Do Government Guarantees Help Financial Stability? Evidence from an Emerging Market

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Abstract

While government led bank capital infusions in US and other developed markets have been usually contingent an external shock or crisis episode, India presents a unique setting where significant capital infusions happen regularly "every year" to stabilize the weak balance sheets of the public sector banks. Do such repeated government sponsored bank capital infusions lower the financial risks and improve the financial stability? We shed light on the question through the through the lens of *repeated capital infusions* in an emerging market. Based on the exhaustive sample of capital infusions by Government of India into the public sector banks for the period 2008-19, we find no unequivocal evidence that capital infusions lower systemic risks for the banks. While capital infusions help lower the network risks, they are associated with significantly higher capital shortfall, signaling a moral hazard problem where treatment banks likely take on more risky investments. However, *larger* infusions help overcome the capital shortfall constraints, but significantly increase the network risks across the banks. Our results highlight the regulatory trade-offs in providing capital infusions to the banks. To the best of our knowledge, this study contributes to the literature by providing the first comprehensive study of how repeated government capital infusions impact *financial stability* in the context of an emerging market.

Keywords: government guarantees, capital infusions, financial stability, systemic risk, default risk, emerging markets,

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Do Government Guarantees Help Financial Stability?

Evidence from an Emerging Market

1. Introduction

The relationship between government guarantees to banks and financial stability has been the subject of intense debate since the global financial crisis (Allen et al., 2015; Allen and Gu, 2018).[1] The post-GFC (i.e. 2010-2018) period and more recently Covid induced global financial compression have witnessed significant interventions in the form of explicit or implicit government guarantees, recapitalizations, and loans in countries around the world. The evidence from the Capital Purchase Program (CPP) related to the US government sponsored Troubled Assets Relief Program (TARP) shows that capital infusion significantly reduced contributions to systemic risk, particularly for larger and safer banks, and those in better local economies (Berger et al., 2020).

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. Do such repeated government sponsored bank capital infusions lower the financial risks and improve the financial stability? Our study addresses this question.

Extant literature finds *conflicting evidence* on the relationship between government guarantees and subsequent bank performance (Allen et al., 2015, Kelley et al., 2016; Acharya et al., 2018; Wilcox and Yasuda, 2019; Iyer et al., 2019). On one hand, *guarantees can increase firm value* by (a) reducing asymmetric information as better monitoring by governments can improve financing for corporates – 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 firm falls into Too big To Fail (TBTF)

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

category; and (d) providing a downside insurance (or put option) value to banks especially during crises periods.

On the other hand, *guarantees can have unintended adverse consequences*: (a) tendency to take on excessive leverage by firms; (b) moral hazard problems arising from increased risk taking by the borrower; (c) unproductive use of capital by the 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 tax payer. The ultimate effect of government guarantees is therefore an open empirical question.

In this paper, we shed light on this debate by studying the effect of government guarantees on improving financial stability and thereby averting financial crisis. Specifically, we ask, "Do government guarantees help lower the systemic risks and help financial stability?", and provide comprehensive evidence through the lens of *repeated capital infusions* in an emerging market. In particular, 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 at least three 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).

(b) 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 (including (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); and (v) Non-banking Financial company (NBFC) crisis, (2018-19)). Finally, global health shocks can amplify macro-financial instability and hence debt vulnerability for the local firms- e.g. Covid-19 shock led to $83 billion emerging market outflows in Mar, 2020 (source: IIF capital flows tracker, April, 2020); and

(c) 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; Olga et al., 2021).

We employ data on 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 2008-2019. The capital infusion data in turn is combined with multiple data sets on firm-level default risk and financial variables and aggregate risk variables (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 control samples that include public sector banks not receiving capital infusion, private banks, public NBFIs and private NBFIs. The treatment banks receiving government capital infusion have in general higher levels of default and systemic risks compared to the control banks and Financial Institutions (FIs). The time series plots imply that treatment sample banks have far higher implicit default and systemic risks compared to control samples, while public and private NBFIs exhibit higher default and systemic risks from 2016 onwards.

Univariate Difference in differences (DID) analysis shows that the default risk for treated banks only increases following capital infusion compared to the other control samples. The default risk rises significantly for treated banks versus control FIs up to three quarters post-infusion. At the same time, the impact of capital infusion on systemic risk of the public sector banks is not significantly different from the control samples. Therefore, univariate results show no support implying reduction of default or systemic risks post infusion for the treated banks.

We next conduct robust difference-in-difference regressions that reveal several effects.

a) We find strong evidence of network effects following capital infusions. In particular, capital infusions to public banks are followed by reduction in risks for control samples - default and capital shortfall risks for rest of the public banks and default risks for other FIs - not receiving capital infusions over the following two to three quarters.
b) Regressions also show that capital infusions are associated with decreases in default and network risks for the treated banks. However, capital infusions are related to significant increases in capital shortfall risks. This implies that while capital infusions help lower the default and network risks, they are associated with significantly higher capital shortfall, signaling a moral hazard problem where treatment banks take on more risky investments.
c) Further examining the effect of larger sized infusions, we find that larger infusions help treated banks overcome the capital shortfall constraints, yet significantly increase the network risks.

The results are robust to alternate control samples, credit risk (PD, PD slope and DTD), systemic risk (NSRSIK, CoVaR and Network risk) and capital infusion measures, and Placebo tests (Appendix A defines all the variables). Our results therefore highlight the "regulatory trade-offs" in providing capital infusions to the banks.

We also examine stress periods characterized by significant jump in capital infusions. Specifically, we consider thee years where that total capital infusions registered significant increases: 2010-11 (1576%), 2015-16 (256%) and 2017-18 (260%), where the percentage numbers capture respectively the percentage increase in capital infusion amounts compared to the previous year. DID regression show that capital infusion during stress periods can help mitigate default and systemic risks overall for the financial institutions by lowering the capital shortfall and network risks, but can lead to increased tail risk exposure of the overall market (CoVaR). We also find additional risks arising from possible moral hazard driven risk taking due to accretion of non-performing loans.

We further study the channels through which capital infusion affect the risks. Capital infusion can be beneficial in reducing credit and systemic risks for stronger banks that have high valuations (market to book), high deposit capital (deposits to assets), strong performance (ROE) and low risks (low loans to assets). Similarly, our findings show that certain high ex ante risk firms also benefitted. In particular, we observe reduction in credit, capital shortfall and network risks for smaller banks (total assets), and those with high interest commitments (low interest coverage ratios). Low Tier 1 capital banks also benefit from capital infusions as they experience lower default and network risks. However we find that larger infusions in above settings can exacerbate default and network risks, and in some cases increase market tail exposure i.e. CoVaR risks.

Finally, we examine if capital infusions help lower aggregate risks. We find that aggregate PD spreads become negative post-infusion implying that aggregate default risk of the treatment firms' decrease compared to the control sample. There is, however, no evidence to show that infusions are related to decreases in aggregate systemic risk measures.

Based on the exhaustive sample of government capital infusion by Government of India into the public sector government banks for the period 2008-19, we find no unequivocal evidence that capital infusions persistently lower systemic risks for Indian banks. In fact, banks receiving capital infusions have consistently been risky throughout the sample period, and capital infusions have not necessarily permanently attenuated the underlying capital shortfall or network risks. The emerging market results stand in contrast to the U.S. market findings. For e.g. Berger et al. (2019) show that US Troubled Assets Relief Program (TARP) significantly reduced contributions to systemic risk, particularly for larger and safer banks, and those in better local economies.

Overall, our study contributes to better understanding of the role of government guarantees in attenuating the 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).

The results from our paper have three main policy implications: *first*, while capital infusions help lower default risks of the recipient banks, policy makers face 'regulatory trade-offs' with respect to mixed effects on systemic risks, as they need to balance the capital shortfall versus network risks. Capital infusions in general lead to lower network risks but higher capital shortfall risks by banks, arising from possible moral hazard concerns. Large infusions are therefore needed to lower capital shortfall risks but they can set off higher network risks. *Second*, during stress periods, policy makers face regulatory challenges as capital infusions in general can help lower capital shortfall, CoVaR and network measures of systemic risk; however, 'large' infusions can increase such risks. *Third*, capital infusions benefit strong as well as weak banks by lowering their credit and systemic risks. Weaker banks include smaller banks, and banks with onerous interest commitments and adverse tier-1 ratios, and hence capital infusions need to be applied to them without exacerbating the moral hard problems.

Our analysis and discussion proceed as follows. Section 2 summarizes the related literature and provides testable hypotheses. Section 3 describes the data and details of the sample construction. Section 4 presents the univariate analysis and results. Section 5 presents the multivariate DID regression tests, and Section 6 provides additional robustness tests of the regressions. Section 7 studies the channels through which capital infusions may affect the underlying risks. Section 8 examines the effects of capital infusions on aggregate level risks. Section 9 concludes.

2. Background literature and testable hypothesis

Extant theoretical literature has examined the valuation of guarantees (Merton, 1977), and the effect of government guarantees on the resolution of underlying firm and aggregate risks in an equilibrium or game theoretic setting The government guarantees imply trade-offs for the policy makers as, one hand, they reduce the probability of a bank run, while, on the other, they increase the probability of a sovereign default. The latter erodes the guarantee's credibility and thus its effectiveness ex ante. By setting the guarantee optimally, the government balances these two effects in order to minimize expected costs of crises (Königa et al., 2014).

Government guarantees also increase the implicit moral hazard and hence the risk taking behaviour of the financial institutions. Gete and Zecchetto (2017) analyze the removal of the credit-risk guarantees provided by the government-sponsored enterprises (GSEs). Cordella et al. (2017) infer that greater guarantees increase risk taking (moral hazard) when informed investors hold a sufficiently large fraction of liabilities. Allen et al (2018) show that guarantees are welfare improving because they induce banks to improve liquidity provision, although that sometimes increases the likelihood of runs or creates distortions in banks' behavior. Leonello (2018) show that government guarantees emerge as a key channel linking banks' and sovereign stability, even in the absence of banks' holdings of sovereign bonds. Ahnet et al (2019) show that the introduction of deposit insurance or wholesale funding guarantees induces excessive encumbrance and fragility.

Other theoretical work has examined the role of bail-ins versus bailouts. Keister and Mitkov (2017) study what macro prudential policies are useful when bailouts crowd out bail-ins. Clayton and Scnab (2020) show that a bail-in regime, which increases use of bail-in debt, is the optimal regulatory policy when liquidation is socially costly due to fire sales or bailouts, and hence bail-ins fully replace bailouts.

Several empirical papers have also examined the role of government guarantees. Chava et al. (2014) show that although primary bond yield spreads increase with an institutions' own tail risk (expected shortfall), systematic tail risk (marginal expected shortfall) of the institution does not affect its yields. Kelly et al (2016) provide evidence that a collective government guarantee for the financial sector lowers index put prices far more than those of individual banks lower and explains the increase in the basket- index put spread. Zhao (2017) shows that guarantee implicitly offered by a government positively Granger causes the sovereign's default risk in the Euro zone. Acharya et al (2018) find that bond credit spreads are sensitive to risk for most financial institutions, but not for the largest financial institutions in US and firms in the non-financial sectors.

Government guarantees can induce interconnections between sovereigns and domestic banks. Correa et al (2014) find that sovereign credit rating downgrades have a large negative effect on bank stock returns for those banks that are expected to receive stronger support from their governments. Fischer et al (2014) analyze the effect of the removal of government guarantees on bank risk taking. Bedendo and Colla (2015) show that an increase in sovereign credit spreads is associated with a statistically and economically significant increase in corporate spreads and, hence, firms' borrowing costs. Denk et al. (2015) find excessive bank credit is characterised by larger values of implicit guarantees and where bank creditors have not incurred losses in "bank failure resolution" cases. Mäkinen et al. (2018) uncover a risk premium associated with implicit government guarantees that is intimately tied to sovereign risk, suggesting that guaranteed banks inherit the risk of the guarantor.

Government guarantees can inject distortions into firm decisions. Gropp et al (2017) report that guaranteed banks keep unproductive firms in business for too long and prevent their exit from the market. Norden at al (2013) find that government capital infusions in banks have a significantly positive impact on borrowing firms' stock returns that is more pronounced for riskier and bank-dependent firms, and for those that borrow from banks that are less capitalized and smaller.

Other papers study the relationships between banks' valuations and government guarantees (Atkeson et al., 2018); cash holdings and state ownership (Chen, et al., 2018); banks earnings management behavior and government guarantees (Dantas et al., 2016); and shareholder-friendly corporate governance and systemic risk in the banking sector (Anginer et al., 2018).

Previous literature on the effects of government guarantees in the context of emerging markets is however sparse, and has examined (a) how government equity ownership in publicly traded firms affects the cost of corporate debt (Borisova et al., 2015); (b) risk spillovers in the connect of Greece from sovereign to corporate credit risk for firms that are bank or government dependent (Augustin et al., 2018); (c) effect of strength of country-level institutions on the relation between state ownership and the value of corporate cash holdings (Chen et al., 2018); (d) the impact of government guarantees on bank performance during a crisis in India (Acharya and Kulkarni, 2017); (e) 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); and (f) impact of implicit Chinese government guarantees on corporate investment and financing policies (Jin et al., 2020).

In this paper, focussing on India, an emerging market that underwent significant policy and regulatory changes, we undertake a comprehensive study of the impact of guarantees on financial stability.

Drawing on the extant literature, we posit six broad research hypotheses that form the bases for our proposed research:

- H1: Effect on default risk: Given that capital infusions help treated banks receive capital injections that can increase the tier-1, capital and lower the ex ante default risk of the underlying firm.
- H2: Effect on systemic risk: Government capital infusions help lower systemic risks of the government guaranteed banks and Financial Institutions (FIs) especially those for large firms.
- H3: Effect on firm level systemic risks: Given that systemic risk can be decomposed into default risk and network risks (Das et al, 2019), government guarantees help lower network risks of the underlying banks and FIs.
- H4: Effect on systemic risk during macro-stress periods: Government capital infusions help lower systemic risks of the government guaranteed banks and FIs especially during crisis periods.
- H5: Systemic Risk Channels: Government capital infusions help lower systemic risks of the government guaranteed banks and FIs through the effects of following channels: improving (i) the capital cushion and thereby lowering the leverage risk, (ii) bank portfolio diversification, (iii) growth potential of firms that can offset high distress risk; (iv) firm level cash holdings that absorb possible shocks, and (v) effective corporate hedging by banks that would lower any shocks to cash flows.
- H6: Effect on sovereign risk: Government capital infusions help lower aggregate sovereign default risk, especially during crisis periods (Correa et al., 2014, Augustin et al., 2018, Fratzscher and Rieth, 2019).

Overall, we extend the literature on government guarantees studying how capital infusions by government can influence the underlying systemic risk, which measures financial stability, and its two components default and network risks. The literature on impact of government guarantees on systemic risks is nascent, and we expect our proposed research make substantive contributions.

Ours to the best of our knowledge is the first study to examine the effect of government guarantees on financial stability using a comprehensive data on capital infusions.

3. Data and summary statistics

In this section, we briefly describe the rules surrounding capital infusion and the source of data for the same. We then describe the other databases used in this study. Next, we shed some light on our control and treatment samples. Finally, we introduce our systemic risk variables.

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 (in Crore -or 10 million- rupees) into public sector banks for the period 2008-2017. The C&AG data is available until 2017; we hand collect data from media sources for two more years and extend the total sample to 2019.

The capital infusion to banks is overall based on the expected Tier 1 capital shortfall, credit requirement in the economy and maintenance of 52% government stake in the banks (Source: Controller & Auditor General of India, Report No. 28, 2017). The process for recapitalisation of public sector banks (PSBs), as explained by the federal Department of Financial services (DFS) is summarized below: (1) Every year, the PSBs project their capital requirements for the year to DFS; (2) PSBs take into account 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). Appendix B, Figures 1, 2 and A1 present the data on capital infusions. The average level of capital infusion has trended up over time, while five banks viz., State Bank of India, IDBI, Punjab National Bank, Bank of India and Central bank of India have received largest capital infusions over the sample period and together account for 51% of the total capital infusions. Out of 21 recipients, each bank was funded on average six out of eleven years. Three years i.e. 2010-11, 2015-16 and 2017-18 witnessed significant increases in capital infusions.

[Insert Figures 1 & 2 here]

3.2. Databases

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

I. The CMIE (Centre for monitoring Indian Economy) Prowess database for data on firm-level financial variables and stock, both firm and index, returns.

Using CMIE, we extract a comprehensive list of financial firms publicly listed in the Indian market. We want firms whose common equity are traded on a primary exchange (BSE/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 non-banking financial institutions or 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 25 private NBFIs - we choose 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. Appendix C lists the names of treatment and various control sample firms used in our study.

[Insert Table 1 here]

Panel D of Appendix A describes the variables extracted from CMIE. We use several financial variables such as assets, leverage, EBIT, loans to assets, and liquidity. Idiosyncratic volatility is calculated as a moving historical average of daily 12-month market-adjusted firm returns.

II. RMI PD and DTD database

Next, we match the identified 76 financial firms against 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 the various measures of probability of default (PD) and distance to default (DTD). Panel B of Appendix A describes the variables sourced from RMI.

III. The Markit CDS data

In this step, we match the CMIE firms with firms from the Markit database. We collect issue-level CDS spread data on various maturities and the aggregate number of contributors. The Complete Restructuring (CR) clause is the most common clause for emerging markets. We, therefore, filter out other clauses (like modified restructuring clause) and only keep the CR clause. We only use US dollar-denominated and senior tier (i.e., senior underlying bond) CDS contracts. The intersection gives us only 14 financial firms consisting of nine public banks, three private banks, one each for private and public NBFIs) with CDS data. Since CDS contracts are mostly traded on firms with sizeable and extensive bond float, our sample picks up large firms with significant debt financing. We extract CDS spread data for 14 firms for the period 2008-2018. Panel B of Appendix A describes all the CDS variables.

IV. Additional firm-level firm level balance sheet data from Capital IQ, and market level data on India and global (U.S.) market factors are sourced from Datastream,

3.3. Control and treatment samples

To conduct our empirical analysis, we form yearly treatment and control samples. Specifically, in a given year, we form five different (i.e. one treatment and four control) samples:

A. Government public sector banks that receive capital infusions are denoted as Treatment firms. These are publicly traded government owned FIs receiving capital infusions.

B. Government public sector banks not receiving infusions are treated as the first control sample.

C. Private banks constitute the second control sample

D. Public NBFIs are treated as the third control sample.

E. Private NBFIs make up the final control sample.

There are overall 24 public sector banks that will be grouped into Treatment (A) and Control (B) samples. Control sample C consists of 16 private sector banks. Control sample D has 14 public NBFIs. The public NBFIs also are 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 are regarded by the Reserve Bank of India as being systemically important (Acharya et al., 2013). Control Sample E has 25 private NBFIs. We choose the top 25 private NBFIs by asset size. Given the small size of control banks and FIs we have, forming matched or propensity score based control samples is not feasible. Hence, we use the pooled control samples B, C, D and E.

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 has in general higher value of assets, leverage debt, cash flows and deposits, and lower market capitalization (differences are significant at 5% level or below) compared to C, D and E control samples (hence we include firm fixed effects in our subsequent regressions to control for firm differences). In rest of the dimensions, the samples seem to be comparable.

[Insert Table 2 here]

3.4. Measures of systemic risk and credit risk

In our study, we use four 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 CoVaR (Acharya et al., 2012; Brownlees and Engle, 2017; Adrian and Brunnermeier, 2016; and Berger et al. 2019). We also use a network risk based measure (Das, 2016; Das et al., 2019), which is additively decomposable and attributable to each FI, and further can be partitioned into credit and network risks.

