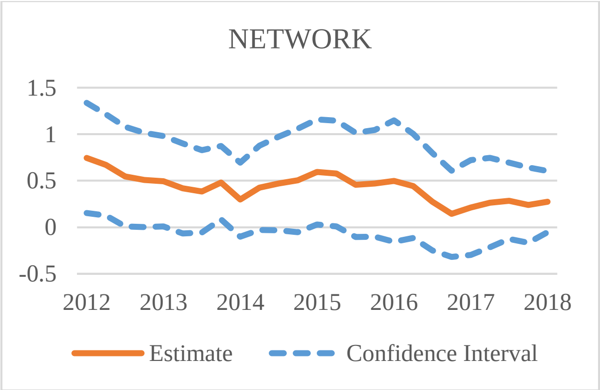


Figure 5: Time series plots of Probability of default (PD) measures over the sample period 2008-2018

We present aggregate time series plots of 12-month PD and PD slope- measured as 5-year PD minus 1-year PD - (both raw and scaled) for the treatment and four different control samples for the sample period. All the variables are defined in Appendix A.

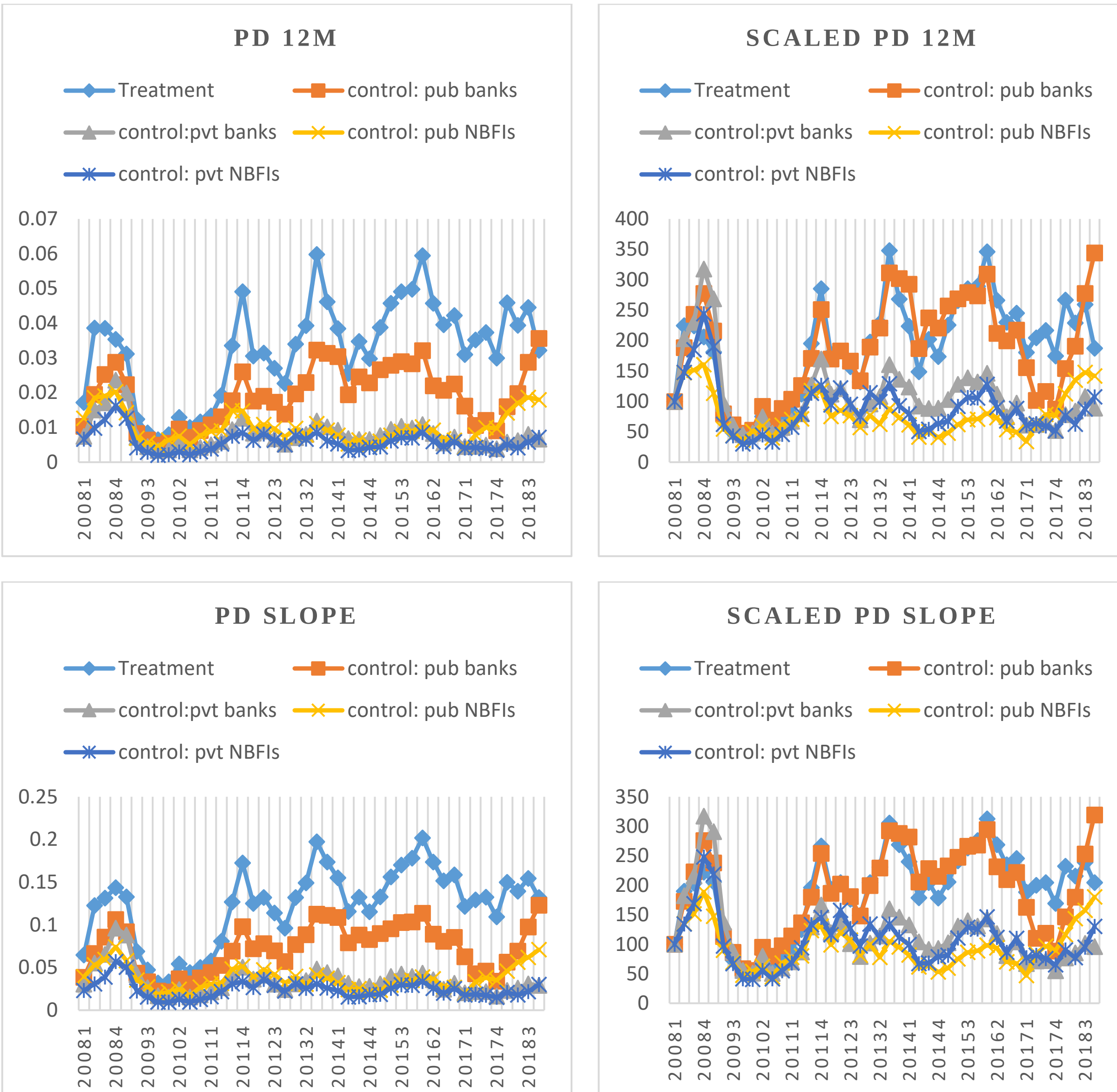


Figure 6: Time series plots of the systemic risk measures around capital infusion over the sample period 2008-2018

We present aggregate quarterly plots (raw and scaled) of Expected capital shortfall (NSRISK), Covariance risk (CoVar) and network risk score at five- percentile level for the treatment and four different control samples for the sample period. All the variables are defined in Appendix A.

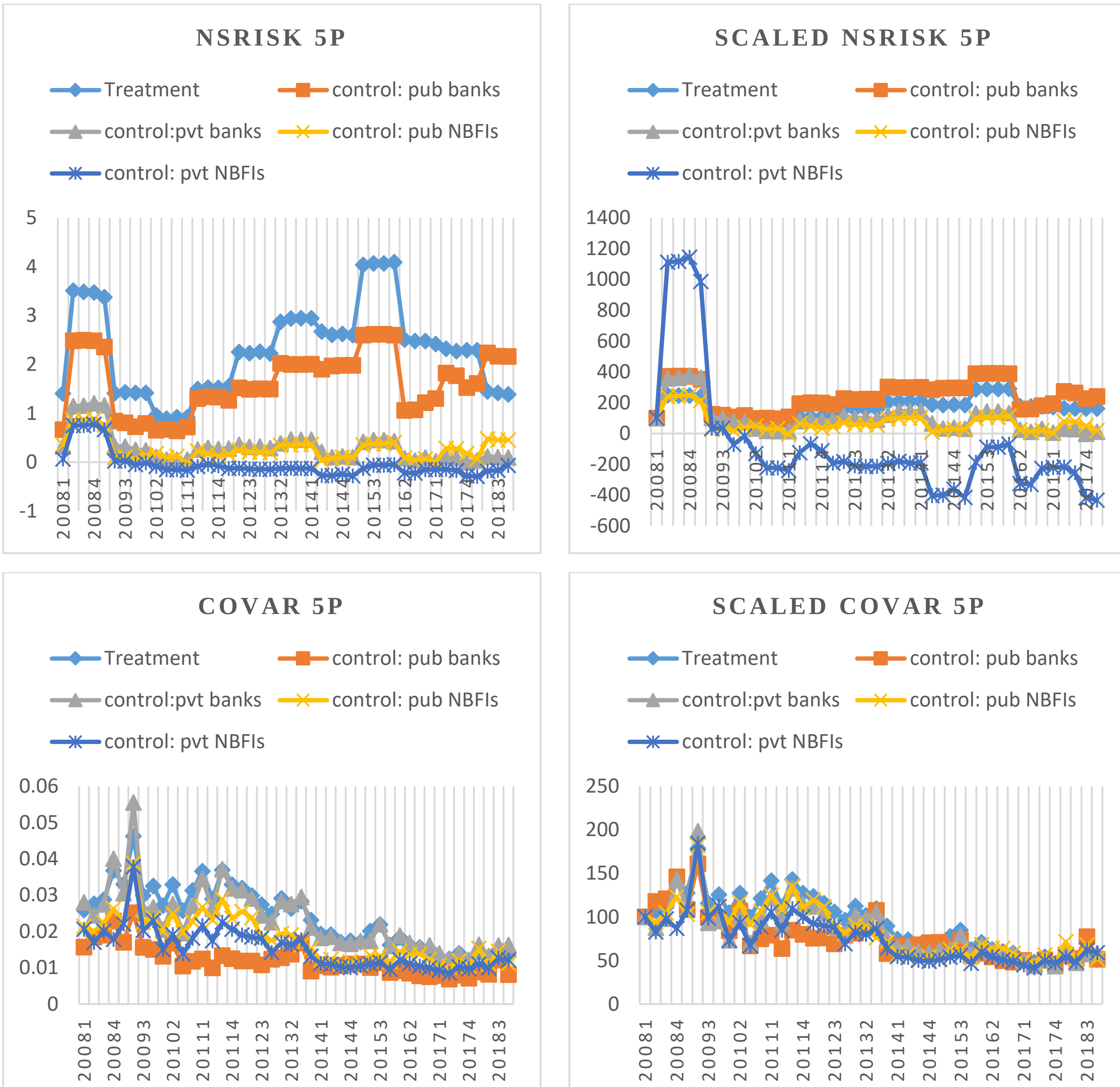
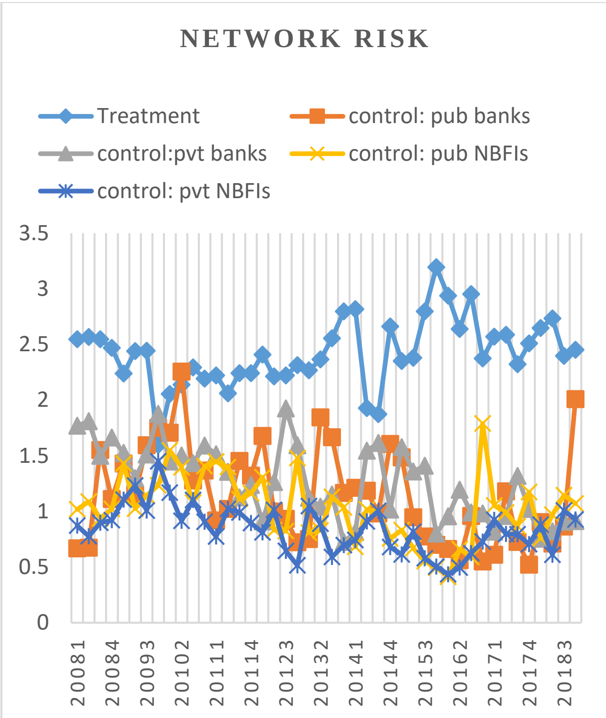


Figure 6: contd.



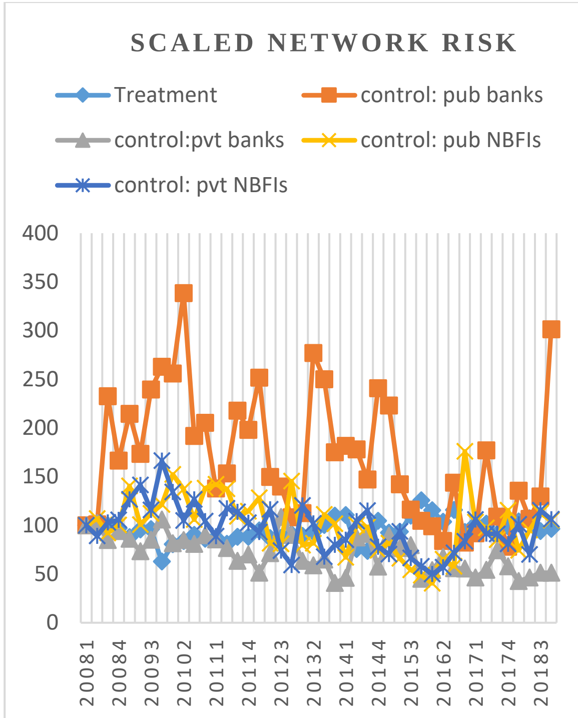


Table 1. Financial sample breakdown

The table shows the CMIE data extraction of financial firms and their breakdown into banks and non-banking financial institutions or NBFIs for the period 2008-2018.

2000-2018		
		sample size
Banks		
Public banks	26	
dropped due to M & As	minus 2	
net public banks		24
Private banks	20	
dropped due to M & As	minus 4	
net private banks		16
NBFIs		
Public	14	
dropped due to lack of data	minus 3	
net public NBFIs		11
Private	505	
dropped	minus 480	
net private NBFIs (consider only top 25 firms by asset size)		25
Excluded non-Fis	105	
Final sample		76

Table 2. Univariate sample attributes

Univariate table showing pairwise sample comparisons of averages of annual financial variables across the sample period. We consider pairwise comparisons between the treatment sample (A. Government bank-with Infusion), and each of four pooled control samples (B. Government banks-No Infusion; C. Private-bank; D. Government-NBFIs; and E. Private-NBFIs). The variables, other than ratios, below are reported in crores- 10 million- rupees.

