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

Madhu Kalimipalli* Vijaya B. Marisetty Olaleye Morohunfolu R. L Shankar

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* Kalimipalli is the corresponding author. Kalimipalli is at the Lazaridis School of Business & Economics Wilfrid Laurier University, Canada, mkalimipalli@wlu.ca; Marisetty is at Department of Financial Engineering and Management, University of Twente v.b.marisetty@utwente.nl; is a Finance PhD student at the Lazaridis School of Business & Economics, Wilfrid Laurier University, Canada, moro8810@mylaurier.ca; and Shankar is at Goizueta Business School, Emory University, rlshankar@emory.edu. The authors thank the National Stock Exchange (NSE), India, and New York University (NYU), New York for funding this project (NSE-NYU 2020 grant). We sincerely thank Sanjiv Das (discussant for the NSE-NYU 2020 conference), Pradeep Yadav and Kose John for valuable inputs. We also acknowledge the comments from the participants at the NSE-NYU 2020 conference, Reserve Bank of India research seminar (2021); University of Twente (2022); Wilfrid Laurier University (2022); 2022 Financial Markets and Corporate Governance conference and PhD symposium, Monash University; 2022 FMA conference; and 2023 Research Symposium on Finance and Economics, IFMR Business School, India.

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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 increase default and systemic risks for the banks. 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. Our difference-in-differences regression results are robust to a battery of tests including alternate estimation methods, risk measures, control samples, endogeneity tests and stress period funding. To the best of our knowledge, this study contributes to the literature by providing the first comprehensive study of how *repeated* government capital infusions may impact financial stability in the context of an emerging market.

Keywords: government guarantees, 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]; 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 (median $2.4 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

[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 actions and systemic risk during the COVID-19 crisis.

Internet Appendix IA, 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]; and (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).

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 institutions (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 60.06% and 38.76% (34.58% and 44.08%) 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. Dynamic DiD plots also show escalation in default, capital shortfall and network risks post-infusion. Our results, overall, are consistent with a possible moral hazard hypothesis causing treated public sector banks to increase their risk exposures thereby aggravating the underlying risks.

We additionally 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 three approaches: two-stage IV, PSM, and Heckman self-selection. Our earlier results still hold. 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, Collectively DiD regression results imply that capital infusions are followed by significant increase in default, capital shortfall and network risks for the public sector banks.

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 critical 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, low diversification, low growth potential (market to book), smaller and less profitable) banks. Similarly, *low risk* (i.e., low leverage banks, high interest coverage and deposit ratio) banks also experience higher risks following infusion. Collectively, our findings imply multiple channels may explain 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. 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 (Norden, Roosenboom, Wang, 2013). Government guarantees help lowers the risks for the

[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).

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 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,

[5] Other papers study the relationships between banks' valuations and government guarantees (Atkeson et al., 2018); cash holdings and state ownership (Chen, et al., 2018); and banks earnings management behavior and government guarantees (Dantas et al., 2016).

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 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),

[6] Source: Controller & Auditor General of India, Report No. 28, 2017.
[7] Monthly USD rupee exchange rates sourced from FRED are used to convert rupee value of infusions to USD.

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 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., 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

[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).

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:

$$(risk\ measure)_{i,t} = \alpha_0 + \alpha_1\ (treatment)_i + \alpha_2\ (post\text{-}infusion)_t + \alpha_3\ (large\ infusion)_t + \beta_0\ (treatment\ X\ post\text{-}infusion)_{i,,t} + \beta_1\ (treatment\ X\ post\text{-}infusion\ X\ large\ infusion)_{i,,t} + \gamma_0\ (controls)_t + \gamma_1\ firm\ fixed\ effects_i + \gamma_2\ \ time\ fixed\ effects_t + error_{i,t} \qquad (1)$$

where the dependent variable is a quarterly default or systemic risk measure. Treated firm *treatment* is measured by *government capital infusion dummy*. $Post\text{-}infusion_{i,t}$ 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 α_1 helps in assessing the post- infusion effect across all the FIs. Treatment dummy refers to the government owned banks receiving the capital infusion, while control firms refer to the pooled private banks (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. β_0 measures the DiD interaction effect of treatment × post-infusion and forms the basis for each testable hypothesis about post- infusion effects. To explore the possible effect of large capital infusions, we also include capital infusion size dummy, which classifies each infusion into high or low based on the median value of all the capital infusions for each year. We consider bank infusions made each year to construct the treatment and control samples for that year. 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

[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).

effects and adjustments for heteroscedasticity using Huber/White robust standard errors, and clustered by bank level.

Table 4 presents the baseline DiD regression results for model (1) for default risk (12-month PD, PD slope and DTD - Panel A) and systemic risk (NSRISK, CoVaR and network - Panel B) measures, using private banks as the control. We consider five percentile threshold levels for NSRISK and CoVaR. For each risk measure, we consider five regression models that respectively include: (1) no fixed effects, (2) only year fixed effects, (3) only quarter fixed effects, (4) both year and firm fixed effects, and (5) both 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 and size - outcomes.

[Insert Table 4 here]

Table 4, Panel A captures four different effects related to different default risk variables . First, there is a strong treatment effect (α_1 coefficient) in that treated banks have significantly higher default risk confirming the earlier event window plots. Second, the capital infusions are associated with significant decreases in default risk (α_2 coefficient), showing positive network effects associated with capital infusions, as they are positively received in the credit market by both treated and private banks. Thirdly, the β_0 coefficient is significantly negative for models 1, 2 and 3 implying that capital infusions lower credit risk for treatment banks. Once we include both time and firm fixed effects (models 4 and 5), however, β_0 becomes significantly positive indicating that capital infusions markedly increase credit risk for treated banks. Finally, large infusions though lower default risks for all firms (α_3), have no incremental effects for treated banks (β_1).

Panel B, Table 4 presents the systemic risk effects associated with capital infusions. We observe that treated banks have significantly high capital shortfall and network risks (α_1) and that capital infusion help lower all three types of systemic risks (α_2) for all FIs. Models 4 and 5 accounting for both time and firm level effects show that that DiD coefficient β_0 is significantly positive, implying that capital infusions significantly increase capital shortfall, and network risks for the treated banks. Large infusions lower capital shortfall risk for all the banks (α_3) but have no incremental effect on treated banks (β_1). CoVaR measure shows no clear signs of risk attenuation.

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 Model 5 values in Table 4. The treated banks post-infusion experience an increase (decrease) in their PD and PD slope (DTD) values by 24.75% and 27.24% (21.32%) respectively as percentage of their respective means. Similarly, treated banks register 22.80%, 28.32% and 11.00% increases in their PD, PD slope and DTD respectively as percentage of their respective standard deviations.[11] In terms of systemic risks, post-infusion, treated banks display 60.06% and 38.76% (34.58% and 44.08%) increases in their NSRISK and network risks respectively with respect to their respective means (standard deviations). Our results show that (a) effect of government infusions is economically significant and (b) impact on systematic risks have 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 quarterly specification.

$$(\textit{risk measure})_{i,t} = \alpha_0 + \beta_0\,(\textit{quarter specific post-infusion})_t + \beta_1\,(\textit{quarter specific large post-infusion dummy})_t + \gamma_0\,(\textit{controls})_t + \gamma_1\,\textit{firm fixed effects}_i + \gamma_2\,\textit{time fixed effects}_t + \textit{error}_{i,t} \quad (2)$$

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 consider three alternate definitions of large infusion dummy (β_1 coefficient): (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

[11] Similarly, based on Model 4 values in Table 4, treated banks experience increase (decrease) in PD and PD slope (DTD) measures respectively 18.92% and 22.79% (17.16%) respectively compared to their respective means; treated banks also see increases of 17.43%, 23.69% and 8.85% respectively in PD, PD slope and DTD compared to their respective standard deviations.

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 Model 5 regressions (from Table 4) 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), 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 Table 5 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 Matched control sample

To alleviate the concerns that we might be using a pooled control sample, we first examine the effect of capital infusion using a matched private bank sample. We implement the annual DiD specification (1) using models (4) and (5) 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]

5.2 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 (4) and (5) from Table 4, which incorporate both time (yearly or quarterly) and firm fixed effects (Internet Appendix, Table IA4, Panel A). We observe that the DiD regression coefficients are significant for both systemic risks measures, and higher in magnitude compared to corresponding coefficients in Table 4. We next implement Quarterly DiD specification (2) (in Panel B) and find that only capital shortfall is highly significant post-infusion. Overall, Section 4.2 baseline results remain robust to tail measures of systemic risk.

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

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

driven by common set of risk factors, and only risky banks would 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). We consider three sets of endogeneity tests below.

5.3.1 Two- Stage Least Squares (SLS) IV approach

We run a 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. Following first stage probit model is used to determine the probability of capital infusion for a public sector bank.

$$\begin{aligned} &\textit{Prob (capital infusion)}_{i,,t} = \alpha_0 + \alpha_1 \textit{ (financial variables)}_{t-1} + \gamma_1 \textit{ (controls)}_{t-1} + \gamma_2 \textit{ firm fixed effects}_{i-1} \\ &\qquad + \gamma_3 \textit{ time fixed effects}_{t-1} + \textit{error}_{i,,t} \end{aligned} \tag{3}$$

where the dependent variable is the dummy variable that identifies for a bank receiving capital infusion. We include the private banks as control firms. The covariates consist of lagged financial and instrumental variables as of the quarter preceding each infusion year (quarter 4 of year *t-1*). Financial variables include total debt to total capital, total assets, interest coverage, and tier 1 ratio. We also use two instrumental variables: (a) Cash flow Beta, which is obtained as the quarterly stock return betas of the banks and FIs with respect to aggregate net foreign capital flows, and (b) policy uncertainty beta, obtained as the quarterly stock return betas of the banks and FIs with respect to aggregate policy economic uncertainty. 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.[13] Results are presented in Table 7. Panel A shows that lagged tier 1 ratio is significantly related to current period infusion and the effects are robust to inclusion of both time and firm level fixed effects. Banks with lower tier 1 ratios previous quarter are more likely to receive current quarter infusion. We implement 2-SLS regressions by first fitting

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[13] 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 difficulty in accessing capital markets for equity funding to shore up their Tier 1 capital, capital infusions may play a greater role. The access to equity markets in turn depends upon the existing capital market conditions. Hence the probability of capital infusion critically depends on the prevailing capital market conditions which is proxied by the responsiveness of individual firm's returns to (a) aggregate net capital flows into the financial markets, as well as (b) macro policy uncertainty.

treatment dummy from first-stage probit model 4 and then using the fitted value as input into the second-stage baseline annual DiD specification (1) (Table 7, panel B).[14] We find that treated banks experience significantly higher default risks, capital shortfall and network risks following capital infusion consistent with baseline Table 4 results. We additionally observe a drop in CoVaR risks implying that treated public sector banks become less vulnerable to the financial system. The Kleibergen-Paap rk Wald F statistic measures weak instruments, and comfortably exceeds the Stock-Yogo (2005) critical value of 10, suggests that the regressions with both firm and quarter fixed effects do not suffer from a weak instrument problem and are valid.

[Insert Table 7 here]

We also reimplement 2-SLS IV approach using the quarterly DiD specification (2) (panels c and D). The first-stage probit model covariates consist of lagged financial and instrumental variables as of the previous quarter. The first stage probit models show that both 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 to aggregate policy uncertainty previous quarter are more likely to receive current quarter infusion. The second stage quarterly DiD specification using fitted values of infusion from probit model 4 shows significant increases in default risk, capital shortfall and network risks following infusion, consistent with Table 5 results and robust to the weak instrument problem based on the Kleibergen-Paap rk Wald F statistic.

5.3.2 Propensity Score Matching (PSM) Approach

We consider an alternative endogeneity test using PSM approach. We implement the annual DiD specification (1) using PSM control sample of unfunded public banks. As described in Section 5.1, for the banks receiving capital infusion in year *k*, we use the last quarter preceding each infusion year (quarter 4 of year *k-1*) as the matching quarter 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

[14] We use two other approaches: (a) winsorize the fitted values to lie between 0 and 1; (b) use the median to convert fitted values to binary numbers that are strictly 0 and 1, and the results are found to be robust.

same matching quarter. Results are presented in Table 8, 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 implement quarterly DiD specification (2) using PSM control sample of public banks (Table 8, Panel B). For the quarterly specification. we use the quarter preceding each infusion quarter to obtain the propensity scores using a logit model. We find capital infusions are followed by significant increase in default, capital shortfall and network risks for the public sector banks; overall the baseline results in Section 4.2 still hold.

[Insert Table 8 here]

5.3.3 Heckman Approach

Endogeneity can, arise from self-selection as risky banks may be targeted for capital infusion. We consider the possibility that infusions may be endogenously determined by the underlying firm based on banks' risk variables. To address this concern, we conduct a Heckman correction applied to the baseline annual DiD specification (1) in Panel A and quarterly DiD specification (2) in Panel B based on control sample of public banks. We run first stage estimation of annual and quarterly versions of probit model (4) – from 2-SLS IV, Table 7, panels A and C respectively– based on the lagged values of the following covariates i.e., Debt to Total Capital, Total Assets, Interest Coverage Ratio, Tier 1 Ratio, CF Beta, Policy Beta, US and Local market factors, firm, and year fixed effects . We then use the inverse Mills ratio (IMR) from the probit model as an additional independent variable in the second stage regression model with firm and quarter fixed effects. Only the second stage regression results for model with quarter and firm fixed effects are reported. We find capital infusions are followed by significant increase in default, capital shortfall and network risks for the public sector banks; the IMR is not significant showing no clear signs of endogeneity. Overall, the baseline Table 4 and 5 results in Section 4.2 still hold.