The four measures of systemic risk capture three different dimensions. MES measures what happens to a firm's equity returns when the market is in distress. NSRISK builds on the MES measure by incorporating information on firm size and leverage, and hence addresses the too-big-to-fail dimension of systemic risk. CoVaR complements MES by measuring the incremental value at risk of the financial system when the firm is in distress (Adrian and Brunnermeier, 2016; Benoit etal, 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. Network-based measures directly model the underlying mechanics of the system by decomposing the systemic risk into network effect (connectivity) and individual bank risk. 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).

Credit risk is measured using two balance sheet risk measures i.e. distance to default (DTD) and probability of default (PD), sourced from the Risk Management Institute (RMI) of the National University of Singapore (NUS). The Credit Risk Initiative (CRI) at RMI uses the Forward intensity model based on Duan, Sun and Wang (2012), and Duan, and Fulop (2013). The forward intensity model is a reduced form model in which the PD is computed as a function of firm-specific and systematic factors. The DTD 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 (see NUS-RMI Credit Research Initiative Technical Report Version: 2016, Global Credit Review, Vol. 6 (2016) 49–132).

In addition to PD and DTD, credit risk is measured using secondary market CDS spreads. Sovereign risk is measured using first principal component of all individual CDS spreads, and the sovereign CDS spread (proxied by State Bank of India).

4. Univariate Tests: Effect of capital infusion on default and systematic risks (Hypotheses 1, 2 & 3)

4.1 Event study tests for credit risk

We first consider the evolution of different credit risk variables around the four-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 based on the overall sample capital infusions for all banks. We observe that treatment sample has the highest default risk levels compared to all control samples. The capital infusion event seems to have no clear reduction on the credit risk for treatment banks post-infusion. Interestingly, the 1-year PD measure seems to experience decline two quarters prior to the capital infusion date, implying an anticipation by the market of a possible infusion. The 1-year PD trends up gradually for next two quarters following infusion and then slowly drops. PD slope, measured as the difference between 5-year and 1-year PDs, signifying long-term market expectation of implicit default, displays a similar evolution. The control sample PDs show no major discernible effects, except that they all experience a minor drop in their risk one quarter prior to the capital infusion event and public NBFIS show increase in PD post-capital infusion date.

To better discern the event study effects, we present scaled PD values, where we normalize the starting values at the pre-event 2 quarter at 100 level and compare joint evolution of treated banks in comparison to control samples. We observe that the treatment sample PD and PD slope both increase up to 2 quarters post-capital infusion event and drop thereafter for one quarter. The public NBFIs experience marked increase in their PDs post public bank capital infusions far exceeding PDs of all other FIs. The treatment banks have relatively lower credit risk levels compared to public NBFIs that exhibit significant credit risk exposures. While private banks experience steady decline in PDs over the ± 4-quarter event window, the private NBFIs PDs trend up from quarter +3.

Overall, the public banks receiving capital infusions have highest default risk levels and show no significant decline in PDs compared to other control firms. Treatment bank PDs go up until quarter +2, followed by a marginal drop for one quarter. Public NBFIs exhibit significant growth in credit risk exposures on a scaled basis.

[Insert Figure 3 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 two- and three- quarter windows using unscaled or raw PD data. Panel A (B) presents the results for 1-year PD (PD slope). Each panel presents post- versus pre- infusion comparison for each sample and then compares such differences between treatment-control pairs. We see increase in PD for treatment sample for two- and three- quarter windows. This is in contrast to decline in PDs observed in control samples. We next compare the differences in post minus pre differences between treatment and control samples. The differences are all positive and significant implying that treatment banks experience significantly higher PDs post-capital infusions in comparison to control samples. PD slope shows similar results. The treatment banks show no significant difference between public-NBFIs consistent with the high-risk profiles of public shadow banks based on Figure 3.

[Insert Table 3 here]

In summary, univariate results imply that treatment banks have in general higher levels of default risk, which only increases following capital infusion compared to the other control samples. Difference in differences (DID) analysis indicates that default risk rises significantly for treated banks versus control firms for +2 and +3 quarters post-infusion. Our results show no support for Hypothesis 2 implying reduction of default risks post infusion.

4.2 Event study tests for systemic risk

We next evaluate the systemic risk evolution following capital infusions. We consider multiple systemic risk proxies i.e. NSRISK, CoVaR and Network risk measures and present their univariate event study results. NSRISK (Figure 4) shows that capital shortfall for treated banks is significantly higher in the event window compared to control firms. There is a marginal drop in 2 quarters following capital infusion. Scaled NRISK plots show that there is a somewhat steady increase in capital shortfall for control sample firms. Private and Public NBFIs display a dramatic capital depletion in the post window. Univariate DID tests (Table 4) show that unscaled capital shortfall for treatment bank worsens (increases) post infusion in relation to the control sample mainly at the +2 quarter interval, but the difference in difference tests show no significant changes in the treatment versus control firms.

[Insert Figure 4 & Table 4 here]

CoVaR results (Figure 5) show that treated banks have higher systemic risk levels compared to all other controls. 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 going up thereafter. CoVaR for all the control firms trend similarly post infusion showing possible network effects in the data. Public NBFIs show elevated CoVaR levels when the data is scaled. The Univariate DID tests in Table 5 however show that treated banks do not experience any unique significant changes in CoVaR compared to control samples.

[Insert Figure 5 & Table 5 here]

Finally, we present network risk results (Figure 6). We find that treated banks have higher network risk levels compared to all other controls. Capital infusion leads to increases in network risks until 2nd quarter post-infusion. There seems to be a drop on network risks for all the firms post-infusion showing possible network effects in the data. The univariate DID tests in Table 6 show that treated banks experience higher network risks up to 3 quarters post-infusion; however, the differences in differences do not show significant changes in network risk compared to control samples.

[Insert Figure 6 & Table 6 here]

In summary, our findings show that all the three systemic risk metrics for treatment firms are significantly higher compared to the control samples. Univariate DID tests however show that the impact of capital infusion on systemic risk of the public sector banks is not significantly different from the control samples. Overall, we find no evidence for Hypotheses 2 and 3 about the reduction of systemic risks.

4.3 Additional tests

We report results based on another balance sheet based credit risk measure i.e. DTD. Results are reported in the online Appendix (Figure A2 and Table A1). Event window plots show that DTD values are significantly lower across the event window implying default risk higher for treated compared to control firms. Public NBFIs have significantly higher default risk compared to Private NBFIs. Scaled DTD values however show that default risk of treated banks goes up initially for one quarter and then declines subsequently until the event date; thereafter DTD drops until quarter +3, showing increased default risk post-infusion. To better examine this, we consider the univariate differences in differences in DTD. DTD changes for treated banks becomes more negative, implying that DTD values go down and hence default risk goes up, post capital infusion. At the same default risk falls for control samples. The differences in differences between treatment and control samples are all negative and significant implying that treatment banks experience significantly higher default risk post-capital infusions. DTD results are therefore in line with trends in PD reported in section 4.1 showing that default risk increases post- infusion for treated banks.

We also present CDS data comparison across the samples (Figure A3 in the Internet Appendix). Average CDS spreads for treatment banks spike one-quarter prior to the infusion date. Following the capital infusion, CDS spreads sharply rise for one quarter followed by a drop the next quarter. The private banks, witness a large drop in CDS Spreads one quarter prior to infusions, also experience high CDS spreads followed by a drop three quarters post-infusion. Scaled CDS plots show that private banks and NBFIs experience higher CDS values compared to the treatment banks.[2]

We further examine how MES is impacted by the capital infusions (Figure A3 and Table A2 in the Internet Appendix report the results). Systemic risk is higher for treatment banks compared to control firms based on both MES 5th and 1st percentile plots. MES for treatment banks registers a

[2] We do not present CDS regressions because of limited data on the control sample firms.

decline one quarter before the capital infusion event and continues to drop for subsequent quarters. Control firms seem to experience a decline in their MES too post capital infusion showing possible network effects. Scaled plots show that private and public NBFIs have higher relatively MES levels following capital infusions. DID tests show that drop in MES for treatment sample is not significant compared to control samples. The only exception is when the control sample of private banks is used; these banks experience a greater decline in MES compared to treated banks following capital infusion. Overall, MES results are consistent with earlier evidence from Section 4.2.

5. Regression Tests: Effect of capital infusion on default and systematic risks (Hypotheses 1, 2 & 3)

5.1 Multivariate regressions

We first consider the following simple regression to understand the impact of capital infusion on our various risk measures:

$$(\textit{risk measure})_{i,,t} = \alpha_0 + \alpha_1 \textit{ post-infusion}_{i,,t} + \gamma_0 \textit{ (controls)}_t + \gamma_1 \textit{ firm fixed effects}_i + \gamma_2 \textit{ time fixed effects}_t + \textit{error}_{i,t} \tag{1}$$

where the dependent variable is a default or systemic risk measure. *Post-infusion*$_{i,t}$ refers to the 2-quarter period dummy post the government capital infusion date, and is defined at the firm-quarter level. The coefficient α_1 forms the basis for assessing the post- infusion effect. Control variables consist of local market (Nifty 50 index returns) and US (default spread, level and slope of term structure, VIX and TED spreads) factors. The regression includes firm and quarter specific fixed effects. We report Huber/White robust standard errors clustered by firm or bank level.

We also consider an alternate version of the model (1) below for only large capital infusions.

$$(\textit{risk measure})_{i,,t} = \alpha_0 + \alpha_1 \textit{ post-large infusion} + \gamma_0 \textit{ (controls)}_t + \gamma_1 \textit{ firm fixed effects}_i + \gamma_2 \textit{ time fixed effects}_t + \textit{error}_{i,t} \tag{2}$$

where *Post-large infusion*$_{i,t}$ is a dummy variable that takes a value of 1 for two quarters after a firm receives a large capital infusion (defined as an infusion that is above the median of the sample). While Model 1 focuses on the relationship between capital infusions and firm-level risk (default or systemic), Model 2 examines the effect of large capital infusions on the same risk factors.

Table 7 reports the results. We see that capital infusions are associated with significant decrease in PD and PD slope variables for the underlying banks. This implies that capital infusions are assessed positively in terms of credit risk for the underlying recipient banks for one-year (PD) and longer five-year (PD slope) horizon. However, interestingly, large capital infusions lead to significantly higher credit risks in terms of both level and slope of PD. While capital infusions are accompanied by lower credit risk estimates, larger capital infusions are associated with enhanced credit risks for the underlying banks.

[Insert Table 7 here]

To investigate this further, we implement model (1) and (2) regressions for different systemic risk variables. We find capital infusion has no effect on capital shortfall (NSRISK) or network risks, but leads to significantly lower CoVaR values, implying reduced incremental tail risks of the financial system conditional on a financial institution being in distress. We also observe that large capital infusions are associated with significantly higher levels of systemic risks in terms of all the three variables i.e. capital shortfall, CoVaR and network risks. Taken together, the results in Table 7 imply that large capital infusions are related to higher credit and systemic risk for the underlying banks, implying possible moral hazard actions by the recipients. Overall, we find that Hypothesis 1 holds in terms of capital infusion but not for larger capital infusions; we find no evidence for Hypotheses 2 and 3.

5.2 Difference-in-Differences (DID) regressions for default risk

We next implement following quarterly difference in difference (DID) specification to examine the hypothesis:

$$(\textit{risk measure})_{i,,t} = \alpha_0 + \alpha_1\,(\textit{treatment})_i + \alpha_2\,(\textit{post-infusion})_t + \beta_0\,(\textit{treatment X post-infusion})_{i,,t} + \gamma_1\,(\textit{controls})_t + \gamma_2\,\textit{firm fixed effects}_i + \gamma_3\,\textit{time fixed effects}_t + \textit{error}_{i,,t} \qquad (3)$$

where risk measure refers to a measure of default or systemic risk. Treated firm *treatment* is measured by *government capital infusion dummy*. *Post-infusion* refers to the two quarter window post the event date when the government capital infusion occurred. The coefficient β_0 forms the basis for each testable hypothesis about post- infusion effects. Treatment sample includes all government owned FIs receiving the capital infusion. Matched control sample consist of each of the control samples B, C, D and E described in Section 3. All regressions include controls (local and US market factors as in model (1) and (2)), and firm and year specific fixed effects and adjustments for heteroscedasticity using Huber/White robust standard errors, and clustered by bank level.

To better understand the effect of large capital infusions, we also consider a slightly extended version of specification (3) below

$$(risk\ measure)_{i,t} = \alpha_0 + \alpha_1\ (treatment)_i + \alpha_2\ (post\text{-}infusion)_t + \alpha_3\ (large\ infusion)_t + \beta_0\ (treatment\ X\ post\text{-}infusion\ )_{i,,t} + \beta_1\ (treatment\ X\ post\text{-}infusion\ \ X\ large\ infusion)_{i,,t} + \gamma_0\ (controls)_t + \gamma_1\ firm\ fixed\ effects_i + \gamma_2\ \ time\ fixed\ effects_t + error_{i,t} \qquad (4)$$

Here we include capital infusion size through a dummy (which classifies each infusion into high or low based on the median value of all the capital infusions for the full sample period). Together with β_0, we assess the coefficient β_1 to evaluate the effect of size capital infusion on the post-infusion risk measures.

Table 8 presents the DID regression results for model (4) for different PD (12 month PD and PD slope) measures. We only report results for 2-quarter post infusion date window using private banks control for brevity. Table 8 captures four different effects that are summarized here. First, there is a strong treatment effect (α_1 coefficient) in that treated banks have significantly higher future PD risks. Second, the capital infusions are associated with significant decreases in PD (α_2 coefficient), showing positive network effects associated with capital infusions, as they are positively received in the credit market for rest of the FIs. Thirdly, the β_0 coefficient is significantly negative implying that capital infusions lower credit risk for treatment banks. Finally, α_3 and β_1 coefficients together show that large capital infusions have respectively no significant standalone or incremental effects for treated firms.

[Insert Table 8 here]

In summary, the DID regressions results show reduction of credit risk following capital infusion for treated banks; however, larger capital infusions have no effect on default risk. Our tests overall imply evidence supporting Hypothesis 1 that capital infusions help lower ex ante default risk of the underlying firm.

5.3 DID regressions for systemic risk

We next present the DID regression results based on specification (4) and using the three systemic risk (NSRISK, CoVaR and Network) measures as the dependent variables. We consider alternate window sizes and control samples, and five and one-percentile threshold levels for NSRISK and CoVaR. 5 percentile As before, we only report results using only 5 % level for 2-quarter post window and private bank control for brevity (other results are consistent and not tabulated). Table 9 presents the results.

We document several key findings. The treatment effect (α_1 coefficient) shows significantly lower capital shortfall and higher network risk levels for the treated banks. The interaction effect (β_0 coefficient) is significantly positive for NSRISK implying that capital infusions increase capital shortfall for treatment banks; however, the interaction effect is significantly negative for network risks showing that capital infusions decrease the network risks. For large capital infusions, β_1 coefficient is significantly negative (positive) for NSRISK (network risk) implying that large capital infusions decrease the capital shortfall but increase the network risks. CoVaR shows no clear signs with respect to risk attenuation.

[Insert Table 9 here]

Collectively, the DID regressions results show that capital infusion can decrease (increase) network (capital shortfall) risks, but yet large scale infusions can respectively exacerbate or lower each of those risks for the recipients. While capital infusions lower the network risks, they could signal a moral hard problem causing treatment banks to take on more risky investments thereby increasing the capital shortfall. Larger capital infusions help overcome the capital shortfall constraints but may increase the network risks across the banks. Hence, overall there is a mixed evidence for Hypotheses 2 and 3.

6. Additional tests

6.1 Endogeneity and the effect of capital infusion on default and systemic risks

Endogeneity can arise from the fact that the risk measure and capital infusion are driven by common set of risk factors, and only specific type of banks would receive capital infusion. We however have a unique setting where only public sector banks receive capital infusion each year. In our implementation, therefore, the public sector banks together serve as the treated banks. On the other hand, there were three sets of control firms who do not receive any (or periodic) infusion. The private banks and NBFIs are not eligible for capital infusion. Public NBFIs also do not receive annual infusions like public sector banks; there were a few isolated capital infusions contingent on episodic crisis events in years 2018 and 2019. Given that only public sector banks received the capital infusions, the DID approach we followed benchmarking to the control firms would address any common shocks to the banks and the underlying credit and systemic risks.

We therefore consider Falsification tests to verify if the capital infusion effects go away if we alter the treatment dates. We set the pseudo capital infusion date as two quarters behind the actual date. We rerun model (4) regressions for all the risk measures. Table 10 presents the results for control sample of private banks. The capital infusion effects all disappear now. For the NSRISK- 5 percentile measure, the effect of capital infusion on expected shortfall seems to be somewhat anticipated two quarters ahead for large sized infusions. However, for more extreme tail risk NSRISK-1 percentile, the capital infusion effects disappear. In summary, our findings indicate that the effects on risk measures documented in section 5.2 and 5.2 are indeed related to the actual capital infusion events.

[Insert Table 10 here]

6.2 Alternate control samples

We consider alternate control samples and present the DID regressions comparing the treatment sample with each of three alternate control samples viz., public sector banks without infusion (control B), private NBFIs (control D), and public NBFIs (control E). We employ the DID specification (2) in the paper and the 2-quarter window post capital infusion date. All the earlier results documented in section 5.2 and 5.3 still hold. In addition, we find that large infusions result in higher PDs for the treatment firms showing the possible impact of moral hazard and risk taking among the banks. We present these results in Table 11.

6.3 Alternate measures of capital infusion

We check the robustness of our results using alternate measures of capital infusion. Capital infusions can be measured in size only 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, total deposits and tier-1 capital. This enables us to better control for recipient banks' size in terms of assets, deposits or tier-l capital. Results are presented in Table 12. We find that capital infusions help lower default risk as before but large capital infusion results in significantly enhanced default risks. While the effect of capital infusion on systemic risks is no longer prominent, large capital infusions exacerbate network risks among banks. In summary, large capital infusions can significantly increase default and network risks of the underlying banks.

[Insert Table 12 here]

6.4 Effect of capital infusion on systemic risk during macro-stress periods (Hypothesis 4)

We next examine the effect of capital infusions on systemic risks of the government guaranteed banks especially during the macro stress or crisis periods. We consider large percentage increase in yearly total capital infusion as a proxy for the macro-stress.

Here we tabulate the annual capital infusion values from Figure 1 and Appendix B in US dollar values (calculated using average exchange rate of 1 USD = Rs 72 for the same period).