	(1) B-A	(2) C-A	(3) D-A	(4) E-A
Total Assets (mi)	-1221***	-2252***	-3340***	-3556***
	(-3.88)	(-9.18)	(-12.45)	(-20.61)
ROE	10.75***	11.63***	15.72***	15.94***
	(11.44)	(14.36)	(16.43)	(21.15)
Loan to Assets	0.45***	3.8***	16.38***	15.4***
	(2.73)	(15.00)	(11.06)	(8.52)
Tier-1 Capital (mi)	-58.52	-60.72***	-82.65	-55.81
	(-2.19)	(-2.65)	(-1.34)	(-1.01)
Total Debt to Common Equity	-40.02***	-36.02***	213.51***	238.85***
	(-6.25)	(-5.85)	(12.24)	(15.02)
Total Debt to Total Capital	-6.12***	-7.08***	1.14	1.7
	(-6.92)	(-6.88)	(0.67)	(1.00)
Interest Coverage Ratio	4.07**	10.79***	113.98***	1517.53***
	(2.53)	(9.88)	(7.3)	(3.02)
Market to Book	0.15***	1.19***	1.03***	1.51***
	(7.08)	(24.89)	(13.08)	(17.57)
Tier 1 Capital Ratio	0.4***	3.68***	15.65***	15.1***
	(4.63)	(27.41)	(19.98)	(15.52)
Debt to Total Assets	-0.01***	0.03***	0.36***	0.27***
	(-4.13)	(6.21)	(25.8)	(22.73)
Deposits to Total Assets	0.01***	-0.09***	-0.82***	-0.8***
	(3.41)	(-11.56)	(-97.91)	(-151.41)

Table 3. Univariate comparisons of default and systemic risk measures around capital infusion

We present pre- and post- comparisons of default risks (1-year PD and PD slope) and systemic risks (NSRISK CoVaR and network risk score), for the treatment and four different control samples for the sample period. We present results for [-1 to +2] quarters around the capital infusion date. Each panel presents pre- and post- differences, and also the pairwise comparison of pre- and post- differences between treatment and control samples. P values of differences at 10% and below are shaded. All the variables are defined in Appendix A.

	A.Treat.	B. Control: pub banks	C. Control: pvt banks	D. Control: pub NBFIs	E. Control: pvt NBFIs	A.Treat.	B. Control: pub banks	C. Control: pvt banks	D. Control: pub NBFIs	E. Control: pvt NBFIs
	-Q1 to +Q2									
	PD 1-year					PD slope				
	Post-pre performance									
pre	0.037	0.028	0.009	0.011	0.006	0.131	0.108	0.036	0.039	0.024
post	0.035	0.023	0.007	0.009	0.005	0.132	0.093	0.032	0.036	0.023
post minus pre	-0.0011	-0.0052	-0.0013	-0.0013	-0.0006	0.0007	-0.0146	-0.0040	-0.0036	-0.0010
t-stat	-0.58	-3.22	-2.25	-1.12	-1.15	0.12	-2.88	-1.74	-0.92	-0.54
P-value	0.5608	0.0014	0.0251	0.2620	0.2516	0.9024	0.0041	0.0821	0.3606	0.5918
	Treatment vs Control differences									
		A Vs B	A Vs C	A Vs D	A Vs E		A Vs B	A Vs C	A Vs D	A Vs E
treat.		-0.0011	-0.0011	-0.0011	-0.0011		0.0007	0.0007	0.0007	0.0007
control		-0.0052	-0.0013	-0.0013	-0.0006		-0.0146	-0.0040	-0.0036	-0.0010
treat minus control		0.0041	0.0002	0.0002	-0.0005		0.0153**	0.0047	0.0043	0.0018
t-stat		(1.64)	(0.10)	(0.08)	(-0.33)		(1.98)	(0.79)	(0.54)	(0.35)
P-value		(0.102)	(0.923)	(0.935)	(0.740)		(0.0482)	(0.430)	(0.586)	(0.728)
	NSRISK 5p					NSRISK 1p				
	Post-pre performance									
pre	2.3388	1.9409	0.2811	0.2643	-0.0836	2.3684	2.0557	0.3706	0.3714	0.0097
post	2.6291	1.7324	0.2600	0.2262	-0.1111	2.6907	1.8136	0.3248	0.2923	-0.0349
post minus pre	0.2903	-0.2085	-0.0211	-0.0381	-0.0275	0.3224	-0.2422	-0.0459	-0.0791	-0.0446
t-stat	1.88	-1.66	-0.34	-0.61	-0.61	2.04	-1.91	-0.75	-1.19	-0.96
P-value	0.0611	0.0967	0.7337	0.5424	0.5450	0.0418	0.0563	0.4561	0.2367	0.3393
	Treatment vs Control differences									
		A Vs B	A Vs C	A Vs D	A Vs E		A Vs B	A Vs C	A Vs D	A Vs E
treat.		0.2903	0.2903	0.2903	0.2903		0.3224	0.3224	0.3224	0.3224
control		-0.2085	-0.0211	-0.0381	-0.0275		-0.2422	-0.0459	-0.0791	-0.0446
treat minus control		0.499**	0.311**	0.328*	0.318**		0.565***	0.368**	0.401**	0.367***
t-stat		(2.51)	(2.01)	(1.68)	(2.49)		(2.79)	(2.35)	(2.00)	(2.81)
P-value		(0.0124)	(0.0442)	(0.0936)	(0.0129)		(0.00540)	(0.0192)	(0.0455)	(0.00500)

Table 3. contd.

	A.Treat.	B. Control: pub banks	C. Control: pvt banks	D. Control: pub NBFIs	E. Control: pvt NBFIs	A.Treat.	B. Control: pub banks	C. Control: pvt banks	D. Control: pub NBFIs	E. Control: pvt NBFIs
						-Q1 to +Q2				
			CoVar 5p					**CoVar 1p**		
						Post-pre performance				
pre	0.0231	0.0236	0.0231	0.0174	0.0150	0.0364	0.0381	0.0363	0.0264	0.0245
post	0.0227	0.0232	0.0234	0.0176	0.0150	0.0349	0.0327	0.0342	0.0256	0.0241
post minus pre	-0.0003	-0.0004	0.0003	0.0002	0.0000	-0.0015	-0.0054	-0.0021	-0.0009	-0.0004
t-stat	-0.32	-0.31	0.31	0.15	-0.05	-0.97	-2.36	-0.85	-0.52	-0.25
P-value	0.7513	0.7550	0.7599	0.8810	0.9610	0.3307	0.0186	0.3976	0.6008	0.8024
						Treatment vs Control differences				
		A Vs B	A Vs C	A Vs D	A Vs E		A Vs B	A Vs C	A Vs D	A Vs E
treat.		-0.0003	-0.0003	-0.0003	-0.0003		-0.0015	-0.0015	-0.0015	-0.0015
control		-0.0004	0.0003	0.0002	0.0000		-0.0054	-0.0021	-0.0009	-0.0004
treat minus control		8.53e-05	-0.001	0.000	0.000		0.004	0.001	-0.001	-0.001
t-stat		(0.05)	(-0.43)	(-0.32)	(-0.23)		(1.40)	(0.19)	(-0.29)	(-0.49)
P-value		(0.957)	(0.668)	(0.752)	(0.821)		(0.161)	(0.851)	(0.773)	(0.627)
			Network risk							
			Post-pre performance							
pre	2.4718	1.9573	1.3817	0.9836	0.8427					
post	2.5882	1.9803	1.2231	1.0271	0.8208					
post minus pre	0.1164	0.0229	-0.1586	0.0435	-0.0219					
t-stat	0.84	0.19	-1.67	0.42	-0.45					
P-value	0.4029	0.8503	0.0959	0.6754	0.6501					
			Treatment vs Control differences							
		A Vs B	A Vs C	A Vs D	A Vs E					
treat.		0.1164	0.1164	0.1164	0.1164					
control		0.0229	-0.1586	0.0435	-0.0219					
treat minus control		0.0935	0.275*	0.0729	0.138					
t-stat		(0.51)	(1.68)	(0.38)	(1.15)					
P-value		(0.613)	(0.0934)	(0.701)	(0.250)					

Table 4. Baseline Annual DiD panel regressions of default and systemic risk

We present the effect of capital infusion on various default (Panel A) and systemic (Panel B) risk measures of the treatment versus control sample private banks using the yearly DiD specification (1) in the paper. The dependent risk variables are scaled by 100 so that coefficients reflect percentage effects. Treated banks receive capital infusion in a given year while control sample firms do not receive infusion for that year. We show private banks control sample regressions based on a 2-quarter window following the capital infusion date. P-values are based on Huber/White robust standard errors (clustered at bank level). All the variables are defined in Appendix A.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	PD 1-year				PD Slope				DTD			
Post Infusion Dummy	-0.776***		-0.704***		-2.177***		-1.934***		0.438***		0.400***	
	(0.122)		(0.126)		(0.318)		(0.330)		(0.0662)		(0.0694)	
Treatment x Post Infusion Dummy	0.374**	0.486***	0.364*	0.494**	1.358***	1.841***	1.331**	1.832***	-0.312***	-0.421***	-0.318**	-0.426***
	(0.146)	(0.164)	(0.198)	(0.208)	(0.421)	(0.455)	(0.562)	(0.584)	(0.104)	(0.114)	(0.116)	(0.123)
Treatment x Large Infusion Dummy			0.670**	0.790**			2.267**	2.558**			-0.232	-0.272
			(0.308)	(0.320)			(0.891)	(0.948)			(0.178)	(0.193)
Treatment x Post Infusion x Large Infusion Dummy			-0.520*	-0.648**			-1.771**	-2.027**			0.208	0.238
			(0.293)	(0.290)			(0.807)	(0.847)			(0.132)	(0.142)
Constant	2.706***	-25.12***	2.775***	-20.16***	7.143***	-82.47***	7.378***	-66.44***	-0.218	19.60***	-0.256	16.97***
	(0.563)	(5.625)	(0.546)	(5.465)	(1.247)	(16.11)	(1.210)	(16.15)	(0.199)	(3.059)	(0.196)	(3.386)
Observations	1,491	1,491	1,491	1,491	1,491	1,491	1,491	1,491	1,073	1,073	1,073	1,073
R-squared	0.644	0.682	0.647	0.685	0.709	0.747	0.712	0.750	0.729	0.760	0.730	0.761
Local Factor	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Quarter FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Table 4. contd.

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	NSRISK_5p				COVAR_5p				Network Risk			
Post Infusion Dummy	-16.31***		-15.52***		-0.119**		-0.114**		-0.221*		-0.186	
	(4.773)		(4.549)		(0.0564)		(0.0538)		(0.118)		(0.111)	
Treatment x Post Infusion Dummy	30.10***	33.06***	25.88**	30.03**	0.0953	0.136	0.0688	0.113	0.486***	0.533***	0.602***	0.650***
	(9.579)	(10.23)	(11.44)	(11.94)	(0.0898)	(0.102)	(0.104)	(0.116)	(0.149)	(0.158)	(0.173)	(0.179)
Treatment x Large Infusion Dummy			8.314	12.66			0.0515	0.0734			0.316	0.343
			(21.18)	(22.75)			(0.110)	(0.119)			(0.290)	(0.301)
Treatment x Post Infusion x Large Infusion Dummy			1.651	-4.064			0.0109	-0.0122			-0.484*	-0.508*
			(21.23)	(21.91)			(0.101)	(0.108)			(0.259)	(0.265)
Constant	245.3***	-2.239	247.1***	76.68	2.031***	-6.379**	2.041***	-5.920**	2.731***	-6.772	2.740***	-4.631
	(28.98)	(204.7)	(27.25)	(176.0)	(0.320)	(2.393)	(0.317)	(2.325)	(0.656)	(7.692)	(0.651)	(7.243)
Observations	1,530	1,520	1,530	1,530	1,520	1,520	1,520	1,520	1,536	1,536	1,536	1,536
R-squared	0.722	0.748	0.722	0.749	0.603	0.668	0.603	0.668	0.266	0.269	0.268	0.272
Local Factor	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Quarter FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Table 5. Quarterly DiD panel regressions of default and systemic risk

We present the effect of capital infusion on various default (Panel A) and systemic (Panel B) risk measures of the treatment versus control sample private banks using the quarterly DiD specification (2) in the paper. The dependent risk variables are all scaled by 100. Treated banks receive capital infusion in a given quarter while control sample firms do not receive infusion for that quarter. We use three alternative measures for large infusions: (a) 8-Quarter Median Large Infusion dummy compares the current quarter infusion to the median of previous 8 quarters (2 years) of infusions; (b) Current Quarter Median Large Infusion dummy is based on the median value of current quarter of infusions; and (c) Modified 8-Quarter Median Large Infusion dummy compares median of previous 8 quarters (2 years) of infusions - and excludes the current quarter. We show private banks control sample regressions based on 2-quarter window following the capital infusion date. P-values are based on Huber/White robust standard errors (clustered at bank level). All the variables are defined in Appendix A.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	PD 12-month				PD Slope			
Quarter Specific Post Infusion Dummy	0.679***				2.502***			
	(0.165)				(0.466)			
8-Quarter Median Large Infusion:		0.353**				1.139***		
		(0.139)				(0.406)		
Current Quarter Median Large Infusion			0.248				1.160**	
			(0.175)				(0.531)	
Modified 8-Quarter Median Large Infusion				0.437**				1.415**
				(0.206)				(0.556)
Constant	-28.66***	47.92***	-18.36***	45.26***	-94.63***	173.8***	-58.94***	165.3***
	(5.831)	(8.885)	(3.843)	(10.07)	(16.78)	(29.27)	(11.27)	(29.81)
Observations	1,491	1,236	1,491	1,236	1,491	1,236	1,491	1,236
R-squared	0.687	0.737	0.678	0.737	0.754	0.788	0.743	0.789
Local Factor	YES	YES	YES	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO	NO	NO	NO
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 5. contd.

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	NSRISK_5p				COVAR_5p				Network Risk			
Quarter Specific Post Infusion Dummy	43.77***				0.0223				0.497***			
	(9.783)				(0.0902)				(0.116)			
8-Quarter Median Large Infusion		1.437				-0.0746				0.423***		
		(14.38)				(0.0606)				(0.147)		
Current Quarter Median Large Infusion			22.94				0.0733				0.171	
			(15.19)				(0.0771)				(0.189)	
Modiefied 8-Quarter Median Large Infusion				25.24				-0.210**				0.369**
				(17.10)				(0.0788)				(0.150)
Constant	-198.0	-88.41	397.4	525.6	-4.293*	1.839	-4.539**	-0.657	-6.096	22.63	1.385	15.06
	(209.2)	(717.2)	(242.3)	(529.3)	(2.285)	(4.649)	(1.739)	(3.964)	(7.177)	(20.10)	(8.041)	(18.56)
Observations	1,530	1,266	1,530	1,266	1,520	1,258	1,520	1,258	1,536	1,272	1,536	1,272
R-squared	0.752	0.791	0.746	0.793	0.667	0.751	0.667	0.753	0.269	0.329	0.259	0.326
Local Factor	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 6. Robustness test: DiD regressions using PSM matched control sample of private banks

We present the effect of capital infusion on default and systemic risk measures using the annual DiD specification (1) in Panel A and quarterly DiD specification (2) in Panel B based on PSM matched control sample of private banks, where PSM scores are based on debt to total asset ratio, total assets and tier-1 ratio covariates. We only present regressions with both firm- and time- fixed effects. P-values are based on Huber/White robust standard errors (clustered at bank level). All the variables are defined in Appendix A.