5.4 Additional robustness tests

We conduct additional robustness tests using alternate (a) control samples of public and private NBFIs, (b) set of network variables, (c) definitions of post-infusion variable and (d) measures for size of capital infusion. Results are presented in the Internet Appendix (Tables IA5 to IA 9). All our baseline results from Section 4.2 hold.

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:

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

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 base line 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 4 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 10. We find that treated banks experience high default risks during stress years (*Teatment x StressYears Dummy*). Capital infusions during the stress years, captured by *Post Infusion x 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 x Post Infusion x StressYears Dummy*). Moreover, the DiD term (*Treatment* x *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 10 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 and high leverage) banks by increasing their equity capital buffer; however, such infusions can increase bank risk taking if such banks resort to moral hazard behavior. Similarly, low loan portfolio banks 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 market to book) and low cash reserves (based on deposit ratio and interest coverage) 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. Smaller (asset) and less profitable

(ROE) 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 11. For brevity, we only present coefficient and significance of the two DiD interaction terms: β_0 (or treatment x post-infusion effect) and β_1 (or treatment x post-infusion x large infusion effect).

[Insert Table 11 here]

We summarize below different channels, respective financial proxies and key findings on default and systemic risks from Table 11.

		Evidence of higher default risk for		Evidence of higher systemic risks for	
channels	proxies	high risk banks characterized by	low risk banks characterized by	high risk banks characterized by	low risk banks characterized by
• Capital cushion	− Tier 1 − leverage	− low tier 1	− low leverage	− low tier 1: NSRSIK & network risk − high leverage: network risk	− low leverage: network risk
• Bank portfolio diversification channel	− loan to assets	− low loan to asset ratio		− 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	− deposit to assets − interest coverage		− 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	− size: total assets − profitability (ROE)	− small firms − less profitable: PD slope	− more profitable: PD	− small firms: NSRISK & network risk − less profitable: NSRISK	− large firms: NSRISK (affected by large cap infusions) − more profitable: network risk

As summarized in the last two columns of the table, capital infusions are followed by significant increase in default and systemic risks for *high risk* (i.e., low tier 1, low diversification, low market to book, smaller and less profitable) banks. Similarly, *low risk* (i.e., low leverage banks, high interest coverage and deposit ratio) banks also experience higher risks following infusion.

Capital infusions significantly increase default and systemic risks for low Tier 1 capital and smaller (total assets) banks, and banks with low valuations (low market to book), low profitability (ROE) and low loan exposure (low loans to assets). Larger capital infusions can further aggravate the capital shortfall risk for large banks. Collectively, our findings indicate that multiple channels may influence the ultimate effect of capital infusions and 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.[15]

[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.

$$(aggregate\ risk\ spread)_{i,,t} = \alpha_0 + \alpha_2\ Post \times infusion\_index + \gamma_0\ (controls)_t + \gamma_1\ time\ fixed\ effects_t + error_{i,t} \quad (5)$$

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.

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[15] 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).

Table 12 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 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 12 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 excess credit and systemic risks among treated banks. Further evidence shows that multiple economic channels may influence the ultimate effect of capital infusions. 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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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 $\mathrm{LRMES}_{i,t} = 1 - \exp(18 \times MES_{i,t})$. 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 kth 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 Wurgker measure of policy uncertainty

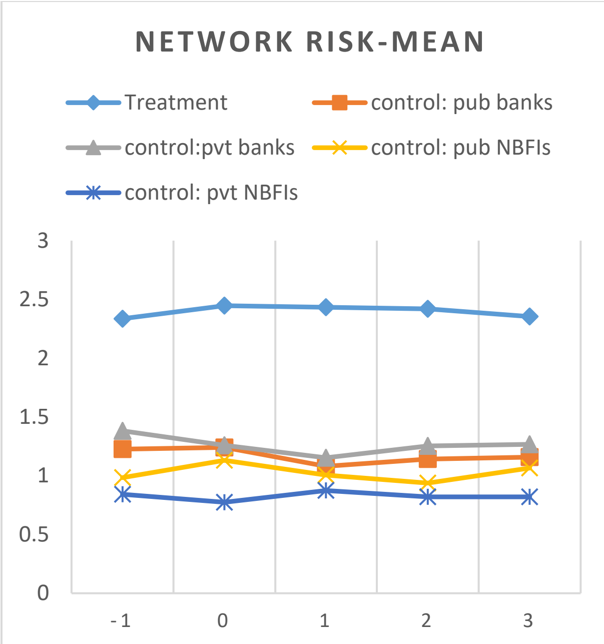
Figure 1: Event window plots of Probability of default (PD) around capital infusion

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.



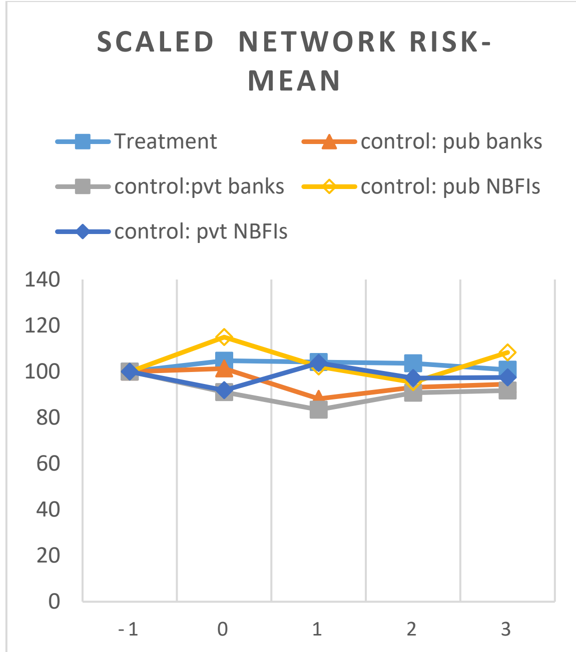


Figure 3: DiD coefficient plots of default and systemic risk measures over the sample period 2008-2018

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.

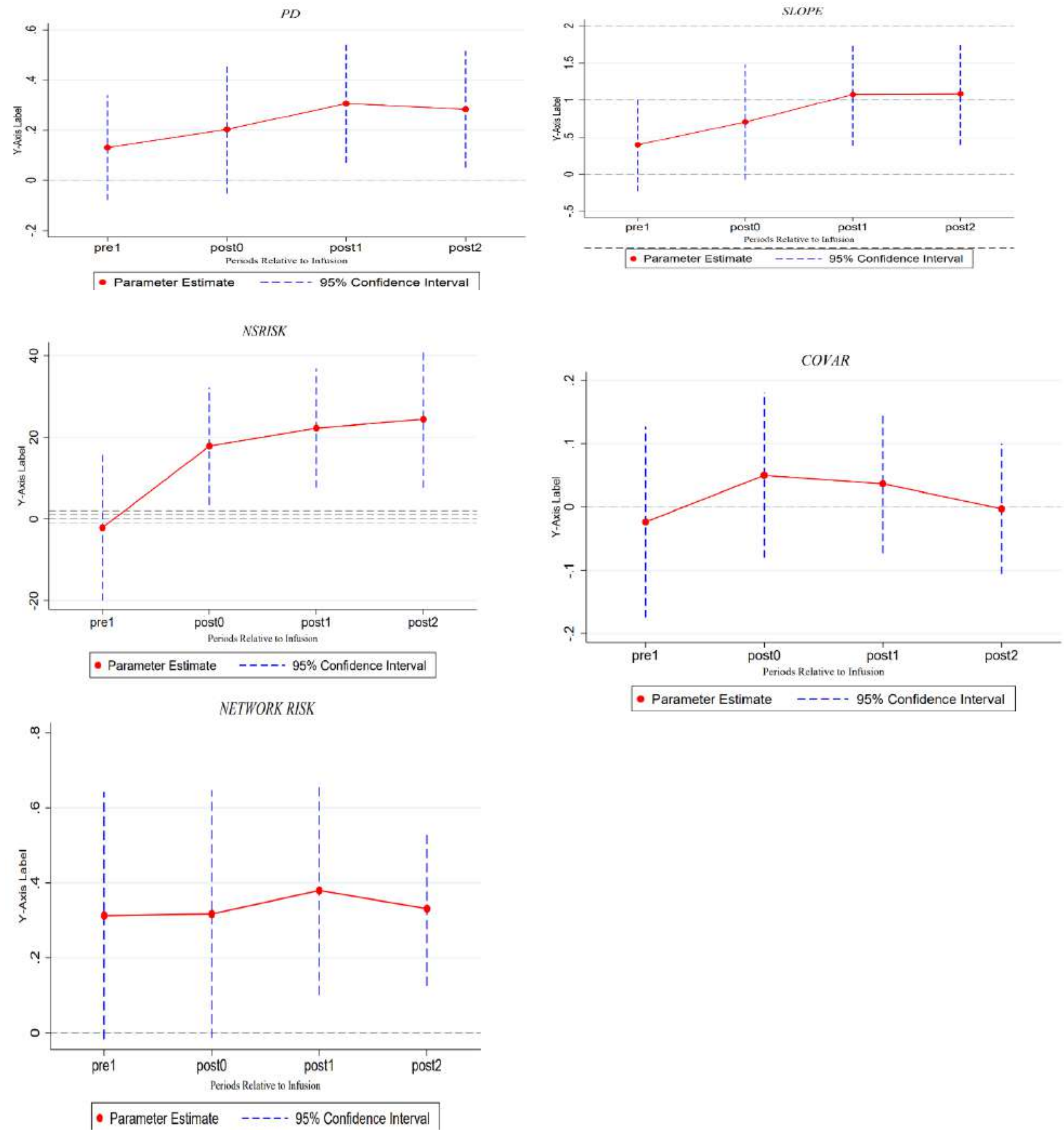


Figure 4: Rolling DiD regression coefficient plots of default and systemic risk measures over the sample period 2008-2018

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.

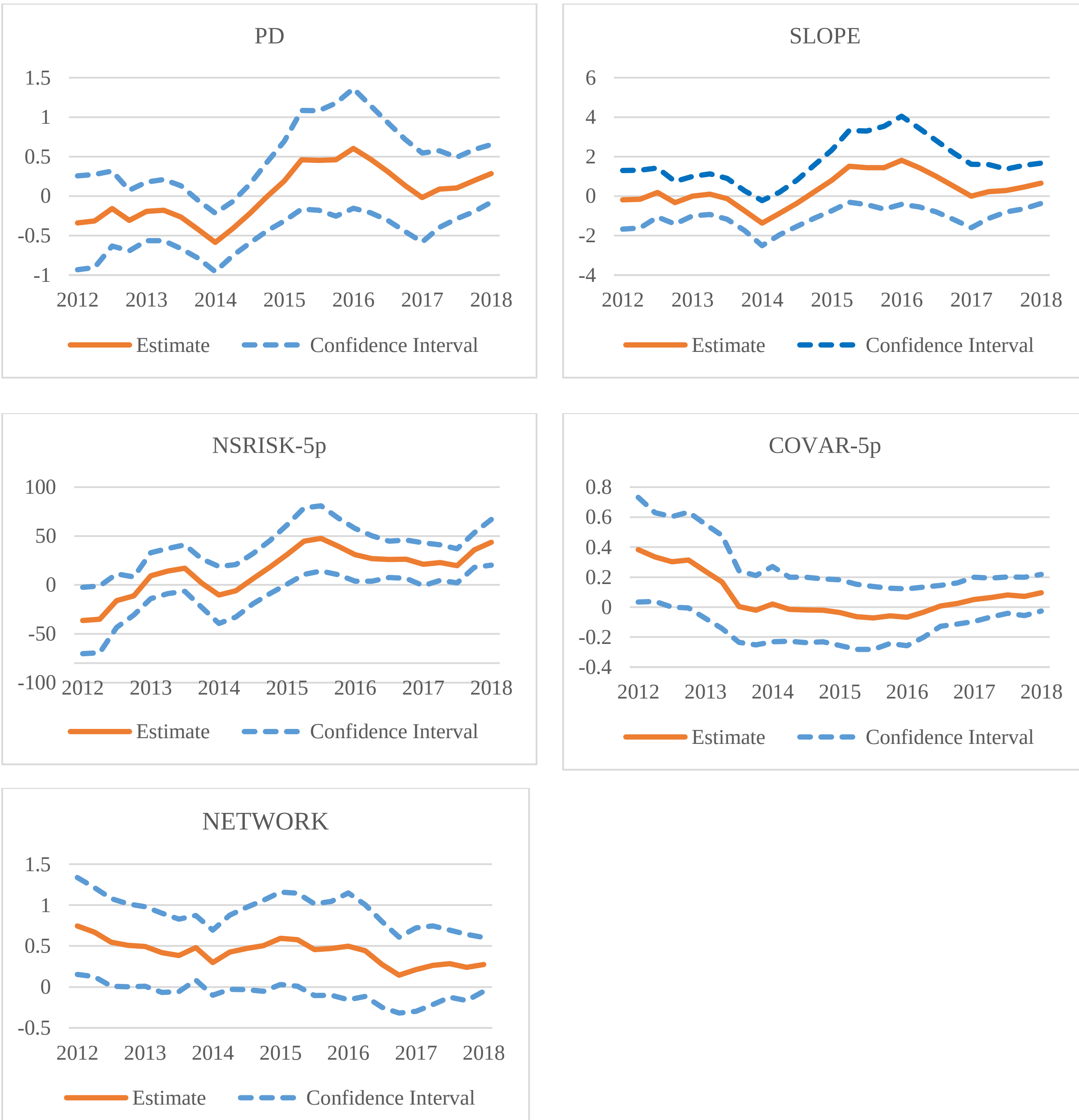


Figure 5: Time series plots of Probability of default (PD) measures over the sample period 2008-2018

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.