2008-09	**2009-10**	**2010-11**	**2011-12**	**2012-13**	**2013-14**	**2014-15**	**2015-16**	**2016-17**	**2017-18**	**2018-19**
$263,888,889	$166,666,667	$2,794,027,778	$1,666,666,667	$1,738,472,222	$1,944,444,444	$970,833,333	$3,472,222,222	$3,472,222,222	$12,500,000,000	$2,881,527,778
	-36.84%	1576.42%	-40.35%	4.31%	11.85%	-50.07%	257.65%	0.00%	260.00%	-76.95%

The table shows that total capital infusions registered significant increases in three years: 2010-11 (1576%), 2015-16 (256%) and 2017-18 (260%), where the percentage numbers capture respective the year-to-year increase in capital infusion amounts. Year 2010-11, according to the Controller and Auditor General Report (Source: Controller & Auditor General of India, Report No. 28, 2017), was marked by capital infusions by Ministry of Finance without any external auditor scrutiny, and hence the initial requisitions by banks were sanctioned as requested. Year 2015- 16 witnessed multiple macro stress events including: policy shock: domestic (Demonetization, 2016), and regulatory shocks (Asset Quality Review, 2015-16; and Insolvency and Bankruptcy Code Implementation, 2016). Finally, year 2017-18, witnessed domestic banking frauds, (2017-18); and developing Non-Banking Financial company (NBFC) crisis, (2018-19)). We therefore define a new dummy, *stressyears*, which captures capital infusions only for the following three years:

- Year 2010-11 infusions: in March 2011
- Year 2015-16 infusions: in March 2016
- Year 2017-18 infusions: in March 2018

We accordingly consider the following augmented version of DID Model (4) with additional interaction terms involving stress years.

$$\begin{aligned}(risk\ measure)_{i,t} = {} & \alpha_0 + \alpha_1\,(treatment)_i + \alpha_2\,(post\text{-}infusion)_t + \alpha_3\,(large\ infusion)_t + \\ & \alpha_4\,(treatment\ X\ stress\ years)_i + \alpha_5\,(post\text{-}infusion\ X\ stress\ years)_t + \alpha_6\,(large\ infusion\ X\ stress\ years)_t + \beta_0\,(treatment\ X\ post\text{-}infusion\ )_{i,,t} + \beta_1\,(treatment\ X\ post\text{-}infusion\ X\ stress\ years)_{i,,t} + \beta_2\,(treatment\ X\ post\text{-}infusion\ \ X\ large\ infusion)_{i,,t} + \beta_3\,(treatment\ X\ post\text{-}infusion\ X\ large\ infusion\ X\ stress\ years\ )_{i,,t} + \gamma_0\,(controls\ )_t + \gamma_1\,firm\ fixed\ effects_i \\ & + \gamma_2\ \ time\ fixed\ effects_t + error_{i,t} \qquad (5)\end{aligned}$$

Table 13 presents the model (5) results. Capital infusions during the stress years, captured by the α_5 coefficient, imply overall significant reductions in credit risks and capital shortfall, and increases in the tail risk exposure of the overall market (CoVaR). However, focusing only on large capital infusions (based on the α_6 coefficient), those executed during the stress years are followed by significant decrease in capital shortfall, but increases in credit risks and tail risk exposures for the overall market. Next focusing on the DID terms (coefficients β_1 and β_3), we find two key results: (a) capital infusions during the stress years are followed by significant incremental reductions in capital shortfall and network risks for the treatment firms; and (b) compared to the large capital infusions during the sample, those in stress are followed by significant incremental increases in capital shortfall and network risks.

[Insert Table 13 here]

Closer examination by implementing the above regression separately for each of three-year windows (results untabulated), shows that most of the systemic risk results are driven by 2011 and 2018 infusions.

Collectively, our results imply that capital infusion during stress periods can help mitigate default and systemic risks overall for the financial institutions at the expense of raising tail risk exposure of the overall market (CoVaR). Furthermore, treatment banks witness incremental reductions in capital shortfall and network risks. However, there are risks arising from moral hazard inducing additional risk taking that can lead to higher capital shortfall and network risks. We therefore find mixed evidence for Hypothesis 4.[3]

6.5 Probit model for capital infusion

We also examine what determines the capital infusion for a public sector bank using the following probit model (results untabulated).

$$Prob\ (capital\ infusion)_{i,,t} = \alpha_0 + \alpha_1\ (treatment)_i + \alpha_2\ (financial\ variables)_{t-1} + \gamma_1\ (controls)_{t-1} + \gamma_2\ firm\ fixed\ effects_{i-1} + \gamma_3\ time\ fixed\ effects_{t-1} + error_{i,,t}$$

where the dependent variable is the dummy variable that identifies for a bank receiving capital infusion. We include the private banks as control firms. Financial variables include lagged values of total debt to common equity, total debt to total capital, deposits to total assets, interest coverage, and tier 1 ratio.

We also use two lagged 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

[3] Results from DID regressions of DTD measure show that capital infusions lower default risk for treatment firms consistent with PD results (Table A4 in the Internet appendix). MES regression results show capital infusions lower MES (Table A5 in the Internet appendix). However, after accounting for treatment firms' leverage, capital shortfall may actually increase as shown by the NSRISK measure.

textual index based on newspaper articles (Baker, Bloom and Davis, 2016). Both firm specific betas are calculated using a moving 3- year window. 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 whetted through external auditors. To the extent that the recipient banks can turn to capital markets for equity funding to shore up their Tier 1 capital, the capital infusions are not needed. Hence the probability of capital infusion critically can depend on the 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.

Our probit results show that lagged debt to equity (positively), deposit ratio (negatively) and Cash flow and policy betas (positively) have significant impact on the probability of receiving capital infusion.

7. Channels of Capital Infusion Effects on Default and Systemic Risks (Hypothesis 5)

We next examine the different channels through which capital infusions may influence the systemic risks. Capital infusions help lower systemic risks of the treatment banks by improving (i) the capital cushion and thereby lowering the leverage risk, (ii) bank portfolio diversification, (iii) growth potential of firms that can offset high distress risk; (iv) firm level cash holdings that absorb possible shocks, and (v) effective corporate hedging by banks that would lower any shocks to cash flows.

Accordingly, we examine the effects 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). We implement the DID specification (4) for capital infusion date using high-low bins formed by the median value of each financial variable. Results are presented in Table 14. 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 do not report the values if the respective coefficients are not significant.

[Insert Table 14 here]

We present our analysis below describing the role of each channel for capital infusion based on relevant financial proxies.

A. Capital cushion channel

Stronger Tier 1 capital and low leverage banks are more likely to have strong capital cushion.

- Tier 1 capital

  We observe that lower Tier 1 cushion firms benefit from capital infusions as they display improvement in default and network risks. Larger capital infusions to undercapitalized firms are however counter predictive by raising the underling default and network risks, signalling possible implicit moral hazard and risk taking motives. Conversely, capital infusions to higher Tier 1 firms are characterized by higher capital shortfall (NSRISK) and tail exposure risk (CoVaR).

- Leverage

  Low leverage banks experience greater reduction in default and network risks. Capital infusions to higher leverage banks are characterized higher NSRISK and CoVaR risks but lower network risks. Large infusions can lower short capital shortfall but increase network risks.

B. Bank portfolio diversification channel

Banks with larger loan portfolios are more likely to diversify their risks.

- Loan/asset ratio

  Low loan to asset firms benefit from capital infusions in terms of reduction of their credit and network risks, but can raise their NSRISK values. Large infusions to such firms however lower capital shortfall and CoVaR, and but lead to higher default and network risks.

C. Growth potential channel

Higher valuation banks are likely to have higher growth potential

- market/book ratio

Low market to book firms witness lower default risk, but higher market to book firms experience lower default risks both one-year and in the long term (5-year) and also lower systemic (i.e. NSRSIK, CoVaR and network) risks. Large infusions however lead to higher CoVaR and network risks.

D. Cash holdings channel

Firms with stronger interest coverage and deposit capital are better buffered and more likely to have higher cash holdings.

- Interest coverage ratio

Lower interest coverage firms with more onerous loan costs as percentage of earnings exhibit reduction in default, capital shortfall and network risks, and hence benefit form capital infusions. Larger capital infusions however to such low interest coverage firms lead to higher risk profiles by raising the underlying default, capital shortfall and network risks, implying moral hazard costs. .

- Deposits/total assets ratio

Low deposit ratio firms show decrease in default risks but higher capital shortfall and CoVaR risks. Stronger deposit ratio firms saw benefit from reduction in network risk but face higher capital shortfall; larger capital infusions however lead to higher work and lower capital shortfall.

E. Corporate hedging channel

Larger and profitable banks are more likely to undertake active corporate hedging activities.

- Total assets

Smaller firms experience reduction in default and network risks, and smaller increase in shortfall risk. Larger firms witness higher capital shortfall and CoVaR risks. Larger infusions lead to lower capital shortfall or CoVaR risks but higher network risks.

- Profitability (ROE).

Firms that are more profitable witness significant reductions in CoVaR and network risks. Less profitable firms experience higher default and capital shortfall risks. Large capital infusions to more profitable firms can lead to higher CoVaR and network risks

Overall, we observe that capital infusions have more significant impact on *ex ante low risk* FIs. Capital infusion can be beneficial in reducing credit and systemic risks for stronger banks that have high valuations (market to book), high deposit capital (deposits to assets), strong performance (ROE) and low risks (low loans to assets). Similarly, our findings show that certain high ex ante risk firms also benefitted. In particular, we observe reduction in credit, capital shortfall and network risks for smaller banks (total assets), and those with high interest commitments (low interest coverage ratios). Low Tier 1 capital banks also experience lower default and network risks. However, larger infusions can exacerbate default and network risks, and in some cases lead to higher market tail exposure i.e. CoVaR risks.

8. Effect of capital infusions on aggregate default and systemic risks (Hypothesis 6)

Finally, we study the impact of capital infusions on aggregate default and systemic risks. If capital infusions are government's(?) periodic funding mechanisms for weaker banks, do they help control the aggregate default and systemic risks? The analyses in the pervious sections mainly focused on form level risks. In this section, we examine the overall impact of capital infusions on aggregate level default and systemic risks. Widespread bank vulnerabilities may lead to expectations of rising defaults, increased financial vulnerability of the economy, increase in possible bailouts, higher future government subsidies, and deficits, and hence an increased sovereign 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. In figures 7, 8, 9 and 10, we consider raw and scaled time series plots respectively for PD, NSRISK, CoVaR and network measures over time for different treatment and control samples.

Figure 7 shows that PD and PD slope measures are significantly higher for treatment banks consistently over time. We also see that the treatment firm 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 (taper tantrum) and 2015-16 (rupee currency crisis). Scaled plots show that private as well as public NBFIs experience high default levels historically, and both private and public NBFIs exhibit elevated default risks far higher than treatment banks since April 2017.

[Insert Figure 7 here]

Next, we examine the systemic risk plots (Figure 8). Capital shortfall (NSRISK) levels are significantly higher for treatment banks compared to control firms, and experience large spikes during the 2015-16 crisis; raw and scaled plots for 5- and 1- percentile levels show that private and public NBFIs experience high capital shortfall towards the end of sample from 2017.

[Insert Figure 8 here]

CoVaR levels - showing the exposures of the market VaR to the tail risk of individual FIs - remain higher for the treatment banks when compared to the control firms (Figure 9). Control private banks and NBFIs show higher CoVaR levels during the global financial crisis; however, the treatment banks continue to exhibit higher levels. While the CoVaR levels have trended down over time, private and public NBFIs display highest level of CoVaR towards the end of the sample.

[Insert Figure 9 here]

Finally, Figure 10 shows that Network risk for treatment firms remains much higher than the control firms. Network risk spike during the 2007 financial crisis and 2015 currency crisis. Similar to other systemic risk plots, private and public NBFIs exhibit high CoVaR towards the end of the sample.

[Insert Figure 10 here]

In summary, the time series plots imply that treatment sample banks have high far higher implicit default and systemic risks compared to control samples, while public and private NBFIs experience higher default and systemic risks from 2016 onwards.

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

$$(aggregate\ default\ or\ systemic\ \ risk\ spreads)_{i,,t} = \alpha_0 + \alpha_2\ infusion\_index{*}\ two\ quarters\ post\ window\ + \\ +\ \gamma_0\ (controls)_t + \gamma_1\ time\ fixed\ effects_t + error_{i,t} \quad (7)$$

where aggregate default or systemic spreads refer to difference between mean risks of treatment and each control sample. We consider four risk measures PD, NSRISK, CoVaR and Network risks. The mean risks are obtained as the cross-sectional averages for each risk variable. We use two infusion indices i.e. Infusion index 1 is the infusion dummy that refers to the quarters where capital infusion takes place; Infusion index 2 is the large infusion dummy that reflects the quarters where large infusions (in terms of number and dollar value) take place. All regressions include controls (local and US market factors as in model (1) and (2)), and year specific fixed effects and Huber/White robust standard errors.

Table 15 presents the results using the private banks control sample. We find that aggregate PD spreads become negative post-infusion implying that aggregate default risk of the treatment firms' decrease compared to the control sample. There is, however, no evidence to show that aggregate systemic risk measures decrease post infusion. Hence, there is a partial support for Hypothesis 6.

[Insert Table 15 here]

9. Summary and conclusions

In this paper, we study the possible effect of government guarantees on promoting financial stability and diffusing financial crises in emerging markets. Based on the exhaustive sample of government capital infusion into the public sector government banks for the period 2008-19, we find that capital infusion can decrease systemic risks but large-scale infusions can exacerbate that risk for the recipients. Capital infusions are associated with decreases in network risk, but can lead to increases in capital shortfall risks. However, large-scale infusions help overcome the capital shortfall constraints but may increase the network risks across the banks. While capital infusions lower the network risks, they could signal a moral hard problem causing treatment banks to take on more risky investments thereby increasing the capital shortfall.

Capital infusion during stress periods can help mitigate default and systemic risks overall for the financial institutions by lowering the capital shortfall and network risks, but at the expense of contributing to tail risk exposure of the overall market (CoVaR), and possible moral hazard driven risk taking on their balance sheets. Capital infusion can be beneficial in reducing credit and systemic risks for stronger banks that have high valuations (market to book), high deposit capital (deposits to assets), strong performance (ROE) and low risks (low loans to assets). However, larger infusions can exacerbate default and network risks, and in some cases lead to increases in market tail exposure i.e. CoVaR 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 a large number of entities or institutions, and (c) has a ripple effect that endangers the existence of the financial system. 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 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 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	Refers to the pubic sector banks receiving capital infusion by the Indian government (in Crore -or 10 million- rupees) for the period 2008-2019. The C&AG data is available until 2017; we hand collect data for two more years and extend the total sample to 2019.
Post Infusion dummy	Refers to the two or three quarter period post-capital infusion
Large infusion dummy	Capital infusion size dummy variable to indicate if the capital infusion for a given bank is above (=1) or below (=0) the median value of all the capital infusion amounts for the total sample period 2008-2019.
Panel B: Credit risk variables (Sources: CDS data: Markit; DTD and PD data: Risk Management Institute (RMI) at the National University of Singapore (NUS); Equity market risk data: CMIE, Datastream-Worldscope)	
CDS spread	Quarterly 5-year CDS spreads aggregated from monthly data
CDS liquidity	The number of unique contributors for the 5-year CDS spreads (composite depth) at the end of the month aggregated into quarterly intervals.
CDS slope	The difference between monthly 10-year and 1-year CDS spreads at the end of the each quarter
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
Ivol	Idiosyncratic volatility (Ivol) calculated as volatility of a moving historical window of 12-month daily market adjusted firm returns
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 $SRISK = E[k(Debt + Equity) - Equity \vert crisis]$. *SRISK* is for each firm *i* in year *t* as follows: $SRISK_{i,t} = k.Debt_{i,t} - (1-k).(1-LRMES_{i,t}).Equity_{i,t}$, where *Debt* is the book value of debt, *Equity* is the market value of equity, and *k* is the prudential capital ratio set to 9% for Indian setting; *LRMES* is the long-run marginal expected short- fall computed as $\text{LRMES}_{i,t} = 1 - \exp(18 \times MES_{i,t})$. 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 $R_{m,t} = \alpha_{system \vert i} + \beta_{system \vert i} R_{i,t} + \beta_{system \vert t} M_{t-1} + \varepsilon_{i,t}$ 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 $CoVar_t^k = \hat{\beta}^k_{system \vert i} (\hat{R}^k_{i,t} - \hat{R}^{50\%}_{i,t})$, and denotes the change in the value at risk of the system when the institution's return is at the k^{th} i.e. 5^{th} or 1^{st} 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 (2020). We incorporate credit quality information into adjacency matrix –that is built using granger causality relations-, in order to compute a single systemic risk score. The score summarizes the level of systemic risk of the all banks, which in turn is decomposed into a specific banklevel contribution.
Panel D: Firm-level variables Annual data at the end of each financial year (i.e. April to March). (Source: CMIE, Datastream - Worldscope)	
Total assets	Total assets refer to sum of all current and non-current assets held by a company as on the last day of an accounting period
Total debt	Total liabilities of a company are the sum of all the resources deployed by it. It includes all sums it owes to the shareholders in the form of share capital and reserves & surpluses, all sums it owes to its lenders in the form of secured and unsecured loans and all current liabilities and provisions. It also includes deferred tax liability.
Net debt	NET DEBT is the difference between Total debt – Cash – Short-term investments

Ebit	EBIT refers to the profits before depreciation, interest, tax and amortisation.
Debt / ebit	Ratio of Debt to EBIT
Debt / book value of equity	Ratio of Debt to Book value of equity
Interest expense	Interest expense refers to the total cost of borrowed funds and the cost of raising borrowings of a company. It includes interest paid on both, long term as well as short term funds, financial charges paid to raise resources through financial instruments such as premium on redemption of debentures and discounts on commercial paper, etc., and expenses incurred by the company to raise deposits and debts. This data field covers the total cost incurred by a company on its borrowed funds. It is therefore used in the measurement of interest incidence, which is essentially the average cost of borrowing for companies
Interest coverage	Interest coverage refers to the ratio of EBIT to Total interest expense
Liquidity	Ratio of Total Debt to Paid up Equity capital
Deposits	Deposits refers to the sum of the outstanding values of a company’s long term and short term deposits.
Deposit ratio	Ratio of Deposits to Total Assets
Net cash flow from operating activities (ncfo)	This data field reports the amount of cash flow generated from operating activities, which is calculated, using the indirect method. To compute net cash flows from operating activities, non-cash charges in the income statement are added back to net income, and non-cash incomes are deducted. Since we want cash flows only from the main business activity, all non-operating incomes and gains are also deducted and all non-operating expenses and losses are added to net income. Further, cash inflow / outflow on account of changes in the working capital of the company are included.
Cash	Cash is defined as "aggregate monetary resources" held by an organisation on the last day of the accounting year. The constituents are: cash in hand, cash in transit, cheques and drafts in hand.
Cash / total assets	Ratio of Cash to Total assets
Net assets	Net assets is the difference between total assets and cash and marketable securities whereas Marketable securities are all securities held by the company which are traded on a recognised exchange or for which there are quoted market prices.
Cash / net assets	Ratio of NET ASSETS to TOTAL 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.
Loans/deposits	Ratio of Loans to Deposits.
Equity capital / total assets	Ratio of Equity capital to Total Assets
Return on assets (roa)	Ratio of company’s Net income (EBIT) to total assets
Capital expenditure (capex)	CAPEX is defined as the ratio of capital expenditure to sales
Book value of equity	Book value of Equity refers to the outstanding reserve plus the paid-up capital at the end of a year is considered for the calculation of book value multiplied by outstanding number of equity shares.
Market to book ratio	Ratio of Market value of equity to Book value of equity
Investment	Sum of the yearly growth in Plant property and equipment (PPE) plus growth in inventory plus R&D expenditure, all deflated by lagged book value of total assets
Market value of equity	Market value of equity refers to the product of no.of shares outstanding multiplied by adjusted closing price of the share at the end of the year

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.
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]
Debt/market value of equity	Ratio of Total Debt to Market value of Equity
Debt minus paid up preference capital /equity ratio	Ratio of the difference between Total Debt and Preference capital scaled by paid up equity share capital
Panel E: Local and Global market variables (Source: Datstream)	
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).