Panel A

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	PD 1-year		PD Slope		NSRISK_1p		NSRISK_5p		COVAR_1p		COVAR_5p		Network Risk	
Post Infusion Dummy	-0.332***		-0.959***		-10.52***		-3.542		0.0128		0.00868		-0.166	
	(0.0733)		(0.189)		(3.528)		(3.131)		(0.116)		(0.0427)		(0.111)	
Treatment x Post Infusion Dummy	-0.249	-0.211	-0.718	-0.511	30.30***	30.04***	25.89***	25.91***	-0.265	-0.168	-0.107	-0.00417	0.450**	0.427**
	(0.161)	(0.157)	(0.496)	(0.478)	(8.306)	(8.093)	(8.294)	(8.144)	(0.196)	(0.186)	(0.0892)	(0.0843)	(0.171)	(0.175)
Constant	3.560***	20.02**	12.90***	80.57***	186.8***	420.7	197.5***	686.2*	4.221***	-1.085	2.666***	4.306	3.036***	43.95***
	(0.446)	(7.361)	(1.089)	(26.43)	(39.33)	(474.1)	(39.37)	(404.7)	(0.555)	(8.368)	(0.202)	(4.606)	(0.529)	(15.35)
Observations	874	874	874	874	918	918	918	918	911	911	911	911	921	921
R-squared	0.815	0.830	0.849	0.863	0.840	0.856	0.852	0.864	0.589	0.618	0.751	0.793	0.396	0.403
Local Factor	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Quarter FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Table 6: contd.

Panel B

VARIABLES	(1) PD 1-year	(2) PD Slope	(3) NSRISK_1p	(4) NSRISK_5p	(5) COVAR_1p	(6) COVAR_5p	(7) Network Risk
Quarter Specific Post Infusion Dummy	0.730*	2.041	39.45**	39.81**	-0.635	-0.511**	0.799**
	(0.428)	(1.373)	(22.33)	(20.76)	(0.586)	(0.244)	(0.431)
Constant	-15.75*	-48.57**	631.6*	-90.28	-1.296	-14.18***	9.981
	(7.931)	(21.38)	(355.4)	(242.7)	(8.263)	(5.032)	(9.568)
Observations	471	471	496	496	493	493	497
R-squared	0.796	0.823	0.868	0.872	0.636	0.812	0.408
Local Factor	YES	YES	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO	NO	NO
Quarter FE	YES	YES	YES	YES	YES	YES	YES

Table 7. Robustness test: DID regressions using PSM matched control sample of public sector banks

We present the effect of capital infusion on default and systemic risk measures using the quarterly DiD specification (2). We accordingly present DiD regressions based on PSM matched control sample of public sector banks not receiving capital infusion, where PSM scores are based on debt to total asset ratio, total assets and tier-1 ratio covariates. We only present regressions with firm- and time-fixed effects. P-values are based on Huber/White robust standard errors (clustered at bank level). All the variables are defined in Appendix A.

VARIABLES	(1) PD 1-year	(2) PD Slope	(3) NSRISK_1p	(4) NSRISK_5p	(5) COVAR_1p	(6) COVAR_5p	(7) Network Risk
Post Infusion Dummy	0.660**	1.916**	30.03**	31.28**	0.432	0.0764	0.738**
	(0.272)	(0.795)	(13.11)	(12.02)	(0.321)	(0.129)	(0.324)
Constant	-47.50**	-152.2***	447.9	-293.9	-5.074	-4.584	-25.62*
	(17.56)	(44.65)	(1,094)	(1,232)	(14.74)	(8.218)	(12.87)
Observations	357	357	355	355	351	351	358
R-squared	0.753	0.785	0.794	0.809	0.684	0.831	0.376
Local Factor	YES	YES	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO	NO	NO
Quarter FE	YES	YES	YES	YES	YES	YES	YES

Table 8. Robustness test: 2-SLS IV DiD regressions based on public sector banks as control samples

We present the effect of capital infusion on default and systemic risk measures using quarterly DiD specification (2) in the paper. We employ public sector banks not receiving capital infusions as the control sample. Panel A presents quarterly first-stage probit model of public sector banks receiving capital infusion as a function of lagged balance sheet covariates and two instrumental variables- policy uncertainty beta and capital flow beta; Panel B presents the quarterly versions of second-stage 2-SLS regressions using probit model (5) as an input. P-values are based on Huber/White robust standard errors (clustered at bank level). KP Wald statistic of F-test of instrumental variables is presented in Panel B. All the variables are defined in Appendix A.

Panel A

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Quarterly regressions (Specification 2)				
Lagged Debt to Total Capital	0.012**	0.016**	0.016	0.009	0.015
	(0.006)	(0.006)	(0.012)	(0.011)	(0.023)
Lagged Total Assets	3.257	1.886	6.951	0.519	-6.078
	(3.195)	(3.585)	(5.984)	(3.052)	(5.346)
Lagged Interest Coverage Ratio	-0.002	-0.001	-0.000	0.002	0.000
	(0.002)	(0.002)	(0.004)	(0.003)	(0.007)
Lagged Tier 1 Ratio	-0.196***	-0.260***	-0.454***	-0.239***	-0.501***
	(0.0666)	(0.0722)	(0.0946)	(0.0827)	(0.169)
Lagged CF Beta	43.24	391.5*	124.6	642.2***	709.7
	(99.72)	(221.1)	(403.6)	(197.3)	(487.1)
Lagged Policy Beta	1.225***	1.742***	1.286	2.339***	2.230*
	(0.297)	(0.457)	(0.942)	(0.458)	(1.192)
Constant	1.286	-1.109	19.48***	-1.059	29.71***
	(0.858)	(0.939)	(4.280)	(1.315)	(6.841)
Observations	838	838	732	732	546
Local Factor	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	YES	YES
Year FE	NO	YES	NO	YES	NO
Quarter FE	NO	NO	YES	NO	YES

Table 8. contd.

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Second Stage of 2SLS regression (Specification 2)													
VARIABLES	PD 1-year		PD Slope		NSRISK_1p		NSRISK_5p		COVAR_1p		COVAR_5p		Network Risk	
Quarter Specific Post Infusion Dummy	0.583*	3.238**	1.340	10.72***	79.36***	236.0***	67.33***	240.3***	-0.0907	1.190	-0.339**	-0.458	0.627**	1.808**
	(0.313)	(1.298)	(0.849)	(3.788)	(16.12)	(73.84)	(17.15)	(74.22)	(0.264)	(1.165)	(0.157)	(0.711)	(0.293)	(0.862)
Constant	6.634***	-46.99***	21.31***	-151.2***	161.9***	-1,010	240.1***	-1,634**	3.427***	-14.02	2.327***	-2.983	3.014***	-10.31
	(0.840)	(12.12)	(2.098)	(34.42)	(47.00)	(786.5)	(52.70)	(740.0)	(0.873)	(8.831)	(0.406)	(4.648)	(0.924)	(11.05)
Observations	550	550	550	550	545	545	545	545	542	542	542	542	550	550
R-squared	0.660	0.475	0.691	0.467	0.665	0.553	0.678	0.536	0.520	0.528	0.681	0.747	0.137	0.033
Local Factor	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Quarter FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Cragg-Donald Wald F	129	15.77	129	15.77	125.1	23.44	125.1	23.44	123.6	24.13	123.6	24.13	120.4	15.25

Table 9. Time-series channel analysis: macro-stress periods

We present the effect of capital infusion on default and systemic risk measures during the "macro-stress" period captured by three significant capital infusion years 2011, 2016 and 2018. We implement the yearly DID specification (1), where the stress dummy refers to the capital infusion dates for the three macro-stress years. We present results for private bank control sample based on 2-quarter window post capital infusion date. P-values are based on are based on Huber/White robust standard errors (clustered at bank level). All the variables are defined in Appendix A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	PD 1-year	PD Slope	NSRISK_1p	NSRISK_5p	COVAR_1p	COVAR_5p	Network Risk
Treatment x Post Infusion Dummy	0.738***	2.753***	29.54***	30.21***	0.301	0.0605	0.720***
	(0.226)	(0.649)	(10.64)	(10.88)	(0.285)	(0.134)	(0.192)
Treatment x Post x Large Infusions	-0.0274	0.103	3.642	5.734	0.00236	0.0996	-0.169
	(0.230)	(0.636)	(14.18)	(13.84)	(0.170)	(0.121)	(0.178)
Treatment x Stress Years Dummy	1.201**	3.948***	3.141	49.79	0.186	0.111	0.518
	(0.458)	(1.423)	(36.77)	(35.06)	(0.502)	(0.217)	(0.314)
Post Infusion x Stress Years Dummy	-0.661***	-1.320***	-6.551	-6.740	-0.792***	-0.442***	-0.0107
	(0.140)	(0.397)	(8.780)	(7.744)	(0.189)	(0.0729)	(0.258)
Large Infusions x Stress Years Dummy	-0.377	-1.295	-22.48	-27.98	-0.194	-0.0316	0.00537
	(0.555)	(1.698)	(43.41)	(43.45)	(0.342)	(0.191)	(0.579)
Treatment x Post Infusion x Stress Years Dummy	-1.803***	-6.290***	-2.444	-43.50	0.156	0.0415	-0.672**
	(0.428)	(1.341)	(40.08)	(38.49)	(0.492)	(0.219)	(0.283)
Treatment x Post x Large Infusions x Stress Years Dummy	0.675	1.928	25.63	32.15	0.113	-0.0745	-0.0409
	(0.511)	(1.396)	(47.69)	(47.51)	(0.428)	(0.232)	(0.576)
Constant	10.86***	16.20**	558.4***	553.4***	11.12***	6.489***	1.503
	(3.172)	(7.240)	(183.7)	(189.7)	(2.286)	(1.174)	(2.872)
Observations	1,491	1,491	1,530	1,530	1,520	1,520	1,536
R-squared	0.687	0.754	0.744	0.749	0.500	0.669	0.272
Local Factor	YES	YES	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO	NO	NO
Quarter FE	YES	YES	YES	YES	YES	YES	YES

Table 10. Cross-sectional channel Analysis: bank -level variables

We present the effect of capital infusion on systemic risk measures through each of the following channels: size (or total assets), tier 1 capital, interest coverage, leverage, loan/assets, deposits/assets, market/book and profitability (ROE). Each year, firms that received infusion in that year are sorted into hgh/low portfolios based on their financial variable value relative to the median for the year. We implement the DiD specifications (1) using high-low bins formed by the median value of each financial variable. We only present coefficient and significance of the DiD interaction term β_0 (or treatment X post-infusion effect). We present results for private bank control sample based on 2-quarter window post capital infusion date. P-values are based on are based on Huber/White robust standard errors (clustered at bank level). All the variables are defined in Appendix A.

	Treatment x Post-infusion dummy									
	default risk		**systemic risks**			**default risk**		**systemic risks**		
	PD	PD slope	NSRISK	CoVar	Network	PD	PD slope	NSRISK	CoVar	Network
	Total assets					*Tier 1*				
high	-0.0418	0.234	-0.0777	0.147	0.411	0.162	0.897	21.48	0.174	0.528**
low	0.602***	2.178***	31.51*	0.0390	0.764***	0.471*	1.789***	22.65*	0.0785	0.764***
	Interest coverage					*Leverage*				
high	0.527**	1.908***	33.50**	0.209	0.767***	0.355	1.491	20.38	0.205	0.717***
low	0.476	1.843**	23.77	-0.0444	0.518**	0.558**	2.027***	27.86	0.0142	0.590***
	Loan to assets					*Deposits to assets*				
high	0.299	1.186*	10.01	0.154	0.555**	0.609**	2.205***	31.47**	0.0494	0.663***
low	0.439	1.798**	39.42**	0.122	0.662***	0.199	0.930	11.97	0.325**	0.668**
	Market to book					*ROE*				
`high	0.0852	0.528	3.523	0.164	0.389*	0.389**	1.394**	26.98	0.146	0.644***
low	0.844**	3.010***	56.42***	0.00218	0.913***	0.659	2.448*	36.43*	0.0358	0.565*

Table 11. Effects on sovereign risk: Examining the effects of capital infusion on Aggregate risk

We present the effect of capital infusion on system wide or aggregate default and systemic risk measures. Aggregate risk measures are obtained as cross-sectional averages of risk across firms for each quarter. We implement the yearly time series specification (4) for aggregate risk spreads, which refer to difference between aggregate spreads of treated public sector banks and control private bank firms. We present results for post 2-quarter window below. P-values are based on Huber/White robust standard errors. All the variables are defined in Appendix A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VARIABLES	PD 1-year			PD Slope			NSRISK_5p			COVAR_5p			Network Risk		
Infusion Index 1	-0.000659			-0.00338			0.0161			0.000991			-0.0588		
	(0.00287)			(0.00843)			(0.229)			(0.00123)			(0.240)		
Post X infusion_index 1	-0.0115**			-0.0273**			0.0301			0.000368			0.115		
	(0.00418)			(0.0103)			(0.258)			(0.00122)			(0.207)		
Infusion Index 2		0.00436			0.0141			-0.0521			-0.00162			0.404	
		(0.00446)			(0.0127)			(0.277)			(0.00139)			(0.375)	
Post X infusion_index 2		-0.0108*			-0.0328**			-0.0427			0.00329			-0.646	
		(0.00545)			(0.0148)			(0.331)			(0.00196)			(0.475)	
Infusion Index 3			0.0106			0.0330			0.198			-0.00410			0.577
			(0.00672)			(0.0203)			(0.345)			(0.00239)			(0.725)
Post X infusion_index 3			-0.00896			-0.0287			0.0307			0.00335			-0.531
			(0.00666)			(0.0188)			(0.342)			(0.00219)			(0.596)
Constant	0.00456	0.00369	-0.00862	0.0307	0.0261	-0.0124	3.019*	3.054*	2.909*	0.00192	0.00307	0.00772	-1.373	-1.601*	-2.214**
	(0.0215)	(0.0252)	(0.0235)	(0.0559)	(0.0622)	(0.0554)	(1.564)	(1.598)	(1.642)	(0.00671)	(0.00726)	(0.00786)	(0.997)	(0.899)	(1.001)
Observations	38	38	38	38	38	38	38	38	38	38	38	38	38	38	38
R-squared	0.820	0.792	0.771	0.849	0.848	0.832	0.791	0.792	0.795	0.651	0.695	0.692	0.610	0.674	0.646
Local Factor	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO

Do Repeated Government Infusions Help Financial Stability? Evidence from an Emerging Market

INTERNET APPENDIX

Internet Appendix IA: Government capital infusion into public sector banks 2008-2018

The table presents the Indian government yearly capital infusions into public sector banks for the period 2008-2018. The rupee value capital infusions are converted into USD based on the exchange rate data from the FRED (Source: Controller & Auditor General of India, Report No. 28, 2017).