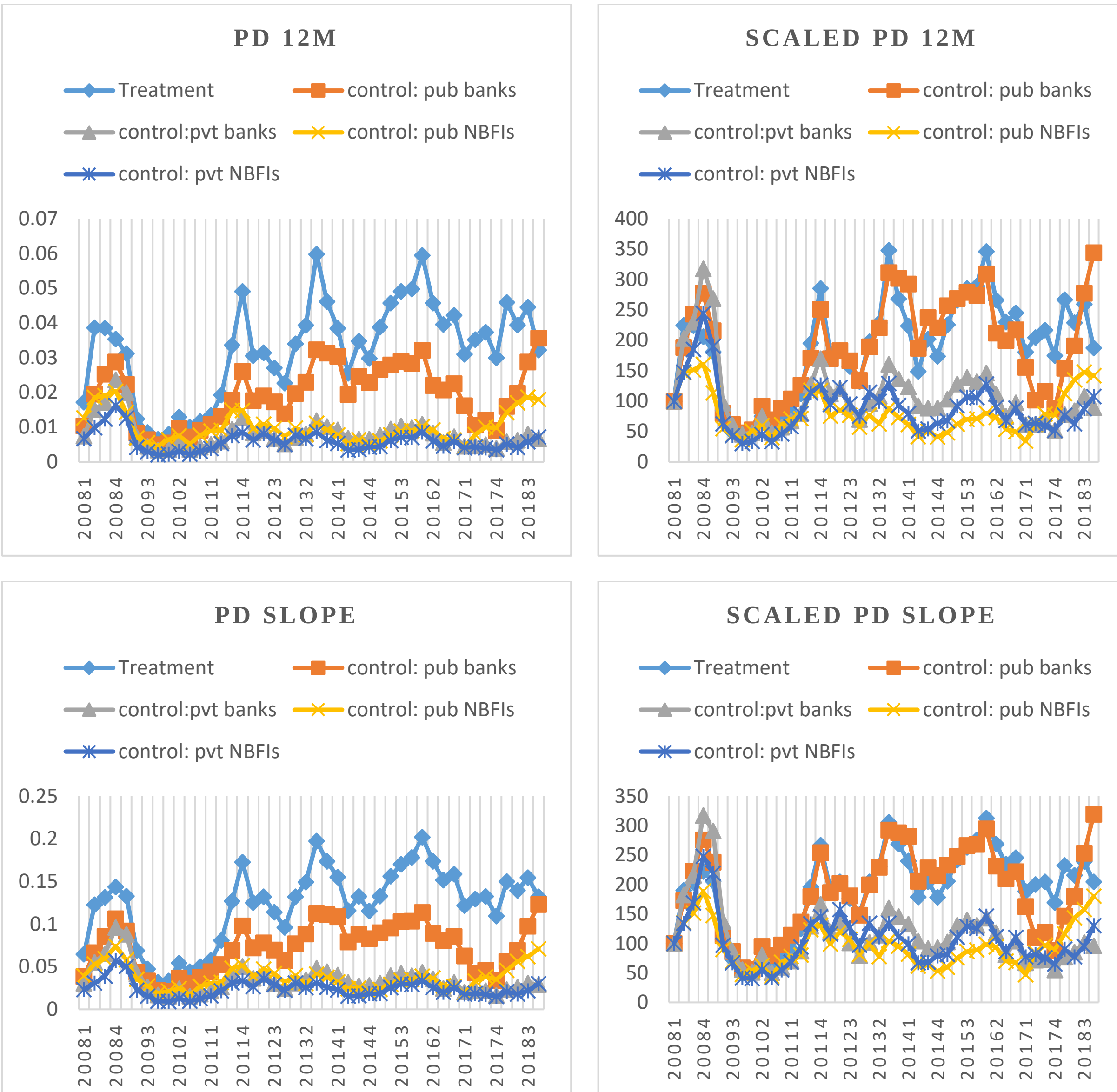


Figure 6: Time series plots of the systemic risk measures around capital infusion over the sample period 2008-2018

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.

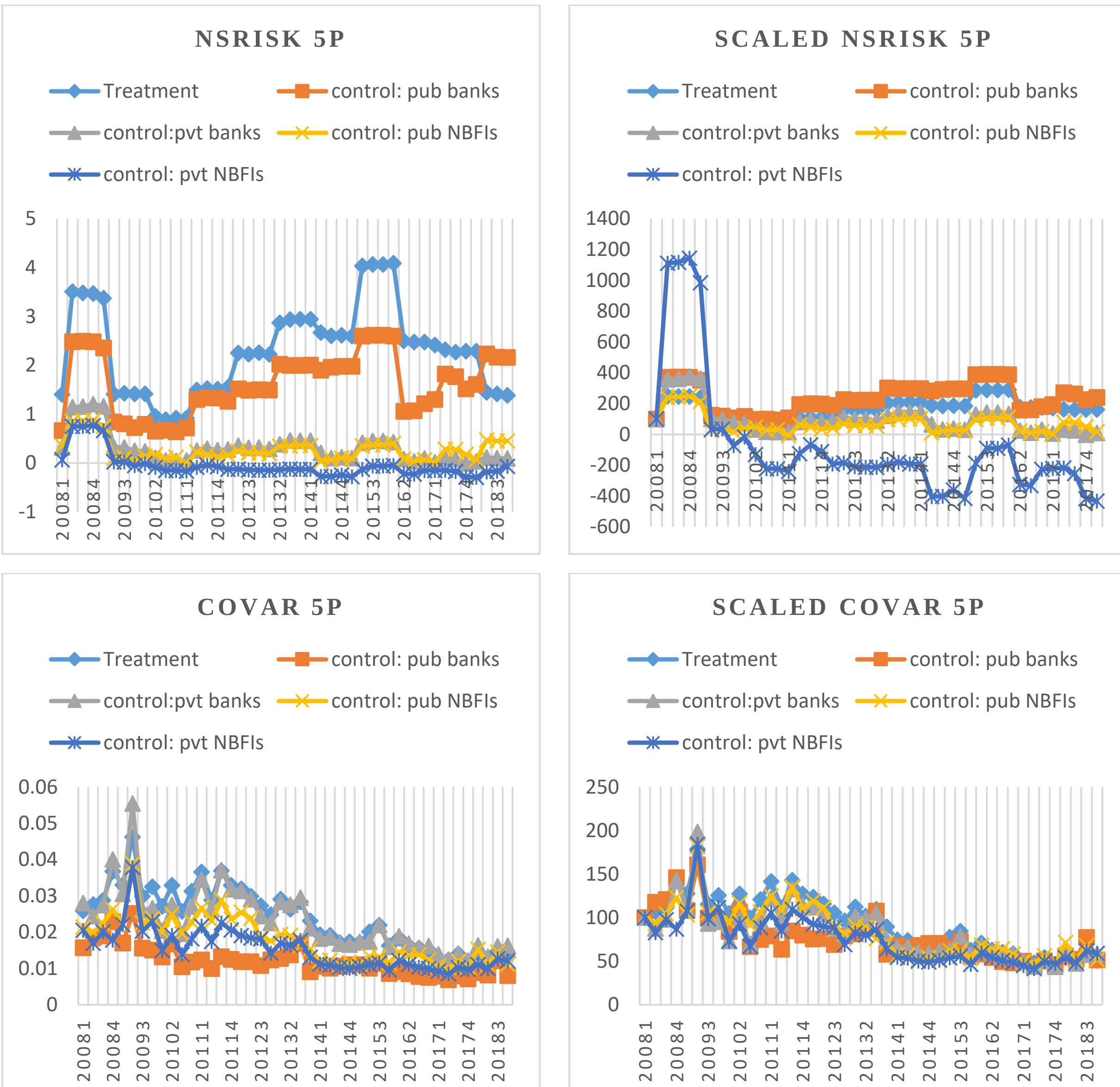
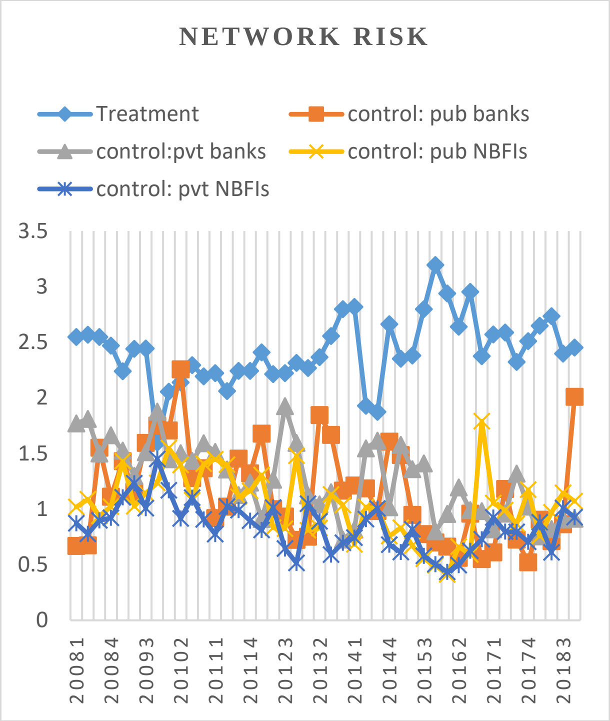


Figure 6: contd.



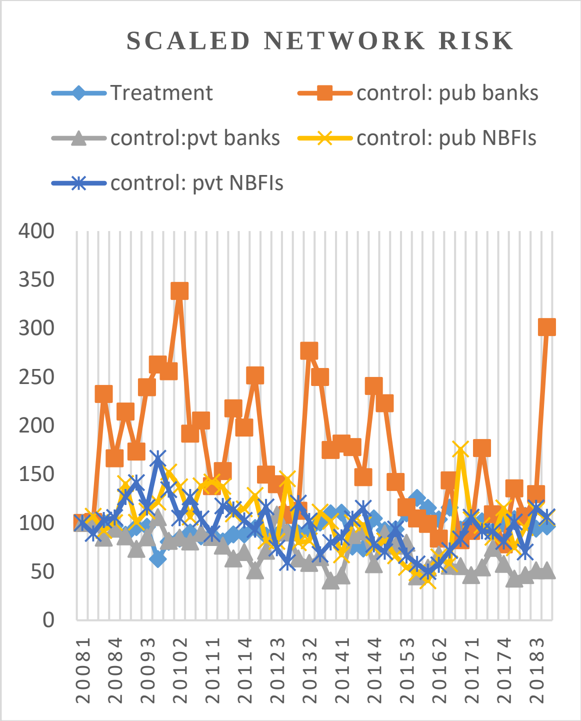


Table 1. Financial sample breakdown

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.