Appendix B: Government capital infusion into public sector banks 2008-2019

The table presents the Indian government yearly capital infusions (in Crore -or 10 million- rupees) into public sector banks for the period 2008-2019. (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**	**2018-19**
Allahabad Bank	-	-	670	-	-	400	320	973	451	1,500	4,844
Andhra Bank	-	-	1,173	-	-	200	120	378	1,100	1,890	2,019
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	2,354
Corporation Bank	-	-	309	-	204	450	-	857	508	2,187	2,555
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	8,247
Punjab & Sind Bank	-	-	-	-	140	100	-	-	-	785	-
Syndicate Bank	-	-	633	-	-	200	460	740	776	2,839	728
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 capital infusions by year	1,900	1,200	20,117	12,000	12,517	14,000	6,990	25,000	25,000	90,000	20,747

Appendix C: List of Treatment and control sample FIs

The table presents the list of treatment (public banks) and control (private banks and private/public NBFCs) sample FIs 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 NBFC
2	G I C Housing Finance Ltd.2008	Public NBFC
3	General Insurance Corpn. Of India2008	Public NBFC
4	Gujarat State Financial Corpn.2008	Public NBFC
5	Housing & Urban Devp. Corpn. Ltd.2008	Public NBFC
6	I F C I Ltd.2008	Public NBFC
7	L I C Housing Finance Ltd.2008	Public NBFC
8	New India Assurance Co. Ltd.2008	Public NBFC
9	P N B Gilts Ltd.2008	Public NBFC
10	P N B Housing Finance Ltd.2008	Public NBFC
11	P T C India Financial Services Ltd.2008	Public NBFC
12	Power Finance Corpn. Ltd.2008	Public NBFC
13	S B I Home Finance Ltd.2008	Public NBFC
14	Tourism Finance Corpn. Of India Ltd.2008	Public NBFC
15	Yule Financing & Leasing Co. Ltd.2008	Public NBFC

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

Figure I. Government capital infusion into public sector banks 2008-2019

The four exhibits below present the distribution of Indian government yearly capital infusions (in Crore -or 10 million- rupees) into public sector banks for the period 2008-2019. (Source: Controller & Auditor General of India, Report No. 28, 2017)

Figure 2. Distribution of Government capital infusion into public sector banks 2008-2019

The exhibit below presents the box-plots showing the distribution of Indian government yearly capital infusions (in Crore -or 10 million- rupees) into public sector banks for the period 2008-2019. (Source: Controller & Auditor General of India, Report No. 28, 2017)

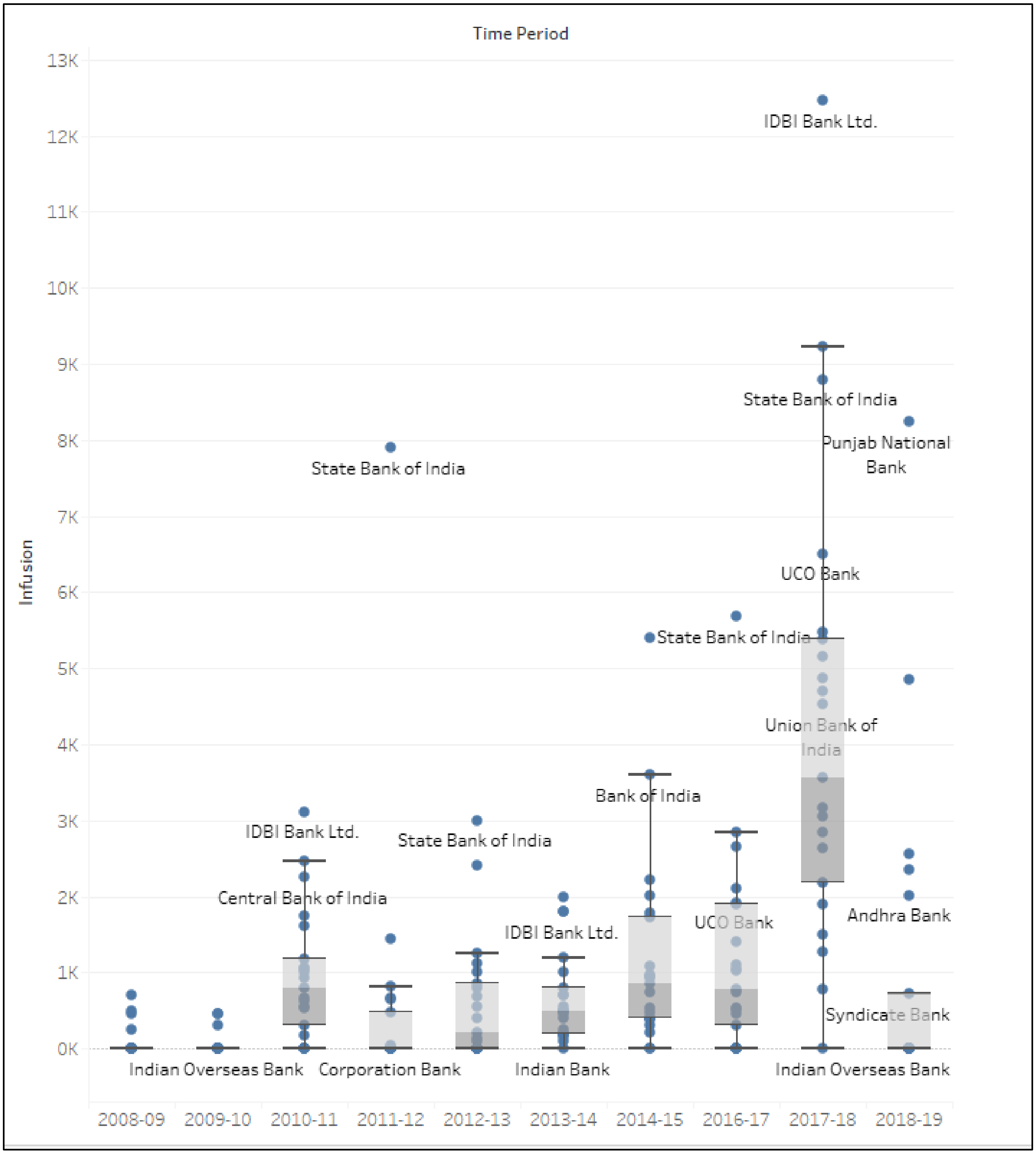


Figure 3: Event window plots of Probability of default (PD) around capital infusion

We present quarterly mean plots (both raw and scaled) of 12 month 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 ± four quarters around the event (period zero), which denotes the capital infusion date. All the variables are defined in Appendix A.

Figure 4: Event window plots of the standardized Expected Capital Shortfall (NSRISK) measure of systemic risk around capital infusion

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

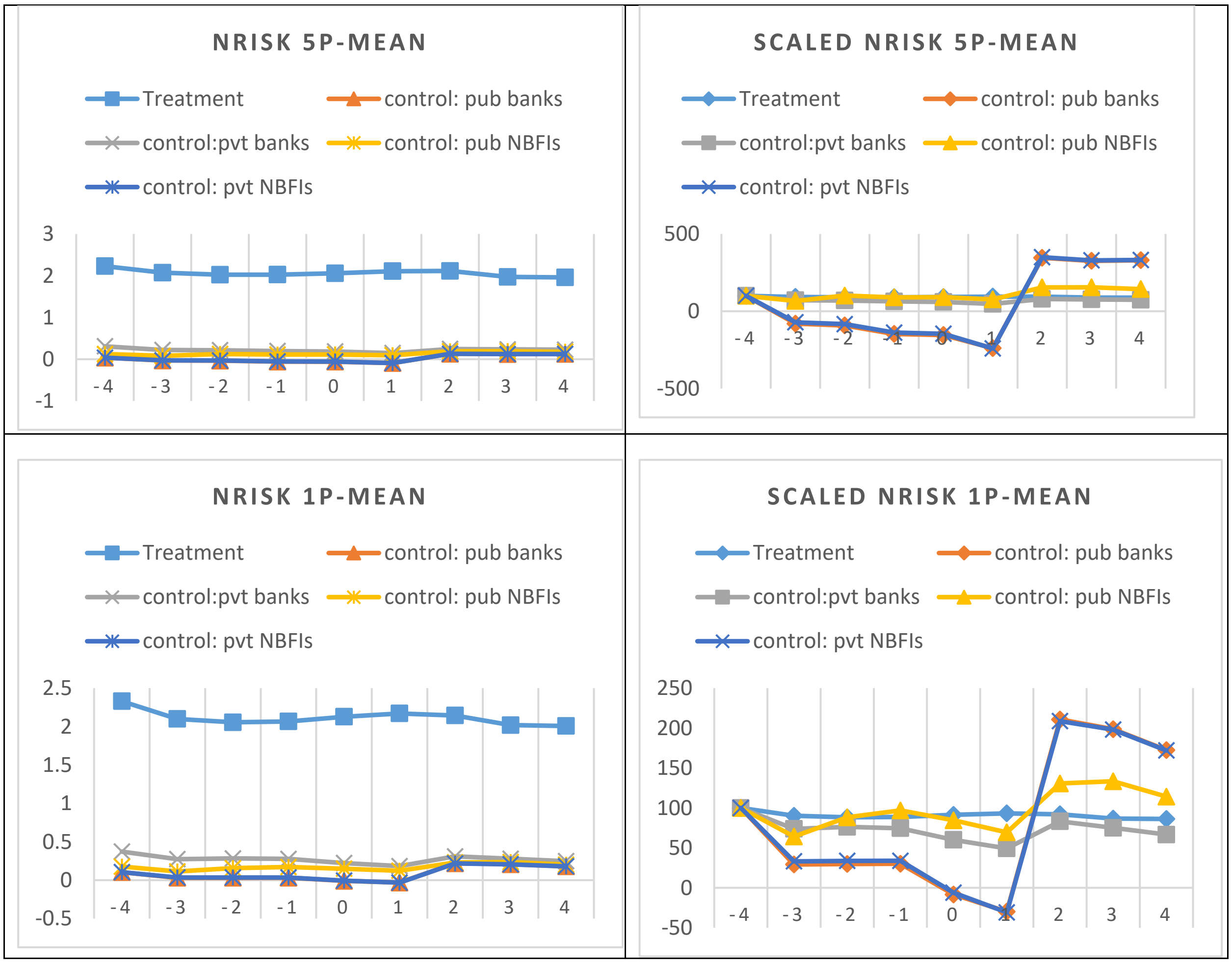


Figure 5: Event window plots of the Covariance (CoVaR) measure of systemic risk around capital infusion

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

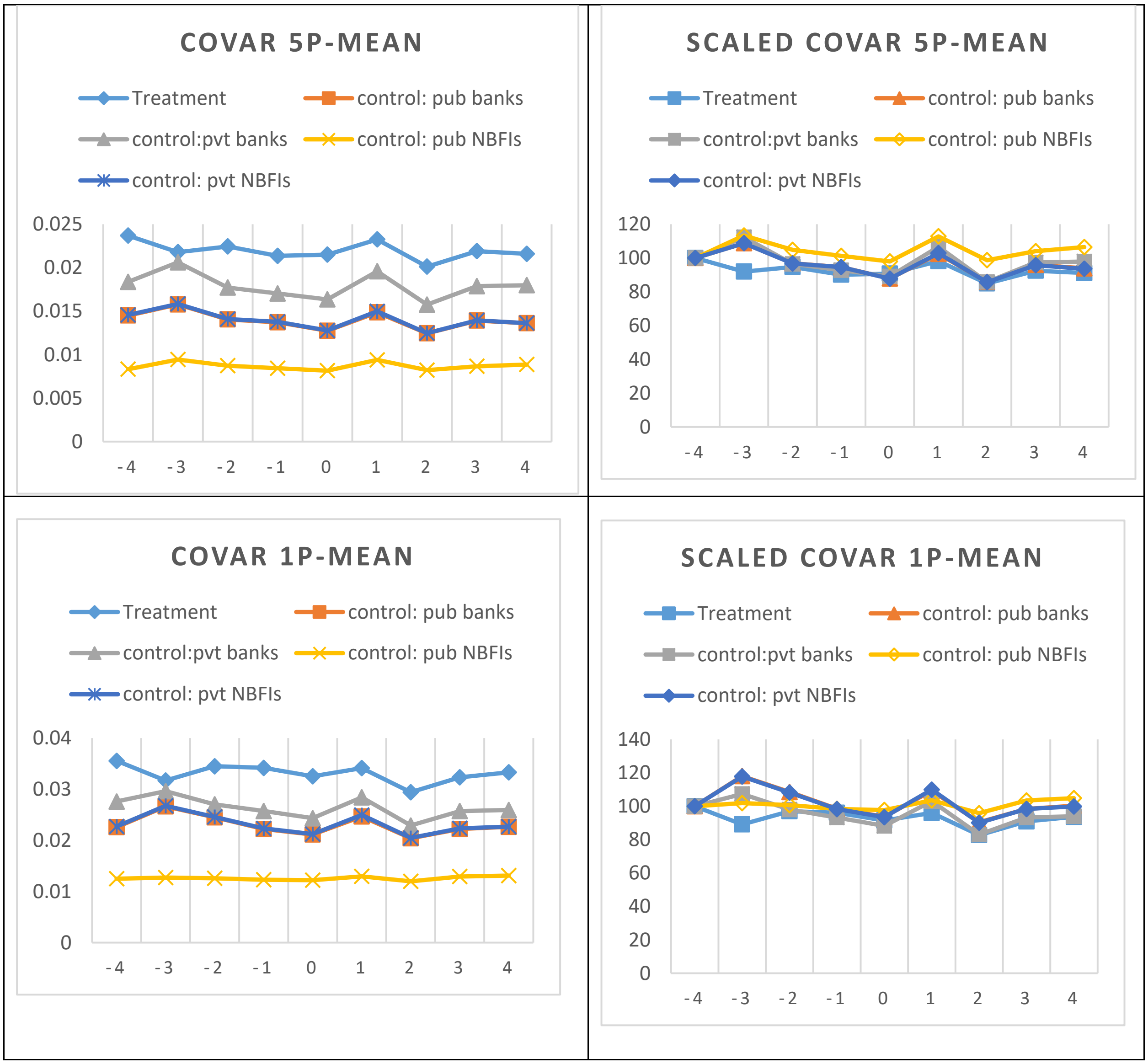
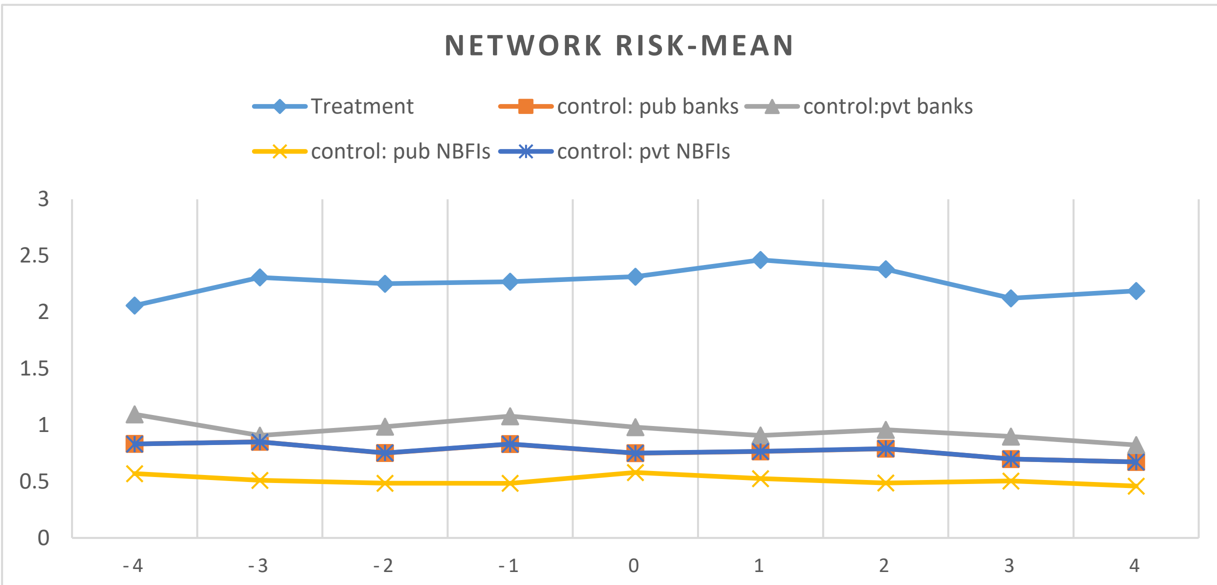


Figure 6: Event window plots of the Network risk score measure of systemic risk around capital infusion

We present quarterly mean and median plots (both raw and scaled) of the Network risk score measure for the treatment and four different control samples for the sample period. We present ± four quarters around the event (period zero), which denotes the capital infusion date. All the variables are defined in Appendix A.



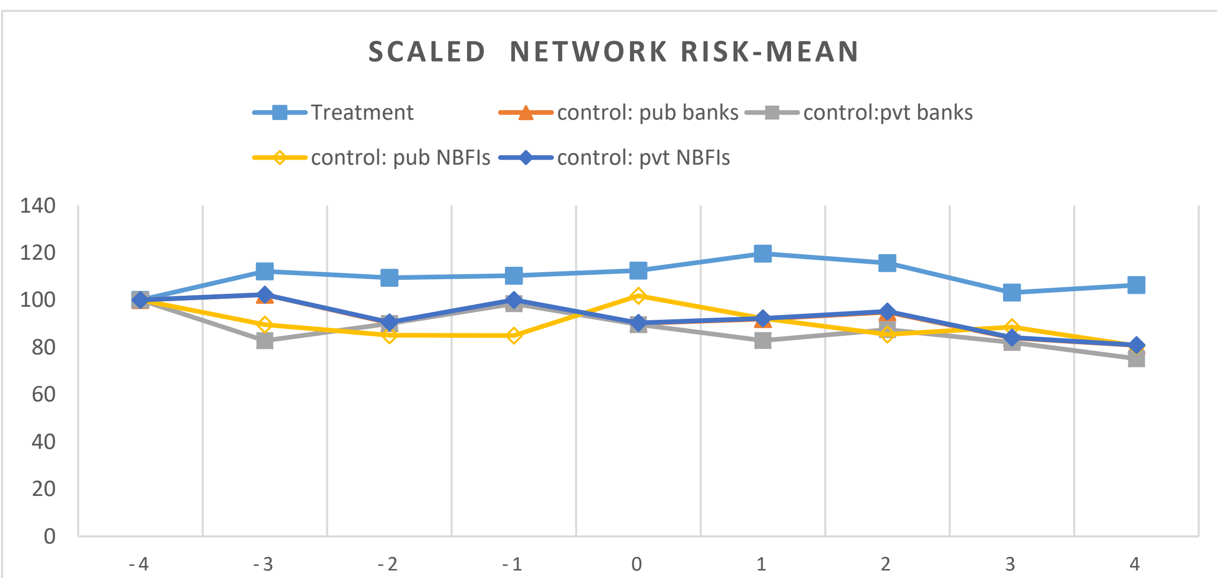


Figure 7: Time series plots of Probability of default (PD) measures over the sample period 2008-2018

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.