Name of Public sector banks	**2008-09**	**2009-10**	**2010-11**	**2011-12**	**2012-13**	**2013-14**	**2014-15**	**2015-16**	**2016-17**	**2017-18**
Allahabad Bank	-	-	₹ 670	-	-	₹ 400	₹ 320	₹ 973	₹ 451	₹ 1,500
Andhra Bank	-	-	₹ 1,173	-	-	₹ 200	₹ 120	₹ 378	₹ 1,100	₹ 1,890
Bank of Baroda	-	-	₹ 2,461	-	₹ 850	₹ 550	₹ 1,260	₹ 1,786	-	₹ 5,375
Bank of India	-	-	₹ 1,010	-	₹ 809	₹ 1,000	-	₹ 3,605	₹ 2,838	₹ 9,232
Bank of Maharashtra	-	-	₹ 940	₹ 470	₹ 406	₹ 800	-	₹ 394	₹ 300	₹ 3,173
Canara Bank	-	-	-	-	-	₹ 500	₹ 570	₹ 947	₹ 748	₹ 4,865
Central Bank of India	₹ 700	₹ 450	₹ 2,253	₹ 676	₹ 2,406	₹ 1,800	-	₹ 535	₹ 1,397	₹ 5,158
Corporation Bank	-	-	₹ 309	-	₹ 204	₹ 450	-	₹ 857	₹ 508	₹ 2,187
Dena Bank	-	-	₹ 539	-	-	₹ 700	₹ 140	₹ 407	₹ 1,046	₹ 3,045
Indian Overseas Bank	-	-	₹ 1,054	₹ 1,441	₹ 1,000	₹ 1,200	-	₹ 2,009	₹ 2,651	₹ 4,694
Indian Bank	-	-	-	-	-	-	₹ 280	-	-	-
Oriental Bank of Commerce	-	-	₹ 1,740	-	-	₹ 150	-	₹ 300	-	₹ 3,571
Punjab National Bank	-	-	₹ 184	₹ 655	₹ 1,248	₹ 500	₹ 870	₹ 1,732	₹ 2,112	₹ 5,473
Punjab & Sind Bank	-	-	-	-	₹ 140	₹ 100	-	-	-	₹ 785
Syndicate Bank	-	-	₹ 633	-	-	₹ 200	₹ 460	₹ 740	₹ 776	₹ 2,839
UCO Bank	₹ 450	₹ 450	₹ 1,613	₹ 48	₹ 681	₹ 200	-	₹ 935	₹ 1,925	₹ 6,507
Union Bank of India	-	-	₹ 793	-	₹ 1,114	₹ 500	-	₹ 1,080	₹ 541	₹ 4,524
United Bank of India	₹ 250	₹ 300	₹ 558	-	₹ 100	₹ 700	-	₹ 480	₹ 1,026	₹ 2,634
Vijaya Bank	₹ 500	-	₹ 1,068	-	-	₹ 250	-	₹ 220	-	₹ 1,277
State Bank of India	-	-	-	₹ 7,900	₹ 3,004	₹ 2,000	₹ 2,970	₹ 5,393	₹ 5,681	₹ 8,800
IDBI Bank Ltd.	-	-	₹ 3,119	₹ 810	₹ 555	₹ 1,800	-	₹ 2,229	₹ 1,900	₹ 12,471
Total in rupees (crores or 10 mi)	₹ 1,900	₹ 1,200	₹ 20,117	₹ 12,000	₹ 12,517	₹ 14,000	₹ 6,990	₹ 25,000	₹ 25,000	₹ 90,000
Total in USD (mi)	**$414.31**	**$255.37**	**$4,362.41**	**$2,401.14**	**$2,237.39**	**$2,342.90**	**$1,117.48**	**$3,809.10**	**$3,781.49**	**$13,489.28**

Internet Appendix IB: List of Treatment and control sample FIs

The table presents the list of treatment (public sector) banks and control sample institutions (private banks and private/public NBFIs) used in the study.

	Name	FI_Type
1	Allahabad Bank	Public bank
2	Andhra Bank [Merged]	Public bank
3	Bank Of Baroda	Public bank
4	Bank Of India	Public bank
5	Bank Of Maharashtra	Public bank
6	Canara Bank	Public bank
7	Central Bank Of India	Public bank
8	Corporation Bank	Public bank
9	Dena Bank	Public bank
10	I D B I Bank Ltd.	Public bank
11	Indian Bank	Public bank
12	Indian Overseas Bank	Public bank
13	Indusind Bank Ltd.2008	Public bank
14	Jammu & Kashmir Bank Ltd.	Public bank
15	Oriental Bank Of Commerce	Public bank
16	Punjab & Sind Bank	Public bank
17	Punjab National Bank	Public bank
18	State Bank Of India	Public bank
19	State Bank Of Mysore [Merged]	Public bank
20	State Bank Of Travancore [Merged]	Public bank
21	Syndicate Bank	Public bank
22	Uco Bank	Public bank
23	Union Bank Of India	Public bank
24	United Bank Of India	Public bank
25	Vijaya Bank	Public bank

1	Axis Bank Ltd.2008	Private bank
2	City Union Bank Ltd.2008	Private bank
3	D C B Bank Ltd.2008	Private bank
4	Dhanlaxmi Bank Ltd.2008	Private bank
5	Federal Bank Ltd.2008	Private bank
6	H D F C Bank Ltd.2008	Private bank
7	I C I C I Bank Ltd.2008	Private bank
8	I D F C First Bank Ltd.2008	Private bank
9	Indusind Bank Ltd.2008	Private bank
10	Karnataka Bank Ltd.2008	Private bank
11	Karur Vysya Bank Ltd.2008	Private bank
12	Kotak Mahindra Bank Ltd.2008	Private bank
13	Lakshmi Vilas Bank Ltd.2008	Private bank
14	R B L Bank Ltd.2008	Private bank
15	South Indian Bank Ltd.2008	Private bank
16	Yes Bank Ltd.2008	Private bank

	Name	FI_Type
1	Coal India Ltd.2008	Public NBFI
2	G I C Housing Finance Ltd.2008	Public NBFI
3	General Insurance Corpn. Of India2008	Public NBFI
4	Gujarat State Financial Corpn.2008	Public NBFI
5	Housing & Urban Devp. Corpn. Ltd.2008	Public NBFI
6	I F C I Ltd.2008	Public NBFI
7	L I C Housing Finance Ltd.2008	Public NBFI
8	New India Assurance Co. Ltd.2008	Public NBFI
9	P N B Gilts Ltd.2008	Public NBFI
10	P N B Housing Finance Ltd.2008	Public NBFI
11	P T C India Financial Services Ltd.2008	Public NBFI
12	Power Finance Corpn. Ltd.2008	Public NBFI
13	S B I Home Finance Ltd.2008	Public NBFI
14	Tourism Finance Corpn. Of India Ltd.2008	Public NBFI
15	Yule Financing & Leasing Co. Ltd.2008	Public NBFI

1	Bajaj Finance Ltd.	Private NBFI
2	Bajaj Finserv Ltd.	Private NBFI
3	Bajaj Holdings & Invst. Ltd.	Private NBFI
4	Capri Global Capital Ltd.	Private NBFI
5	Cholamandalam Investment & Finance Co. Ltd.	Private NBFI
6	Dewan Housing Finance Corpn. Ltd.	Private NBFI
7	Edelweiss Financial Services Ltd.	Private NBFI
8	Gruh Finance Ltd. [Merged]	Private NBFI
9	Housing Development Finance Corpn. Ltd.	Private NBFI
10	Indiaco Ventures Ltd	Private NBFI
11	I D F C Ltd.	Private NBFI
12	Indiabulls Ventures Ltd.	Private NBFI
13	J S W Holdings Ltd.	Private NBFI
14	Kalyani Investment Co. Ltd.	Private NBFI
15	L & T Finance Holdings Ltd.	Private NBFI
16	Magma Fincorp Ltd.	Private NBFI
17	Mahindra & Mahindra Financial Services Ltd.	Private NBFI
18	Motilal Oswal Financial Services Ltd.	Private NBFI
19	Muthoot Finance Ltd.	Private NBFI
20	Pilani Investment & Inds. Corpn. Ltd.	Private NBFI
21	Repco Home Finance Ltd	Private NBFI
22	S R E I Infrastructure Finance Ltd.	Private NBFI
23	Shriram City Union Finance Ltd.	Private NBFI
24	Shriram Transport Finance Co. Ltd.	Private NBFI
25	Sundaram Finance Ltd.	Private NBFI

Figure IA1. Government capital infusion into public sector banks 2008-2018

The exhibit below presents the distribution of Indian government yearly capital infusions (in USD million) into public sector banks for the period 2008-2018. (Source: Controller & Auditor General of India, Report No. 28, 2017).

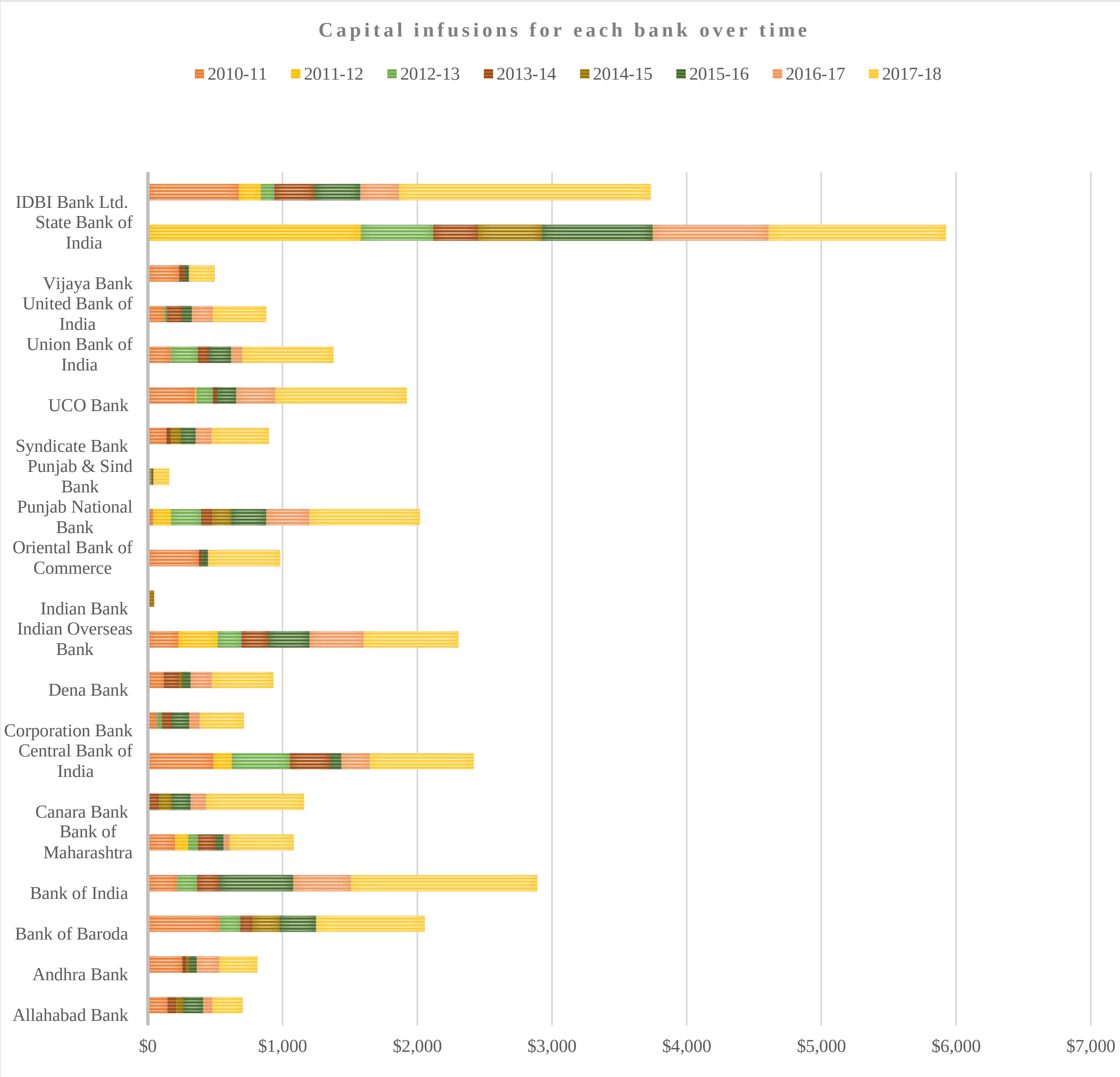


Figure IA2. Distribution of Government capital infusion into public sector banks 2008-2018

The exhibit below presents the box-plots showing the distribution of Indian government yearly capital infusions (in USD million) into public sector banks for the period 2008-2018. Banks receiving large size infusions are shown as outliers each year. (Source: Controller & Auditor General of India, Report No. 28, 2017).