-Q1 to +Q2

	CoVar 5p: A.Treat.	B. Control: pub banks	C. Control: pvt banks	D. Control: pub NBFIs	E. Control: pvt NBFIs	CoVar 1p: A.Treat.	B. Control: pub banks	C. Control: pvt banks	D. Control: pub NBFIs	E. Control: pvt NBFIs
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

	A.Treat.	B. Control: pub banks	C. Control: pvt banks	D. Control: pub NBFIs	E. Control: pvt NBFIs
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 (Hypotheses 1, 2 & 3)

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. 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)	(13)	(14)	(15)
VARIABLES	PD 1-year					PD Slope					DTD				
Treatment Dummy	3.279***	3.080***	3.843***			10.08***	9.655***	11.95***			-1.307***	-1.376***	-1.728***		
	(0.421)	(0.428)	(0.375)			(1.301)	(1.321)	(1.179)			(0.289)	(0.389)	(0.359)		
Post Infusion Dummy	-0.817***	-0.759***		-0.776***		-2.705***	-2.296***		-2.177***		0.670***	0.492***		0.439***	
	(0.125)	(0.113)		(0.122)		(0.373)	(0.317)		(0.318)		(0.148)	(0.0941)		(0.0665)	
Large Infusions	-1.226***	-0.432	-1.267***			-2.821***	-0.146	-2.958***			0.558***	0.118	0.589***		
	(0.347)	(0.357)	(0.345)			(0.944)	(0.917)	(0.950)			(0.166)	(0.197)	(0.159)		
Treatment x Post Infusion Dummy	-0.889**	-0.830**	-1.671***	0.299*	0.391**	-1.552	-1.609	-4.141***	1.386***	1.657***	-0.111	-0.00163	0.532***	-0.297***	-0.369***
	(0.353)	(0.331)	(0.312)	(0.154)	(0.168)	(1.063)	(0.994)	(0.977)	(0.478)	(0.498)	(0.193)	(0.163)	(0.142)	(0.106)	(0.111)
Treatment x Post x Large Infusions	0.951**	0.377	0.938**	0.125	0.162	1.804*	0.0306	1.760	-0.0463	0.314	-0.192	0.0674	-0.180	-0.0257	-0.0971
	(0.356)	(0.326)	(0.358)	(0.184)	(0.173)	(1.055)	(0.947)	(1.065)	(0.570)	(0.534)	(0.163)	(0.140)	(0.164)	(0.101)	(0.104)
Constant	3.020***	1.685***	2.404***	2.706***	-26.11***	10.75***	3.662***	8.706***	7.143***	-84.40***	-0.114	0.238	0.322	-0.219	20.57***
	(0.530)	(0.527)	(0.487)	(0.560)	(5.919)	(1.824)	(1.238)	(1.691)	(1.248)	(16.99)	(0.686)	(0.297)	(0.777)	(0.198)	(3.419)
Observations	1,491	1,491	1,491	1,491	1,491	1,491	1,491	1,491	1,491	1,491	1,073	1,073	1,073	1,073	1,073
R-squared	0.391	0.459	0.372	0.644	0.682	0.431	0.509	0.412	0.709	0.747	0.273	0.354	0.247	0.729	0.760
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	NO	NO	NO	YES	YES	NO	NO	NO	YES	YES	NO	NO	NO	YES	YES
Year FE	NO	YES	NO	YES	NO	NO	YES	NO	YES	NO	NO	YES	NO	YES	NO
Quarter FE	NO	NO	YES	NO	YES	NO	NO	YES	NO	YES	NO	NO	YES	NO	YES

Table 4. contd.

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VARIABLES	NSRISK_5p					COVAR_5p					Network Risk				
Treatment Dummy	186.4***	209.6***	230.8***			-0.0105	-0.0225	0.0509			0.835***	1.040***	1.062***		
	(28.99)	(28.09)	(25.24)			(0.201)	(0.222)	(0.211)			(0.283)	(0.296)	(0.293)		
Post Infusion Dummy	-63.85***	-33.85***		-16.33***		-0.0884*	-0.132***		-0.119**		-0.326***	-0.202**		-0.221*	
	(12.95)	(7.499)		(4.871)		(0.0488)	(0.0378)		(0.0564)		(0.0756)	(0.0947)		(0.118)	
Large Infusions	-73.73**	-56.30*	-77.02**			-0.0971	0.0540	-0.102			0.0989	0.104	0.0823		
	(29.13)	(31.67)	(28.46)			(0.204)	(0.227)	(0.205)			(0.382)	(0.407)	(0.383)		
Treatment x Post Infusion Dummy	49.31*	12.39	-11.74	45.34***	49.87***	0.0136	0.0978	-0.0709	0.141	0.179	0.429*	0.216	0.117	0.506***	0.556***
	(24.75)	(20.79)	(18.95)	(14.50)	(15.30)	(0.136)	(0.110)	(0.136)	(0.141)	(0.155)	(0.248)	(0.251)	(0.240)	(0.174)	(0.182)
Treatment x Post x Large Infusions	2.491	-1.398	1.560	-25.34	-28.63	0.194	0.0435	0.193	-0.0752	-0.0724	-0.233	-0.221	-0.238	-0.0334	-0.0379
	(27.00)	(22.77)	(27.12)	(20.52)	(21.38)	(0.164)	(0.134)	(0.163)	(0.165)	(0.179)	(0.317)	(0.323)	(0.319)	(0.151)	(0.162)
Constant	112.5***	140.0***	63.86*	245.6***	171.2	0.419**	2.240***	0.352*	2.031***	-5.939**	1.245***	2.065***	0.996***	2.731***	-6.546
	(38.00)	(35.89)	(37.28)	(29.50)	(265.5)	(0.199)	(0.300)	(0.206)	(0.319)	(2.567)	(0.271)	(0.665)	(0.266)	(0.657)	(7.956)
Observations	1,530	1,530	1,530	1,530	1,530	1,520	1,520	1,520	1,520	1,520	1,536	1,536	1,536	1,536	1,536
R-squared	0.342	0.401	0.325	0.723	0.750	0.341	0.446	0.340	0.603	0.668	0.132	0.140	0.127	0.266	0.269
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	NO	NO	NO	YES	YES	NO	NO	NO	YES	YES	NO	NO	NO	YES	YES
Year FE	NO	YES	NO	YES	NO	NO	YES	NO	YES	NO	NO	YES	NO	YES	NO
Quarter FE	NO	NO	YES	NO	YES	NO	NO	YES	NO	YES	NO	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. 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. 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)	(13)	(14)
VARIABLES														
	PD 1-year		PD Slope		NSRISK_1p		NSRISK_5p		COVAR_1p		COVAR_5p		Network Risk	
Post Infusion Dummy	-0.331***		-0.958***		-10.65***		-3.662		0.0120		0.00880		-0.166	
	(0.0732)		(0.189)		(3.513)		(3.126)		(0.116)		(0.0427)		(0.110)	
Treatment x Post Infusion Dummy	-0.297	-0.268	-0.868	-0.711	45.29**	45.14**	39.51**	39.58**	-0.169	-0.0801	-0.121	-0.0229	0.501**	0.482**
	(0.273)	(0.259)	(0.801)	(0.747)	(18.19)	(17.55)	(18.93)	(18.27)	(0.189)	(0.178)	(0.137)	(0.143)	(0.236)	(0.234)
Treatment x Post x Large Infusions	0.0894	0.107	0.281	0.376	-27.93	-28.21	-25.38	-25.55	-0.179	-0.164	0.0259	0.0349	-0.0956	-0.104
	(0.369)	(0.346)	(1.122)	(1.050)	(28.88)	(28.77)	(30.08)	(29.97)	(0.213)	(0.230)	(0.183)	(0.192)	(0.346)	(0.354)
Constant	3.545***	20.24**	12.86***	81.34***	190.7***	380.1	201.1***	649.4	4.246***	-1.320	2.663***	4.356	3.051***	43.76***
	(0.442)	(7.459)	(1.088)	(26.96)	(40.13)	(508.9)	(40.18)	(430.2)	(0.554)	(8.470)	(0.203)	(4.589)	(0.542)	(15.52)
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	0.842	0.857	0.853	0.865	0.589	0.619	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: 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 both annual and quarterly DiD specifications (1) and (2) respectively in the paper. We employ public sector banks not receiving capital infusions as the control sample. Panels A and B capture annual specification, while Panels C and D summarize quarterly regression results. Panels A and C respectively present annual and 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; Panels B and D respectively present the annual and quarterly versions of second-stage 2-SLS regressions using probit model (4) as an input. Annual (quarterly) probit model uses one-year (quarter) lagged variables. 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 Panels B and D. All the variables are defined in Appendix A.

Panel A

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Annual regressions (Specification 1)				
Lagged Debt to Total Capital	0.004	0.004	0.000	-0.001	0.007
	(0.009)	(0.011)	(0.014)	(0.019)	(0.033)
Lagged Total Assets	6.857	8.819	13.48*	4.503	-5.754
	(4.881)	(5.766)	(7.214)	(5.518)	(13.56)
Lagged Interest Coverage Ratio	0.000	-0.001	0.000	0.000	-0.002
	(0.003)	(0.004)	(0.004)	(0.006)	(0.006)
Lagged Tier 1 Ratio	-0.333***	-0.476***	-0.591***	-0.426***	-0.732***
	(0.077)	(0.085)	(0.097)	(0.127)	(0.215)
Lagged CF Beta	90.33	210.9	99.90	384.3	694.6
	(130.8)	(262.7)	(412.5)	(277.9)	(500.5)
Lagged Policy Beta	1.681***	0.688	0.748	1.100	0.741
	(0.449)	(0.699)	(1.121)	(0.880)	(2.206)
Constant	3.844***	-0.108	12.76***	-1.933	20.10**
	(1.022)	(1.365)	(4.604)	(2.867)	(8.126)
Observations	838	838	790	732	656
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 7. contd.

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Second Stage of 2SLS regression (Specification 1)													
VARIABLES	PD 1-year		PD Slope		NSRISK_1p		NSRISK_5p		COVAR_1p		COVAR_5p		Network Risk	
Treatment Dummy														
Post Infusion Dummy	-1.096***		-2.738***		-22.43**		-17.80**		-0.241*		-0.076		-0.085	
	(0.107)		(0.248)		(8.080)		(7.414)		(0.118)		(0.061)		(0.175)	
Large Infusions														
Treatment x Post Infusion Dummy	0.136*	0.177**	0.320	0.424*	16.24***	28.83***	14.05**	28.22***	0.093	-0.042	-0.003	-0.091***	0.128***	0.152***
	(0.074)	(0.081)	(0.203)	(0.238)	(4.943)	(4.507)	(5.275)	(4.517)	(0.060)	(0.050)	(0.039)	(0.016)	(0.045)	(0.041)
Treatment x Post x Large Infusions	0.074	0.074	0.198	0.258	2.236	4.039	2.122	3.702	-0.057	-0.072	-0.007	-0.01	-0.021	-0.017
	(0.089)	(0.110)	(0.252)	(0.312)	(6.249)	(7.420)	(6.465)	(7.451)	(0.052)	(0.055)	(0.029)	(0.025)	(0.079)	(0.076)
Constant	-0.174	7.000***	0.925	24.66***	57.88	376.9***	70.84	393.6***	4.628***	1.450***	2.554***	0.969***	1.618**	2.968***
	(0.787)	(0.228)	(2.042)	(0.715)	(52.46)	(24.22)	(48.75)	(25.83)	(0.719)	(0.386)	(0.404)	(0.243)	(0.727)	(0.353)
Observations	722	722	722	722	715	715	715	715	712	712	712	712	720	720
R-squared	0.612	0.420	0.646	0.424	0.668	0.507	0.674	0.522	0.528	0.435	0.694	0.573	0.150	0.142
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
Kleibergen-Paap rk Wald F statistic	15.80	79.29	15.80	79.29	16.02	80.18	16.02	80.18	16.52	79.77	16.52	79.77	13.42	81.85

Table 7. contd.

Panel C

VARIABLES	(1)	(2)	(3)	(4)	(5)
	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

Panel D

	(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
Kleibergen-Paap rk Wald F statistic	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 8. 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 annual DiD specification (1) in Panel A and quarterly DiD specification (2) in Panel B. 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. 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	-0.331***		-0.958***		-10.65***		-3.662		0.0120		0.00880		-0.166	
	(0.0732)		(0.189)		(3.513)		(3.126)		(0.116)		(0.0427)		(0.110)	
Treatment x Post Infusion Dummy	-0.297	-0.268	-0.868	-0.711	45.29**	45.14**	39.51**	39.58**	-0.169	-0.0801	-0.121	-0.0229	0.501**	0.482**
	(0.273)	(0.259)	(0.801)	(0.747)	(18.19)	(17.55)	(18.93)	(18.27)	(0.189)	(0.178)	(0.137)	(0.143)	(0.236)	(0.234)
Treatment x Post x Large Infusions	0.0894	0.107	0.281	0.376	-27.93	-28.21	-25.38	-25.55	-0.179	-0.164	0.0259	0.0349	-0.0956	-0.104
	(0.369)	(0.346)	(1.122)	(1.050)	(28.88)	(28.77)	(30.08)	(29.97)	(0.213)	(0.230)	(0.183)	(0.192)	(0.346)	(0.354)
Constant	3.545***	20.24**	12.86***	81.34***	190.7***	380.1	201.1***	649.4	4.246***	-1.320	2.663***	4.356	3.051***	43.76***
	(0.442)	(7.459)	(1.088)	(26.96)	(40.13)	(508.9)	(40.18)	(430.2)	(0.554)	(8.470)	(0.203)	(4.589)	(0.542)	(15.52)
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	0.842	0.857	0.853	0.865	0.589	0.619	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 8. 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
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 9. Robustness test: Heckman DID regressions based on public sector banks as control samples

We present the results of Heckman procedure applied to the annual DiD specification (1) in Panel A and quarterly DiD specification (2) in Panel B based on control sample of public banks. We accordingly conduct first stage estimation of annual and quarterly versions of probit model (4) from Table 7, panels A and C respectively for public sector banks receiving capital infusion, based on the following covariates i.e., lagged values of Debt to Total Capital, Total Assets, Interest Coverage Ratio, Tier 1 Ratio, CF Beta, Policy Beta, US and Local market factors, firm and year fixed effects . We then use the inverse Mills ratio (IMR) from the probit model as an additional independent variable in the second stage regression model with firm and quarter fixed effects. Only the second stage regression results for changes are reported. 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)
VARIABLES	PD 1-year	PD Slope	NSRISK_1p	NSRISK_5p	COVAR_1p	COVAR_5p	Network Risk
Treatment x Post Infusion Dummy	0.714*	2.270**	38.10*	35.54*	0.537*	0.0489	0.727**
	(0.362)	(1.026)	(20.08)	(20.52)	(0.298)	(0.201)	(0.329)
Treatment x Post x Large Infusions	0.0987	0.365	5.239	7.525	0.0475	0.0637	-0.151
	(0.208)	(0.607)	(14.76)	(15.39)	(0.179)	(0.0773)	(0.185)
IMR	0.110	0.332	-27.12	-23.06	-0.588*	-0.164	0.0738
	(0.360)	(1.038)	(20.88)	(23.05)	(0.322)	(0.226)	(0.197)
Constant	-16.81***	-53.72***	279.4	-25.34	-13.04*	-4.337	-3.614
	(5.339)	(14.57)	(502.6)	(465.2)	(7.016)	(3.984)	(7.556)
Observations	825	825	818	818	815	815	823
R-squared	0.684	0.721	0.691	0.687	0.560	0.723	0.170
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 9. 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	0.679***	2.216***	43.33**	42.98**	0.342	0.0207	0.381*
	(0.232)	(0.655)	(18.66)	(18.73)	(0.287)	(0.168)	(0.192)
IMR	0.0978	0.295	-27.55	-23.36	-0.599*	-0.164	0.0489
	(0.372)	(1.079)	(21.29)	(23.47)	(0.331)	(0.231)	(0.197)
Constant	-15.61***	-50.35***	237.1	-82.83	-9.841	-3.438	0.254
	(4.480)	(12.47)	(491.0)	(431.6)	(6.242)	(3.779)	(6.015)
Observations	825	825	818	818	815	815	823
R-squared	0.685	0.723	0.694	0.691	0.556	0.722	0.161
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. 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 11. 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 2 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 two DiD interaction terms β_0 (or treatment X post-infusion effect) and β_1 (or treatment X post-infusion X large 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.

		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	Treatment x Post	-0.0418	0.234	-0.0777	0.147	0.411	0.162	0.897	21.48	0.174	0.528**
	Treatment x Post x Large Infusions	0.518*	1.688*	43.11***	-0.0577	-0.228	0.267	0.861	9.551	-0.0372	-0.305
low	Treatment x Post	0.602***	2.178***	31.51*	0.0390	0.764***	0.471*	1.789***	22.65*	0.0785	0.764***
	Treatment x Post x Large Infusions	-0.229	-0.560	-21.66	0.108	0.109	0.112	0.403	2.741	0.0758	-0.183
				Interest coverage					*Leverage*		
high	Treatment x Post	0.527**	1.908***	33.50**	0.209	0.767***	0.355	1.491	20.38	0.205	0.717***
	Treatment x Post x Large Infusions	-0.169	-0.462	-7.044	-0.0561	-0.432	0.207	0.776	17.84	-0.0532	-0.420*
low	Treatment x Post	0.476	1.843**	23.77	-0.0444	0.518**	0.558**	2.027***	27.86	0.0142	0.590***
	Treatment x Post x Large Infusions	0.259	0.938	14.28	0.225	0.0485	-0.0840	-0.209	-0.638	0.135	0.0286
				Loan to assets					*Deposits to assets*		
high	Treatment x Post	0.299	1.186*	10.01	0.154	0.555**	0.609**	2.205***	31.47**	0.0494	0.663***
	Treatment x Post x Large Infusions	0.190	0.792	27.10	0.00824	-0.176	-0.163	-0.345	-1.529	0.0402	3.62e-05
low	Treatment x Post	0.439	1.798**	39.42**	0.122	0.662***	0.199	0.930	11.97	0.325**	0.668**
	Treatment x Post x Large Infusions	0.153	0.461	-8.492	0.0549	-0.129	0.396	1.252	24.18	-0.133	-0.330
				Market to book					*ROE*		
high	Treatment x Post	0.0852	0.528	3.523	0.164	*0.389**	*0.389***	*1.394***	26.98	0.146	0.644***
	Treatment x Post x Large Infusions	0.172	0.670	9.952	-0.0448	-0.231	0.238	0.956	25.96	0.0247	-0.423*
low	Treatment x Post	0.844**	3.010***	56.42***	0.00218	0.913***	0.659	2.448*	36.43*	0.0358	0.565*
	Treatment x Post x Large Infusions	-0.0378	-0.0991	2.400	0.232	-0.136	0.0164	0.103	-5.156	0.0484	0.142

Table 12. 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

Additional Robustness Tests for Section 5.4

Here we provide additional robustness tests of the baseline specifications (1) and (2), mentioned in Section 5.4 of the paper.

Alternate control samples – private and public NBFIs

We consider two additional control samples consisting of private (control D) and public (control E) NBFIs and examine the robustness of our Section 4.2 results. The private NBFIs are not eligible for capital infusion. Public NBFIs do not receive periodic government infusions like public sector banks; there were a few isolated capital infusions contingent on episodic crisis events in year 2018 and 2019. We present the annual (Table IA5) and quarterly (Table IA6) DiD regressions comparing the treatment sample with each of 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. We also implement PSM matched NBFIs as control samples (untabulated) and find that our results hold.

Alternate network risk variables

We consider alternate set of network variables and examine if the earlier capital infusion results hold. We consider two network risks 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. Fewer nodes with stronger connections imply 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. We use quarterly firm level data to estimate both measures and use them to implement the DiD specification (1) (Internet Appendix, Table IA7). DiD coefficients show that capital infusions lead to significant increase in the degree - or number of connections for each node - for the treated banks post infusion. Hence Section 4.2 results are robust to Degree measure of network risk. Betweenness centrality goes up significantly for all the firms post infusion and shows no incremental effect for treated banks.

Alternate definition of *Post* variable

We also 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 presents the results; 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 Model 5 regressions from Table 4 that include quarter and firm fixed effects (tabulated in Internet Appendix, Table IA9). We find that Table 4 results with respect to post-infusion effects on treatment banks still hold. In addition, we observe that large capital infusions result in significantly enhanced default risks for treated firms in the post-infusion period. Large capital infusions however have no incremental effects on systemic risks.

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).

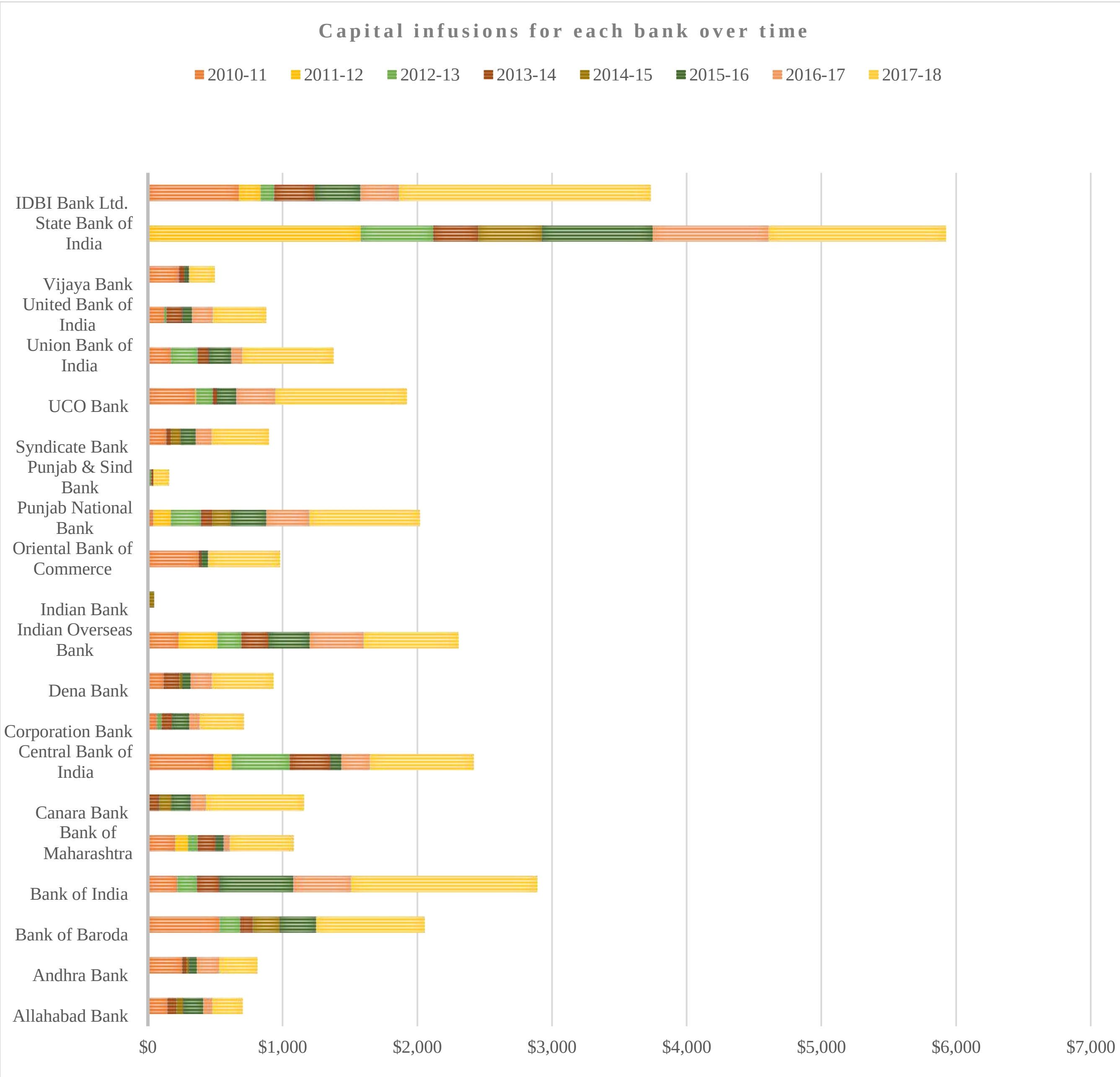


Figure IA2. Distribution of Government capital infusion into public sector banks 2008-2018

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).

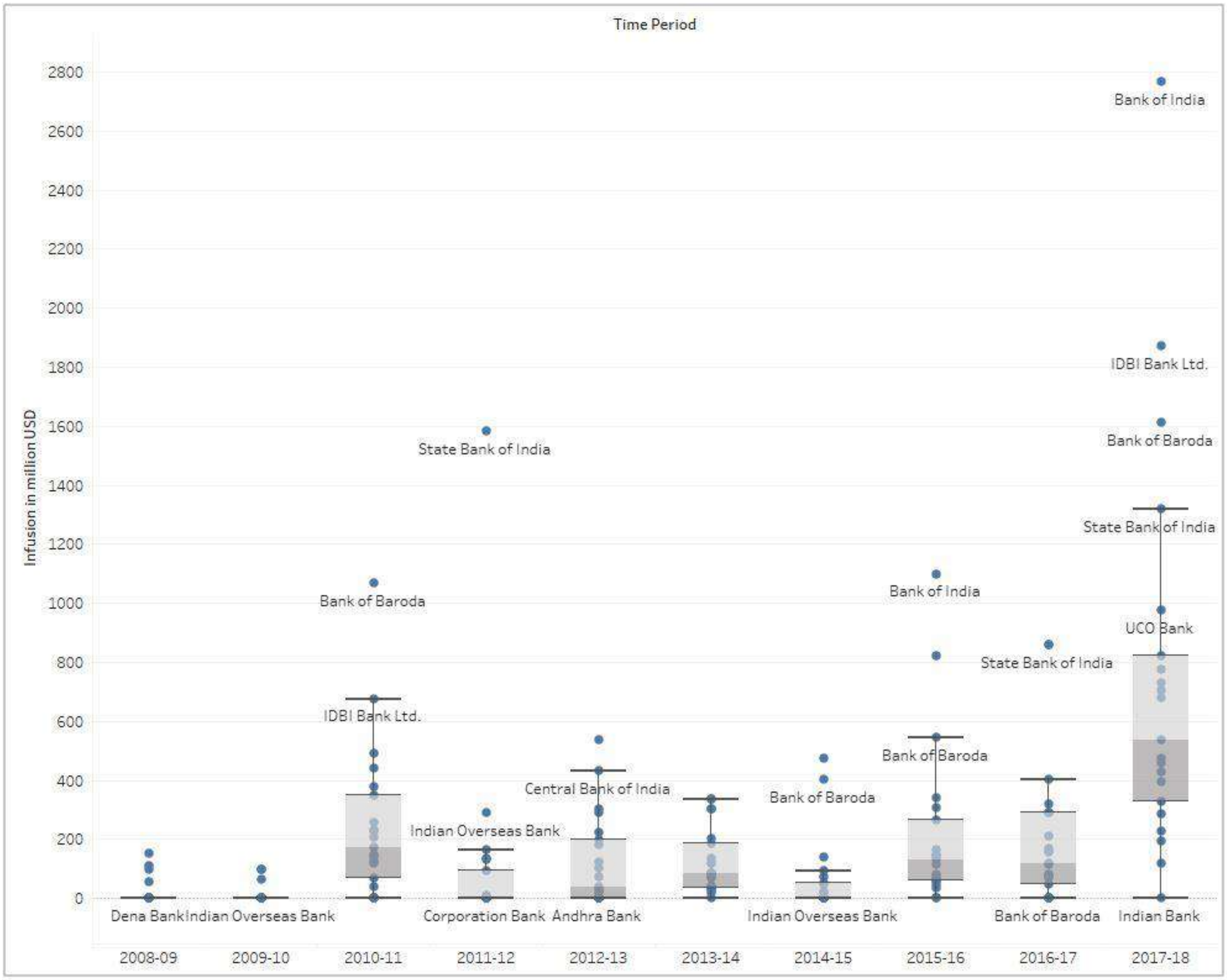


Figure IA3. Government capital infusion into public sector banks 2008-2018

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).