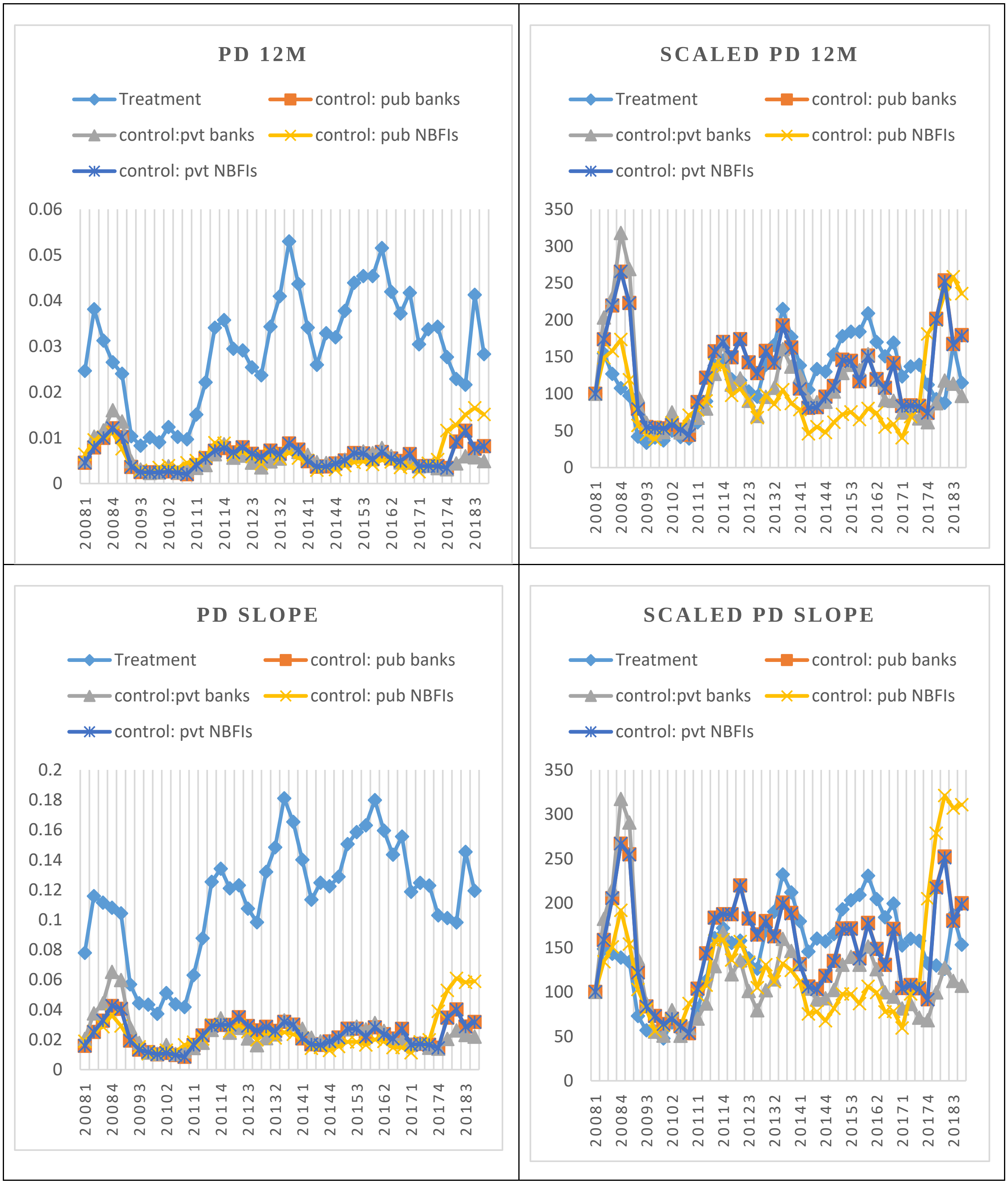


Figure 8: Time series plots of standardized Expected Capital Shortfall (NSRISK) measure of systemic risk over the sample period 2008-2018

We present aggregate quarterly plots (raw and scaled) of NSRISK 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.

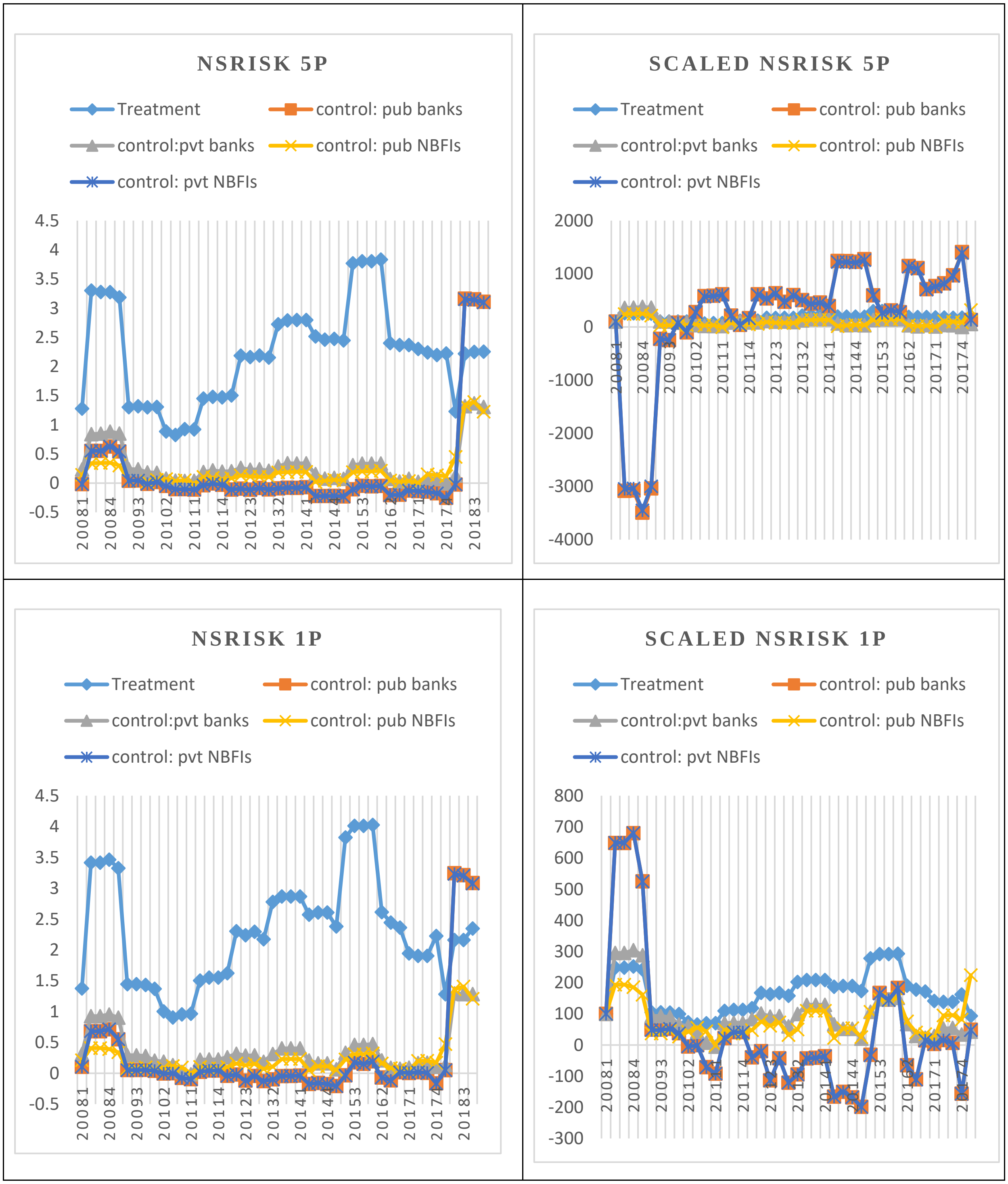


Figure 9: Time series plots of the Covariance (CoVaR) measure of systemic risk over the sample period 2008-2018

We present aggregate quarterly plots (raw and scaled) of CoVaR 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.

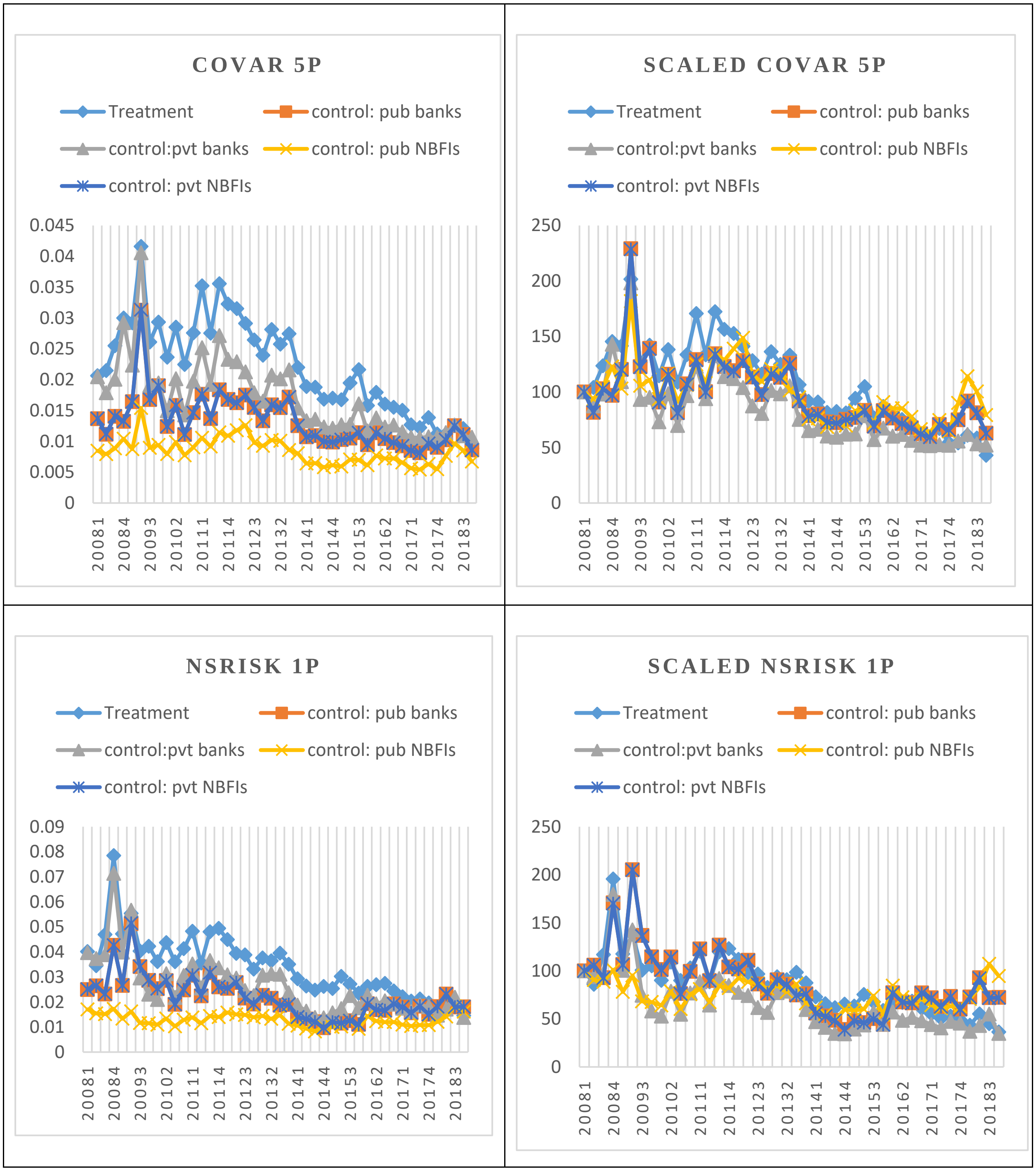


Figure 10: Time series plots of the Network risk score measure of systemic risk over the sample period 2008-2018

We present aggregate quarterly plots (raw and scaled) of Network risk measure for the treatment and four different control samples for the sample period. All the variables are defined in Appendix A.

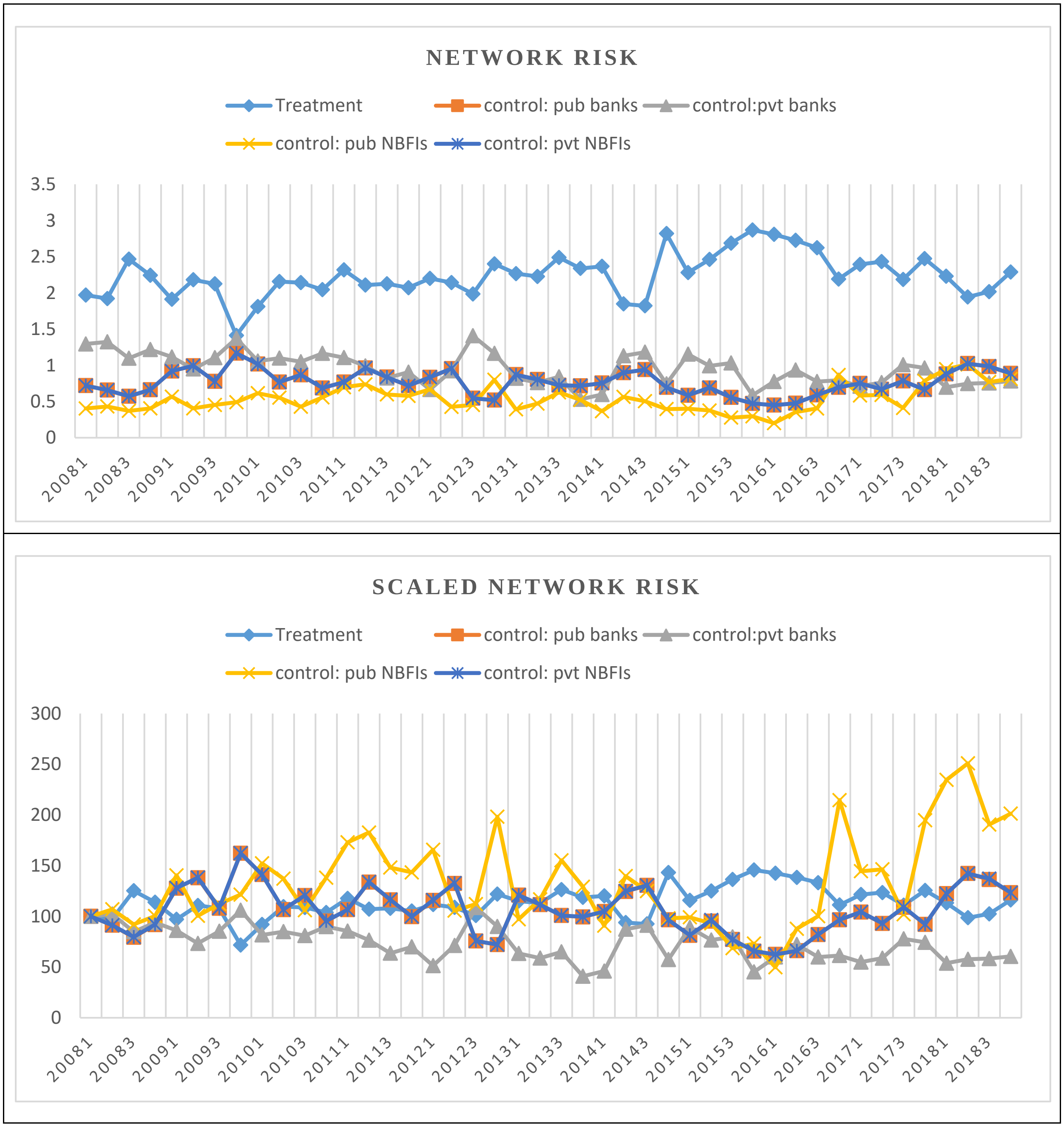


Table 1. Financial sample breakdown

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. Govt_bank-No Infusion; C. Private_bank; D. Govt_NBFC; and E. Top 25 Private_NBFC). 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)	284.3***	189.5***	298.4***	320***
	(-16.21)	(-9.47)	(-16.76)	(-18.22)
ROE	-8.27***	-6.69***	-10.78***	-11.00***
	(-7.01)	(-10.00)	(-14.37)	(-16.98)
Loan to Assets	-0.76*	-3.66***	-16.24***	-15.26***
	(-2.56)	(-16.90)	(-5.63)	(-6.52)
Tier 1 Capital (mi)	192.2***	569.6**	789**	520.5
	(-12.53)	(-2.9)	(-2.72)	(-1.69)
Total Debt to Common Equity	49.18***	19.63***	-229.90***	-255.24***
	(-8.1)	(-3.76)	(-12.99)	(-23.43)
Total Debt to Total Capital	5.64***	4.37***	-3.84*	-4.40***
	(-4.4)	(-4.94)	(-2.27)	(-3.71)
Interest Coverage Ratio	-5.41***	-9.22***	-112.41***	-1515.95***
	(-4.15)	(-8.19)	(-6.78)	(-4.26)
Market to Book	-0.10**	-1.12***	-0.96***	-1.44***
	(-2.97)	(-27.17)	(-10.56)	(-24.46)
Tier 1 Capital Ratio	-0.74***	-3.55***	-15.52***	-14.97***
	(-4.53)	(-31.13)	(-12.03)	(-14.07)
Debt to Total Assets	0.03***	-0.03***	-0.36***	-0.28***
	-12.85	(-7.95)	(-25.13)	(-34.36)
Deposits to Total Assets	-0.02***	0.09***	0.83***	0.81***
	(-5.08)	(-14.54)	(-389.34)	(-196.08)
Observations	1056	1628	1408	2024

Table 3. Univariate comparisons of Probability of Default (PD) around capital infusion

We present pre- and post- comparisons of 12 month PD (Panel A) and PD slope- measured as 5 year PD minus 1 year PD (Panel B) for the treatment and four different control samples for the sample period. We present results for ± 2 and 3 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.

Panel A

	±2Q					±3Q				
	PD 1 year									
	Post-pre performance									
	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
pre	0.027	0.005	0.005	0.005	0.005	0.028	0.005	0.005	0.005	0.005
post	0.031	0.004	0.004	0.006	0.004	0.030	0.004	0.004	0.006	0.004
post-pre	0.004	0.000	-0.001	0.001	0.000	0.003	0.000	-0.001	0.001	0.000
t-stat	1.736	-0.786	-1.706	0.853	-0.911	1.351	-0.903	-2.162	1.110	-1.031
P-value	0.083	0.432	0.089	0.394	0.362	0.177	0.367	0.031	0.268	0.303
	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.	0.004	0.004	0.004	0.004		0.003	0.003	0.003	0.003	
control	0.000	-0.001	0.001	0.000		0.000	-0.001	0.001	0.000	
treat-control	0.004	0.005	0.003	0.004		0.003	0.004	0.002	0.003	
t-stat	3.576	3.937	2.381	3.623		2.950	3.464	1.636	3.001	
P-value	0.000	0.000	0.018	0.000		0.004	0.001	0.103	0.003	

Panel B

	±2Q					±3Q				
	PD slope (PD 5yr-PD 1yr)									
	Post-pre performance									
pre	0.105	0.020	0.022	0.019	0.020	0.107	0.020	0.023	0.019	0.021
post	0.115	0.018	0.018	0.021	0.018	0.114	0.018	0.018	0.021	0.018
post-pre	0.011	-0.002	-0.004	0.002	-0.002	0.007	-0.002	-0.005	0.002	-0.002
t-stat	1.524	-0.931	-1.935	0.659	-1.027	1.062	-1.276	-2.720	0.793	-1.370
P-value	0.128	0.352	0.054	0.510	0.305	0.289	0.202	0.007	0.428	0.171
	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.	0.011	0.011	0.011	0.011		0.007	0.007	0.007	0.007	
control	-0.002	-0.004	0.002	-0.002		-0.002	-0.005	0.002	-0.002	
treat-control	0.012	0.015	0.009	0.013		0.009	0.012	0.005	0.010	
t-stat	3.614	4.140	2.402	3.661		2.731	3.495	1.403	2.776	
P-value	0.000	0.000	0.017	0.000		0.007	0.001	0.162	0.006	

Table 4. Univariate comparisons of Expected Capital Shortfall (NSRISK) around capital infusion

We present pre- and post- comparisons of NSRISK 5 percentile (Panel A) and one percentile (Panel B) - for the treatment and four different control samples for the sample period. We present results for ± 2 and 3 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.