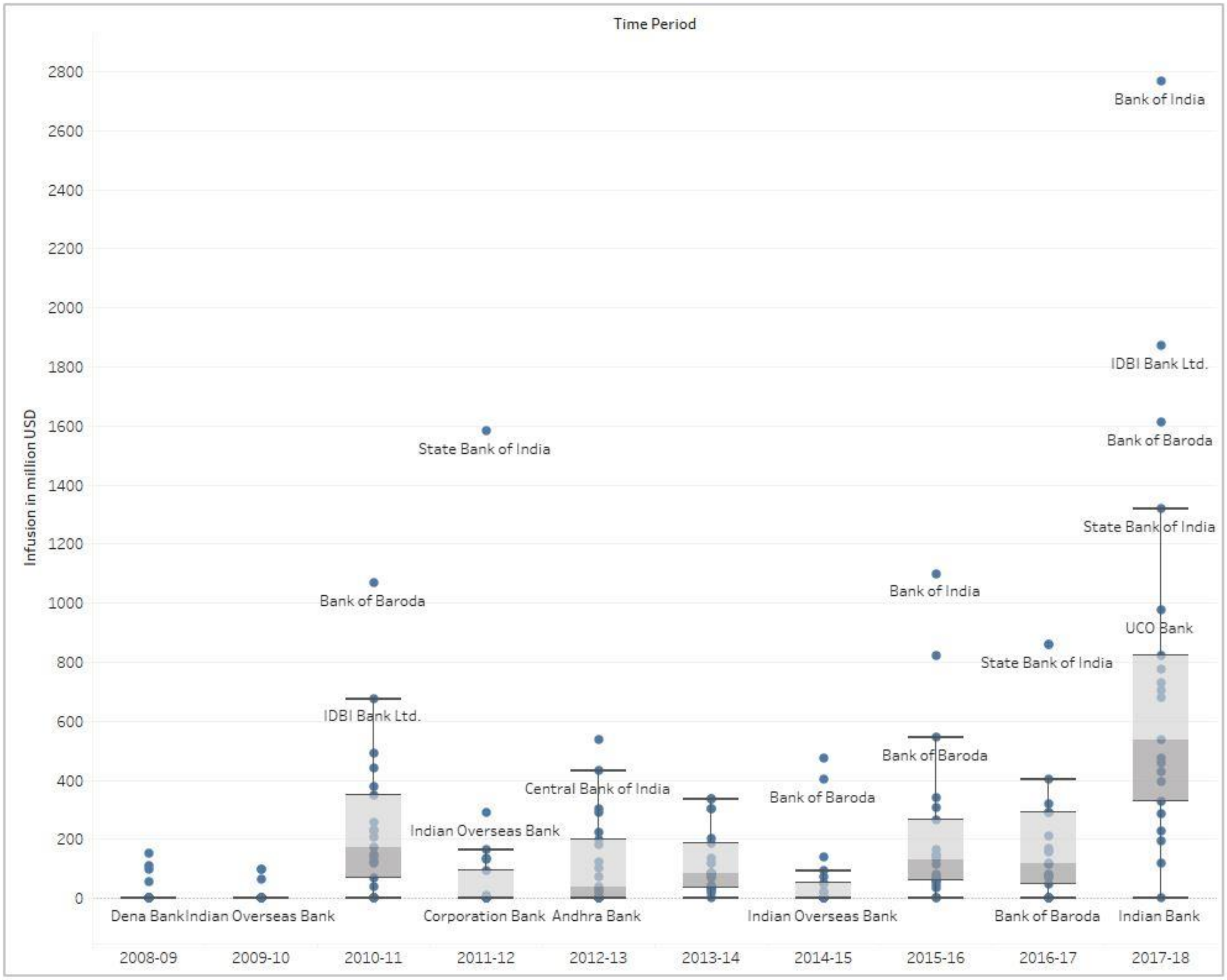
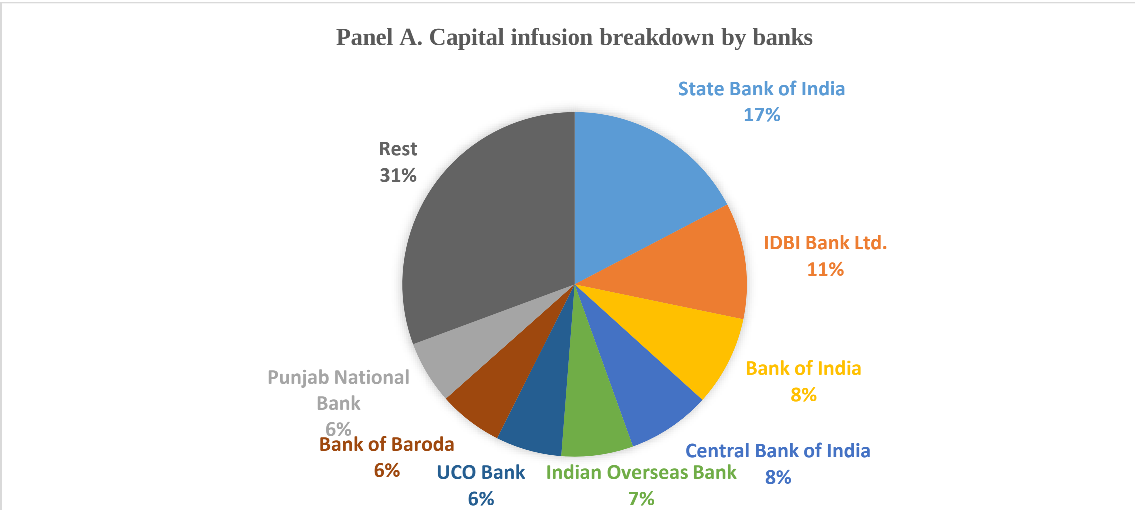
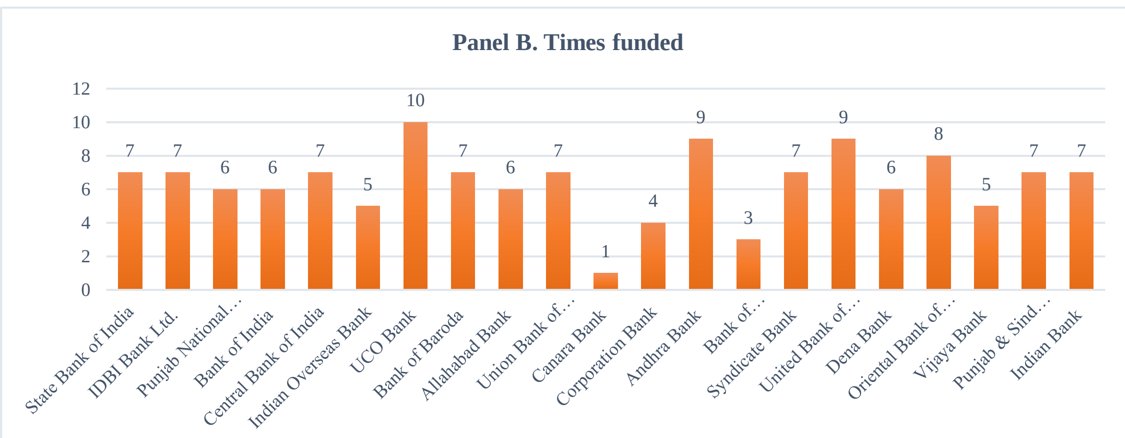


Figure IA3. Government capital infusion into public sector banks 2008-2018

The exhibits below present the breakdown of Indian government yearly capital infusions into public sector banks(panel A), number of times each bank funded (panel B) and total time-series variation (panel) for the period 2008-2018. Capital infusions are converted into USD based on the exchange rate data from the FRED (Source: Controller & Auditor General of India, Report No. 28, 2017).





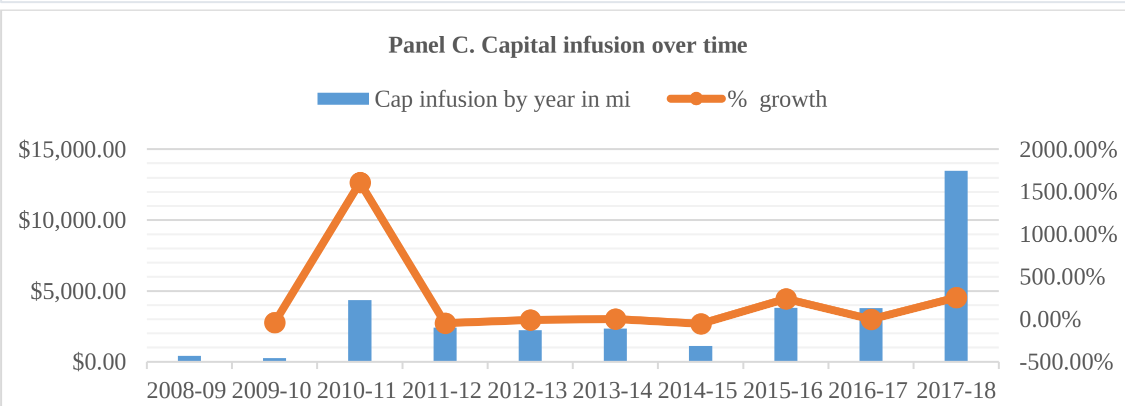
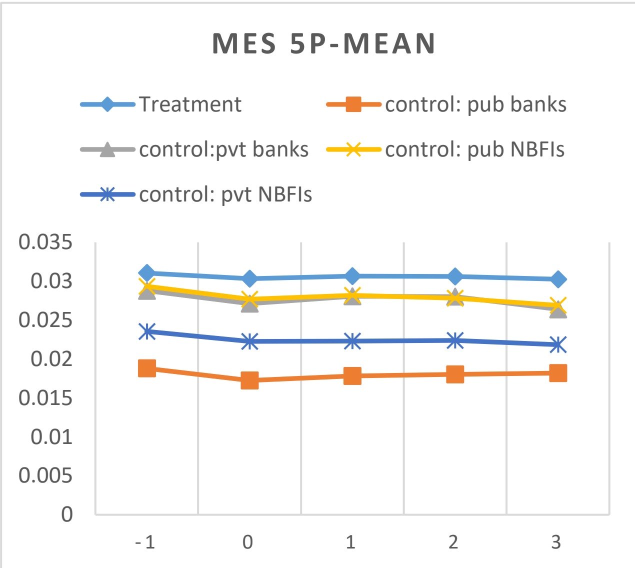


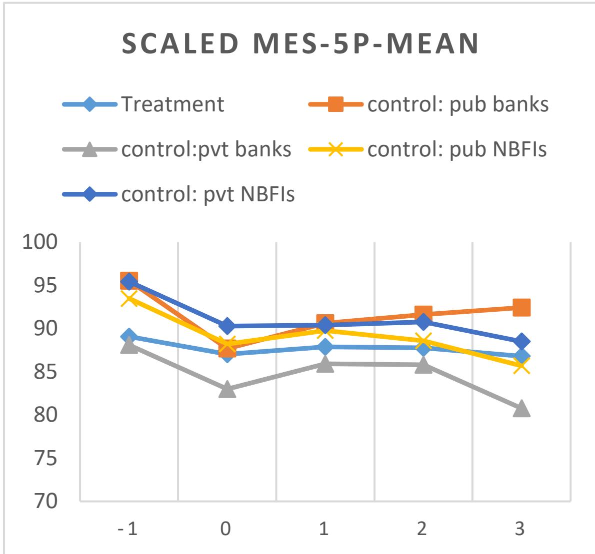
Figure IA4: Event window plots of Distance to Default (DTD) around capital infusion

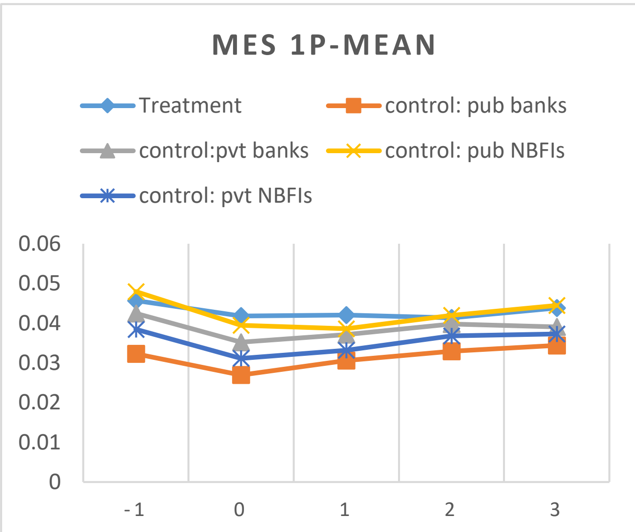
We present quarterly mean plots (both raw and scaled) of DTD for the treatment and four different control samples for the sample period. We present [-1 to +3] quarters around the infusion event (period zero), which denotes the capital infusion quarter. All the variables are defined in Appendix A.