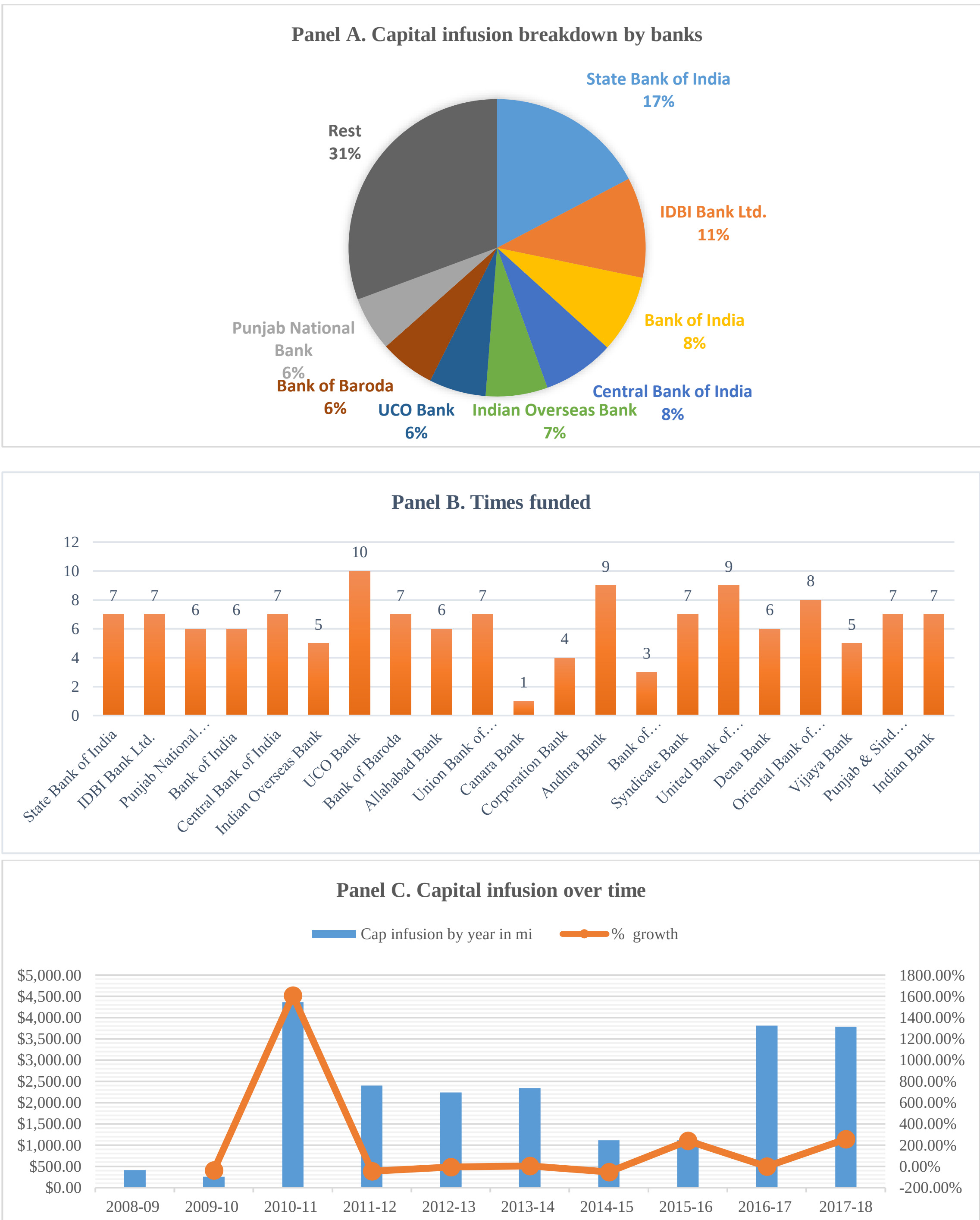


Figure IA4: Event window plots of Distance to Default (DTD) around capital infusion

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.

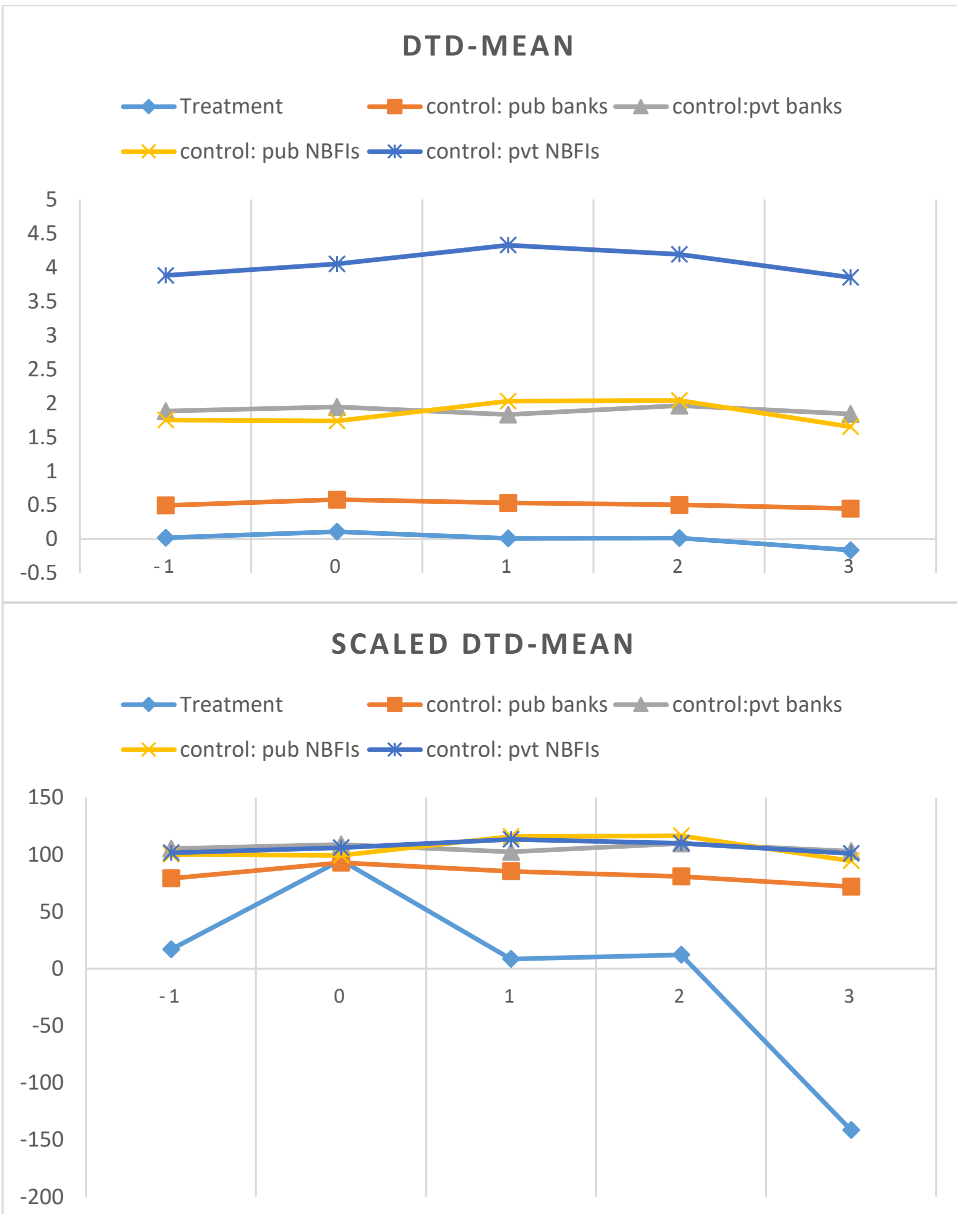
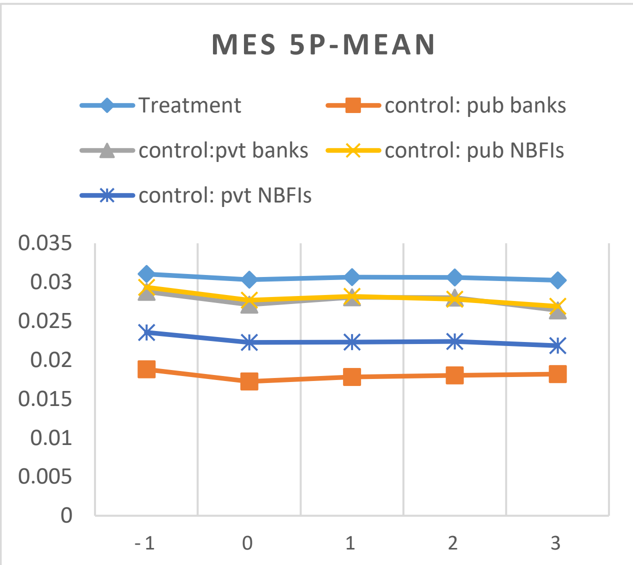
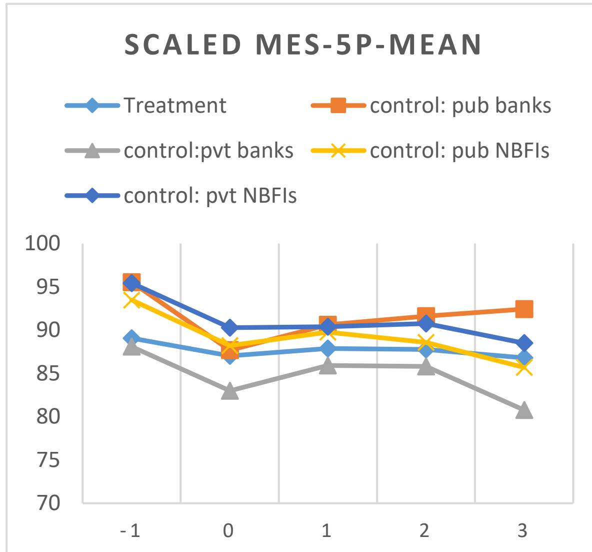
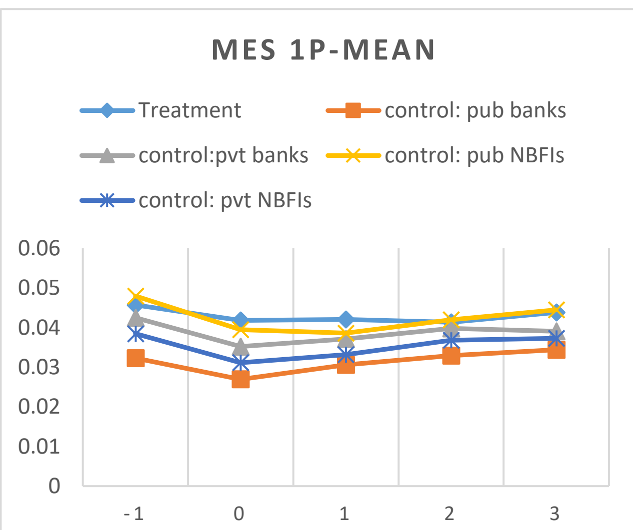


Figure IA5: Event window plots of the Margin Expected Shortfall (MES) measure of systemic risk around capital infusion

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.







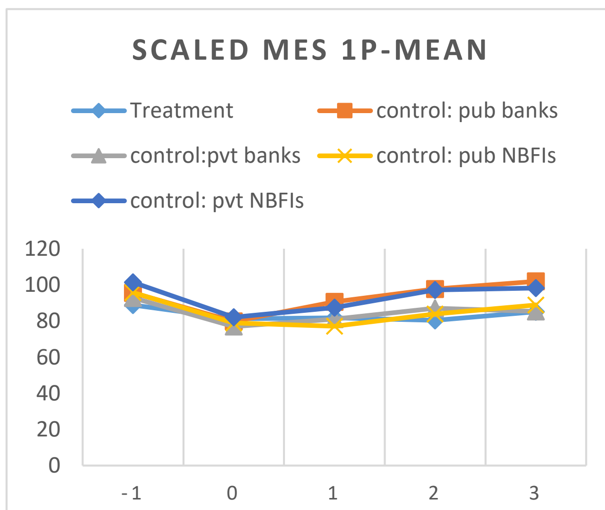
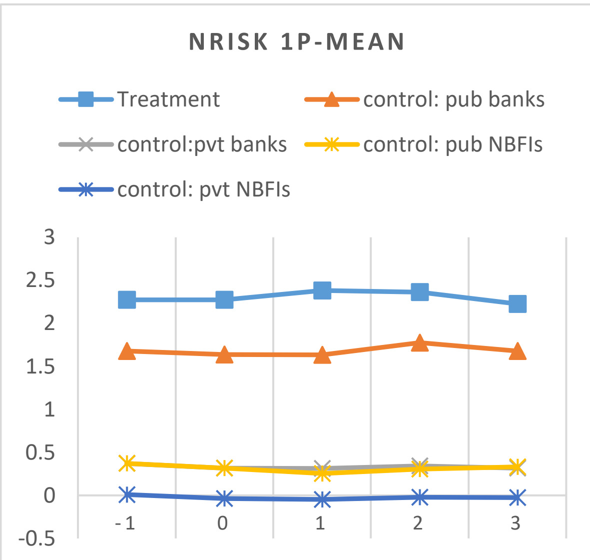
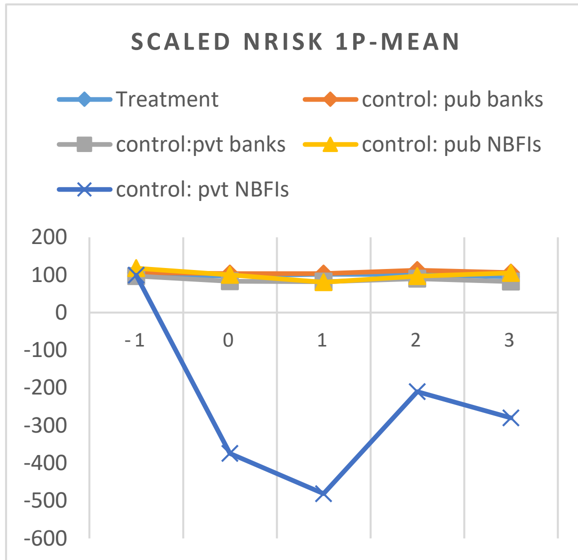
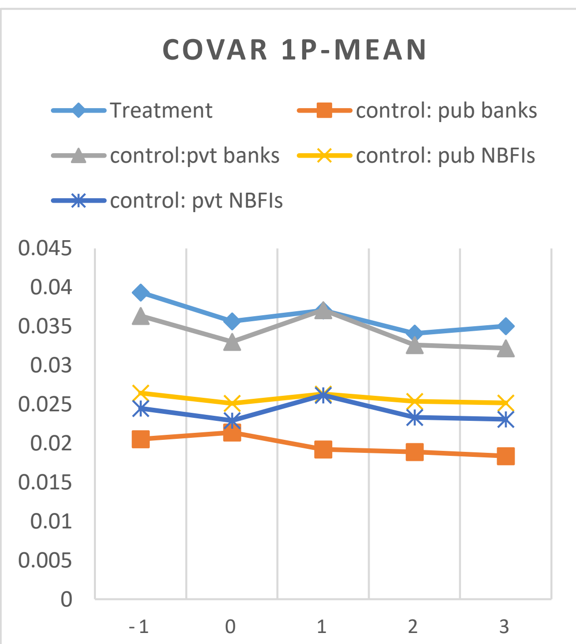


Figure IA6: Event window plots of NSRISK and CoVaR measures of systemic risk at 1-percentile level over the sample period 2008-2018

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.







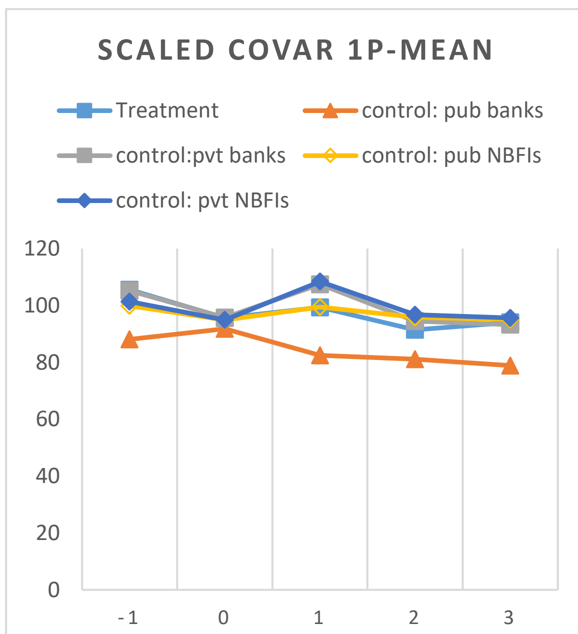
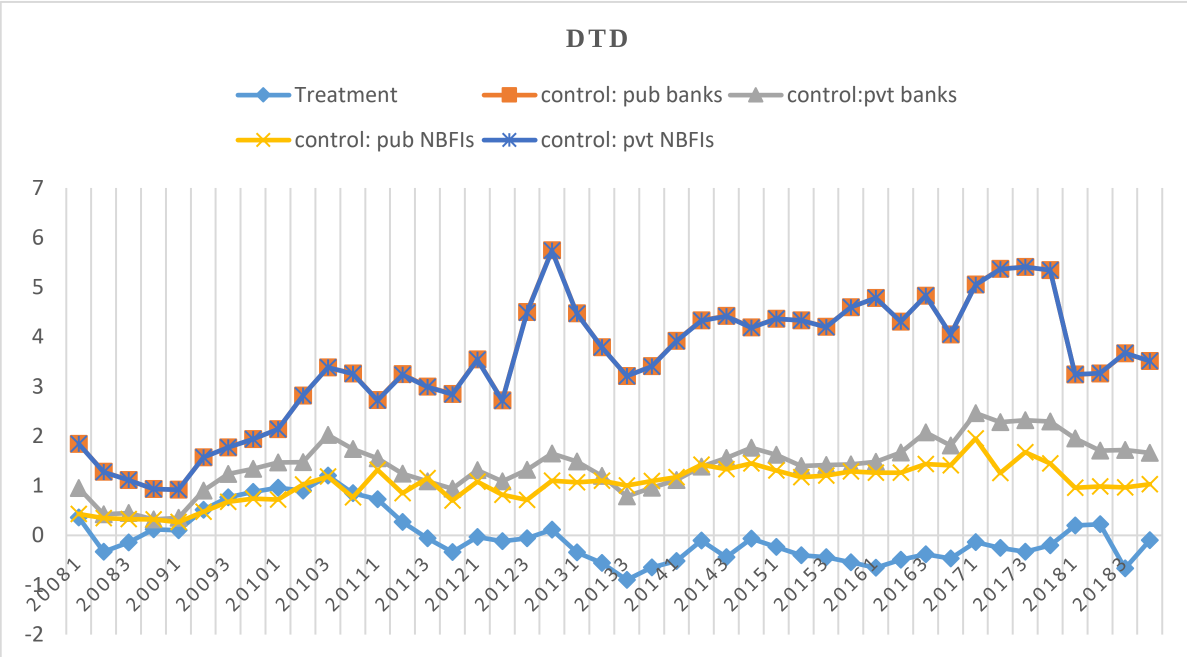


Figure IA7: Time series plots of Distance to Default (DTD) measure over the sample period 2008-2018

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.



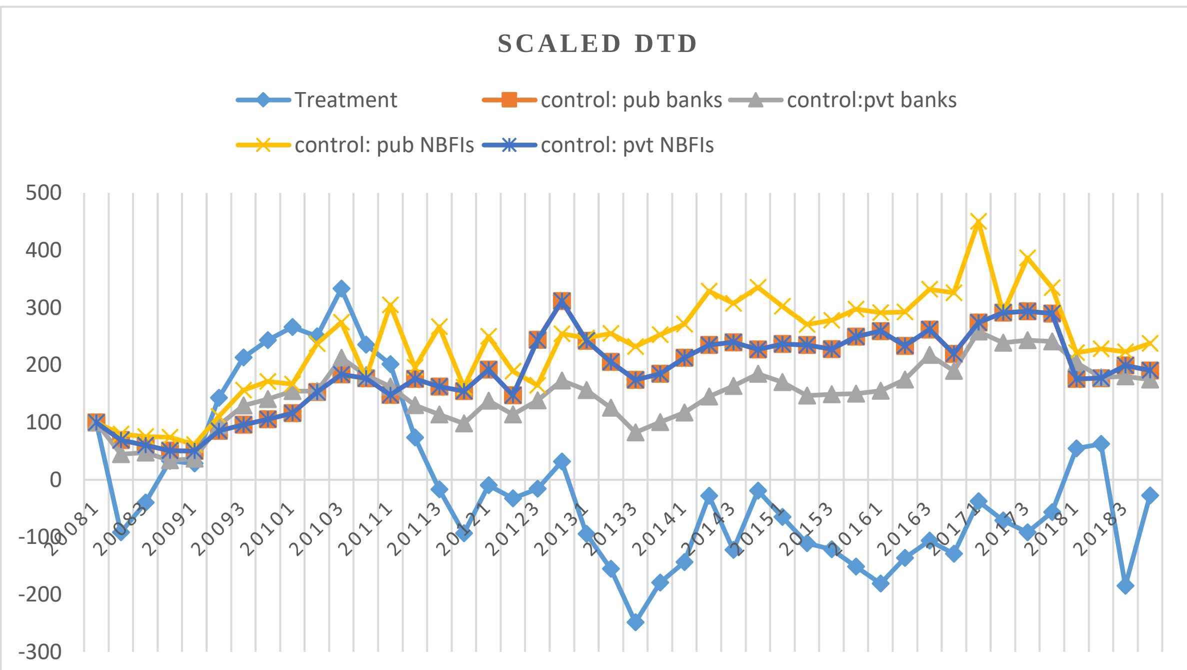


Figure IA8: Time series plots of the Margin Expected Shortfall (MES) measure of systemic risk over the sample period 2008-2018

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.

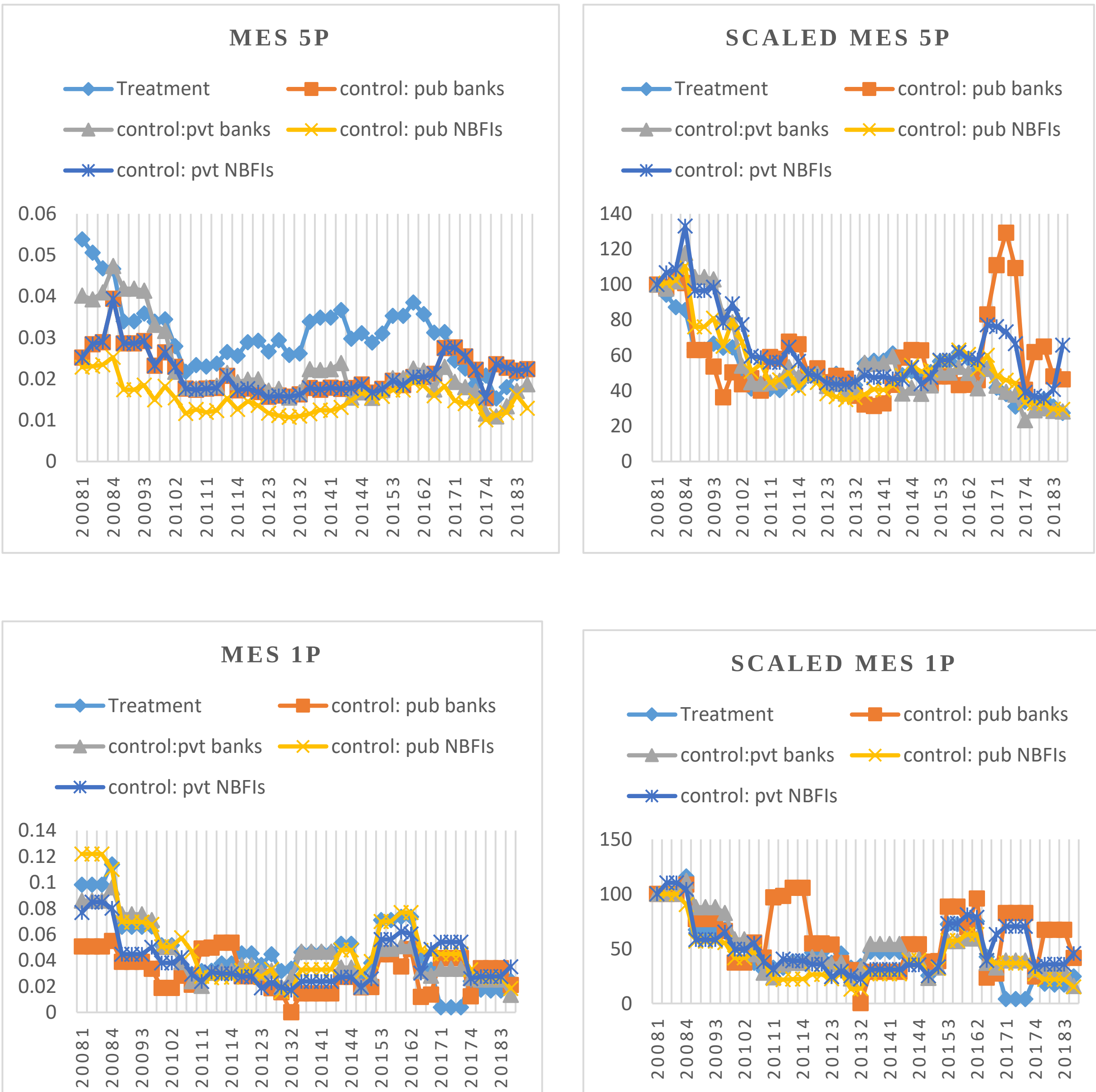


Figure IA9: Time series plots of the NSRISK and CoVaR measures of systemic risk at 1-percentile level over the sample period 2008-2018

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.

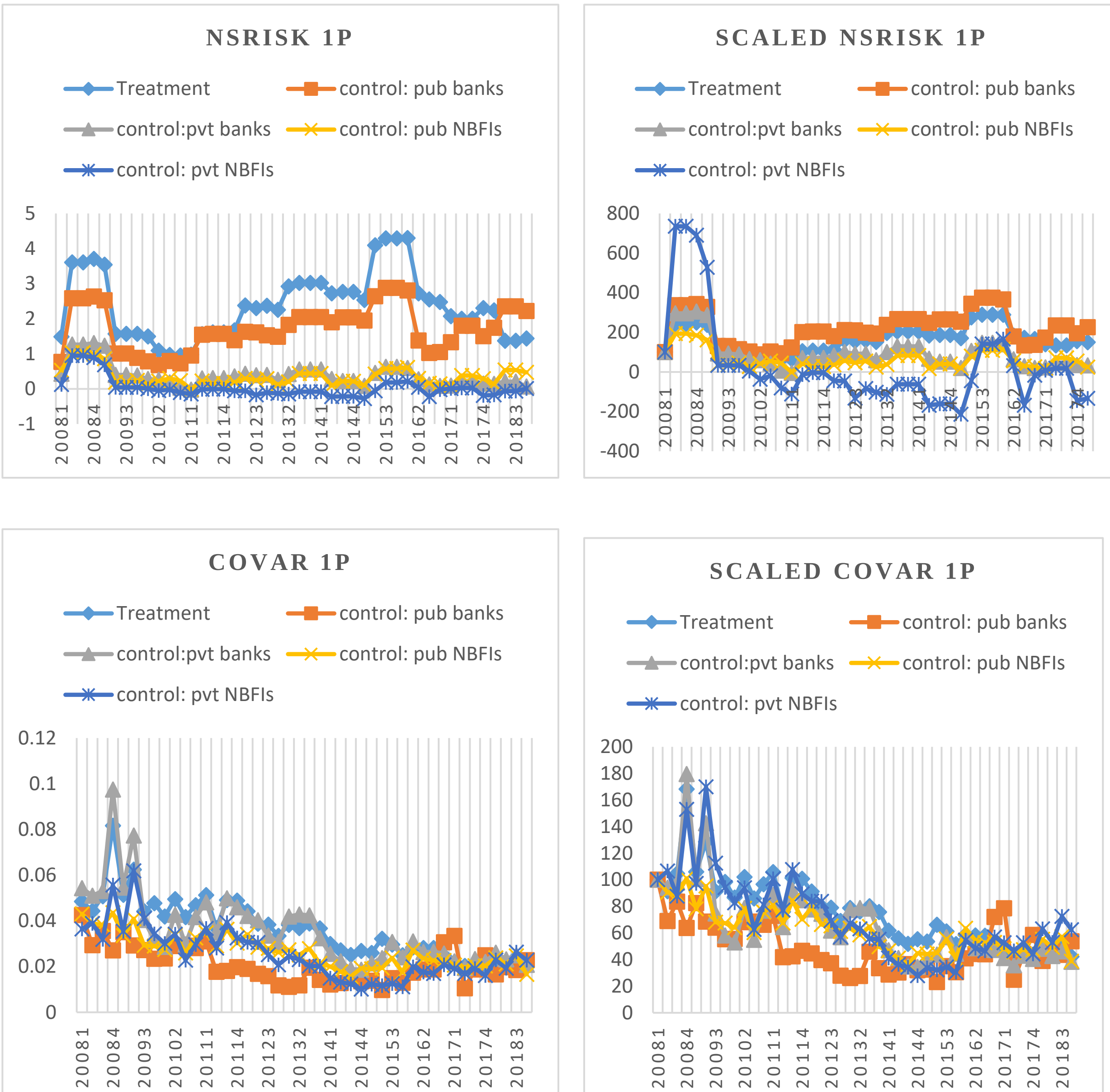


Table IA1. Univariate comparisons of Distance to Default (DTD) around capital infusion

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 1- percentile level for the treatment versus control sample private banks using the annual DiD specification (1) in the paper. 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)	(5)
VARIABLES			MES_5p		
Treatment Dummy	-0.150	0.316	0.290		
	(0.206)	(0.206)	(0.225)		
Post Infusion Dummy	-0.662***	-0.0903		-0.178**	
	(0.0885)	(0.0653)		(0.0665)	
Large Infusions	0.129	0.106	0.128		
	(0.241)	(0.232)	(0.244)		
Treatment x Post Infusion Dummy	0.500***	-0.0473	-0.136	0.293*	0.331**
	(0.159)	(0.148)	(0.132)	(0.153)	(0.157)
Treatment x Post x Large Infusions	0.131	0.163	0.126	0.105	0.111
	(0.206)	(0.179)	(0.215)	(0.128)	(0.125)
Constant	0.749**	2.902***	0.243	2.965***	-8.979**
	(0.309)	(0.318)	(0.297)	(0.332)	(3.627)
Observations	1,530	1,530	1,530	1,530	1,530
R-squared	0.427	0.540	0.405	0.677	0.705
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 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)
VARIABLES	NSRISK_1p		COVAR_1p	
Post Infusion Dummy	-19.94***		-0.259*	
	(4.743)		(0.150)	
Treatment x Post Infusion Dummy	48.48***	53.73***	0.629**	0.662**
	(14.27)	(15.09)	(0.248)	(0.266)
Treatment x Post x Large Infusions	-30.39	-35.45	-0.457*	-0.448
	(20.65)	(21.30)	(0.268)	(0.285)
Constant	226.6***	704.5**	2.899***	-7.079
	(32.80)	(342.7)	(0.706)	(6.679)
Observations	1,530	1,530	1,520	1,520
R-squared	0.716	0.747	0.478	0.502
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. contd.

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	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***		-2.332***		-18.07***		-0.0811		-0.167	
	(0.137)		(0.356)		(5.556)		(0.0658)		(0.146)	
Treatment x Post Infusion Dummy	0.333**	0.473***	1.321***	1.745***	41.82**	47.94***	0.114	0.133	0.478**	0.549***
	(0.151)	(0.168)	(0.480)	(0.497)	(15.32)	(16.35)	(0.147)	(0.162)	(0.174)	(0.184)
Treatment x Post x Large Infusions	0.0347	0.0825	-0.328	0.117	-26.80	-31.14	-0.148	-0.148	-0.0738	-0.0742
	(0.174)	(0.164)	(0.532)	(0.499)	(20.60)	(21.76)	(0.164)	(0.180)	(0.154)	(0.172)
Constant	2.816***	-30.74***	6.966***	-94.40***	232.0***	143.1	2.328***	-4.671*	2.233***	-2.103
	(0.680)	(7.092)	(1.532)	(20.06)	(36.26)	(329.7)	(0.291)	(2.602)	(0.616)	(9.840)
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	0.685	0.718	0.635	0.681	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***		-1.526***		-14.58***		-0.0805**		-0.0960	
	(0.107)		(0.285)		(4.372)		(0.0380)		(0.0862)	
Treatment x Post Infusion Dummy	0.222	0.280*	1.073**	1.247**	50.92***	54.92***	0.140	0.158	0.434***	0.454***
	(0.160)	(0.166)	(0.493)	(0.496)	(15.04)	(15.58)	(0.128)	(0.136)	(0.159)	(0.163)
Treatment x Post x Large Infusions	0.109	0.140	-0.205	0.0734	-30.52	-32.79	-0.154	-0.159	-0.0407	-0.0238
	(0.202)	(0.195)	(0.627)	(0.602)	(20.98)	(21.57)	(0.161)	(0.172)	(0.157)	(0.164)
Constant	2.921***	-18.02***	8.397***	-53.17***	263.0***	101.5	2.279***	-2.928	2.561***	-2.296
	(0.500)	(5.214)	(1.164)	(14.99)	(29.55)	(252.9)	(0.224)	(1.820)	(0.468)	(6.089)
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	0.757	0.773	0.632	0.671	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. 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)
VARIABLES	degree		between centrality	
Post Infusion Dummy	-0.154		8.433**	
	(0.230)		(4.128)	
Treatment x Post Infusion Dummy	0.992***	0.978***	5.360	3.102
	(0.345)	(0.343)	(4.594)	(4.646)
Treatment x Post x Large Infusions	-0.612*	-0.664*	-5.982	-5.599
	(0.356)	(0.357)	(4.604)	(4.368)
Constant	6.384***	30.72	18.25	2,584***
	(1.820)	(19.14)	(16.49)	(899.5)
Observations	1,536	1,536	1,536	1,536
R-squared	0.149	0.197	0.081	0.168
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 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	-0.0755		-0.312*		-0.234		0.178***		-0.239*	
	(0.0642)		(0.170)		(4.198)		(0.0413)		(0.123)	
Large Infusions										
Treatment x Post Infusion Dummy	0.358*	0.659***	1.296**	2.215***	25.53**	28.29**	-0.0551	0.0425	0.453***	0.501***
	(0.200)	(0.218)	(0.578)	(0.616)	(11.67)	(12.43)	(0.0832)	(0.101)	(0.159)	(0.169)
Treatment x Post x Large Infusions	0.0694	0.0801	0.315	0.396	2.314	1.385	0.0549	0.0548	-0.0803	-0.0815
	(0.269)	(0.249)	(0.767)	(0.714)	(19.87)	(18.25)	(0.0815)	(0.0883)	(0.178)	(0.180)
Constant	3.061***	-15.59***	8.162***	-46.59***	243.2***	622.0***	1.819***	-3.832**	3.094***	3.295
	(0.499)	(3.027)	(1.105)	(8.626)	(29.67)	(212.6)	(0.311)	(1.478)	(0.716)	(7.460)
Observations	1,491	1,491	1,491	1,491	1,530	1,530	1,520	1,520	1,536	1,536
R-squared	0.634	0.687	0.704	0.752	0.722	0.748	0.605	0.667	0.264	0.267
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

	(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	-0.428***		-0.947***		-25.76***		-0.0256		-0.403**	
	(0.126)		(0.329)		(6.568)		(0.0570)		(0.194)	
Large Infusions										
Treatment x Post Infusion Dummy	0.448*	0.875***	1.799**	3.067***	30.63**	38.77***	-0.0226	0.0402	0.653***	0.739***
	(0.238)	(0.258)	(0.690)	(0.716)	(12.64)	(13.78)	(0.116)	(0.139)	(0.177)	(0.189)
Treatment x Post x Large Infusions	0.0467	0.0732	0.284	0.394	1.562	-0.554	0.0670	0.0754	-0.0307	-0.0303
	(0.269)	(0.257)	(0.763)	(0.732)	(18.85)	(18.07)	(0.0875)	(0.0943)	(0.172)	(0.171)
Constant	3.408***	5.665**	9.289***	3.417	272.5***	602.1***	1.174**	6.336***	2.931***	-0.641
	(0.575)	(2.627)	(1.387)	(5.415)	(37.68)	(201.6)	(0.487)	(1.485)	(1.074)	(4.283)
Observations	1,085	1,085	1,085	1,085	1,113	1,113	1,105	1,105	1,118	1,118
R-squared	0.637	0.684	0.713	0.757	0.734	0.751	0.615	0.657	0.276	0.281
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	-0.942***	-0.935***	-1.022***	-2.559***	-2.539***	-2.802***	-12.54**	-12.71**	-13.49***	-0.365***	-0.361***	-0.383***	-0.200	-0.183	-0.214
	(0.180)	(0.180)	(0.188)	(0.462)	(0.461)	(0.479)	(4.688)	(4.922)	(4.378)	(0.0701)	(0.0711)	(0.0655)	(0.204)	(0.206)	(0.210)
Treatment x Post Infusion Dummy	0.260	0.260	0.391**	1.159**	1.162**	1.560***	29.71***	30.30***	30.15***	0.101	0.0951	0.155	0.487**	0.451**	0.495***
	(0.164)	(0.166)	(0.146)	(0.497)	(0.501)	(0.433)	(10.58)	(10.99)	(9.798)	(0.118)	(0.119)	(0.104)	(0.185)	(0.181)	(0.159)
Treatment x Post Large Infusion-Assets Ratio Dummy	0.586***			1.768***			8.698			0.0932			0.122		
	(0.184)			(0.559)			(18.32)			(0.124)			(0.190)		
Treatment x Post Large Infusion-Deposits Ratio Dummy		0.558***			1.676***			6.839			0.102			0.204	
		(0.178)			(0.547)			(17.78)			(0.135)			(0.177)	
Treatment x Post Large Infusion-Tier 1 capital Ratio Dummy			0.552*			1.630*			17.16			-0.110			0.228
			(0.301)			(0.853)			(22.98)			(0.133)			(0.168)
Constant	14.70***	14.38***	15.70***	26.73***	25.80***	29.72***	533.2***	530.4***	563.8***	8.245***	8.186***	8.109***	1.665	1.508	2.058
	(3.320)	(3.252)	(3.489)	(7.045)	(6.854)	(7.618)	(149.9)	(149.4)	(152.4)	(1.253)	(1.273)	(1.256)	(3.083)	(3.101)	(2.923)
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	0.689	0.688	0.687	0.753	0.753	0.751	0.749	0.749	0.749	0.669	0.669	0.669	0.270	0.271	0.271
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