Panel A

	±2Q					**±3Q**				
	NSRISK 5p									
	Post-pre performance									
	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
pre	2.024	-0.045	0.206	0.119	-0.042	2.040	-0.040	0.211	0.107	-0.037
post	2.111	0.020	0.197	0.144	0.020	2.064	0.055	0.210	0.160	0.055
post-pre	0.087	0.066	-0.009	0.025	0.062	0.024	0.095	-0.001	0.053	0.092
t-stat	0.549	0.719	-0.180	0.634	0.680	0.161	0.847	-0.025	1.288	0.815
P-value	0.584	0.472	0.857	0.526	0.497	0.872	0.398	0.980	0.199	0.416

	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.	0.087	0.087	0.087	0.087	0.024	0.024	0.024	0.024
control	0.066	-0.009	0.025	0.062	0.095	-0.001	0.053	0.092
treat-control	0.021	0.096	0.061	0.025	-0.071	0.025	-0.029	-0.068
t-stat	0.211	1.376	0.893	0.248	-0.576	0.318	-0.374	-0.546
P-value	0.833	0.170	0.373	0.804	0.565	0.751	0.709	0.585

Panel B

	±2Q					**±3Q**				
	NSRISK 1p									
	Post-pre performance									
pre	2.061	0.031	0.280	0.164	0.035	2.073	0.031	0.278	0.147	0.035
post	2.157	0.094	0.246	0.177	0.093	2.111	0.132	0.257	0.196	0.131
post-pre	0.096	0.063	-0.034	0.013	0.058	0.037	0.101	-0.021	0.050	0.096
t-stat	0.601	0.685	-0.657	0.313	0.627	0.247	0.892	-0.397	1.139	0.849
P-value	0.548	0.494	0.511	0.755	0.531	0.805	0.373	0.692	0.255	0.396

	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.	0.096	0.096	0.096	0.096	0.037	0.037	0.037	0.037
control	0.063	-0.034	0.013	0.058	0.101	-0.021	0.050	0.096
treat-control	0.033	0.130	0.083	0.039	-0.064	0.058	-0.012	-0.059
t-stat	0.326	1.757	1.129	0.380	-0.502	0.696	-0.149	-0.463
P-value	0.745	0.080	0.260	0.704	0.616	0.487	0.881	0.644

Table 5. Univariate comparisons of Covariance (CoVaR) around capital infusion

We present pre- and post- comparisons of CoVaR 5 percentile (Panel A) and one percentile (Panel B) - for the treatment and four different control samples for the sample period. We present results for ± 2 and 3 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 5% and below are shaded. All the variables are defined in Appendix A.

Panel A

CoVar 5p

	±2Q					±3Q				
Post-pre performance										
	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
pre	0.022	0.014	0.017	0.009	0.014	0.022	0.015	0.018	0.009	0.015
post	0.022	0.014	0.018	0.009	0.014	0.022	0.014	0.018	0.009	0.014
post-pre	0.000	0.000	0.000	0.000	0.000	0.000	-0.001	-0.001	0.000	-0.001
t-stat	-0.173	-0.302	0.258	0.216	-0.273	-0.080	-0.954	-0.599	-0.098	-0.947
P-value	0.863	0.763	0.796	0.829	0.785	0.937	0.340	0.549	0.922	0.344
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.	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	
control	0.000	0.000	0.000	0.000		-0.001	-0.001	0.000	-0.001	
treat-control	0.000	-0.001	0.000	0.000		0.001	0.001	0.000	0.001	
t-stat	0.024	-0.678	-0.641	-0.005		0.779	0.680	0.006	0.775	
P-value	0.981	0.498	0.522	0.996		0.436	0.497	0.996	0.439	

Panel B

CoVar 1p

	±2Q					±3Q				
Post-pre performance										
pre	0.034	0.023	0.026	0.012	0.023	0.033	0.024	0.027	0.013	0.025
post	0.032	0.023	0.026	0.012	0.023	0.032	0.022	0.026	0.013	0.023
post-pre	-0.003	-0.001	-0.001	0.000	-0.001	-0.001	-0.002	-0.002	0.000	-0.002
t-stat	-1.351	-0.543	-0.330	0.018	-0.476	-0.810	-1.297	-0.792	0.057	-1.247
P-value	0.178	0.587	0.742	0.985	0.634	0.419	0.195	0.429	0.954	0.213
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.	-0.003	-0.003	-0.003	-0.003		-0.001	-0.001	-0.001	-0.001	
control	-0.001	-0.001	0.000	-0.001		-0.002	-0.002	0.000	-0.002	
treat-control	-0.002	-0.002	-0.003	-0.002		0.001	0.000	-0.002	0.000	
t-stat	-1.290	-1.462	-2.371	-1.360		0.394	0.209	-1.426	0.344	
P-value	0.198	0.145	0.019	0.175		0.694	0.835	0.155	0.731	

Table 6. Univariate comparisons of Network risk score measure around capital infusion

We present pre- and post- comparisons of Network risk score for the treatment and four different control samples for the sample period. We present results for ± 2 and 3 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 5% and below are shaded. All the variables are defined in Appendix A.

	±2Q					±3Q				
	Network risk									
	Post-pre performance									
	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
pre	2.261	0.792	1.032	0.484	0.792	2.276	0.812	0.990	0.493	0.812
post	2.421	0.778	0.933	0.506	0.779	2.322	0.752	0.921	0.505	0.753
post-pre	0.161	-0.014	-0.099	0.022	-0.013	0.045	-0.060	-0.069	0.013	-0.059
t-stat	1.141	-0.289	-1.263	0.342	-0.282	0.350	-1.294	-0.956	0.202	-1.278
P-value	0.255	0.772	0.207	0.733	0.778	0.727	0.196	0.340	0.840	0.202
	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.	0.161	0.161	0.161	0.161		0.045	0.045	0.045	0.045	
control	-0.014	-0.099	0.022	-0.013		-0.060	-0.069	0.013	-0.059	
treat-control	0.174	0.260	0.139	0.174		0.105	0.114	0.033	0.105	
t-stat	1.417	2.044	1.140	1.414		0.991	1.055	0.316	0.983	
P-value	0.158	0.042	0.256	0.159		0.323	0.292	0.752	0.327	

Table 7. Panel regressions of default and systemic risks (Hypotheses 1, 2 & 3)

We present the effect of capital infusion of PD, Systemic and Network Risk measures using the specification (1) and (2) in the paper. We consider sample regressions based on ± 2 quarter window post capital infusion date below. 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)
VARIABLES	PD_12_month		Slope		NSRISK_5p		COVAR_5p		Network Risk	
Post Infusion Dummy	-0.825***		-2.013***		-1.896		-0.0894**		0.0730	
	(0.0596)		(0.135)		(1.547)		(0.0369)		(0.127)	
Large Infusions		0.719***		2.562***		33.19***		1.496***		1.410***
		(0.0331)		(0.103)		(4.030)		(0.0240)		(0.0239)
Constant	2.767***	5.541***	7.674***	19.18***	272.2***	292.3***	2.470***	-1.545***	2.185***	1.521***
	(0.727)	(0.486)	(1.608)	(1.390)	(40.87)	(47.84)	(0.274)	(0.301)	(0.716)	(0.329)
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
Observations	1,018	1,018	1,018	1,018	1,004	1,004	999	999	1,010	1,010
R-squared	0.560	0.380	0.624	0.413	0.586	0.360	0.629	0.527	0.174	0.163

Table 8. DID panel regressions of default risk (Hypothesis 1)

We present the effect of capital infusion on various default risk measures of the treatment versus control sample banks using the DID specification (3) in the paper. We consider pairwise comparison with each of the four control samples, as defined in Section 3, but only present 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	PD_12_month					PD Slope				
Treatment Dummy	2.803**	2.803**	2.980**			8.567**	8.549**	9.259**		
	(1.345)	(1.354)	(1.341)			(3.467)	(3.481)	(3.465)		
Post Infusion Dummy	-0.311***	-0.411***		-0.394***		-1.196***	-1.220***		-1.177***	
	(0.0470)	(0.0793)		(0.0810)		(0.157)	(0.195)		(0.199)	
Large Infusions	-0.128	-0.132	-0.125			0.686	0.684	0.684		
	(1.351)	(1.358)	(1.349)			(3.468)	(3.482)	(3.472)		
Treatment x Post Infusion Dummy	-0.110**	-0.176**	-0.362***	-0.347**	-0.526***	0.345	0.117	-0.636	-0.361**	-1.099***
	(0.0441)	(0.0827)	(0.0266)	(0.132)	(0.0662)	(0.454)	(0.280)	(0.449)	(0.175)	(0.307)
Treatment x Post x Large Infusions	-0.196*	-0.133	-0.200*	0.0320	-0.0292	-0.790	-0.566*	-0.791	-0.0966	-0.301
	(0.105)	(0.116)	(0.105)	(0.155)	(0.126)	(0.475)	(0.304)	(0.477)	(0.212)	(0.350)
Constant	2.645***	0.0333	2.471***	3.142***	5.617***	9.313***	-1.195	8.399***	9.031***	18.96***
	(0.411)	(0.468)	(0.438)	(0.525)	(0.430)	(1.353)	(1.111)	(1.412)	(1.195)	(1.437)
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	NO	NO	NO	YES	YES	NO	NO	NO	YES	YES
Year FE	NO	YES	NO	YES	NO	NO	YES	NO	YES	NO
Quarter FE	NO	NO	YES	NO	YES	NO	NO	YES	NO	YES
Observations	1,491	1,491	1,491	1,491	1,491	1,491	1,491	1,491	1,491	1,491
R-squared	0.481	0.567	0.483	0.641	0.560	0.553	0.644	0.552	0.702	0.614

Table 9. DID panel regressions of systemic risk (Hypotheses 2 & 3)

We present the effect of capital infusion on NSRISK, CoVaR and Network systemic score measures, at 5% thresholds, for the treatment versus control sample banks using the DID specification (4) in the paper. We consider pairwise comparison with each of the four control samples, as defined in Section 3. We present results for private bank control sample based on 2-quarter window post 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	NSRISK_5p					COVAR_5p					Network Risk				
Treatment Dummy	186.7*	193.0*	199.2*			-0.300	-0.272	-0.235			2.010***	2.030***	2.090***		
	(99.58)	(106.5)	(100.0)			(0.369)	(0.347)	(0.353)			(0.702)	(0.719)	(0.701)		
Post Infusion Dummy	-20.95***	-1.230		-0.0152		-0.115*	-0.0855		-0.0866		-0.141	-0.126		-0.118	
	(4.641)	(5.404)		(5.242)		(0.0644)	(0.0558)		(0.0564)		(0.0877)	(0.0866)		(0.0877)	
Large Infusions	16.07	8.739	15.76			0.352	0.328	0.349			-1.085	-1.106	-1.085		
	(99.87)	(106.7)	(100.3)			(0.327)	(0.303)	(0.325)			(0.699)	(0.717)	(0.699)		
Treatment x Post Infusion Dummy	43.69***	31.34***	26.17***	17.89**	13.79***	-0.134	-0.152	-0.225*	-0.138	-0.212	-0.638***	-0.666***	-0.751***	-0.783***	-0.863***
	(9.646)	(4.871)	(8.875)	(8.043)	(4.838)	(0.145)	(0.132)	(0.125)	(0.138)	(0.132)	(0.100)	(0.0925)	(0.0510)	(0.0942)	(0.0384)
Treatment x Post x Large Infusions	-47.22***	-34.78***	-46.87***	-22.30**	-34.03***	0.212	0.222*	0.215	0.207	0.198	0.938***	0.965***	0.938***	1.081***	1.054***
	(11.91)	(7.845)	(11.67)	(9.781)	(8.553)	(0.136)	(0.124)	(0.134)	(0.130)	(0.141)	(0.112)	(0.106)	(0.113)	(0.108)	(0.108)
Constant	65.06*	30.73	44.85	275.2***	292.8***	0.279	2.490***	0.106	2.283***	-0.0339	1.218***	1.418**	1.087***	2.765***	2.420***
	(35.60)	(28.13)	(35.81)	(30.57)	(28.68)	(0.203)	(0.269)	(0.208)	(0.271)	(0.250)	(0.231)	(0.666)	(0.257)	(0.618)	(0.256)
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
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	0.427	0.519	0.426	0.718	0.629	0.340	0.447	0.340	0.598	0.491	0.174	0.180	0.174	0.262	0.255

Table 10. Placebo tests: Effect of capital infusion on default and systemic risks (Hypotheses 1, 2 & 3)

We present the Placebo tests for the effect of capital infusion on default and systemic risk measures by setting the capital infusion date as the lagged two-month period. We consider pairwise comparison with each of the four control samples, as defined in Section 3. We present results for private bank control sample using the DID specifications (3) and (4) in the paper 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)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
VARIABLES	PD_12_month		Slope		NSRISK_5p		NSRISK_1p		COVAR_5p		COVAR_1p		Network Risk	
Placebo Post Infusion t-2	0.335***		1.107***		24.27***		26.53***		-0.0598		-0.101		0.144	
	(0.0455)		(0.146)		(3.611)		(3.945)		(0.0386)		(0.0883)		(0.0947)	
Treatment x Placebo Post Infusion t-2	0.389	0.602	0.950	1.723	7.401	16.53*	3.796	15.02	0.0967**	0.00745	-0.106	-0.160	0.176	0.264
	(0.511)	(0.587)	(1.464)	(1.718)	(7.979)	(9.308)	(10.50)	(11.75)	(0.0404)	(0.0177)	(0.216)	(0.230)	(0.899)	(0.881)
Treatment x Placebo Post t-2 x Large Infusions	-0.548	-0.624	-1.569	-1.838	-24.15***	-25.55**	-22.38*	-23.84*	-0.0148	-0.0178	0.167	0.152	-0.465	-0.461
	(0.512)	(0.581)	(1.467)	(1.705)	(8.668)	(9.934)	(11.05)	(12.37)	(0.0384)	(0.0366)	(0.213)	(0.237)	(0.898)	(0.892)
Constant	3.591***	5.102***	10.40***	17.68***	292.0***	275.1***	276.7***	267.4***	2.310***	-0.0493	4.015***	-0.868	2.905***	2.625***
	(0.511)	(0.436)	(1.144)	(1.390)	(28.33)	(31.15)	(31.16)	(29.87)	(0.275)	(0.248)	(0.526)	(0.721)	(0.635)	(0.253)
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
Observations	1,491	1,491	1,491	1,491	1,530	1,530	1,530	1,530	1,520	1,520	1,520	1,520	1,536	1,536
R-squared	0.633	0.553	0.699	0.610	0.720	0.628	0.713	0.611	0.598	0.491	0.454	0.389	0.258	0.252

Table 11. Alternate control samples: Effect of capital infusion on default and systemic risks (Hypotheses 1, 2 & 3)

We present DID tests comparing the treatment sample of public infusion banks with each of alternate control samples: public sector banks without infusion (control B), private NBFIs (control D), and public NBFIs (control E). We use the DID specifications (3) and (4) in the paper 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.

	PD						NSRISK - 5p					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Control sample B		Control sample D		Control sample E		Control sample B		Control sample D		Control sample E	
Post Infusion Dummy	0.0790		0.0683		0.0274		-4.288		-1.209		-1.288	
	(0.141)		(0.0725)		(0.0536)		(11.54)		(6.751)		(4.264)	
Treatment x Post Infusion Dummy	-0.971***	-0.868***	-0.955***	-0.886***	-0.899***	-0.890***	20.98	10.32	18.16*	12.75**	20.97***	15.33***
	(0.109)	(0.0444)	(0.0434)	(0.0388)	(0.0353)	(0.0231)	(12.63)	(7.047)	(9.324)	(5.914)	(7.068)	(4.439)
Treatment x Post x Large Infusions	1.064***	1.056***	1.062***	1.058***	1.054***	1.054***	-20.26*	-35.67***	-22.08**	-34.83***	-23.79**	-33.62***
	(0.105)	(0.108)	(0.104)	(0.108)	(0.105)	(0.107)	(10.89)	(9.077)	(9.734)	(8.720)	(9.005)	(8.474)
Constant	2.158***	2.757***	2.324***	2.707***	2.666***	2.552***	272.4***	351.4***	257.6***	327.4***	291.8***	282.5***
	(0.702)	(0.284)	(0.596)	(0.243)	(0.448)	(0.176)	(42.10)	(41.06)	(38.43)	(35.02)	(30.01)	(27.10)
Local Factor	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Quarter FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Observations	1,010	1,010	1,241	1,241	1,899	1,899	1,004	1,004	1,233	1,233	1,880	1,880
R-squared	0.182	0.171	0.283	0.279	0.413	0.412	0.586	0.364	0.680	0.564	0.752	0.701

	CoVar - 5p						Network risk					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Control sample B		Control sample D		Control sample E		Control sample B		Control sample D		Control sample E	
Post Infusion Dummy	-0.352***		-0.0394		-0.100**		0.0790		0.0683		0.0274	
	(0.0755)		(0.0746)		(0.0402)		(0.141)		(0.0725)		(0.0536)	
Treatment x Post Infusion Dummy	0.0953	-0.218	-0.203	-0.217	-0.106	-0.192	-0.971***	-0.868***	-0.955***	-0.886***	-0.899***	-0.890***
	(0.131)	(0.139)	(0.140)	(0.133)	(0.124)	(0.126)	(0.109)	(0.0444)	(0.0434)	(0.0388)	(0.0353)	(0.0231)
Treatment x Post x Large Infusions	0.212	0.193	0.204	0.197	0.211	0.205	1.064***	1.056***	1.062***	1.058***	1.054***	1.054***
	(0.127)	(0.147)	(0.134)	(0.143)	(0.128)	(0.136)	(0.105)	(0.108)	(0.104)	(0.108)	(0.105)	(0.107)
Constant	2.424***	-0.0175	2.536***	0.129	2.296***	0.317	2.158***	2.757***	2.324***	2.707***	2.666***	2.552***
	(0.276)	(0.277)	(0.241)	(0.246)	(0.189)	(0.215)	(0.702)	(0.284)	(0.596)	(0.243)	(0.448)	(0.176)
Local Factor	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
US Factors	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Quarter FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Observations	999	999	1,214	1,214	1,864	1,864	1,010	1,010	1,241	1,241	1,899	1,899
R-squared	0.631	0.527	0.631	0.522	0.632	0.560	0.182	0.171	0.283	0.279	0.413	0.412

Table 12. Effects of capital infusion using standardized capital infusion measure (Hypotheses 1, 2 & 3)

We present the effect of standardized capital infusion on default and systemic risk measures. 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 DID model (4) results for private bank control sample 2-quarter window post the 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)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VARIABLES		PD_12_month			Slope			NSRISK_5p			COVAR_5p			Network Risk	
Post Infusion Dummy	-0.423***	-0.425***	-0.430***	-1.258***	-1.267***	-1.272***	-1.139	-0.987	-1.190	-0.0848	-0.0841	-0.0827	-0.156*	-0.158*	-0.163*
	(0.0852)	(0.0852)	(0.0899)	(0.208)	(0.209)	(0.221)	(5.677)	(5.647)	(6.326)	(0.0565)	(0.0565)	(0.0588)	(0.0920)	(0.0924)	(0.0905)
Treatment x Post Infusion Dummy	-0.431***	-0.442***	-0.407***	-0.779**	-0.819***	-0.690**	-8.007	-7.414	-6.043	0.0649	0.0679	0.0652	0.0801	0.0708	0.112
	(0.118)	(0.118)	(0.109)	(0.299)	(0.298)	(0.262)	(9.022)	(9.299)	(7.369)	(0.101)	(0.101)	(0.0961)	(0.160)	(0.156)	(0.158)
Treatment x Post Large Infusion-Assets Ratio Dummy	0.393**			1.130**			18.67			-0.0447			0.445***		
	(0.172)			(0.536)			(16.74)			(0.0751)			(0.138)		
Treatment x Post Large Infusion-Deposits Ratio Dummy		0.426**			1.263**			16.58			-0.0550			0.475***	
		(0.183)			(0.563)			(17.03)			(0.0757)			(0.142)	
Treatment x Post Large Infusion-Tier 1 capital Ratio Dummy			0.438*			1.175			17.01			-0.0656			0.476***
			(0.240)			(0.725)			(22.62)			(0.142)			(0.174)
Constant	2.959***	2.943***	3.025***	8.496***	8.434***	8.710***	265.7***	266.7***	269.7***	2.311***	2.315***	2.307***	2.606***	2.593***	2.683***
	(0.562)	(0.562)	(0.557)	(1.298)	(1.300)	(1.284)	(34.07)	(33.52)	(34.25)	(0.286)	(0.287)	(0.279)	(0.634)	(0.635)	(0.624)
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	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
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	0.644	0.645	0.644	0.704	0.705	0.704	0.719	0.719	0.719	0.598	0.598	0.598	0.263	0.264	0.262

Table 13. Effects of capital infusion during macro-stress periods (Hypothesis 4)

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 DID specification (6), 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.

VARIABLES	(1) PD_12_month	(2) Slope	(3) NSRISK_5p	(4) COVAR_5p	(5) NSRISK_1p	(6) COVAR_1p	(7) Network Risk
Treatment Dummy	5.346***	15.08***	419.2***	-0.985***	403.8***	0.396***	3.919***
	(0.0766)	(0.349)	(5.584)	(0.120)	(5.764)	(0.113)	(0.0306)
Post Infusion Dummy	-0.255***	-1.012***	-13.29***	-0.264***	-14.16**	-0.200**	0.0672
	(0.0559)	(0.181)	(4.647)	(0.0771)	(5.684)	(0.0890)	(0.0770)
Large Infusions	-2.238***	-5.663***	-98.03***	0.428***	-88.96***	0.447***	-1.986***
	(0.127)	(0.380)	(7.661)	(0.124)	(7.667)	(0.122)	(0.103)
Treatment x Post Infusion Dummy	-0.308***	-0.184	42.41***	0.0246	43.75***	-0.0219	-0.605***
	(0.113)	(0.310)	(10.40)	(0.100)	(10.97)	(0.102)	(0.160)
Treatment x Post x Large Infusions	-0.130	-0.534	-67.83***	0.157	-71.47***	0.162*	0.666***
	(0.164)	(0.372)	(13.09)	(0.0947)	(13.16)	(0.0914)	(0.204)
Post Infusion x Stress Years Dummy	-0.211**	-0.658**	-14.95***	0.372***	2.414	0.469***	0.0118
	(0.0826)	(0.292)	(4.693)	(0.0659)	(6.946)	(0.112)	(0.145)
Large Infusions x Stress Years Dummy	0.416*	1.826***	-121.7***	0.239***	-135.9***	0.245***	-0.0334
	(0.228)	(0.614)	(16.10)	(0.0842)	(15.97)	(0.0791)	(0.199)
Treatment x Post Infusion x Stress Years Dummy	0.0940	0.154	-39.28***	-0.453	-60.56***	-0.588*	-1.068***
	(0.139)	(0.265)	(13.97)	(0.279)	(13.71)	(0.303)	(0.379)
Treatment x Post x Large Infusions x Stress Years Dummy	0.257	0.390	136.9***	0.0571	149.6***	0.0443	1.226***
	(0.197)	(0.448)	(17.50)	(0.277)	(16.86)	(0.283)	(0.421)
Constant	2.306***	8.958***	29.55	0.513***	79.93**	-0.751***	0.770***
	(0.299)	(1.005)	(25.52)	(0.178)	(31.72)	(0.226)	(0.206)
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	NO	NO	NO	NO	NO	NO	NO
Observations	1,491	1,491	1,530	1,520	1,233	1,214	1,241
R-squared	0.567	0.623	0.650	0.499	0.594	0.531	0.285

Table 14. Systemic Risk Channels: Examining channels through which capital infusion effects are realized (Hypothesis 5)

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). We implement the DID specifications (3) and (4) for capital infusion date 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 do not report the values if the respective coefficients are not significant. 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	post infusion	-0.146**	-0.507**	21.41**	0.267***	-0.475***			22.04***	0.184**	
	post large infusion				-0.164***	0.591***					
low	post infusion	-0.415***	-0.514***	21.16*		-0.905***	-1.344***	-1.458***			-1.207***
	post large infusion			-46.05**		1.434***	1.215***	1.454***			1.513***
		Interest coverage					leverage				
high	post infusion	-0.252***	-0.397**			-0.740***	-0.303***		25.95***	0.134***	-0.316***
	post large infusion					1.054***		-0.782***	-31.84*		0.581***
low	post infusion	-1.606***	-2.620***	-29.48**	0.236***	-1.847***	-0.366**	-0.459***	20.65***		-0.807***
	post large infusion	1.255**	2.001**	28.01**		2.234***			-31.84*		1.083***
		Loan to assets					deposits to assets				
high	post infusion		0.833***						27.08*		-1.263***
	post large infusion		-7.358***		-0.243*				-46.00**		1.718***
low	post infusion	-3.517***		163.3***		-2.619***	-0.282***		23.46***	0.123**	
	post large infusion	4.386***	10.18***	-143.2***	-0.460***	3.435***	0.216*		-7.450		
		market to book					roe				
high	post infusion	-0.139**	-0.426**		-0.407***	-1.769***				-0.780***	-2.469***
	post large infusion	-0.227*		-28.76***	0.438***	2.150***			-48.13***	0.775***	2.836***
low	post infusion	-0.424***		27.13*				0.803*	32.72***		
	post large infusion										

Table 15. Effects on sovereign risk: Examining the effects of capital infusion effects on Aggregate risk (Hypothesis 6)

We present the effect of capital infusion on system wide or aggregate systemic risk measures. We implement the time series specification (7) for aggregate risk measures. We present results for all control samples for ± 2 quarter window below. P-values are based on robust standard errors. All the variables are defined in Appendix A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	PD_A_C_Spread		NSRISK_A_C_Spread		COVAR_A_C_Spread		Network_Risk_A_C_Spread	
infusion_index1 x post	-0.00588***		0.0964		-0.000829		0.149	
	(0.00204)		(0.102)		(0.000638)		(0.175)	
infusion_index2 x post		-0.00364		0.270		-0.000431		0.149
		(0.00257)		(0.181)		(0.000420)		(0.109)
Constant	0.0194***	0.0194***	2.081***	2.081***	0.00249*	0.00249*	0.917***	0.917***
	(0.00361)	(0.00361)	(0.353)	(0.353)	(0.00126)	(0.00126)	(0.180)	(0.180)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	44	44	43	43	43	43	44	44
R-squared	0.875	0.851	0.799	0.811	0.806	0.798	0.490	0.488

INTERNET APPENDIX

Figure A1. Government capital infusion into public sector banks 2008-2019

The exhibits below present the breakdown of Indian government yearly capital infusions (in Crore - or 10 million- rupees) into public sector banks for the period 2008-2019. (Source: [Controller & Auditor General of India](), Report No. 28, 2017)

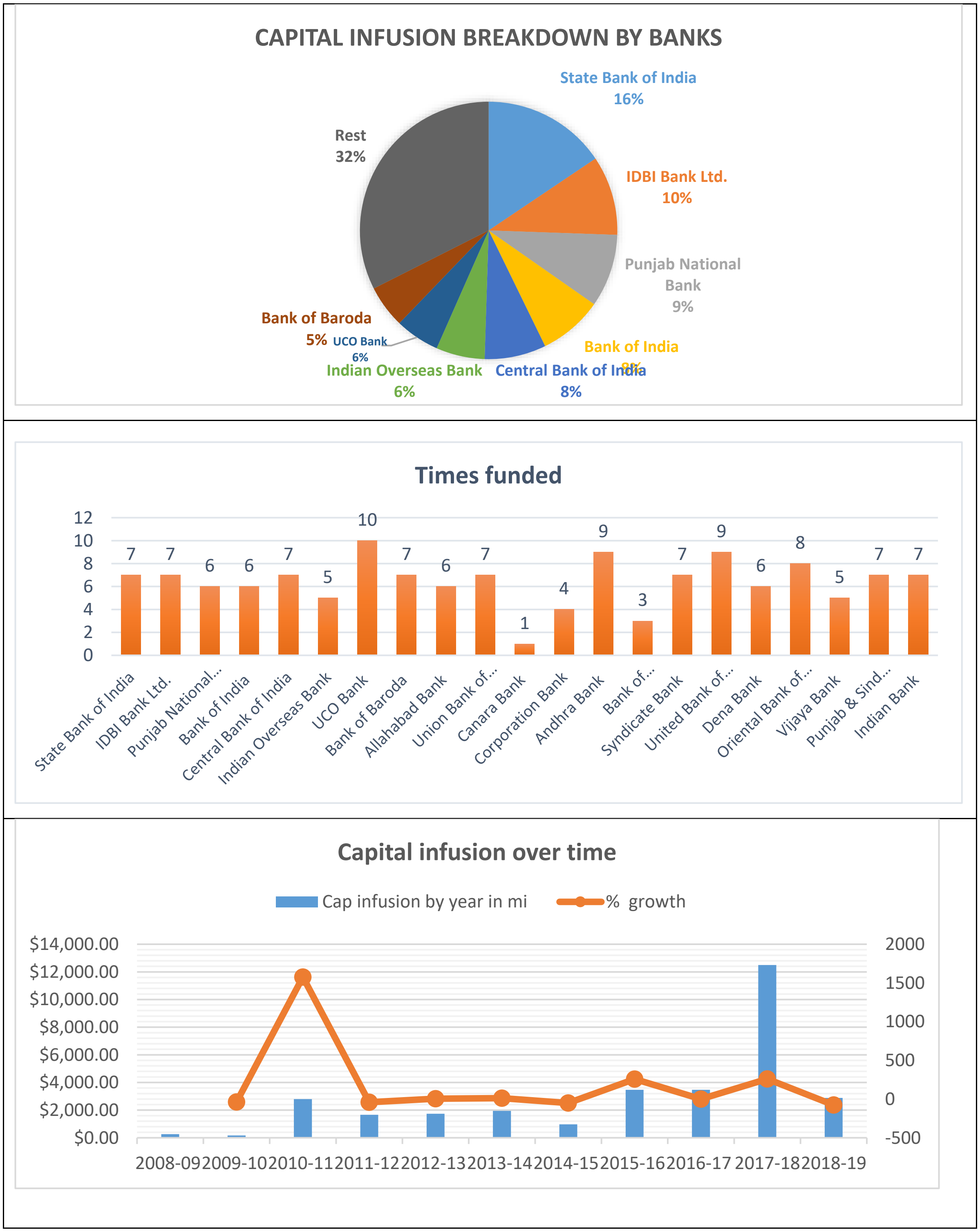


Figure A2: Event window plots of Distance to Default (DTD) around capital infusion

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 ± four quarters around the event (period zero), which denotes the capital infusion date. All the variables are defined in Appendix A.

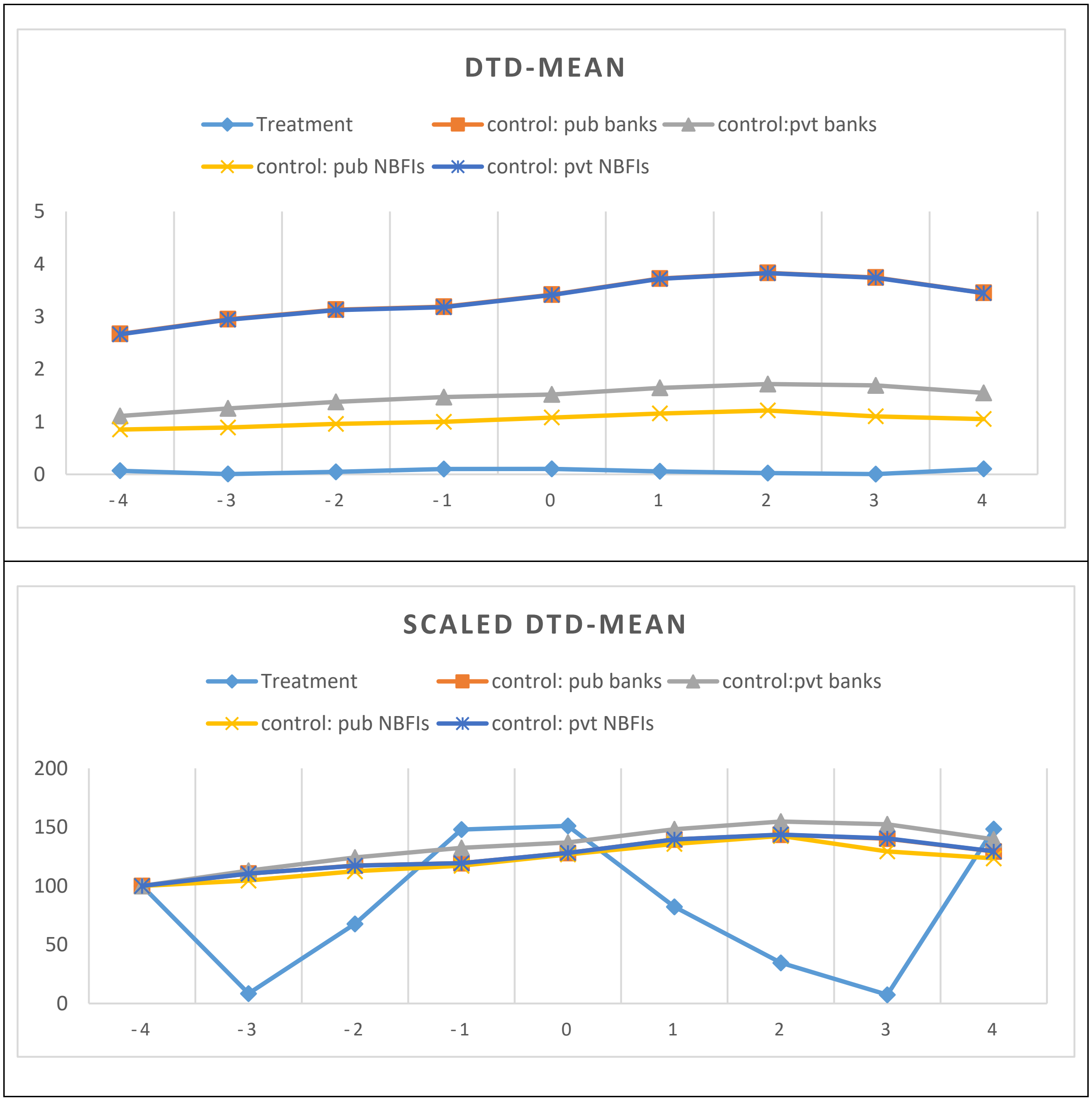


Figure A3: Event window plots of Credit default swap (CDS) spreads around capital infusion

We present quarterly mean plots (both raw and scaled) of CDS spreads for the treatment and four different control samples for the sample period. We present ± four quarters around the event (period zero), which denotes the capital infusion date. All the variables are defined in Appendix A.

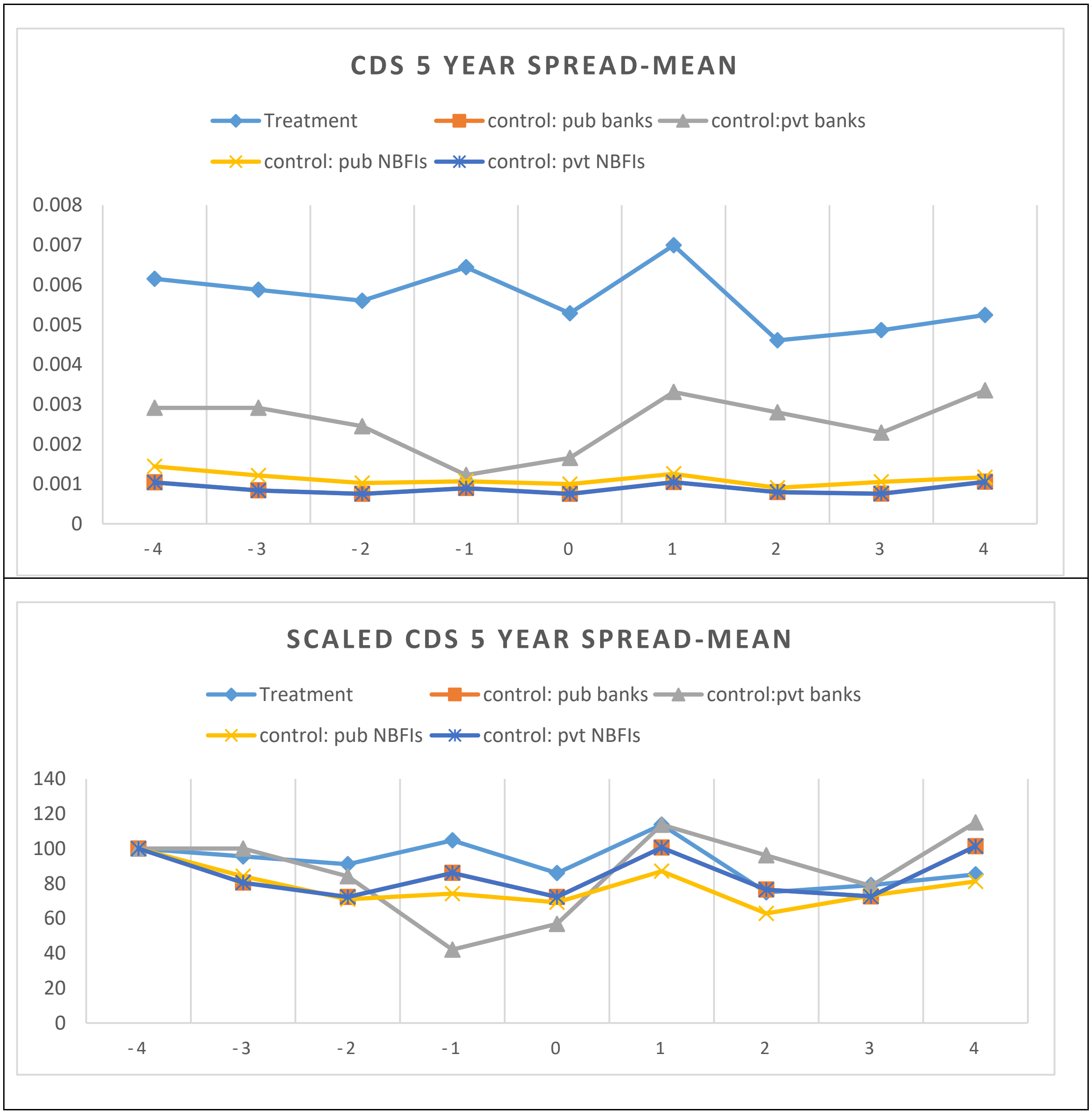


Figure A4: Event window plots of the Margin Expected Shortfall (MES) measure of systemic risk around capital infusion

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 ± four quarters around the event (period zero), which denotes the capital infusion date. All the variables are defined in Appendix A.

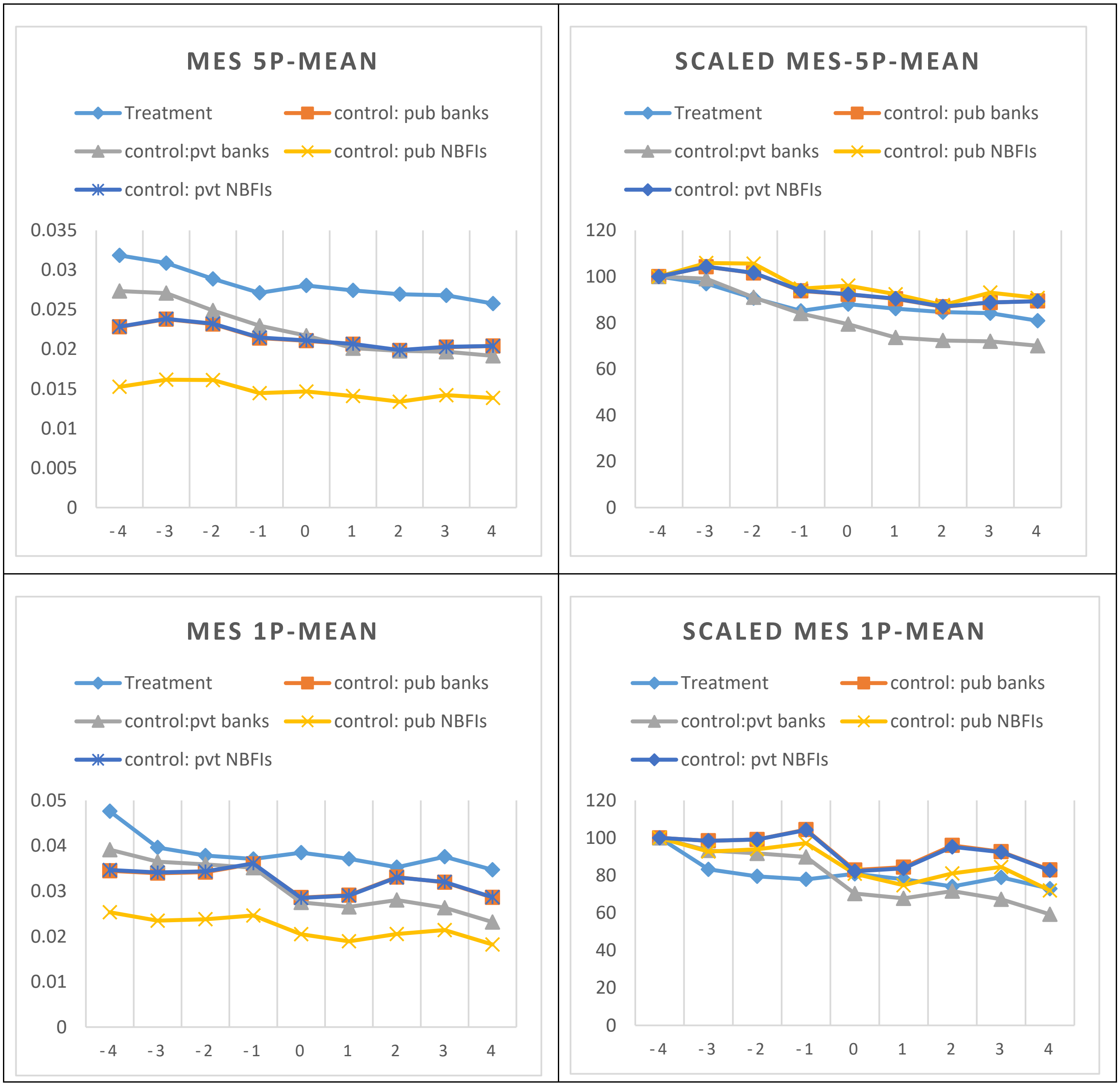


Figure A5: Time series plots of Distance to Default (DTD) measure over the sample period 2008-2018

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.

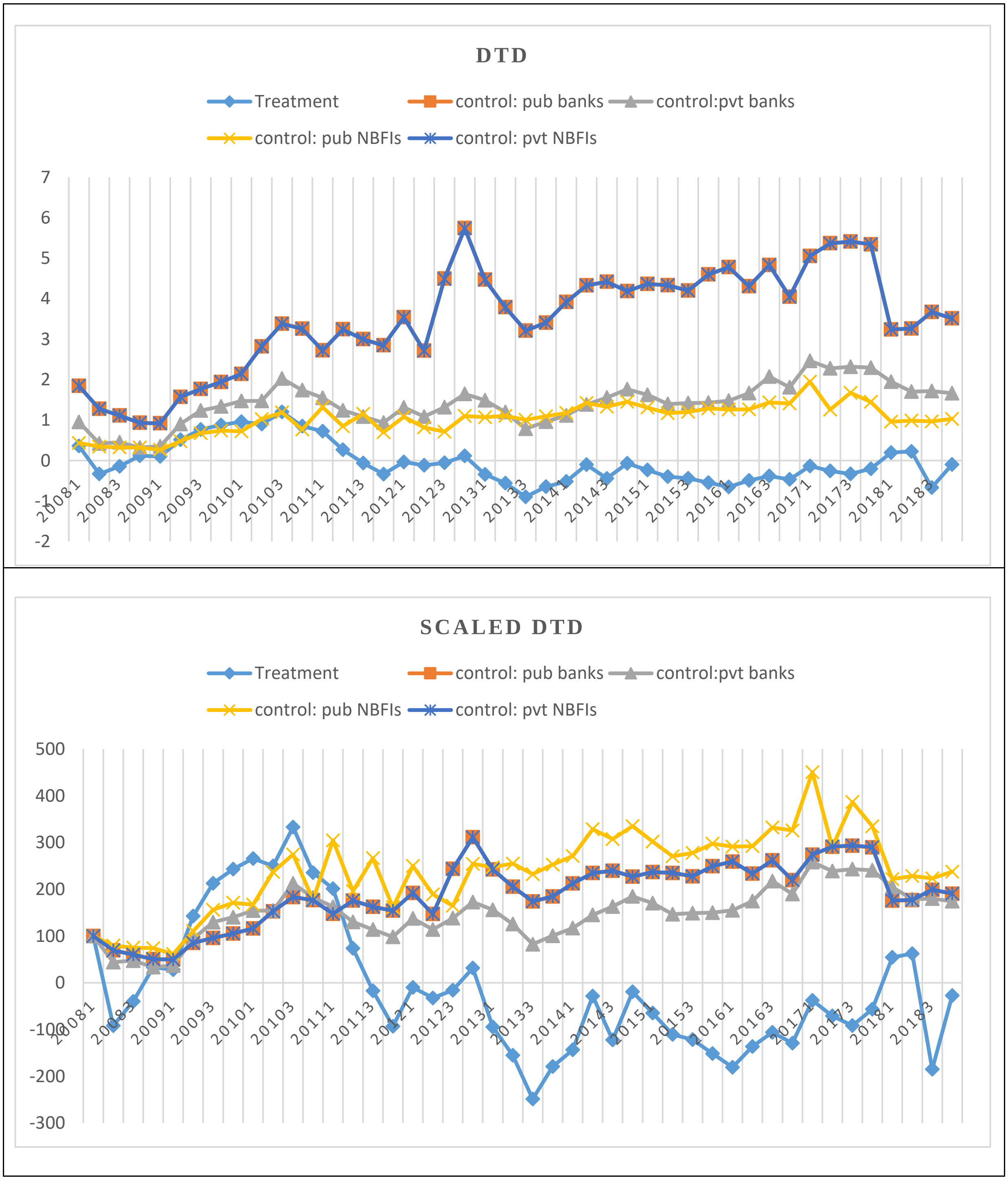


Figure A6: Time series plots of the Margin Expected Shortfall (MES) measure of systemic risk over the sample period 2008-2018

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.

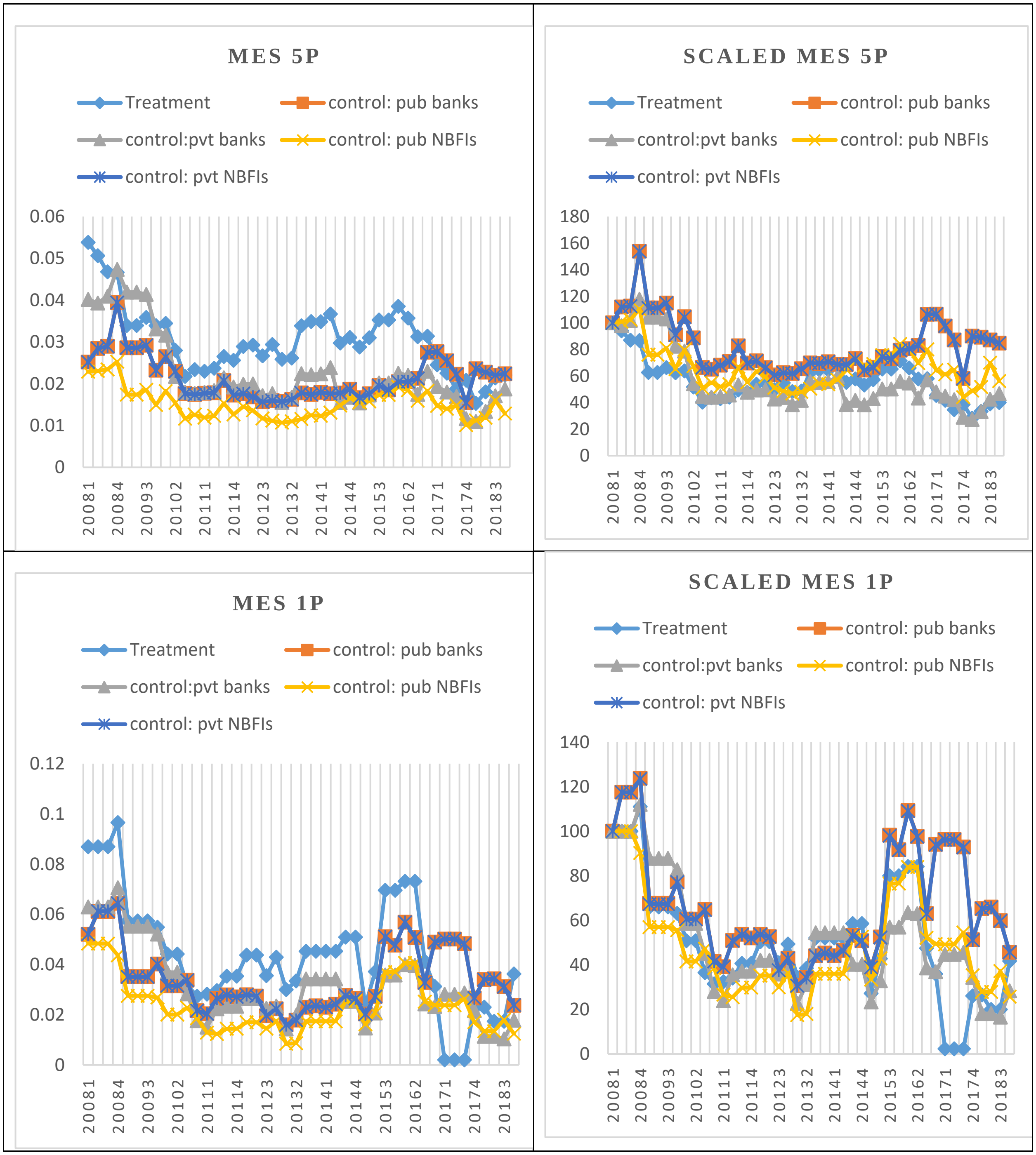


Table A1. Univariate comparisons of Distance to Default (DTD) around capital infusion

We present pre- and post- comparisons of DTD for the treatment and four different control samples for the sample period. We present results for ± 2 and 3 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.

	±2Q					±3Q				
	DTD									
	Post-pre performance									
	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
pre	0.074	3.160	1.424	0.979	3.151	0.048	3.090	1.367	0.949	3.082
post	0.040	3.778	1.682	1.186	3.773	0.029	3.766	1.685	1.158	3.762
post-pre	-0.034	0.618	0.258	0.207	0.621	-0.019	0.676	0.318	0.209	0.680
t-stat	-0.362	1.900	2.179	1.346	1.915	-0.215	2.119	2.741	1.373	2.135
P-value	0.717	0.058	0.030	0.179	0.056	0.830	0.034	0.006	0.170	0.033
	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.	-0.034	-0.034	-0.034	-0.034		-0.019	-0.019	-0.019	-0.019	
control	0.618	0.258	0.207	0.621		0.676	0.318	0.209	0.680	
treat-control	-0.652	-0.292	-0.241	-0.655		-0.696	-0.337	-0.228	-0.699	
t-stat	-3.451	-4.225	-2.999	-3.478		-3.986	-4.933	-2.804	-4.015	
P-value	0.001	0.000	0.003	0.001		0.000	0.000	0.005	0.000	

Table A2. Univariate comparisons of Margin Expected Shortfall (MES) around capital infusion

We present pre- and post- comparisons of MES 5 percentile (Panel A) and one percentile (Panel B)- for the treatment and four different control samples for the sample period. We present results for ± 2 and 3 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.

Panel A

	±2Q					**±3Q**				
	MES 5p									
	Post-pre performance									
	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
pre	0.028	0.022	0.024	0.015	0.022	0.029	0.023	0.025	0.016	0.023
post	0.027	0.020	0.020	0.014	0.020	0.027	0.020	0.020	0.014	0.020
post-pre	-0.001	-0.002	-0.004	-0.002	-0.002	-0.002	-0.003	-0.005	-0.002	-0.003
t-stat	-0.581	-1.775	-2.651	-0.905	-1.782	-1.403	-2.220	-3.433	-0.982	-2.225
P-value	0.562	0.076	0.008	0.366	0.075	0.161	0.027	0.001	0.326	0.026
	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.	-0.001	-0.001	-0.001	-0.001		-0.002	-0.002	-0.002	-0.002	
control	-0.002	-0.004	-0.002	-0.002		-0.003	-0.005	-0.002	-0.003	
treat-control	0.001	0.003	0.001	0.001		0.001	0.003	0.000	0.001	
t-stat	1.348	3.284	0.830	1.357		0.670	3.120	-0.214	0.676	
P-value	0.178	0.001	0.407	0.175		0.503	0.002	0.831	0.500	

Panel B

	±2Q					**±3Q**				
	MES 1p									
	Post-pre performance									
pre	0.037	0.035	0.036	0.024	0.035	0.038	0.035	0.036	0.024	0.035
post	0.036	0.031	0.027	0.020	0.031	0.037	0.031	0.027	0.020	0.031
post-pre	-0.001	-0.004	-0.008	-0.004	-0.004	-0.002	-0.003	-0.009	-0.004	-0.004
t-stat	-0.448	-1.991	-3.524	-1.509	-2.101	-0.540	-1.705	-3.866	-1.245	-1.796
P-value	0.654	0.047	0.000	0.132	0.036	0.589	0.089	0.000	0.214	0.073
	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.	-0.001	-0.001	-0.001	-0.001		-0.002	-0.002	-0.002	-0.002	
control	-0.004	-0.008	-0.004	-0.004		-0.003	-0.009	-0.004	-0.004	
treat-control	0.003	0.007	0.003	0.003		0.002	0.007	0.002	0.002	
t-stat	1.021	2.685	1.189	1.101		0.673	2.799	0.784	0.739	
P-value	0.308	0.008	0.236	0.272		0.501	0.005	0.434	0.461	

Table A3. Univariate panel regressions of DTD (Hypothesis 1)

Regression of DTD and MES Risk Variables with Robust Standard Errors (Clustered at Bank Level). We present the effect of capital infusion on DTD and MES Risk measures using the specification (1) in the paper. We consider sample regressions for ± 2 quarter window around the capital infusion date below. P-values are based on robust standard errors. All the variables are defined in Appendix A.

	(1)	(2)	(3)	(4)
	DTD		MES_5p	
Post Infusion Dummy	0.247***		-0.0281	
	(0.0233)		(0.0338)	
Large Infusions		-0.0670***		1.677***
		(0.0165)		(0.0258)
Constant	-0.302	-1.481***	3.944***	-0.343
	(0.196)	(0.208)	(0.263)	(0.311)
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
Observations	1,015	1,015	1,004	1,004
R-squared	0.697	0.540	0.675	0.450

Table A4. DID panel regressions of DTD (Hypothesis 1)

We present the effect of capital infusion on DTD of the treatment versus control sample banks using the DID specification (3) in the paper. We consider pairwise comparison with each of the four control samples, as defined in Section 3, but only present 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.

	(1)	(2)	(3)	(4)	(5)
VARIABLES			DTD		
Treatment Dummy	-1.885**	-1.889**	-2.078**		
	(0.728)	(0.736)	(0.755)		
Post Infusion Dummy	0.306**	0.258**		0.244**	
	(0.110)	(0.101)		(0.101)	
Large Infusions	0.0364	0.0404	0.0341		
	(0.604)	(0.610)	(0.602)		
Treatment x Post Infusion Dummy	-0.121	-0.0662	0.154	0.0409	0.256***
	(0.159)	(0.132)	(0.122)	(0.119)	(0.0913)
Treatment x Post x Large Infusions	0.0854	0.0370	0.0884	-0.0640	-0.0169
	(0.114)	(0.0731)	(0.117)	(0.0460)	(0.0866)
Constant	0.658	1.779***	0.872	-0.370*	-1.319***
	(0.633)	(0.454)	(0.704)	(0.187)	(0.370)
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
Observations	1,073	1,073	1,073	1,073	1,073
R-squared	0.417	0.496	0.417	0.723	0.649

Table A5. DID panel regressions of MES (Hypothesis 2)

We present the effect of capital infusion on MES of the treatment versus control sample banks using the DID specification (4) in the paper. We consider pairwise comparison with each of the four control samples, as defined in Section 3, but only present 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.

	(1)	(2)	(3)	(4)	(5)
VARIABLES			MES_5p		
Treatment Dummy	-0.330	-0.175	0.0519		
	(0.292)	(0.177)	(0.267)		
Post Infusion Dummy	-0.535***	-0.0132		-0.0198	
	(0.0783)	(0.0647)		(0.0650)	
Large Infusions	0.653**	0.475***	0.634**		
	(0.277)	(0.149)	(0.261)		
Treatment x Post Infusion Dummy	0.177	-0.0409	-0.358***	-0.0195	-0.337***
	(0.156)	(0.114)	(0.111)	(0.110)	(0.118)
Treatment x Post x Large Infusions	-0.178	0.0516	-0.156	0.0394	-0.167
	(0.143)	(0.100)	(0.125)	(0.0945)	(0.132)
Constant	0.352	2.821***	-0.0174	3.198***	0.798**
	(0.287)	(0.300)	(0.320)	(0.275)	(0.353)
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
Observations	1,530	1,530	1,530	1,530	1,530
R-squared	0.378	0.535	0.370	0.671	0.509