Figure IA5: Event window plots of the Margin Expected Shortfall (MES) measure of systemic risk around capital infusion

We present quarterly mean and median plots (both raw and scaled) of MES five- and one- percentile measures for the treatment and four different control samples for the sample period. We present [-1 to +3] quarters around the infusion event (period zero), which denotes the capital infusion quarter. All the variables are defined in Appendix A.







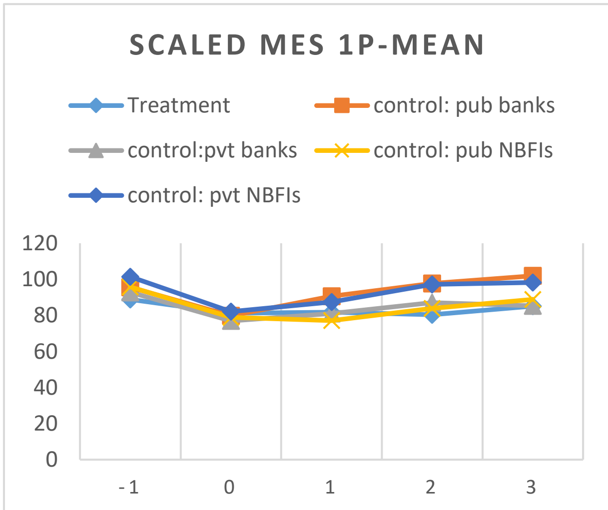
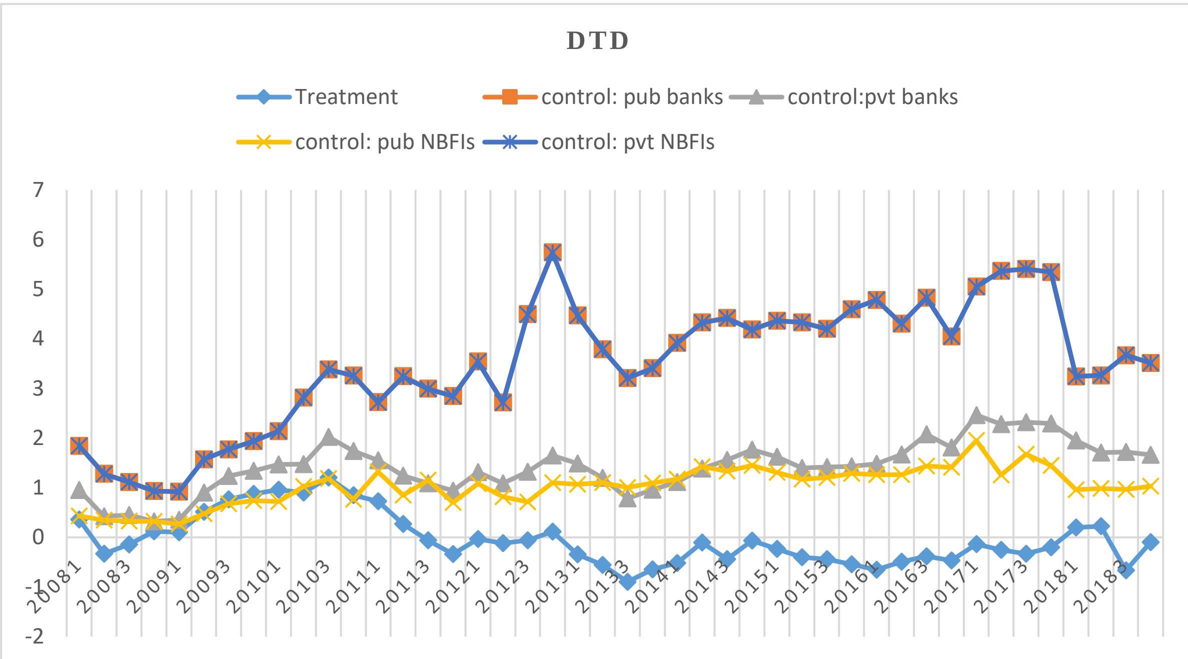


Figure IA6: Event window plots of NSRISK and CoVaR measures of systemic risk at 1-percentile level over the sample period 2008-2018

We present quarterly mean plots (both raw and scaled) of Expected capital shortfall (NSRISK), Covariance risk (CoVar) at one – percentile level for the treatment and four different control samples for the sample period. We present ± four quarters around the infusion event (period zero), which denotes the capital infusion quarter. All the variables are defined in Appendix A.

Figure IA7: Time series plots of Distance to Default (DTD) measure over the sample period 2008-2018

We present aggregate time series plots of DTD (both raw and scaled) for the treatment and four different control samples for the sample period. All the variables are defined in Appendix A.



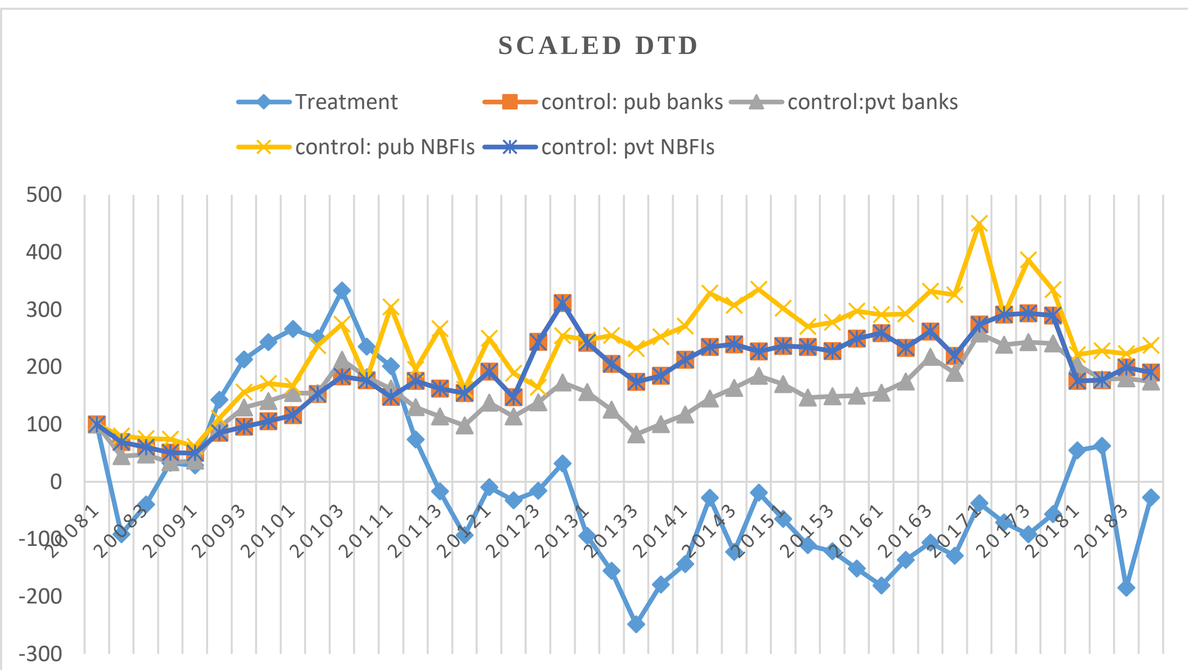
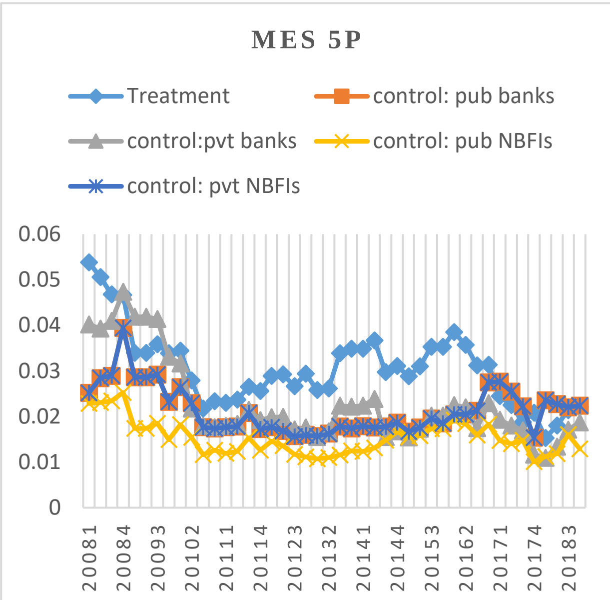
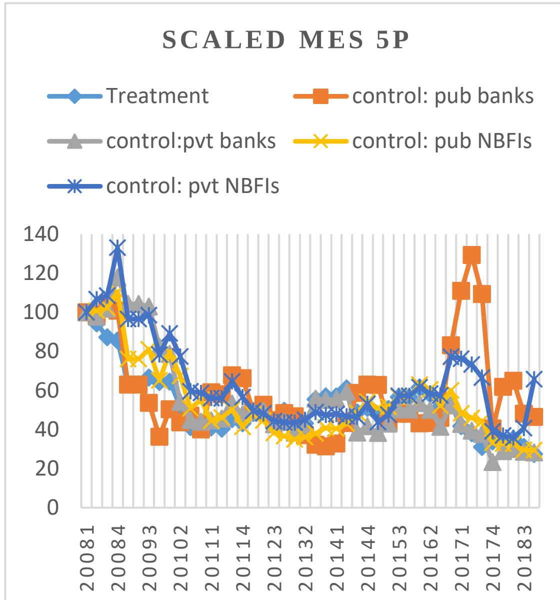
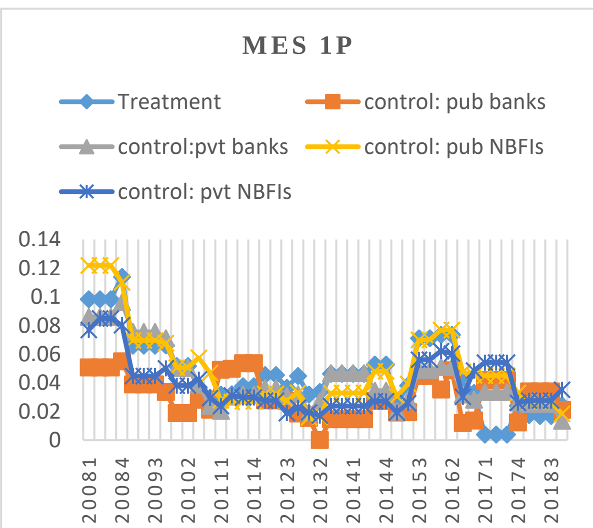


Figure IA8: Time series plots of the Margin Expected Shortfall (MES) measure of systemic risk over the sample period 2008-2018

We present aggregate quarterly plots (both raw and scaled) of MES five- and one- percentile measures for the treatment and four different control samples for the sample period. All the variables are defined in Appendix A.







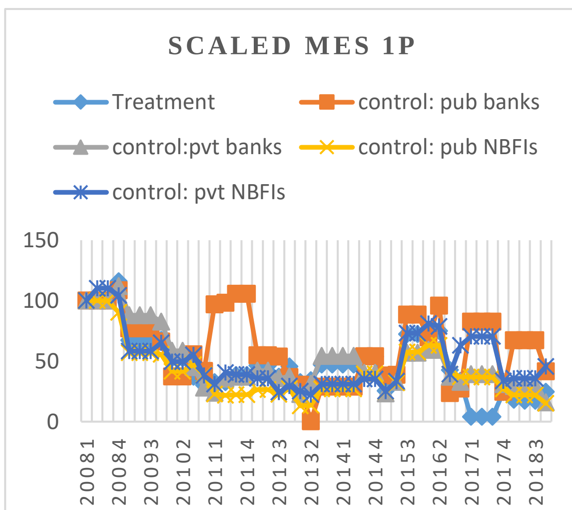
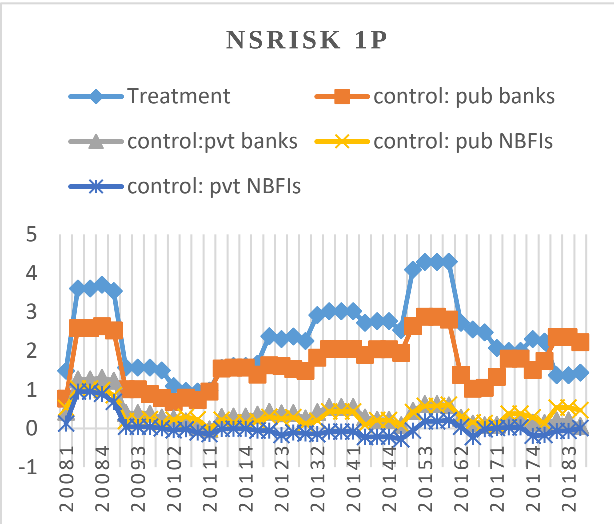
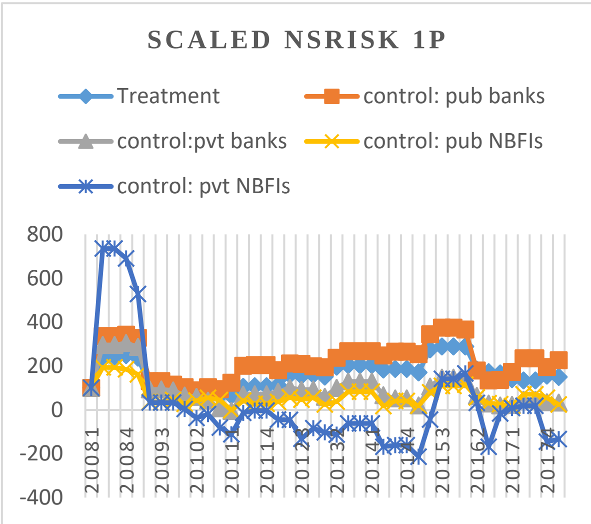
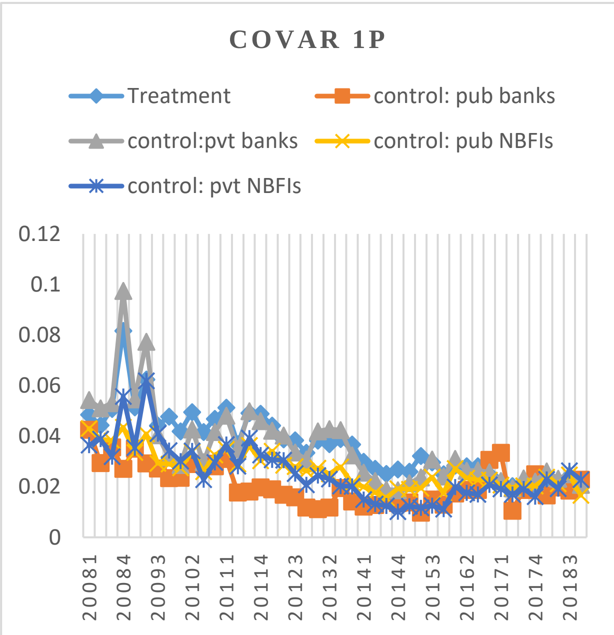


Figure IA9: Time series plots of the NSRISK and CoVaR measures of systemic risk at 1-percentile level over the sample period 2008-2018

We present aggregate quarterly plots (both raw and scaled) of Expected Capital Shortfall (NSRISK) and Covariance risk (CoVaR) one- percentile measures for the treatment and four different control samples for the sample period. All the variables are defined in Appendix A.







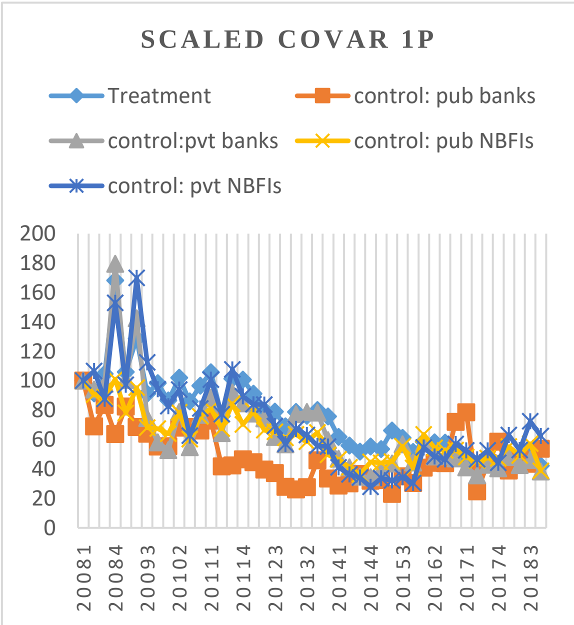


Table IA1. Univariate comparisons of Distance to Default (DTD) around capital infusion

We present pre- and post- comparisons of DTD for the treatment and four different control samples for the sample period. We present results for [-1 to +2] quarters around the capital infusion date. Each panel presents pre- and post- differences, and also the pairwise comparison of pre- and post- differences between treatment and control samples. P values of differences at 10% and below are shaded. All the variables are defined in Appendix A.

	A.Treat.	B. Control: pub banks	C. Control: pvt banks	D. Control: pub NBFIs	E. Control: pvt NBFIs
			DTD		
			Post-pre performance		
pre	-0.1075	0.2410	1.8824	1.7543	3.8794
post	-0.1265	0.3402	1.9156	1.8930	4.1604
post minus pre	-0.0190	0.0992	0.0332	0.1388	0.2810
t-stat	-0.21	1.13	0.15	0.70	0.74
P-value	0.837	0.259	0.880	0.483	0.458
		Treatment vs Control differences			
		A Vs B	A Vs C	A Vs D	A Vs E
treat.		-0.0190	-0.0190	-0.0190	-0.0190
control		0.0992	0.0332	0.1388	0.2810
treat minus control		-0.118	-0.0522	-0.158	-0.300
t-stat		(-0.93)	(-0.26)	(-0.83)	(-0.62)
P-value		(0.353)	(0.796)	(0.405)	(0.535)

Table IA2. Univariate comparisons of Margin Expected Shortfall (MES) around capital infusion

We present pre- and post- comparisons of DTD and MES 5- percentile (Panel A) and 1- percentile (Panel B)- for the treatment and four different control samples for the sample period. We present results for [-1 to +2] quarters around the capital infusion date. Each panel presents pre- and post- differences, and also the pairwise comparison of pre- and post- differences between treatment and control samples. P values of differences at 10% and below are shaded. All the variables are defined in Appendix A.

	A.Treat.	B. Control: pub banks	C. Control: pvt banks	D. Control: pub NBFIs	E. Control: pvt NBFIs	A.Treat.	B. Control: pub banks	C. Control: pvt banks	D. Control: pub NBFIs	E. Control: pvt NBFIs
	-Q1 to +Q2									
	MES 5p					**MES 1p**				
	Post-pre performance									
pre	0.0289	0.0304	0.0288	0.0293	0.0236	0.0376	0.0505	0.0425	0.0480	0.0385
post	0.0311	0.0269	0.0277	0.0279	0.0223	0.0424	0.0384	0.0373	0.0400	0.0336
post minus pre	0.0021	-0.0035	-0.0011	-0.0015	-0.0012	0.0047	-0.0121	-0.0052	-0.0079	-0.0048
t-stat	2.07	-2.92	-0.82	-0.81	-1.24	1.86	-4.75	-2.29	-2.15	-2.59
P-value	0.0390	0.0036	0.4099	0.4179	0.2155	0.0628	0.0000	0.0221	0.0322	0.0099
	Treatment vs Control differences									
		A Vs B	A Vs C	A Vs D	A Vs E		A Vs B	A Vs C	A Vs D	A Vs E
treat.		0.0021	0.0021	0.0021	0.0021		0.0047	0.0047	0.0047	0.0047
control		-0.0035	-0.0011	-0.0015	-0.0012		-0.0121	-0.0052	-0.0079	-0.0048
treat minus control		0.0056***	0.0032*	0.0036*	0.0034**		0.0168***	0.0099***	0.0127***	0.0096***
t-stat		(3.56)	(1.87)	(1.86)	(2.14)		(4.69)	(2.92)	(2.93)	(2.99)
P-value		(0.000384)	(0.0618)	(0.0636)	(0.0328)		(3.16e-06)	(0.00361)	(0.00346)	(0.00284)

Table IA3. DiD panel regressions of MES

We present the effect of capital infusion on MES measured at 5 percentile level for the treatment versus control sample private banks using the yearly DiD specification (1) in the paper. The dependent risk variable is scaled by 100 so that coefficients reflect percentage effects. Regressions employ a 2-quarter window following the capital infusion date. P-values are based on Huber/White robust standard errors (clustered at bank level). All the variables are defined in Appendix A.

	(1)	(2)	(3)	(4)
VARIABLES	MES_5p			
Post Infusion Dummy	-0.176**		-0.155**	
	(0.0672)		(0.0647)	
Treatment x Post Infusion Dummy	0.346***	0.387***	0.308*	0.344**
	(0.118)	(0.125)	(0.155)	(0.160)
Treatment x Large Infusion Dummy			0.207	0.171
			(0.154)	(0.156)
Treatment x Post Infusion x Large Infusion Dummy			-0.0920	-0.0514
			(0.151)	(0.147)
Constant	2.953***	-8.990**	2.983***	-7.924**
	(0.328)	(3.598)	(0.333)	(3.406)
Observations	1,530	1,530	1,530	1,530
R-squared	0.676	0.705	0.677	0.705
Local Factor	YES	YES	YES	YES
US Factors	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	NO	YES	NO
Quarter FE	NO	YES	NO	YES

Table IA4. Robustness test: DID panel regressions of systemic risk measures at 1 – percentile level

We present the effect of capital infusion on systemic risk (NSRISK and CoVaR) measured at 1-percentile level for the treatment versus control sample private banks using both the annual DID specification (1) (Panel A) and quarterly DiD specification (2) (Panel B), We show private banks control sample regressions based on a 2-quarter window following the capital infusion date. P-values are based on Huber/White robust standard errors (clustered at bank level). All the variables are defined in Appendix A.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	NSRISK_1p				COVAR_1p			
Post Infusion Dummy	-19.92***		-20.33***		-0.258*		-0.228*	
	(4.644)		(4.256)		(0.150)		(0.133)	
Treatment x Post Infusion Dummy	30.20***	32.91***	26.33**	30.40**	0.354	0.399	0.391	0.438
	(9.755)	(10.49)	(11.50)	(11.95)	(0.239)	(0.263)	(0.256)	(0.281)
Treatment x Large Infusion Dummy			-3.241	2.971			0.274	0.321
			(19.34)	(21.26)			(0.301)	(0.324)
Treatment x Post Infusion x Large Infusion Dummy			10.27	2.658			-0.293	-0.333
			(19.48)	(20.23)			(0.243)	(0.267)
Constant	226.3***	489.7*	226.8***	508.6*	2.899***	-9.802	2.918***	-7.824
	(32.27)	(279.4)	(30.70)	(262.0)	(0.715)	(6.135)	(0.707)	(5.031)
Observations	1,530	1,530	1,530	1,530	1,520	1,520	1,520	1,520
R-squared	0.714	0.744	0.714	0.744	0.476	0.500	0.476	0.500
Local Factor	YES	YES	YES	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	NO	YES	NO	YES	NO
Quarter FE	NO	YES	NO	YES	NO	YES	NO	YES

Table IA4. contd.

Panel B

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	NSRISK_1p				COVAR_1p			
Quarter Specific Post Infusion Dummy	43.14***				0.170			
	(9.601)				(0.224)			
8-Quarter Median Large Infusion:		0.455				-0.314**		
		(14.90)				(0.134)		
Current Quarter Median Large Infusion			21.83				0.00624	
			(15.09)				(0.186)	
Modified 8-Quarter Median Large Infusion:				26.20				-0.285**
				(17.87)				(0.134)
Constant	302.8	-1,429	896.5**	-749.0	-5.618	-12.30	-2.561	-6.820
	(300.4)	(983.9)	(359.4)	(789.5)	(5.255)	(7.684)	(3.269)	(5.684)
Observations	1,530	1,266	1,530	1,266	1,520	1,258	1,520	1,258
R-squared	0.747	0.783	0.742	0.785	0.498	0.585	0.498	0.584
Local Factor	YES	YES	YES	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO	NO	NO	NO
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES

Table IA5. Robustness test: Alternate control samples in Annual DiD panel regressions

We present the effect of capital infusion on default and systemic risk measures using the annual DiD specification (1) in the paper. We present private (Panel A) and public (Panel B) non-banking financial institutions (NBFIs) as control samples in regressions based on a 2-quarter window following the capital infusion date. P-values are based on Huber/White robust standard errors (clustered at bank level). All the variables are defined in Appendix A.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	PD 1-year		PD Slope		NSRISK_5p		COVAR_5p		Network Risk	
Post Infusion Dummy	-0.879***		-2.334***		-18.18***		-0.0818		-0.167	
	(0.137)		(0.354)		(5.533)		(0.0663)		(0.146)	
Treatment x Post Infusion Dummy	0.353**	0.520***	1.126**	1.812***	25.96***	30.27***	0.0264	0.0498	0.434***	0.507***
	(0.144)	(0.173)	(0.422)	(0.475)	(9.270)	(10.48)	(0.0826)	(0.0936)	(0.148)	(0.163)
	2.816***	-30.09***	6.971***	-93.48***	231.9***	-104.8	2.330***	-5.902**	2.233***	-2.666
Constant	(0.682)	(6.697)	(1.520)	(18.86)	(35.66)	(268.7)	(0.292)	(2.571)	(0.615)	(9.409)
Observations	1,238	1,238	1,238	1,238	1,233	1,233	1,214	1,214	1,241	1,241
R-squared	0.610	0.656	0.690	0.736	0.683	0.716	0.634	0.680	0.285	0.295
Local Factor	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Quarter FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Table IA5. contd.

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	PD 1-year		PD Slope		NSRISK_5p		COVAR_5p		Network Risk	
Post Infusion Dummy	-0.581***		-1.525***		-14.51***		-0.0802**		-0.0959	
	(0.108)		(0.284)		(4.284)		(0.0381)		(0.0862)	
Treatment x Post Infusion Dummy	0.287*	0.363**	0.949**	1.290***	32.47***	35.55***	0.0468	0.0642	0.409***	0.440***
	(0.145)	(0.155)	(0.403)	(0.421)	(10.34)	(10.90)	(0.0719)	(0.0778)	(0.127)	(0.130)
Constant	2.921***	-17.29***	8.397***	-52.79***	262.5***	-60.67	2.278***	-3.714**	2.561***	-2.411
	(0.502)	(4.896)	(1.159)	(14.16)	(29.07)	(204.8)	(0.225)	(1.656)	(0.468)	(5.922)
Observations	1,837	1,837	1,837	1,837	1,880	1,880	1,864	1,864	1,899	1,899
R-squared	0.678	0.703	0.750	0.773	0.755	0.771	0.631	0.670	0.415	0.419
Local Factor	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Quarter FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Table IA6. Robustness test: Alternate control samples in quarterly DiD panel regressions

We present the effect of capital infusion on default and systemic risk measures using the quarterly DiD specification (2) in the paper. We present private (Panel A) and public (Panel B) non-banking financial institutions (NBFIs) as control samples in regressions based on a 2-quarter window following the capital infusion date. P-values are based on Huber/White robust standard errors (clustered at bank level). All the variables are defined in Appendix A.

Panel A

	(1)	(2)	(3)	(4)	(5)
VARIABLES	PD 1-year	PD Slope	NSRISK_5p	COVAR_5p	Network Risk
Quarter Specific Post Infusion Dummy	0.602***	2.132***	37.51***	-0.018	0.397***
	(0.158)	(0.442)	(9.546)	(0.101)	(0.110)
Constant	-31.92***	-100.6***	-268.3	-4.321	-0.264
	(6.433)	(18.04)	(275.2)	(2.798)	(8.511)
Observations	1,238	1,238	1,233	1,214	1,241
R-squared	0.659	0.740	0.718	0.680	0.292
Local Factor	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO
Quarter FE	YES	YES	YES	YES	YES

Panel B

	(1)	(2)	(3)	(4)	(5)
VARIABLES	PD 1-year	PD Slope	NSRISK_5p	COVAR_5p	Network Risk
Quarter Specific Post Infusion Dummy	0.617***	2.215***	47.64***	-0.0460	0.433***
	(0.167)	(0.455)	(10.29)	(0.0766)	(0.102)
Constant	-21.31***	-67.47***	-242.7	-2.055	-2.304
	(5.414)	(15.99)	(204.3)	(1.667)	(5.628)
Observations	1,837	1,837	1,880	1,864	1,899
R-squared	0.708	0.779	0.774	0.670	0.420
Local Factor	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO
Quarter FE	YES	YES	YES	YES	YES

Table IA7. Robustness test: Alternate network risk variables in DID panel regressions

We present the effect of capital infusion on default and systemic risk measures using the annual DID specification (1) in the paper using alternate network risk variables. We employ two additional network risk variables i.e., degree and between centrality (betcent). We present private banks as control samples in regressions based on a 2-quarter window following the capital infusion date. P-values are based on Huber/White robust standard errors (clustered at bank level). All the variables are defined in Appendix A.

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
VARIABLES	degree				betcent			
Post Infusion Dummy	-0.160		-0.158		8.376*		9.516**	
	(0.232)		(0.219)		(4.148)		(3.819)	
Treatment x Post Infusion Dummy	0.685**	0.648**	0.990***	0.976***	2.355	0.319	6.106	4.175
	(0.275)	(0.283)	(0.349)	(0.348)	(3.250)	(3.546)	(4.453)	(4.444)
Treatment x Large Infusion Dummy			-0.0339	-0.0178			10.16	14.09
			(0.582)	(0.611)			(10.01)	(9.380)
Treatment x Post Infusion x Large infusion Dummy			-0.580	-0.647			-15.62	-18.99*
			(0.614)	(0.623)			(10.91)	(10.26)
Constant	6.446***	30.63	6.382***	30.61	18.85	2,584***	19.12	2,671***
	(1.824)	(19.19)	(1.822)	(18.87)	(16.43)	(900.3)	(16.44)	(894.4)
Observations	1,536	1,536	1,536	1,536	1,536	1,536	1,536	1,536
R-squared	0.147	0.195	0.149	0.197	0.080	0.167	0.082	0.170
Local Factor	YES	YES	YES	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	NO	YES	NO	YES	NO
Quarter FE	NO	YES	NO	YES	NO	YES	NO	YES

Table IA8. Robustness test: Alternate definitions of *Post Infusion* dummy variable in DID panel regressions

We present the effect of capital infusion on default and systemic risk measures of the treatment versus control sample private banks using the annual DID specification (1) in the paper. The private banks control sample regressions are shown based on a 2-quarter window following the capital infusion date. Panel A defines *Post Infusion* dummy as equal to 1 in the 3 subsequent quarters after infusion quarter; Panel B is similar to Panel A, except that the infusion quarter – i.e., quarter 0 - is dropped in the regressions. P-values are based on Huber/White robust standard errors (clustered at bank level). All the variables are defined in Appendix A.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	PD 1-year		PD Slope		NSRISK_5p		COVAR_5p		Network Risk	
Post Infusion Dummy	-0.150**		-0.239		-21.63***		-0.194***		-0.232	
	(0.0715)		(0.209)		(3.731)		(0.0459)		(0.144)	
Treatment x Post Infusion Dummy	0.00237	0.486***	0.295	1.841***	24.43***	33.06***	0.0578	0.136	0.403***	0.533***
	(0.130)	(0.164)	(0.385)	(0.455)	(7.774)	(10.23)	(0.0684)	(0.102)	(0.124)	(0.158)
Constant	3.419***	-25.12***	8.878***	-82.47***	287.2***	-2.239	2.390***	-6.379**	3.210***	-6.772
	(0.479)	(5.625)	(1.037)	(16.11)	(29.33)	(204.7)	(0.283)	(2.393)	(0.651)	(7.692)
Observations	1,491	1,491	1,491	1,491	1,530	1,530	1,520	1,520	1,536	1,536
R-squared	0.630	0.682	0.699	0.747	0.722	0.748	0.603	0.668	0.265	0.269
Local Factor	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Quarter FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Table IA8. contd.

Panel B

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	PD 1-year		PD Slope		NSRISK_5p		COVAR_5p		Network Risk	
Post Infusion Dummy	-0.383***		-0.840***		-32.87***		-0.0281		-0.253	
	(0.0937)		(0.250)		(5.527)		(0.0511)		(0.159)	
Treatment x Post Infusion Dummy	-0.0331	0.470**	0.357	1.955***	26.36***	32.76**	0.0286	0.120	0.416***	0.601***
	(0.138)	(0.179)	(0.383)	(0.457)	(9.534)	(12.59)	(0.0711)	(0.108)	(0.137)	(0.173)
Constant	3.912***	4.720*	10.21***	-2.576	322.5***	429.6**	1.207**	5.477***	3.157***	-3.749
	(0.596)	(2.609)	(1.448)	(6.212)	(43.35)	(188.0)	(0.516)	(1.862)	(1.072)	(4.078)
Observations	1,085	1,085	1,085	1,085	1,113	1,113	1,105	1,105	1,118	1,118
R-squared	0.634	0.672	0.706	0.744	0.734	0.750	0.615	0.657	0.268	0.274
Local Factor	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Quarter FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Table IA9. Robustness test: Alternate definitions of *large infusion* in DID panel regressions

We present the effect of capital infusion on default and systemic risk measures using the annual DID specification (1) in the paper. We categorize the capital infusion as large using three alternate standardized infusion measures: ratio of capital infusion to total assets, ratio of capital infusion to total deposits and ratio of capital infusion to tier-1 capital. We present private banks as control samples in regressions based on a 2-quarter window following the capital infusion date. P-values are based on Huber/White robust standard errors (clustered at bank level). All the variables are defined in Appendix A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VARIABLES	PD 1-year			PD Slope			NSRISK_5p			COVAR_5p			Network Risk		
Post Infusion Dummy	-0.851***	-0.851***	-0.973***	-2.293***	-2.287***	-2.650***	-9.806**	-9.279*	-13.28***	-0.374***	-0.391***	-0.372***	-0.207	-0.213	-0.232
	(0.172)	(0.173)	(0.195)	(0.439)	(0.442)	(0.502)	(4.679)	(4.619)	(4.307)	(0.0635)	(0.0629)	(0.0619)	(0.213)	(0.215)	(0.216)
Treatment x Post Infusion Dummy	0.317	0.332*	0.386**	1.337***	1.416***	1.577***	23.13*	27.00*	26.12**	0.186*	0.106	0.121	0.355**	0.377**	0.439***
	(0.188)	(0.176)	(0.143)	(0.485)	(0.445)	(0.390)	(13.52)	(13.36)	(12.32)	(0.105)	(0.116)	(0.117)	(0.154)	(0.154)	(0.147)
Treatment x Large Infusion-Assets Ratio Dummy	1.484***			4.421***			42.76*			-0.0299			0.345		
	(0.371)			(1.156)			(23.28)			(0.124)			(0.226)		
Treatment x Large Infusion-Deposits Ratio Dummy		1.488***			4.411***			41.73*			-0.0354			0.280	
		(0.376)			(1.177)			(23.30)			(0.133)			(0.230)	
Treatment x Large Infusion-Tier 1 capital Ratio Dummy			0.891**			2.595*			29.77			0.123			0.218
			(0.424)			(1.292)			(27.77)			(0.163)			(0.248)
Treatment x Post Infusion x Large Infusion-Assets Ratio Dummy	-0.748***			-2.235**			-8.712			-0.0980			0.173		
	(0.264)			(0.851)			(18.60)			(0.120)			(0.228)		
Treatment x Post Infusion x Large Infusion-Deposits Ratio Dummy		-0.778***			-2.386***			-17.07			0.103			0.176	
		(0.248)			(0.799)			(17.94)			(0.118)			(0.217)	
Treatment x Post Infusion x Large Infusion-Tier 1 capital Ratio Dummy			-0.296			-0.966			3.369			-0.0328			0.182
			(0.223)			(0.753)			(17.95)			(0.111)			(0.239)
Constant	16.13***	16.09***	15.79***	31.02***	30.75***	29.83***	602.3***	584.5***	590.8***	8.042***	8.405***	8.441***	2.627	2.513	2.317
	(3.637)	(3.671)	(3.425)	(7.978)	(8.081)	(7.403)	(166.9)	(163.4)	(166.4)	(1.236)	(1.230)	(1.240)	(2.976)	(2.966)	(3.064)
Observations	1,491	1,491	1,491	1,491	1,491	1,491	1,530	1,530	1,530	1,520	1,520	1,520	1,536	1,536	1,536
R-squared	0.697	0.697	0.688	0.760	0.759	0.752	0.752	0.751	0.751	0.669	0.668	0.668	0.276	0.274	0.273
Local Factor	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table A10. Effects on sovereign risk: Examining the effects of capital infusion effects on Aggregate risk

We present the effect of capital infusion on system wide or aggregate systemic risk measures obtained as cross-sectional averages of each risk for treatment or each control sample firms for each quarter. We implement the yearly time series specification (4) for aggregate risk spreads, which refer to difference between aggregate spreads of treated public sector banks and private (Panel A) or public (Panel B) NBFI control firms. We present results based on a 2-quarter window following the capital infusion date. P-values are based on robust standard errors. All the variables are defined in Appendix A.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VARIABLES	PD 1-year			PD Slope			NSRISK_5p			COVAR_5p			Network Risk		
Infusion Index 1	-0.000563			-0.00349			0.00123			0.0167			-0.226		
	(0.00291)			(0.00866)			(0.00101)			(0.240)			(0.250)		
Post X infusion_index 1	-0.0118**			-0.0296**			-0.00915			0.0482			0.132		
	(0.00454)			(0.0120)			(0.00106)			(0.272)			(0.204)		
Infusion Index 2		0.00347			0.0117			-0.000314			-0.0951			0.510	
		(0.00453)			(0.0130)			(0.00152)			(0.285)			(0.326)	
Post X infusion_index 2		-0.0101*			-0.0318*			0.00185			-0.0333			-0.855*	
		(0.00567)			(0.0158)			(0.00147)			(0.347)			(0.477)	
Infusion Index 3			0.00988			0.0315			0.000996			0.172			0.644
			(0.00670)			(0.0199)			(0.00255)			(0.375)			(0.575)
Post X infusion_index 3			-0.00930			-0.0307			0.000559			0.0199			-0.551
			(0.00676)			(0.0191)			(0.00189)			(0.368)			(0.559)
Constant	0.00262	0.00229	-0.0102	0.0290	0.0258	-0.0144	-0.00246	-0.00179	-0.00213	3.346*	3.404*	3.245*	-0.798	-1.155	-1.782
	(0.0230)	(0.0265)	(0.0254)	(0.0626)	(0.0689)	(0.0635)	(0.00527)	(0.00575)	(0.00564)	(1.659)	(1.683)	(1.748)	(1.113)	(1.179)	(1.167)
Observations	38	38	38	38	38	38	38	38	38	38	38	38	38	38	38
R-squared	0.815	0.779	0.766	0.840	0.829	0.820	0.878	0.880	0.873	0.802	0.803	0.804	0.555	0.667	0.585
Local Factor	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO

Table IA10. contd.

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VARIABLES		PD 1-year			PD Slope			NSRISK_5p			COVAR_5p			Network Risk	
Infusion Index 1	0.001			-0.000963			0.000575			0.00395			0.0661		
	(0.00312)			(0.00931)			(0.000870)			(0.255)			(0.185)		
Post X infusion_index 1	-0.0131***			-0.0342***			0.000506			0.00419			0.00905		
	(0.00454)			(0.0116)			(0.000711)			(0.286)			(0.179)		
Infusion Index 2		0.00540			0.0182			-0.000836			-0.0590			0.525*	
		(0.00491)			(0.0142)			(0.00141)			(0.322)			(0.271)	
Post X infusion_index 2		-0.0118*			-0.0369**			0.00154			-0.0392			-0.619	
		(0.00575)			(0.0156)			(0.00139)			(0.368)			(0.404)	
Infusion Index 3			0.0120			0.0386*			-0.000914			0.218			0.784
			(0.00719)			(0.0217)			(0.00273)			(0.382)			(0.552)
Post X infusion_index 3			-0.0101			-0.0340*			0.00132			0.0626			-0.492
			(0.00704)			(0.0197)			(0.00169)			(0.378)			(0.485)
Constant	0.00423	0.00331	-0.0103	0.0279	0.0232	-0.0212	0.00141	0.00201	0.00326	3.122*	3.159*	3.020	-1.065	-1.289	-1.946**
	(0.0233)	(0.0273)	(0.0257)	(0.0628)	(0.0700)	(0.0638)	(0.00374)	(0.00380)	(0.00401)	(1.723)	(1.757)	(1.777)	(0.978)	(0.827)	(0.859)
Observations	38	38	38	38	38	38	38	38	38	38	38	38	38	38	38
R-squared	0.804	0.767	0.748	0.829	0.819	0.804	0.912	0.916	0.913	0.786	0.787	0.791	0.656	0.746	0.712
Local Factor	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO