Coverage Levels in Deposit Insurance: to Increase or not to Increase

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ABSTRACT

This paper studies the impact on welfare of changes in coverage levels within deposit insurance schemes. The paper builds on previous literature by adding the possibility of bailouts for too-big-to-fail banks and incorporating a time lag between deposit payout and recoveries. Banks are also allowed to adjust deposit rates, and I include the effect this has on welfare. I show how to link theoretical results in this expanded model to observable variables, and I apply it to Colombia's 2017 increase in its coverage level. I estimate all the model's parameters from data and calculate the impact on welfare of this increase in coverage. Benefits outweigh costs, although the net effect is modest in size and sensitive to some of the parameters. Key variables are size, the probability of default and the impact the change in the coverage level has on the amount of insured deposits. Bailouts have mixed effects but overall raise the costs of increasing coverage levels. So does including a time lag between payout and recoveries. Allowing banks to adjust deposit rates also leads to larger costs because of higher deposit rates.

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I. Introduction

Deposit insurance schemes (DIS) protect small depositors and reduce the risk of inefficient runs within the banking sector. They are created to support financial stability. At the same time, DIS lower depositors' incentives to monitor banks since they are protected from potential losses. Their existence might allow banks to take more risks, creating moral hazard and increasing risk within the system. The moral hazard pitfall highlights the need for designing DIS carefully. A key feature for balancing benefits and risks is limited coverage: the guarantee offered is partial, usually up to a maximum per person per bank.

The importance of limited coverage is widely recognized by practitioners, but guidance about how to determine its level is vague. In its central policy document, *The Core Principles for Effective Deposit Insurance Systems*, the International Association of Deposit Insurers (IADI) states that coverage should be *limited, credible, and cover the large majority of depositors but leave a substantial amount of deposits exposed to market discipline.*[1] The intuition behind this statement is reasonable, but as guidance it is insufficient: how are "the large majority of depositors" or "a substantial amount of deposits" defined?[2] Moreover, when should these limits—commonly referred to as coverage levels—be changed, and what considerations should DIS take into account when doing so?

The goal of this paper is to contribute to the literature on coverage levels and their impact on welfare. I build on an analytical structure proposed by Dávila and Goldstein (2020). They develop a framework to measure the impact on welfare of a change in the coverage level. I expand their model by including several additional features. I then show how to link all of the theoretical results to observables. I use this expanded characterization and a quasi-natural experiment to quantify how changing the coverage level impacts welfare. The experiment I use is an increase in the coverage level that happened in Colombia in 2017. I also show how the result depends on the variables used to calculate it, highlighting how costs and benefits change when inputs are modified. To my knowledge, this is the first paper that computes the effect of changing coverage levels in a precise way using both a theoretical model and empirical bank data.

The role of deposit insurance within the global financial architecture is first analyzed in the seminal paper by Diamond and Dybvig (1983). Many authors have built on this model, but most of the models proposed do not include limited coverage.[3] Theory regarding this aspect of DIS is scarce.[4] Relevant literature starts with Cooper and Ross (2002), who expand the Diamond and Dybvig model by incorporating moral hazard and monitoring by depositors. They are one of the first references to discuss the effects of limited coverage, but they do so tangentially and do not advocate for a particular level.[5] Manz (2009) analyzes coverage levels analytically. He builds

[1] International Association of Deposit Insurers (2014).

[2] An earlier, unpublished guidance paper by the IADI mentions that insuring 80% of depositors and 20% of total deposits is adequate, but underscores that this is merely a rule of thumb presented at a 2002 IADI conference.

[3] A recent reference is Allen, Carletti, Goldstein, and Leonello (2018). They find that government guarantees may be welfare improving because they prompt banks to provide liquidity.

[4] As reviewed in Gorton and Winton (2003), for example, none of the extensions of Diamond and Dybvig (1983) up to that moment even discuss partial coverage.

[5] In fact, they seem to discourage the idea of partial insurance. They argue that it can lead to moral hazard without

a model using a global game framework in which players privately observe noisy signals of the underlying state of the world. Other literature that presents ideas or analyses related to optimal coverage levels includes Angkinand and Wihlborg (2010) and Morrison and White (2011). The former uses country data to show that risk varies in a quadratic form with regards to coverage levels. Morrison and White (2011) present an agency-type model in which they examine the role of deposit insurance, specifically the relationship between coverage levels and the soundness of the banking sector. More recent papers include Shy, Stenbacka, and Yankov (2016) and Egan, Hortaçsu, and Matvos (2017). Shy et al. (2016) do not advocate for using partial coverage levels because there is a social dead-weight loss associated with them. Findings in Egan et al. (2017) are closely related to coverage levels since instability in banks is associated with uninsured depositors.

All things considered, however, none of these authors present a framework that can be linked to observable variables to study changes in coverage levels. The paper by Dávila and Goldstein (2020) changes this. They find that changes in coverage levels impact welfare through four sufficient statistics, and that this continues to be the case when they relax some of the model's assumptions. They also present preliminary ideas of how this model could be linked to observables, but highlight practical challenges to achieve this.

I build on their model in several ways. First, I add the possibility of government bailouts when a solvent bank faces the possibility of a bank run. This expands the role played by DIS beyond deposit insurance payout when banks fail. It incorporates a feature usually associated with "too-big-to-fail" (TBTF) institutions. Whereas practitioners have tried to move away from bailouts since the last global financial crisis, we have yet to see a different resolution tool used successfully to resolve a failing systemic bank. Moreover, prohibiting bailouts might not even be desirable, as argued by Keister (2016). He points out that removing bailouts might raise incentives for depositors to withdraw early if there is the expectations that others might to so. This increases the probability of runs and lowers welfare in the economy.[6]

Second, I incorporate a time lag between deposit payout and the recovery of assets from the failing bank. This is a minor adjustment in terms of the model, but makes it closer to what happens in the real world, where liquidating assets usually takes time. It is particularly relevant in cases in which insured deposits are lower than expected recoveries from banks' assets. Not having this time difference implies that there is no financial cost associated with payout in these instances. However, it is usually the case that deposit funds need to be deployed immediately while recoveries will take months to be reimbursed to the DIS.

Dávila and Goldstein (2020) show how their main result needs to be expanded by an additional term when they allow rates paid by banks to vary because of the change in coverage. I incorporate this effect—a fiscal externality—as a third enhancement to the expanded model and show how it

curbing the probability of runs.

[6] A relevant discussion about banks' behaviour and its implications on bailouts versus other alternatives is presented in Acharya and Yorulmazer (2007) and Acharya and Yorulmazer (2008). Górnicka and Zoican (2016) expand the discussion and study resolution at a supranational level. Schilling (2020) analyzes resolution strategies more broadly and how they impact depositors' behaviour.

increases costs overall. I also shows how this effect is different for banks that are bailed out than for banks that face liquidation and deposit payout in such scenario. Adding this effect on rates is relevant because it incorporates potential moral hazard in the aggregate result: it captures banks' reaction to a broader safety net.

I aggregate the extensions proposed in an equation that characterizes the impact on wealth of a change in the coverage level. I then show how to link all terms in this equation—the expanded model—to observables. This makes the methodology easier to use as a practical tool to think through the benefits and costs of changing the coverage level. It also shows the intuition behind the terms that comprise the model and the data needed to calculate them.

I apply the methodology to measure the impact on welfare of a change in the level of coverage that happened recently in Colombia. The quasi-natural experiment that I make use of occurred in 2017, when coverage was increased from COP (Colombian pesos) 20 to COP 50 million (USD 15,000 approximately).[7] This allows me to access data—insured deposits, for example—at both pre- and post-increase coverage levels.

In order to incorporate the moral hazard component, one needs an estimate of the impact that changing coverage has on rates. This requires going beyond the model. I estimate this effect using a fixed-effects regression with appropriate controls. Moreover, the framework relies on a couple of parameters that are not directly observable. Both terms are required to calculate probabilities of failure. I thus use a simplified version of the model proposed by Merton (1974) and the generalized method of moments to estimate them.

Benefits outweigh costs: the net effect of the increase in the coverage level is USD 12.71 million. This result is sensitive to some of the parameters used. Key variables are size, the probability of default and the change in the percentage of insured deposits because of the increase in the coverage level. The total result is also dominated by a particular bank where insured deposits increased substantially due to the change. In general, bailouts augment costs and lower benefits, making increases in coverage levels less desirable. Incorporating a time lag between payout and recoveries has a similar effect. Deposit rates increased because of the increase in coverage, so incorporating the fiscal externality adds to costs as well. All in all, the expanded model reduces benefits by more than a third of what they would have been per the original model proposed by Dávila and Goldstein (2020), using the same data and assumptions.

The remainder of this paper is organized as follows. Section II presents the key features and the intuition behind the model proposed. Section III details the way to connect each term in the model to observables. Section IV begins with a brief overview of Colombia's banking sector and the data used. It then details the estimation of parameters and the impact that the change in the coverage level had on rates. Section V presents the impact on welfare of the 2017 increase in the coverage level in Colombia and how these results change when parameters vary. Section VI concludes. Additional results and derivations are included in several appendices.

[7] Using the COP/USD exchange rate as of December 2019.

II. Modeling Deposit Insurance

A. The Model by Davila and Goldstein

Dávila and Goldstein (2020) build on the framework developed by Diamond and Dybvig (1983). Their model has a similar setup, but they extend the original analytical structure in several ways. This allows them to focus on partial deposit insurance and determine the welfare impact of changes in the coverage levels under a variety of setups. Since my model is an extension of their framework, I present their setup in some detail. This is also useful to introduce notation and key assumptions.

The model has three dates, $t = 0, 1, 2$, and a single consumption good. There is a unit mass of ex-ante identical depositors (consumers) and a representative bank. There is also a continuum of identical taxpayers and a benevolent policymaker. Different decisions are taken by these actors at different points in time. There is a continuum of aggregate states of the economy that will be realized and known by participants at $t = 1$. These states are denoted by $s \in [\underline{s}, \bar{s}]$ and are distributed according to a cdf $F(\cdot)$.

At $t = 0$, each depositor i deposits an amount D_{0i} in the bank. Deposits at $t = 0$ are distributed according to $G(\cdot)$ and have a total mass given by $\bar{G} = \int_0^{\overline{D}} dG(i)$. At $t = 1$, each depositor decides how much money to keep in the bank, D_{1i}. There are no further inflows and this is the main decision depositors face. Following Diamond and Dybvig (1983), some of the depositors are early consumers (λ) and withdraw all their deposits at $t = 1$. The remaining are late consumers (1-λ) and would like to keep their money in the bank until $t = 2$. Depositors also have additional wealth not deposited in the bank. Early depositors receive this wealth as a stochastic endowment, $Y_{1i}(s)$, at $t = 1$; late depositors receive an amount $Y_{2i}(s)$ at $t = 2$.

At $t = 1$, the bank pays depositors a gross return R_1 for each unit of consumption good deposited at $t = 0$. This return is taken as fixed and exogenous in the model's main characterization. The bank earns a return on each unit of the consumption good deposited, which depends on the materialized state s: it earns a return $\rho_1(s)$ and $\rho_2(s)$ at $t = 1$ and $t = 2$, respectively. Both $\rho_1(s)$ and $\rho_2(s)$ are continuous and increasing in the realization of s. As in the original Diamond and Dybvig (1983) model, there are two possible scenarios for the bank at $t = 2$: it fails or not. This depends on two variables: the state s realized at $t = 1$, and the decision taken by late consumers. They can keep their money in the bank until $t = 2$ or decide to withdraw it early at $t = 1$.

Dávila and Goldstein (2020) divide possible scenarios at $t = 2$ into three regions depending on the state of the economy realized. Lower values of s correspond to states of the world where banks are less profitable. Thus, if s is low, the bank fails no matter what depositors do at $t = 1$. In contrast, if s is high, the bank survives no matter what depositors' actions are. In the middle, when s is between two critical values, $\hat{s} < s < s^*$, the decisions taken by depositors at $t = 1$ are key. If too many late depositors decide to withdraw their money, the bank will collapse due to a bank run; otherwise it survives. If the bank collapses, either because of a fundamental failure or a run, deposit insurance is triggered and depositors are paid up to the coverage level δ. Determining the value of δ is the policymaker's responsibility. This decision is taken at $t = 0$.

In case of failure, depositors are initially paid with resources recovered from the bank itself. These resources are equal to the available funds in the bank minus a dead weight loss associated with failure. The percentage recovered from the failed bank is depicted as $\chi(s) \in [0,1]$. Additional funds and any costs associated with them will be borne by taxpayers. The shortfall between the promised payment to insured depositors and what is recovered from the bank is presented as $T(s)$. The cost of raising these funds is characterized by a convex function, $\kappa(T(s))$, where $\kappa(0) = 0$ and $\lim_{T\to\infty} \kappa(T) = \infty$. Taxpayers have an endowment $Y_\tau(s)$.

Social welfare in the economy is presented as the sum of the expected utility of depositors and taxpayers. As a function of δ, $W(\delta) = \int_0^{\overline{D}} V_i(\delta, R_1) dG(i) + V_\tau(\delta, R_1)$, where $V_i(\delta, R_1)$ is depositor i utility for a given coverage level (δ) and deposit rate (R_1). $V_\tau(\delta, R_1)$ is taxpayers' utility, which depends on the same two variables. The equation of interest is the change in W with respect to a change in δ. Formally:

$$\frac{dW}{d\delta} = \int_0^{\overline{D}} \frac{dV_i}{d\delta} dG(i) + \frac{dV_\tau}{d\delta}. \tag{1}$$

If $C_{1i}(s)$ is consumption of early depositors and $C_{2i}(s)$ is that of late depositors, expected depositors' utility will be given by $V_i(\delta, R_1) = \lambda E_s[U(C_{1i}(s))] + (1-\lambda)E_s[U(C_{2i}(s))]$. Similarly, taxpayers' utility will be $V_\tau(\delta, R_1) = E_s[U(C_\tau(s))]$, where $C_\tau(s)$ is taxpayers' consumption.

By characterizing the utility of both depositors and taxpayers depending on the realized state s and the three regions introduced before, Equation (1) leads to the following first-order approximation of the change in welfare due to a change in coverage:[8]

$$\frac{dW}{d\delta} \approx -\frac{\partial q^F}{\partial \delta} \int \left[C_j^N(s^*) - C_j^F(s^*)\right] dj + q^F E_s^F \left[\int \frac{\partial C_j^F}{\partial \delta} dj\right], \tag{2}$$

where q^F is the unconditional probability of bank failure, $C_j^F(s^*)$ corresponds to the consumption of both depositors and taxpayers if the bank fails, and $C_j^N(s^*)$ is consumption if it survives; both are calculated at a specific state s^*. $E_s^F[\cdot]$ is a conditional expectation over failure states.

B. Extending the Model

I extend the main characterization proposed by Dávila and Goldstein (2020) in three ways. First, I incorporate the possibility that banks are bailed out rather than allowed to fail when facing a bank run. Compared to the case when a bank fails and insured deposits are reimbursed by taxpayers, in a bailout all creditors are supported. One can argue that this resolution strategy might be problematic, but it is still the first—if not the only—option for addressing a potential failure in a bank considered TBTF. These banks are more resilient nowadays, and several measures have been deployed to make failure less probable. But liquidating and paying deposit insurance in a big, interconnected bank is still to be tested. Second, Davila and Goldstein assume that recovered

[8] The authors also present this equation in terms of utility functions, which is exact. This approximation follows an expansion of utilities around $C_j^F(s^*)$ that allows them to work in terms of the consumption good directly rather than in terms of utility.

assets can be used to pay deposit insurance without any delay. In reality, selling and liquidating assets takes time. Including this in the model makes fiscal costs closer to what they are in the real world. This is relevant, in particular, in cases where insured deposits are substantially lower than recovery rates, which is the case for many jurisdictions. Third, the authors show that their results change when deposit rates are allowed to vary as a consequence of changing coverage levels. I incorporate this feature into the model, including how it is impacted by bailouts and the time lag between deposit payout and recoveries. I end this section by aggregating the extensions proposed in an equation that characterizes the overall impact on wealth of a change in the coverage level.

B.1. Bailouts

I assume that bailouts occur in the case a bank faces a panic run. Failure is now only possible if the state of the economy, s, is sufficiently low and the bank fails no matter what depositors' actions are. Bailouts will thus depend on s. The funds needed to avoid the run, which are characterized by $B(s)$, will also depend on s. They will be equal to the difference between available funds in the bank and expected deposit redemptions. Raising them will also have a financial cost, κ, similarly to what happens with funds used to pay for deposit insurance in case of failure. The cost of any bailout will thus be $(1+\kappa)B(s)$.

When we include bailouts, the utility of depositors and taxpayers will still be characterized by three regions, depending on the state of the world s. For low values of s, the bank fails. For high values of s, the bank survives no matter what depositors' actions are. In the middle, when s is between two critical values, $\hat{s} < s < s^*$, the decisions taken by depositors at $t = 1$ are key. Bailouts might happen in this region. If depositors run on the bank, taxpayers will bail it out and allow it to continue operating. They will do this by injecting the amount of liquidity needed, $B(s)$. Expected utility of depositors, depending on the realized state s and the three regions introduced before, will thus be[9]:

$$E_s[U(C_{ti}(s))] = \int_{\underline{s}}^{\hat{s}(R_1)} U(C_{ti}^F(s))dF(s) + \int_{\hat{s}(R_1)}^{s^*(\delta,R_1)} [\pi U(C_{ti}^B(s)) + (1-\pi)U(C_{ti}^N(s))]dF(s) + \int_{s^*(\delta,R_1)}^{\bar{s}} U(C_{ti}^N(s))dF(s), \quad (3)$$

where each of the three integrals corresponds to one of the regions discussed before: fundamental failure, multiple equilibria depending on the actions taken by depositors, and non-failure. $C_{ti}^F(s)$ corresponds to consumption of depositors if the bank fails, and $C_{ti}^N(s)$ is consumption if it does not. π is the probability that a failure occurs within the region of multiple equilibria—the probability of a bank run within this region, $\pi \in [0,1]$. For the moment, this is assumed to be an i.i.d. sunspot, i.e., an extrinsic random variable. $\hat{s}(R_1)$ and $s^*(\delta, R_1)$ are thresholds that define the areas covered by each of the three integrals. Both depend on R_1, but the latter also depends on δ. $C_{ti}^B(s)$

[9] An equivalent equation follows for taxpayers, with C_τ instead of C_{ti}.

corresponds to the consumption of depositors if the bank does not fail, but if that is the case because of a bailout. This only happens if depositors run on the bank in the region with multiple equilibria, which happens with probability π.

In fact, Equation (3) does not have a region with multiple equilibria anymore. The second and third integrals characterize regions of no failure in all cases, although in some instances this will be because of a bailout. In the case of a bailout, early consumers will receive the same funds as if there had been no failure, but late depositors' consumption will change: $C_{ti}^{B}(s) = [\alpha_B(s) + (1 - \zeta(\lambda, R_1))]D_{0i}R_1 + \frac{B(s)}{1-\lambda} + Y_{2i}(s)$. For taxpayers, consumption will be diminished by the funds deployed and the financial cost associated with them: $C_{\tau}^{B}(s) = C_{\tau}^{N}(s) - (1+\kappa)B(s)$.

Deriving Equation (3) with respect to coverage will lead to a modified version of Equation (2)[10]:

$$\frac{dW}{d\delta} \approx -\frac{\partial q^F}{\partial \delta} \int \left[C_j^N(s^*) - C_j^B(s^*)\right] dj + q^{FF} E_s^{FF}\left[\int \frac{\partial C_j^F}{\partial \delta} dj\right] + q^{PF} E_s^{PF}\left[\int \frac{\partial C_j^B}{\partial \delta} dj\right], \qquad (4)$$

where q^{FF} is the probability of a fundamental bank failure, and q^{PF} is the probability of a panic bank failure. $C_j^F(s)$, $C_j^N(s)$ and $C_j^B(s)$ are defined as before, and include both taxpayers and depositors. $E_s^{FF}[\cdot]$ and $E_s^{PF}[\cdot]$ are conditional expectations over fundamental and panic failure states, respectively.

Compared to Equation (2), which has two terms, including bailouts modifies the impact of changes in coverage levels on welfare in two ways. With regards to the first term, differences in consumption are now between consumption when there is no failure, $C_j^N(s)$, and consumption when there is a bailout, $C_j^B(s)$—both calculated at state s^*. Similarly, the second term in Equation (2) is now partitioned into two expressions differentiating changes associated with fundamental and panic failures. For the case of panic failures, consumption is that associated with bailout scenarios.

I include bailouts only for TBTF banks when I apply the methodology later on, but the derivations would not change if a different approach for determining eligible banks was applied. Equation (4) characterizes the impact on welfare for any bank that is subject to a bailout.

B.2. A Time Lag Between Payout and Recovery

The model proposed by Davila and Goldstein uses assets from the failed bank to pay depositors in the case of bankruptcy. Thus, in case of failure taxpayers pay the difference between insured deposits and recovered assets, whenever the former is greater than the latter:

$$T(s) = \max\left\{\int_0^{\overline{D}} \min\{D_{0i}R_1, \delta\} dG(i) - \chi(s)\rho_1(s)D_0, 0\right\}.$$

However, the model assumes that assets from the failed bank can be recovered without delay. In reality, liquidating assets is a process that usually takes time. Assets might have legal issues that

[10] Detailed derivations for $C_{ti}^{B}(s)$ and this equation are presented in Appendix A.

need to be solved—or at least understood—before attempting to sell them. Valuations might be required. Operational and administrative issues are also common when a bank is forced to close.

In contrast, deposit payout needs to be quick. This is best practice among DIS, and key for them to be useful. To account for this, payout needs to be independent of recoveries—and will not depend on s anymore. I thus define deposit payout to be equal to insured deposits:

$$T = \int_0^{\overline{D}} \min\{D_{0i}R_{,}\delta\} dG(i).$$

To incorporate recovered assets back into the model, I define a new variable $\phi(s)$, which captures what taxpayers will recover by liquidating assets from the failed bank. If insured deposits are greater than what is recovered, only this latter amount will go back to taxpayers. If, in contrast, recoveries are greater than insured deposits, they will only get back what they paid—insured deposits. Thus, $\phi(s)$ will be the minimum between insured deposits and actual recoveries from bank assets. Formally:

$$\phi(s) = \min\left\{\int_0^{\overline{D}} \min\{D_{0i}R, \delta\} dG(i), \chi(s)\rho_1(s)D_0\right\}.$$

Consumption by taxpayers in failure states, in the original model, was equal to $C_\tau^F(s) = Y_\tau(s) - T(s) - \kappa(T(s))$. This will now be given by $C_\tau^F(s) = Y_\tau(s) - T - \kappa(T) + \phi(s)$. Equations (2) and (4) continue to be valid when the time lag is included, but results will change if recoveries are higher than insured deposits.

B.3. Allowing Deposit Rates to Change

Equation (2) is the central result presented in Dávila and Goldstein (2020), but the authors discuss how it can be extended in several ways. One that is relevant is allowing R_1 to vary when the coverage level changes. I incorporate this feature into the model, including both bailouts and the time lag between deposit payout and recoveries. Since now the model includes variation in R_1, as well as in δ, Equation (1) becomes:

$$\begin{aligned}
\frac{dW}{d\delta} &= \int_0^{\overline{D}} \frac{dV_i}{d\delta} dG(i) + \frac{dV_\tau}{d\delta}, \\
&= \int_0^{\overline{D}} \frac{\partial V_i}{\partial \delta} dG(i) + \frac{\partial V_\tau}{\partial \delta} + \left(\int_0^{\overline{D}} \frac{\partial V_i}{\partial R_1} dG(i) + \frac{\partial V_\tau}{\partial R_1}\right) \frac{dR_1}{d\delta}.
\end{aligned}$$

Assuming that competitive banks choose R_1 at date $t = 0$ to maximize depositors' expected utilities, R_1 will be given by the rate that solves $\frac{\partial V}{\partial R_1} = 0$, where V is depositors' utility, $V = \int_0^{\overline{D}} V_i(\delta, R_1) dG(i)$. Since $\int_0^{\overline{D}} \frac{\partial V_i}{\partial R_1} dG(i) = 0$, allowing R_1 to change augments Equation (2) by incorporating an additional term—a fiscal externality—which is equal to $\frac{\partial V_\tau}{\partial \delta} \frac{dR_1}{d\delta}$. Thus, the impact of a change in coverage in wealth when R_1 is allowed to vary will be given by:

$$\frac{dW}{d\delta} \approx -\frac{\partial q^F}{\partial \delta} \int \left[C_j^N(s^*) - C_j^F(s^*)\right] dj + q^F E_s^F \left[\int \frac{\partial C_j^F}{\partial \delta} dj\right] + \frac{\partial V_\tau}{\partial R_1}\frac{dR_1}{d\delta}, \tag{5}$$

where the first set of terms is defined as per Equation (2), and the last term is the fiscal externality that appears as banks change R_1 in response to the change in the coverage level δ.

A similar reasoning for the case with bailouts will lead to the impact of coverage having an additional term:

$$\frac{dW}{d\delta} \approx -\frac{\partial q^F}{\partial \delta} \int \left[C_j^N(s^*) - C_j^B(s^*)\right] dj + q^{FF} E_s^{FF} \left[\int \frac{\partial C_j^F}{\partial \delta} dj\right] + q^{PF} E_s^{PF} \left[\int \frac{\partial C_j^B}{\partial \delta} dj\right] + \frac{\partial V_\tau}{\partial R_1}\frac{dR_1}{d\delta}, \tag{6}$$

where the first terms are defined as per Equation (4), and $\frac{\partial V_\tau}{\partial \delta}\frac{dR_1}{d\delta}$ has the same meaning as per Equation (5). Although the interpretation is the same, I expand this term later on and show how it differs in both cases.

B.4. The Extended Model

I consolidate Equations (5) and (6) into an aggregate expression that integrates the possibility of bailouts. I assume TBTF banks will be bailed out in case there is a run; smaller banks will not. In order to make the model linked to data, I include a bank subscript k to those terms that are bank specific. I aggregate the effect on all banks to get the total impact on welfare. The change in wealth in the extended model will thus be given by:

$$\frac{dW}{d\delta} \approx \sum_{k=1}^{n} \underbrace{-q_k^F \frac{\partial \log q_k^F}{\partial \delta} \int \left[C_{j,k}^N(s_k^*) - C_{j,k}^B(s_k^*)\right] dj}_{\text{term 1}} + \underbrace{q_k^{FF} E_s^{FF} \left[\int \frac{\partial C_{j,k}^F}{\partial \delta} dj\right] + q_k^{PF} E_s^{PF} \left[\int \frac{\partial C_{j,k}^B}{\partial \delta} dj\right]}_{\text{term 2}} + \underbrace{\frac{\partial V_{\tau,k}}{\partial R_k}\frac{dR_k}{d\delta}}_{\text{term 3}}, \tag{7}$$

where n corresponds to the number of banks in the economy; $k = (1, \ldots, n_1)$ are considered to be TBTF. As presented before, $C_{j,k}^B(s)$ will be different for TBTF banks than for other banks (non-systemic banks, hereafter) that will not be bailed out.[11]

[11] Specifically, for $k = (1, \ldots, n_1)$, $C_{j,k}^B(s) = [\alpha_{B,k} + (1 - \zeta_k(\lambda, R_k))]D_{0i,k}R_k + \frac{B_k(s)}{1-\lambda} + Y_{2i}(s)$ for late depositors, and $C_{j,k}^B(s) = C_{\tau,k}^N(s) - (1 + \kappa_k)B_k(s)$ for taxpayers. I use R_k to denote the rate paid by bank k, instead of $R_{1,k}$, to

III. Connecting the Model to Observables

To illustrate how each component of Equation (7) can be calculated, I have separated it into three terms. In this section I show how to connect each of these terms to data.

A. *Term 1 - Marginal Benefits*

Term 1 is a bank's unconditional probability of failure multiplied by the change in the semi-elasticity of this probability with respect to coverage and by the drop in aggregate consumption at state s_k^*. For an increase in coverage, this term captures additional consumption because of a lower probability of default. Term 1 can be further decomposed into three terms:

$$\textit{Marginal benefit} = -\underbrace{q_k^F}_{\text{term 1a}}\underbrace{\frac{\partial \log q_k^F}{\partial \delta}}_{\text{term 1b}}\underbrace{\int\left[C_{j,k}^N(s_k^*) - C_{j,k}^B(s_k^*)\right] dj}_{\text{term 1c}}. \tag{8}$$

A.1. Term 1a - Unconditional Probability of Failure

q_k^F is each bank's unconditional probability of failure. This probability depends on the size of the regions associated with the possibility of failure and on π, the probability of a run:

$$q_k^F(\delta, R_k) = \underbrace{F_k(\hat{s_k}(R_k))}_{q_k^{FF}} + \underbrace{\pi[F_k(s_k^*(\delta, R_k)) - F_k(\hat{s_k}(R_k))]}_{q_k^{PF}}. \tag{9}$$

Per Equation (9), the probability of a bank failing has two components. The first one is the probability of a fundamental failure, q_k^{FF}. It depends on the distribution $F_k(\cdot)$ at a specific state $\hat{s_k}(R_k)$ and is different for each bank. The second component corresponds to the probability of a failure due to actions taken by late depositors, q_k^{PF}. It further depends on π and on the distribution $F_k(\cdot)$ at state $s_k^*(\delta, R_k)$, which is a function of the coverage level δ also.

Following equations presented in Dávila and Goldstein (2020), $\hat{s_k}(R_k)$ and $s_k^*(\delta, R_k)$ correspond to the levels of s_k that satisfy the following equations:

$$\frac{R_k - \rho_{1,k}(\hat{s_k})}{1 - \frac{1}{\rho_{2,k}(\hat{s_k})}} = (1-\lambda)R_k \qquad\qquad \frac{R_k - \rho_{1,k}(s_k^*)}{1 - \frac{1}{\rho_{2,k}(s_k^*)}} = (1-\lambda)R_k\zeta_k(\delta, R_k),$$

where $\zeta_k(\delta, R_k)$ denotes insured deposits as a fraction of total deposits at bank k, and $\rho_{1,k}(s_k)$ and $\rho_{2,k}(s_k)$ have the same meaning as in the original model but are now bank specific. Assuming monotonically increasing functions for $\rho_{1,k}(s_k) = \rho_{2,k}(s_k) = s_k$, the following set of equations characterize solutions for $\hat{s_k}(R_k)$ and $s_k^*(\delta, R_k)$:

simplify notation. For $k = (n_1 + 1, \ldots, n)$, $C_{j,k}^B(s) = C_{j,k}^F(s)$ for both depositors and taxpayers.

$$\hat{s}_k(R_k) = \frac{\lambda R_k \pm \sqrt{(\lambda R_k)^2 + 4R_k(1-\lambda)}}{2} \tag{10}$$

$$s_k^*(\delta, R_k) = \frac{R_k(1-\zeta_k+\lambda\zeta_k) \pm \sqrt{R_k^2(1-\zeta_k+\lambda\zeta_k)^2 + 4R_k(1-\lambda)\zeta_k}}{2}. \tag{11}$$

Further, assuming a lognormal distribution for s_k, the cdf for the banks' gross returns will be given by $F_k(\cdot)$, with parameters μ_k and σ_k for the respective normal distribution:

$$F_k(s) = \int_0^{s_k(\cdot)} \frac{1}{\sqrt{2\pi}x\sigma_k} \exp\left(-\frac{(\log x - \mu_k)^2}{2\sigma_k^2}\right) dx, \tag{12}$$

where μ_k and σ_k can be estimated directly from data.

Adding all up, to calculate q_k^F, besides ζ_k, R_k, μ_k and σ_k, which one can get from data, we need an estimate for π. Furthermore, to calculate $\hat{s_k}(R_k)$ and $s_k^*(\delta, R_k)$, we need an estimate, or make an assumption, about the proportion of early depositors λ.

A.2. Term 1b - Sensitivity of the Probability of Failure to a Change in Coverage

$\frac{\partial \log q_k^F}{\partial \delta}$ is the semi-elasticity of the unconditional probability of failure with respect to coverage. This corresponds to the percentage change in q_k^F with respect to an absolute change in δ. Thus:

$$\frac{\partial \log q_k^F}{\partial \delta} = \frac{1}{q_k^F} \frac{\partial q_k^F}{\partial \delta}. \tag{13}$$

The first part of this equation is the inverse of the unconditional probability of failure (term 1a). The second term can be calculated by deriving Equation (9) with respect to δ:[12]

$$\frac{\partial q_k^F}{\partial \delta} \approx \pi f_k(s_k^*(\delta, R_k)) \frac{\partial s_k^*}{\partial \delta},$$

where: a) $f_k(s_k^*(\delta, R_k))$ is given by the pdf of a lognormal distribution with associated normal, $N \sim (\mu_k, \sigma_k)$, evaluated at $s_k^*(\delta, R_k)$; b) $s_k^*(\delta, R_k)$ follows Equation (11); and c) $\frac{\partial s_k^*}{\partial \delta}$ can be decomposed using the chain rule.[13] Thus, $\frac{\partial s_k^*}{\partial \delta} = \frac{\partial s_k^*}{\partial \zeta_k} \frac{\partial \zeta_k}{\partial \delta}$, where the first term captures the change in the limits of the second region due to the change in the percentage of insured deposits, and the second term is the change in these deposits due to the change in coverage. Both can be calculated from data.

A.3. Term 1c - Consumption Gap at Marginal State s_k^*

Term 1c in Equation (8) is the drop in aggregate consumption at the limit state s_k^* in case there is a run on bank k. This term is different for TBTF banks than for non-systemic ones.

[12] We can also compute this second term directly instead of as a first order approximation: $\frac{\partial q_k^F}{\partial \delta} = \pi \left[F_k(s_k^*(\delta_{t+1}, R_k)) - F_k(s_k^*(\delta_t, R_k))\right]$, where t corresponds to the month before coverage was changed.

[13] This can also be calculated directly: $\frac{\partial s_k^*}{\partial \delta} = \frac{s_{k,t+1}^*(\delta_{t+1}, R_k) - s_{k,t}^*(\delta_t, R_k)}{\delta_{t+1} - \delta_t}$.

Non-systemic Banks: For non-systemic banks, $C^B_{j,k}(s) = C^F_{j,k}(s)$ for both depositors and taxpayers. Following derivations presented in Dávila and Goldstein (2020):

$$\int \left[C^N_{j,k}(s^*_k) - C^F_{j,k}(s^*_k)\right] dj = (\rho_{2,k}(s^*_k) - 1)(\rho_{1,k}(s^*_k) - \lambda R_k)D_{0,k} + (1 - \chi_k(s^*_k))\rho_{1,k}(s^*_k)D_{0,k} + \kappa_k(T_k(s^*_k)). \tag{14}$$

The first term in Equation (14) is the bank's expected return between $t = 1$ and $t = 2$, which is lost if the bank fails. The second term corresponds to the dead weight loss because of the failure itself. The third term is the cost of raising additional money to pay for deposit insurance.

Equation (14) is still valid when there is a time lag between payout and recoveries.[14] However, the results will change since $T_k(\cdot)$ is equal to insured deposits and will no longer depend on s: $T_k = \int_0^{\overline{D}_k} \min\{D_{0i,k}R_k, \delta\}dG(i) = D_{0,k}R_k\zeta_k(\delta, R_k)$. Thus, $\kappa_k(T_k)$ will not depend on s either. In the original model taxpayers only need to fund payments if recoveries are less than insured deposits. When there is a time lag between payout and recoveries they always do.

To calculate Equation (14), one needs an estimate for $\chi_k(\cdot)$ and to define $\kappa_k(\cdot)$.[15] $\chi_k(\cdot)$ is the rate of recovery of bank assets in a failed scenario. One can use an estimate for all banks, leveraging on historical data, or calculate this for each bank per the composition of its assets. $\kappa_k(\cdot)$ can be approximated by a linear function $\kappa_k(\cdot) = H_k T_k(\cdot)$, assuming H_k is constant over failure states. In the case there is a DIS funded ex-ante, H_k can be estimated as the difference between the expected return of bank k, μ_k, and the expected return of funds invested within the scheme, μ_τ.

TBTF Banks: In the case of TBTF banks, $C^B_{j,k}(s) = C^N_{i,k}(s)$ for early depositors, $C^B_{j,k}(s) = [\alpha_{B,k} + (1 - \zeta_k)]D_{0i,k}R_k + \frac{B_k(s)}{1-\lambda} + Y_{2i}(s)$ for late depositors, and $C^B_{j,k}(s) = C^N_{\tau,k}(s) - (1 + \kappa_k)B_k(s)$ for taxpayers.

In order for the bailout to be effective, $B_k(s)$ needs to cover the difference between the available funds and those demanded by depositors in case of a run. Assuming partially insured depositors will only leave deposits up to the maximum level of coverage, $B_k(s)$ needs to be equal to:

$$B_k(s) = \frac{(R_k - \rho_{1,k}(s))D_{0,k}}{(1 - 1/\rho_{2,k}(s))} - (1 - \lambda)R_k\zeta_k D_{0,k}.$$

Per this equation, the amount needed for a successful bailout depends on the state s. No money will be needed if s is equal to $s^*_k(\delta, R_k)$: $B_k(s^*_k) = 0$; the amount required is maximum when $s = \hat{s_k}(R_k)$. Thus, at $s = s^*_k(\delta, R_k)$ the consumption gap will be zero for both taxpayers and early depositors. For late depositors, it will be equal to $C^N_{j,k}(s) - [\alpha_{B,k} + (1 - \zeta_k)]D_{0i,k}R_k$. Aggregating this among all late depositors, term 1c will be equal to $(1 - \lambda)(\rho_{2,k}(s^*_k) - 1)(1 - \zeta_k)D_{0,k}R_k$.[16]

[14] This is presented in detail in Appendix A.

[15] $D_{0,k}$, $\rho_{1,k}(s^*_k)$, $\rho_{2,k}(s^*_k)$ and R_k were already discussed.

[16] The detailed derivation for the consumption gap for late depositors is presented in Appendix A and characterized by Equation (A1) for any state s.

B. *Term 2 - Marginal Costs*

The second term in Equation (7) is a bank's probability of failure multiplied by the change in consumption because of the change in coverage. I refer to this term as marginal costs, but it can be positive in some cases because of the possibility of bailouts, as will be shown below. I present the details about how to calculate term 2 by further splitting it into two terms:

$$Marginal\ cost = \underbrace{q_k^{FF} E_s^{FF}\left[\int \frac{\partial C_{j,k}^F}{\partial \delta} dj\right]}_{\text{term 2a}} + \underbrace{q_k^{PF} E_s^{PF}\left[\int \frac{\partial C_{j,k}^B}{\partial \delta} dj\right]}_{\text{term 2b}}. \tag{15}$$

B.1. Term 2a - Marginal Cost of Increasing Coverage over Fundamental Failure States

The first term in Equation (15) is the expected marginal cost of increasing coverage over fundamental failure states multiplied by the probability of a fundamental failure. One can start with aggregate consumption in failure states:

$$\int_0^{\overline{D}_k} C_{ti,k}^F(\delta, R_k) dG(i) + C_{\tau,k}^F = \chi_k(s)\rho_{1,k}(s)D_{0,k} - \kappa_k(T_k) + \overline{Y}_{j,k}(s), \tag{16}$$

where $\overline{Y}_{j,k}(s) = \int_0^{\overline{D}_k} Y_{ti,k}(s)dG(i) + Y_{\tau,k}(s)$.[17] Deriving Equation (16) with respect to δ:

$$= -\kappa'(T)\frac{\partial}{\partial \delta}\int_0^{\overline{D}} \min\{D_{0i}R_1, \delta\} dG(i).$$

Replacing $\kappa_k'(T_k) = H_k$, and substituting insured deposits for $D_{0,k}R_k\zeta_k(\delta, R_k)$, term 2a in Equation (15) can be expressed as follows:

$$q_k^{FF} E_s^{FF}\left[\int \frac{\partial C_{j,k}^F}{\partial \delta} dj\right] = -q_k^{FF} H_k D_{0,k} R_k \frac{\partial \zeta_k(\delta, R_k)}{\partial \delta}. \tag{17}$$

B.2. Term 2b - Marginal Cost of Increasing Coverage over Panic Failure States

The second term in Equation (15) is the expected marginal cost of increasing coverage over panic failure states multiplied by the probability of a panic failure. The expected marginal cost will be different for TBTF than for other banks since it depends on $C_{j,k}^B$.

Non-systemic Banks: For non-systemic banks there will be no bailouts, so $C_{j,k}^B(s) = C_{j,k}^F(s)$, for both depositors and taxpayers. Thus, term 2b will be similar to term 2a as per Equation (17):

$$q_k^{PF} E_s^{PF}\left[\int \frac{\partial C_{j,k}^F}{\partial \delta} dj\right] = -q_k^{PF} H_k D_{0,k} R_k \frac{\partial \zeta_k(\delta, R_k)}{\partial \delta}. \tag{18}$$

[17] I show in Appendix A how to derive Equation (16).

TBTF Banks: For early depositors, $C^B_{j,k}(s) = C^N_{j,k}(s)$ and $\frac{\partial C^N_{j,k}}{\partial \delta}(s) = 0$. For late depositors, $\frac{\partial C^B_{j,k}(s)}{\partial \delta} = (\rho_{2,k}(s) - 1)(1-\lambda)D_{0,k}R_k\frac{\partial \zeta_k}{\partial \delta} + \frac{\partial B_k(s)}{\partial \delta}$. For taxpayers, $\frac{\partial C^B_{j,k}(s)}{\partial \delta} = -\frac{\partial (1+\kappa_k)B_k(s)}{\partial \delta}$. Aggregating depositors and taxpayers:[18]

$$\int \frac{\partial C^B_{j,k}(s)}{\partial \delta} dj = ((\rho_{2,k}(s) - 1) + \kappa'_k(\cdot))(1-\lambda)D_{0,k}R_k\frac{\partial \zeta_k(\delta, R_k)}{\partial \delta}.$$

Going back to Equation (15), we can express term 2b for TBTF banks as follows:[19]

$$q^{PF}_k E^{PF}_s\left[\int \frac{\partial C^B_{j,k}}{\partial \delta} dj\right] = (1-\lambda)D_{0,k}R_k\frac{\partial \zeta_k(\delta, R_k)}{\partial \delta}\left[q^{PF}_k(H_k - 1) + \pi\int_{\hat{s}_k}^{s^*_k} sdF(s)\right]. \tag{19}$$

B.3. Aggregating Marginal Costs

For non-systemic banks, Equations (17) and (18) can be consolidated into one expression:

$$-q^{FF}_k H_k D_{0,k}R_k\frac{\partial \zeta_k(\delta, R_k)}{\partial \delta} - q^{PF}_k H_k D_{0,k}R_k\frac{\partial \zeta_k(\delta, R_k)}{\partial \delta} = -q^F_k H_k D_{0,k}R_k\frac{\partial \zeta_k(\delta, R_k)}{\partial \delta}.$$

For TBTF banks we get a similar expression with one additional term:

$$\begin{aligned}
&- q^{FF}_k H_k D_{0,k}R_k\frac{\partial \zeta_k(\delta, R_k)}{\partial \delta} + (1-\lambda)D_{0,k}R_k\frac{\partial \zeta_k(\delta, R_k)}{\partial \delta}\left[q^{PF}_k(H_k - 1) + \pi\int_{\hat{s}_k}^{s^*_k} sdF(s)\right] \\
&= -q^F_k H_k D_{0,k}R_k\frac{\partial \zeta_k(\delta, R_k)}{\partial \delta} + D_{0,k}R_k\frac{\partial \zeta_k(\delta, R_k)}{\partial \delta}\left[q^{PF}_k[(H_k(2-\lambda) - (1-\lambda)] + (1-\lambda)\pi\int_{\hat{s}_k}^{s^*_k} sdF(s)\right], \\
&= \left(- q^F_k H_k + \underbrace{\left[q^{PF}_k[H_k(2-\lambda) - (1-\lambda)] + (1-\lambda)\pi\int_{\hat{s}_k}^{s^*_k} sdF(s)\right]}_{\text{TBTF effect}}\right)D_{0,k}R_k\frac{\partial \zeta_k(\delta, R_k)}{\partial \delta}.
\end{aligned}$$

Interestingly, the additional term is positive, meaning that it diminishes the cost for TBTF banks—actually making the aggregate impact positive also since the TBTF effect is larger than $q^F_k H_k$ for small values of λ.

C. Term 3 - The Fiscal Externality

The last term in Equation (7), term 3, appears as banks react to the change in coverage by changing R_k. It is composed of the change in the utility of taxpayers due to the change in the rate in each bank, $\frac{\partial V_{\tau,k}}{\partial R_k}$, and the change in the rate due to the change in coverage, $\frac{dR_k}{d\delta}$. In this section I expand $\frac{\partial V_{\tau,k}}{\partial R_k}$. The change in the rate needs to be estimated with data.

[18] Detailed derivations are presented in Appendix A. This result corresponds to Equation (A2).

[19] $q^{PF}_k E^{PF}_s[\cdot] = \pi\int_{\hat{s}_k}^{s^*_k}[\cdot]dF(s)$.

The utility of taxpayers can be expressed as $V_{\tau,k} = E_s[U(C_{\tau,k}(s))]$ when decomposed by each bank's contribution to that utility. Expressing it in terms of the three regions, deriving it with respect to R_k, and approximating this expression linearly it can be divided in four terms:

$$\begin{aligned}\frac{\partial V_{\tau,k}}{\partial R_k} \approx \underbrace{q_k^{FF} E_s^{FF}\left[\frac{\partial C_{\tau,k}^F}{\partial R_k}\right]}_{\text{term 3a}} + \underbrace{q_k^{PF} E_s^{PF}\left[\frac{\partial C_{\tau,k}^B}{\partial R_k}\right]}_{\text{term 3b}} + \underbrace{(C_{\tau,k}^B(s_k^*) - C_{\tau,k}^N(s_k^*))\pi f_k(s_k^*)\frac{\partial s_k^*}{\partial R_k}}_{\text{term 3c}} \\ + \underbrace{[C_{\tau,k}^F(\hat{s_k}) - C_{\tau,k}^N(\hat{s_k}) - \pi(C_{\tau,k}^B(\hat{s_k}) - C_{\tau,k}^N(\hat{s_k}))] f_k(\hat{s_k})\frac{\partial \hat{s}_k}{\partial R_k}}_{\text{term 3d}}.\end{aligned} \tag{20}$$

Since this expression depends on $C_{\tau,k}^B$, I expand it separately for non-systemic and TBTF banks.

Non-systemic Banks: As presented before, for non-systemic banks $C_{\tau,k}^B(s) = C_{\tau,k}^F(s)$. So:

$$\begin{aligned}\frac{\partial V_{\tau,k}}{\partial R_k} \approx \underbrace{q_k^F E_s^F\left[\frac{\partial C_{\tau,k}^F}{\partial R_k}\right]}_{\text{term 3(a+b)}} + \underbrace{(C_{\tau,k}^F(s_k^*) - C_{\tau,k}^N(s_k^*))\pi f_k(s_k^*)\frac{\partial s_k^*}{\partial R_k}}_{\text{term 3c}} \\ + \underbrace{(C_{\tau,k}^F(\hat{s_k}) - C_{\tau,k}^N(\hat{s_k}))(1-\pi) f_k(\hat{s_k})\frac{\partial \hat{s}_k}{\partial R_k}}_{\text{term 3d}}.\end{aligned} \tag{21}$$

Equation (21) is composed of three terms, since terms 3a and 3b have been consolidated into one expression. Terms 3c and 3d correspond to the difference in taxpayers' consumption between failure and non-failure states, $C_{\tau,k}^F(s) - C_{\tau,k}^N(s) = -[\kappa_k(T_k) + T_k] + \phi_k(s)$, at s_k^* and $\hat{s}_k$, respectively. This difference is multiplied by π and $(1-\pi)$, respectively, and by the change in the limit s state per the change in the rates. This change can be calculated using Equations (10) and (11) for a determined change in R_k. Regarding term 3(a+b), one can begin by deriving $C_{\tau,k}^F(s) = Y_\tau(s) - [\kappa_k(T_k) + T_k] + \phi_k(s)$ with respect to R_k:

$$\frac{\partial C_{\tau,k}^F(s)}{\partial R_k} = -\left(\kappa_k'(\cdot) + 1\right)\frac{\partial T_k}{\partial R_k} + \frac{\partial \phi_k(s)}{\partial R_k}.$$

This expression depends on whether recoveries are greater than insured depositors:

$$\begin{aligned}\frac{\partial C_{\tau,k}^F(s)}{\partial R_k} &= -(\kappa_k'(\cdot) + 1)\psi_k(\delta, R_k) && \text{if } T_k > \phi_k(s), \\ &= -\kappa_k'(\cdot)\psi_k(\delta, R_k) && \text{if } T_k \leq \phi_k(s),\end{aligned}$$

where $\psi_k(\delta, R_k) = \int_0^{\frac{\delta}{R_k}} D_{0i,k} dG(i)$ is fully-covered deposits at bank k. It is equal to the change in insured deposits per change of unit of rate R_k. Incorporating this term back into the expectation and replacing $\kappa_k'(\cdot) = H_k$, term 3(a+b) will be equal to:

$$q_k^F E_s^F \left[\frac{\partial C_{\tau,k}^F}{\partial R_k}\right] = -q_k^F \left[H_k + F_k(s_k^\diamond)\right] \psi_k(\delta, R_k),$$

where $s_k^\diamond = \frac{R_k \zeta_k}{\chi_k}$.[20] Finally, the aggregate term for the total change in the utility of taxpayers in the case of a non-systemic bank is:

$$\begin{aligned}\frac{\partial V_{\tau,k}}{\partial R_k} \approx -q_k^F \left[F_k(s_k^\diamond) + H_k\right] \psi_k(\delta, R_k) - [(1+H_k)T_k - \phi_k(s_k^*)]\pi f_k(s_k^*)\frac{\partial s_k^*}{\partial R_k} \\ - [(1+H_k)T_k - \phi_k(\hat{s_k})](1-\pi) f_k(\hat{s_k})\frac{\partial \hat{s_k}}{\partial R_k}.\end{aligned} \tag{22}$$

TBTF Banks: For TBTF banks, term 3c is absent since $(C_{\tau,k}^B(s_k^*) - C_{\tau,k}^N(s_k^*)) = 0$. Thus:

$$\begin{aligned}\frac{\partial V_{\tau,k}}{\partial R_k} \approx \underbrace{q_k^{FF} E_s^{FF}\left[\frac{\partial C_{\tau,k}^F}{\partial R_k}\right]}_{\text{term 3a}} + \underbrace{q_k^{PF} E_s^{PF}\left[\frac{\partial C_{\tau,k}^B}{\partial R_k}\right]}_{\text{term 3b}} \\ + \underbrace{[C_{\tau,k}^F(\hat{s_k}) - C_{\tau,k}^N(\hat{s_k}) - \pi(C_{\tau,k}^B(\hat{s_k}) - C_{\tau,k}^N(\hat{s_k}))] f_k(\hat{s_k})\frac{\partial \hat{s_k}}{\partial R_k}}_{\text{term 3d}}.\end{aligned} \tag{23}$$

Term 3a in Equation (23) is similar to term 3(a+b) for non-systemic banks, only that it is multiplied by the probability of fundamental failure, q_k^{FF}. To expand term 3b, we derive consumption in the case of a bailout, $C_{\tau,k}^B(s) = C_{\tau,k}^N(s) - (1+\kappa_k)B_k(s)$, with respect to R_k:

$$\frac{\partial C_{\tau,k}^B(s)}{\partial R_k} = -(1+\kappa_k'(\cdot))D_{0,k}\left[\frac{\rho_{2,k}(s)}{\rho_{2,k}(s)-1} - (1-\lambda)\zeta_k\right].$$

Multiplying by q_k^{PF}, and substituting $q_k^{PF} E_s^{PF}[s/(s-1)] = \pi \int_{\hat{s}_k}^{s_k^*} s/(s-1) dF(s)$:

$$q_k^{PF} E_s^{PF}\left[\frac{\partial C_{\tau,k}^B(s_k)}{\partial R_k}\right] = -[1+H_k]D_{0,k}\left[\pi \int_{\hat{s}_k}^{s_k^*} \frac{s}{s-1} dF(s) - q_k^{PF}(1-\lambda)\zeta_k\right]. \tag{24}$$

All the quantities to calculate Equation (24) are known; the integral can be computed numerically.

Lastly, term 3d in Equation (23) can be easily expanded in terms of known quantities:

$$\begin{aligned}&[C_{\tau,k}^F(\hat{s_k}) - C_{\tau,k}^N(\hat{s_k}) - \pi(C_{\tau,k}^B(\hat{s_k}) - C_{\tau,k}^N(\hat{s_k}))] f_k(\hat{s_k})\frac{\partial \hat{s_k}}{\partial R_k} \\ &\qquad = -[(1+H_k)(T_k - \pi B_k(\hat{s})) - \phi_k(\hat{s})] f_k(\hat{s_k})\frac{\partial \hat{s_k}}{\partial R_k}.\end{aligned}$$

[20] $s_k^\diamond$ corresponds to the value where recoveries are equal to insured deposits for bank k.

Adding all up, for TBTF banks the change in utility of taxpayers because of a change in R_k is:

$$\frac{\partial V_{\tau,k}}{\partial R_k} \approx -q_k^{FF}\left[F_k(s_k^{\diamond}) + H_k\right]\psi_k(\delta, R_k) - [1+H_k]D_{0,k}\left[\pi\int_{\hat{s}_k}^{s_k^*}\frac{s}{s-1}dF(s) - q_k^{PF}(1-\lambda)\zeta_k\right]$$
$$- \left[(1+H_k)(T_k - \pi B_k(\hat{s})) - \phi_k(\hat{s})\right]f_k(\hat{s_k})\frac{\partial \hat{s_k}}{\partial R_k}. \quad (25)$$

IV. Colombia's 2017 Coverage Increase

In April 2017, Colombia increased the deposit insurance coverage level for banks and similar institutions. This happened after many years of keeping it constant. It was an administrative decision taken by the DIS to restore the value of coverage in nominal terms. The coverage level was increased by 150%, from COP 20 to COP 50 million (USD 15,000 approx).

I use this event to study the impact on welfare of changing coverage levels. I have access to data both at the pre- and post-increase levels, which are needed to estimate Equation (7). Moreover, the fact that the change was sudden and exogenous—not linked to anything happening in the financial sector—allows me to estimate the effect it had on rates and include the impact this change on rates had on welfare.

A. Colombia's Financial Sector and its DIS

Colombia's financial system is composed of roughly 50 banks or similar deposit-taking institutions. A handful, mostly local players, dominate the market in terms of size. Some banks are linked together as part of broader financial conglomerates. In terms of their balance sheet, loans comprise about 70% of assets, investments 20% and cash roughly 5%; other assets comprise the remaining 5%. On the liability side, deposits account for 65% of total assets, equally distributed among saving accounts and term deposits, and with a lower participation of demand deposits. Most deposits are in Colombian pesos; dollar-denominated deposits are negligible.

The Colombian government created FOGAFIN (*Fondo de Garantías de Instituciones Financieras*) following a financial crisis in the early 1980s. One of its main responsibilities is the development and administration of a DIS.[21] The scheme is compulsory for all deposit-taking institutions. It covers several types of deposit accounts. The most relevant ones are demand deposits, saving accounts and term deposits. Deposit insurance payment is triggered when the banking supervisor orders the liquidation of a member institution. FOGAFIN claims to be able to pay insured depositors within 7 days of the closure of a failing entity.

The DIS is funded by quarterly contributions of its members. They pay an annual fixed-fee of 0.3% of their deposits plus or minus a variable risk-adjusted fee. Effective fees range from 0.15% to 0.45%. As of June 2020, FOGAFIN had a fund (created by the accumulation of premiums charged) equivalent to approximately 5.5% of total deposits in the system.

[21] Colombia has another DIS for financial cooperatives. This scheme is administered separately.

B. The Data

I use monthly information from banks' aggregate balance sheets since January 2010 until December 2018. Raw data are available at the banking supervisor's webpage.[22] I limit to data from banks that account for at least 0.5% of total deposits in the system to validate that they are relevant within the deposit market.[23] These 16 institutions account for 95.9% of deposits and 94.5% of assets within Colombia's banking sector.

To calculate the average return of banks, μ_k, and their variability, σ_k, I use data until March 2017. This is the month before the change in the coverage level happened. I estimate χ_k, the rate of recovery of bank assets in a failed scenario, using a simple exercise and data from March 2017 as well. For each bank I first estimate the amount of losses that would make it insolvent. I use deteriorated loans as a percentage of total loans as a proxy for further losses after failure. I then apply a 50% recovery rate to deteriorated loans and other assets and add to this the remaining "good loans" to estimate available assets.[24] Finally, I deduct a 3% recovery cost to obtain the estimated recovery rate.[25]

For other variables I use information as of March 2017, if they correspond to the period before the change, and as of April 2017, otherwise. Summary statistics for all relevant variables are presented in Table I. Detailed numbers per bank are presented in Table III in Appendix B.

Table I. Summary Statistics of Relevant Variables

Statistic	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
μ_k	0.162	0.045	0.082	0.130	0.158	0.175	0.252
σ_k	0.036	0.016	0.013	0.025	0.036	0.043	0.072
χ_k	0.735	0.087	0.473	0.720	0.754	0.780	0.836
R_k	1.062	0.012	1.042	1.057	1.062	1.067	1.086
$\zeta_{k,t}$	0.136	0.104	0.026	0.075	0.094	0.193	0.414
$\zeta_{k,t+1}$	0.192	0.130	0.062	0.110	0.143	0.229	0.513
ψ_k	0.083	0.077	0.0001	0.035	0.054	0.112	0.267
$D_{0,k}$	7.399	7.265	0.648	3.091	4.962	8.958	26.405

Note: This table reports summary statistics of the data used for the analyses in this paper. μ_k is the median return over equity (ROE) for each bank from Jan 2010 - March 2017; σ_k is the standard deviation of the ROE for this same time frame. χ_k is the recovery rate of bank assets in a failed scenario. R_k is the implied interest rate at March 2017, calculated as total interest rate expenses by total interest-bearing liabilities; to match the way this is used in the derivations it is presented gross (one plus the rate). $\zeta_{k,t}$ is insured deposits / total deposits as of March 2017, and $\zeta_{k,t+1}$ is the same ratio one month after. ψ_k is the percentage of fully-covered deposits at March 2017. $D_{0,k}$ corresponds to total deposits for this date as well; this amount is presented in USD billion.

[22] `https://www.superfinanciera.gov.co`.

[23] I also exclude one small entity that has less than 1% of its deposits insured; insured deposits seem to have been reduced at the higher coverage level per the data. This exclusion does not materially impact the results.

[24] The 50% follows estimates for recoveries in Latin America presented in La Porta, Lopez-de Silanes, and Zamarripa (2003) and Felsovalyi and Hurt (1998).

[25] This 3% cost is in line with estimates by Dermine and De Carvalho (2006) and references cited therein.

The median return over equity (μ_k) is 16.2%, and the mean standard deviation within individual banks (σ_k) is 3.6%. The recovery rate (χ_k) has a mean of 73.5% and ranges between 47% and 83%. This is very much in line with estimates of recoveries for Colombian banks of 73.7%, as presented in Fogafin (2009). It is also in line with values reported in Matvos (2013) for the USA between 2007 and 2013.[26] Implied interest rates (R_k) range roughly from 4% to 8%. Average insured deposits ($\zeta_{k,t}$) were 13.6% before coverage was increased and 19.2% afterwards ($\zeta_{k,t+1}$). Average fully-covered deposits (ψ_k) are 8.3% of total deposits.[27] Finally, deposits per bank ($D_{0,k}$) are USD 7.4 billion on average; the biggest bank in the sample has approximately USD 26.4 billion in deposits.

Other values needed to calculate Equation (7) are μ_τ, π and λ. I use $\mu_\tau = 0.07$, which corresponds broadly to the return of FOGAFIN's investment fund during the last 10 years. The estimation of π and λ follows.

C. Estimation of Parameters

I use what is commonly referred to as the 'Merton model' to estimate a time-series of probabilities of default. Then, I use the the generalized method of moments (GMM) to estimate π and λ based on these probabilities and Equation (9). Details about the Merton model and the GMM are presented in Appendix C.

One of the major constraints for using the Merton model in developing markets is the absence of publicly available stock prices. This is the case for Colombia's banking sector.[28] Since I need to estimate only two parameters, I use data from those two banks with the most complete information for the period of analysis.[29] Following the procedure presented in Appendix C, I calculate their distances to default (DD) and then transform these into probabilities using an exponential function. The DD are shown in the left panel of Figure 1; the probabilities are depicted in the right panel.

With these probabilities as inputs, I use the GMM. The equation I want to minimize by changing $\theta = (\lambda, \pi)$ is the following:

$$g(\theta; y_{1:T}) = \frac{1}{T}\sum_{t=1}^{T} \mathbb{E}\left[q^F_{Merton,t} - q^F_t(\theta)\right],$$

where q^F_{Merton} are the probabilities per the Merton model and $q^F(\theta)$ are calculated per Equation (9).[30] I include two lagged values of the probabilities as instruments and use a weighting matrix calculated using the Newey-West estimate with two lags (Newey and West (1987)). I use a constrained optimization routine with initial values for $\theta = (0.05, 0.15)$.[31] The resulting parameters

[26] Additional results for particular asset classes are also reported in Shibut and Singer (2015) and references cited therein.

[27] I estimate this using information presented by buckets at the banking supervisor's website.

[28] Relevant references are Romero, Quintero, Mosquera, et al. (2013) and Souto and Abrego (2008). León (2012) uses information from money market spreads to try to work around this limitation.

[29] These are Bancolombia and Banco de Bogotá. To be consistent with what I use in the rest of the paper, I use data from 2010 until 2018.

[30] Details about this equation and the steps used to estimate the parameters are presented in Appendix C.

[31] These values are proposed by Dávila and Goldstein (2020).

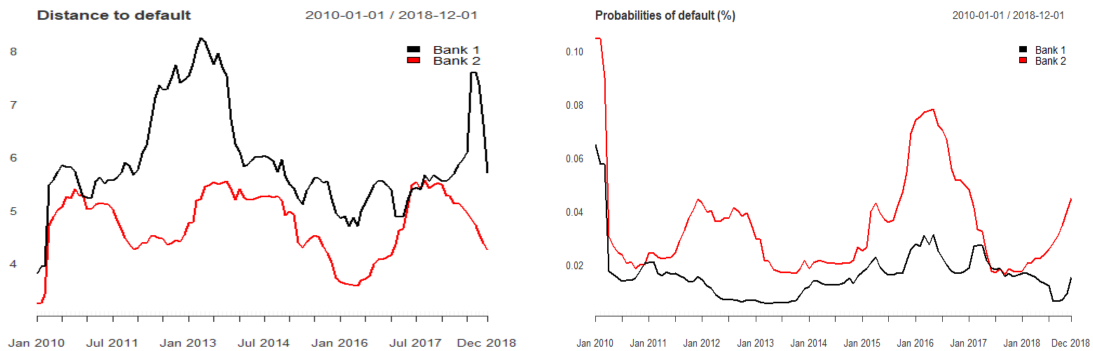

Figure 1. Estimated Distances to Default and Associated Probabilities

Note: The panels in this figure show the estimated distance to default (left panel) and probability of default (right panel, shown as percentages) for both banks analyzed.

are $\lambda = 0.01$ and $\pi = 0.09$. The result for λ follows the positive constraint embedded in the optimization; I use 1% as the lower limit. π, on the other hand, is found to be 9%. Its 95% confidence interval is between 5% and 12%.

D. The Impact on Rates

Besides the estimation of parameters, to calculate term 3 in Equation (7) one needs to estimate the change in the rate R_k due to the change in coverage, $\frac{dR_k}{d\delta}$. This expression could be either positive or negative—the rate might increase or decrease following a change in coverage. Dávila and Goldstein (2020) state that in most cases R_k should increase when coverage is increased. This is indeed what I find.

To estimate $\frac{dR_k}{d\delta}$ I use a fixed-effects model with banks' risk variables and the monetary interest rate as controls. The model is the following:

$$r_{it} = \mu_i + \alpha_t + \eta_t + \beta' BankInd_{i,t-j} + e_{it},$$

where i corresponds to the individual bank, $i = 1, \ldots, N$, and t corresponds to the time script, $t = 1, \ldots, T$. The dependent variable, r_{it}, is the interest rate paid by bank i at time t. μ_i represents fixed effects for bank. η_t corresponds to the rate set by the monetary authority at t. α_t is a dummy that equals 1 when the coverage level is COP 50 million and zero otherwise. $BankInd_{i,t-j}$ is a $N \times T$ by k matrix, and β is a $1 \times k$ vector, where k is the number of banks' risk variables included. e_{it} is the standard error. $BankInd_{i,t-j}$ is included with a lag of $j = 3$ months because data are usually available with this lag.

The impact that the change in coverage had on deposit rates, $\frac{dR_k}{d\delta}$, is equal to 8×10^{-3}. This value is significant at a 1% level. Details about the model, the variables used and their summary statistics are presented in Appendix D.

V. Empirical Results

This section details the impact that Colombia's 2017 increase in the coverage level had on welfare. I use Equation (7) and the data and parameters previously presented. I include as TBTF those banks that have been classified as such by the banks' supervisor. I also conduct several sensitivity analyses to understand the main drivers of the results. Finally, I briefly discuss how the extensions presented in this paper impact the results.

A. *Impact of the 2017 Increase on Welfare*

Columns 1-3 of Table II present the results for each of the three terms that make up Equation (7). The aggregate impact is shown in columns 4 and 5, and as a percentage of each bank's assets in column 6. Each row corresponds to an individual bank. Consolidated results for all banks are presented in the lower panel of the table.

Table II. Costs, Benefits, the Fiscal Externality and Net Impact on Wealth

	Marginal benefit (USD)	Marginal cost (USD)	Fiscal externality (USD)	Agg impact (USD)	Total impact (TI) (USD M)	TI / Assets (%)
1*	3.3	0.4	-63.4	-59.7	-3.83	-0.014
2	7.6	-3.0	-2.7	2.0	0.11	0.002
3	148.2	-109.3	-20.3	18.5	1.52	0.015
4*	0.2	0.0	-1.4	-1.2	-0.09	-0.000
5	2.7	-0.2	-0.3	2.3	0.18	0.005
6	32.7	-3.9	-2.1	26.7	1.92	0.028
7*	0.0	0.0	-0.0	-0.0	-0.00	-0.000
8	17.7	-2.8	-1.9	13.0	0.82	0.007
9	0.0	-0.0	-0.0	0.0	0.00	0.000
10*	0.0	0.0	-0.0	-0.0	-0.00	-0.000
11	2.2	-0.2	-0.2	1.7	0.10	0.001
12	0.0	-0.0	-0.0	-0.0	-0.00	-0.000
13	0.0	-0.0	-0.0	0.0	0.00	0.000
14	20.0	-21.2	-7.6	-8.8	-0.68	-0.057
15	110.0	-5.2	-1.7	103.1	12.64	1.183
16	1.5	-1.1	-0.1	0.3	0.01	0.002
M	21.6	-9.2	-6.4	6.1	0.79	0.073
Md	2.5	-0.2	-0.8	0.2	0.01	0.001
Tot	346.2	-146.4	-101.7	98.0	12.71	0.007

Note: This table reports results for aggregate benefits and costs per Equation (7). Each row corresponds to a bank; those marked with an * are considered to be TBTF. The last three rows are the mean, the median and the sum of each column, respectively. With regards to columns, the first column is term 1 (the marginal benefit). The second column is term 2 (the marginal cost). The third column is term 3 (the fiscal externality). Column 4 is the aggregate impact on wealth per unit of increase of coverage, $\frac{dW_k}{d\delta}$. All these columns are in USD. The fifth column is column 4 capitalized at the ROE of each bank times the increase in coverage (USD 10,000 approx); it is presented in millions of USD. Column 6 is column 5 divided by the assets of each bank.

On average, a USD 1 increase in coverage generates USD 22 of benefit via lower probabilities of default and avoided sunk costs. This benefit is higher for banks that have a high probability of unconditional failure (e.g., banks number 3, 14 and 15) and for banks that combine a relevant size with a moderate probability of failure (e.g., banks number 6 and 8). In the case of TBTF banks (marked with an *), it is highest for bank 1. Banks 7, 9, 10, 12 and 13 report zero for all terms shown in Table II because their probability of failure is extremely low.

In terms of marginal costs, since these are also related to the unconditional probability of failure, banks with higher benefits tend to have higher costs; size and profitability play a role here as well. Average costs per dollar of increase in coverage are USD 9. As discussed before, for TBTF banks marginal costs are positive, since increasing the coverage level diminishes the money needed for a bailout. This is in fact the case for bank 1 (for others it is approximately zero).

The fiscal externality is highest for this bank as well. For other TBTF banks it is low because their probability of default is very low. It is a relevant quantity, nonetheless, since it is higher than benefits and will make the total impact become negative. For non-systemic banks it is highest for those with high marginal costs. Overall, the average fiscal externality cost is a little less than marginal costs, USD 6 per dollar increase in coverage.

Averages in these three columns are higher than medians since they are influenced by a few banks' high numbers. Median values are lower, at USD 2.5, USD 0.2 and USD 0.8, respectively. Detailed results per bank are presented in Appendix E.

Columns 4-6 present aggregate results for each bank. The fourth column shows the impact on wealth per unit of increase in coverage, $\frac{dW_k}{d\delta}$. The impact is positive for most banks, but negative for banks 1, 4 and 14. TBTF banks tend to have negative numbers, even if they are small for some of them, since the fiscal externality is higher because of bailouts. In the case of non-systemic banks, the magnitude of the effect is driven by the probability of default. This is the case for banks 3 and 15. It is also highly dependent on the change in insured deposits caused by the increase in coverage. Banks 14 and 15 have increases in insured deposits of 15.3 and 9.1 percentage points, respectively. This increase impacts both marginal costs directly and the fiscal externality through changes in $\hat{s_k}$ and s_k^*. All in all, the aggregate effect for the banking sector is positive, on average around USD 6 for every dollar by which coverage is increased.

Column five presents the results from column four multiplied by the actual change in coverage, USD 10,000 approx, and capitalized at each bank's ROE, μ_k.[32] The total impact of the 2017 increase in coverage is USD 790 thousand per bank in average. The total benefit is USD 12.71 million. Following the analysis of benefits and costs presented earlier, some banks add to this value and others subtract from it. Results for bank 15 dominate in terms of magnitude. In terms of variables, size is important, as could be expected. Financial fragility is also key, as captured by each bank's unconditional probability of failure. The distribution of its insured deposits matters too. Finally, column six presents the aggregate effect on welfare divided by each bank's assets. This number varies substantially by bank; it is 0.007% in aggregate.

[32] I assume the impact on wealth is a perpetuity and calculate its present value by discounting these flows by the ROE of each bank.

B. Sensitivity Analysis

I conduct two types of analysis in order to study the sensitivity of results to inputs. On the one hand, I vary the estimated parameters in the model: λ and π. On the other, I examine how results vary when I change inputs that are directly linked to data. I present results varying the recovery rate, χ_k, changing the riskiness of banks by modifying the variability of their returns, σ_k, and modifying the amount of each bank's insured deposits, ζ_k. Most of the analysis is presented with respect to the total impact of the increase in coverage—last value in column five (Table II).

B.1. Varying Assumptions

Figure 2 presents how the impact on welfare changes when λ and π vary. Following results obtained when estimating both parameters, I present the analysis for $\lambda = (0, \ldots, 0.05)$ and $\pi = (0, \ldots, 0.15)$. Results vary linearly with both parameters but in opposite directions. For all values of λ the effect of the change in coverage on welfare continues to be positive. With regards to π, it becomes negative if this value is less than 4%. This is just outside of its 95% confidence interval.

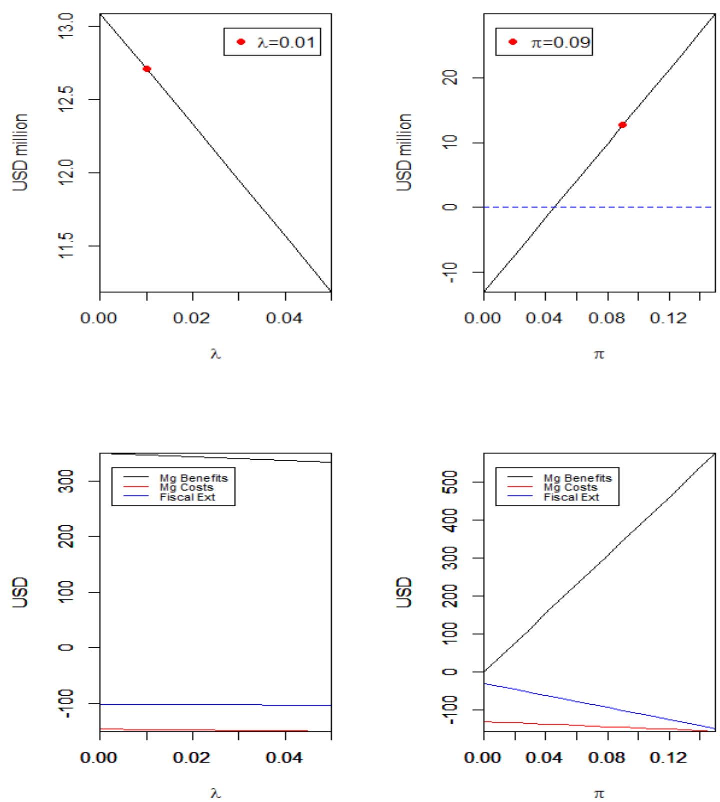

Figure 2. Sensitivity Analysis: Varying Assumptions
Note: The upper panels in this figure show how the total impact (column 5 in Table II) changes when λ or π vary. The left panel shows how it varies when the proportion of early depositors, λ, changes. The panel on the right presents the variation when the probability of a run, π, changes. The lower panels present marginal benefits, marginal costs and the fiscal externality separately for each of these scenarios.

A higher λ diminishes the positive effect that increasing coverage has on welfare, although the impact is small. Its effect on the individual terms calculated in Equation (7) is mixed; it mostly affects the marginal benefits. A higher value for π increases the positive impact on welfare, mainly through higher marginal benefits. This happens because higher π values increase the probability of failure, so the benefits of reducing it through a higher coverage level are greater. Marginal costs are less impacted because the effect on TBTF cancels part of the increase in costs for non-systemic banks. Lower values of π impact results in the opposite way. For values below 4% benefits are no longer greater than costs. Detailed plots of the effect that varying λ and π has on the individual terms of Equation (7) are presented in Appendix F.

B.2. Varying Inputs Linked to Data

Figure 3 illustrates how the total impact changes for different values of χ_k, σ_k and ζ_k. Detailed values for the marginal benefit, the marginal cost and the fiscal externality, as previously defined, are presented there too.

The total impact on welfare varies inversely with the recovery rate, as shown in the upper left plot of Figure 3. The effect increases directly for low levels of χ_k, however, because the fiscal externality is very substantial at those levels. This is because insured deposits will be higher than expected recoveries, so taxpayers will have to assume this difference—plus the financing costs associated with it. The fiscal externality will be similar to marginal costs when recovery rates are equal to insured deposits, which is approximately where the plot has an inflection point. For other values the effect is linear and its reduction comes from the effect χ_k has on the consumption gap, term 1c in Equation (7). If all the money is recovered, $\chi_k = 1$, there will be no marginal benefit due to avoiding failure—at least no benefit associated with the dead weight loss. This benefit increases as the recovery rate decreases and is maximum when $\chi_k = 0$. On the other hand, as can be seen in the lower left panel, marginal costs are not impacted by changes in χ_k.

With regards to σ_k, riskier banks have higher probabilities of unconditional failure, q_k^F. This has an impact on costs, benefits and the fiscal externality, as presented in the lower middle plot of Figure 3. Benefits increase less than the sum of marginal costs and the fiscal externality do. The net effect is that the positive impact of the increase in coverage would be smaller if banks are riskier, as shown in the upper middle plot of this same figure. It becomes negative if volatility increased more than 20%. The fiscal externality dominates at this point.

Finally, changing insured deposits generates the biggest drop in the aggregate impact on welfare. The upper right panel of Figure 3 shows the effect of increasing this value from approximately 19% to 50%. For this exercise, I keep the increase in insured deposits due to the change in coverage as per the data—I modify insured deposits before and after the increase in coverage by the same amount.[33] A higher percentage of insured deposits diminishes the marginal benefits, as can be observed in the lower right panel of Figure 3. Similarly, the fiscal externality becomes more negative, since higher insured deposits will generate higher financing costs. All in all, higher insured deposits quickly

[33] Figure 3 shows the adjusted value of insured deposits for all banks after the increase in coverage.

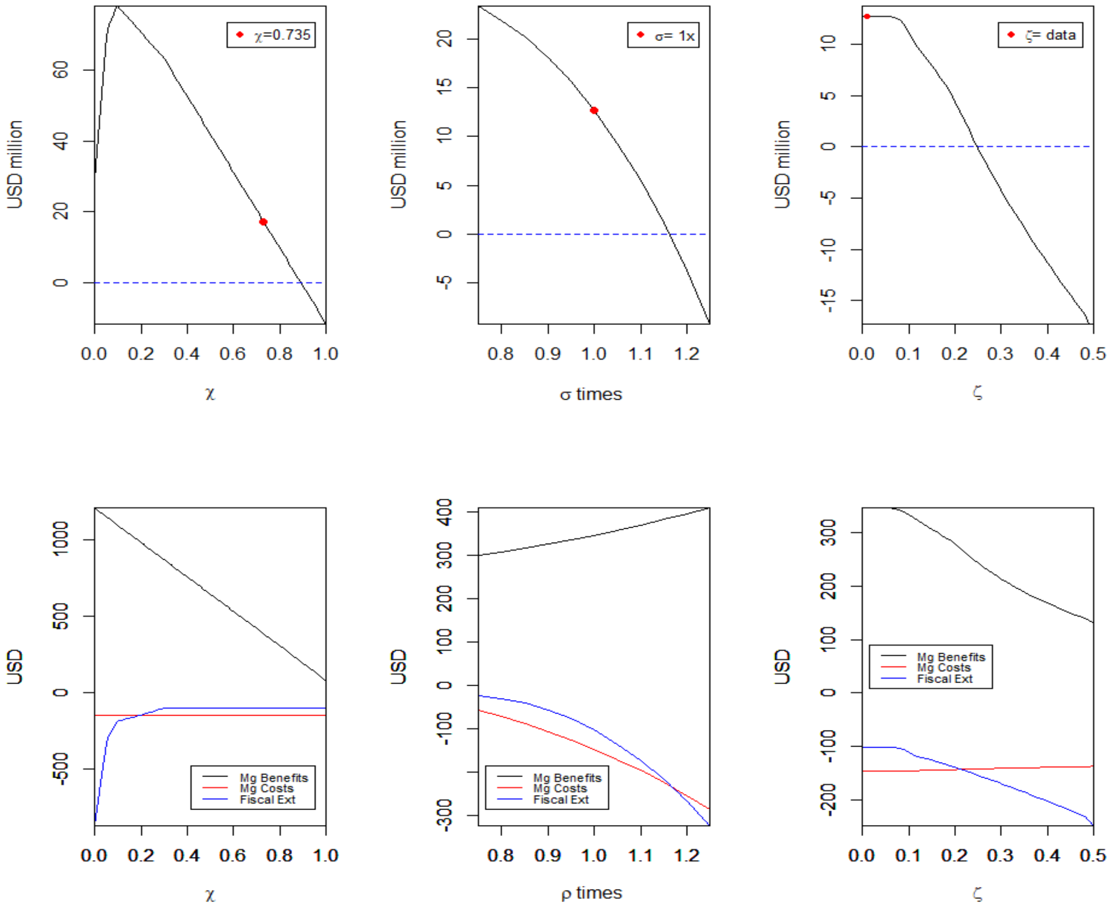

Figure 3. Sensitivity Analysis: Varying Input Linked to Data

Note: The panels in the top of this figure show how the total impact (column 5 in Table II) changes when inputs linked to data vary. The left panel shows how it varies when the recovery rate changes, the middle one when the riskiness of banks change, and the panel on the right when insured deposits as a percentage of total deposits change. The panels in the bottom present marginal benefits, marginal costs and the fiscal externality separately for each of these scenarios.

turn the aggregate impact into a negative figure (when they are higher than 25%). Detailed plots for the effect that varying the inputs linked to data has on the individual terms of Equation (7) are presented in Appendix F.

In summary, the impact on welfare continues to be positive when varying slightly key assumptions or inputs linked to data. But it is sensitive to changes in several of them. If the probability of a run, π, is very low, the benefits will diminish substantially, while part of the costs remain. Net impact will be negative. A similar situation happens with recovery rates, although in this case for high values of χ_k. If recovery rates are 90% or higher, there would be no benefits associated with increasing the coverage level, while some of its marginal costs and the fiscal externality remain. A riskier financial system increases both benefits and costs associated with higher coverage levels, but because of the fiscal externality the aggregate effect is negative. For increases greater than 20% in volatility costs outweigh benefits. Finally, a higher proportion of insured deposits increases fiscal costs and makes the net impact on welfare negative. This happens with only a small increment in insured deposits from actual levels.

C. Impact of Extensions

Results for Equation (2), using the same data and parameters used previously to calculate Equation (7), are USD 20.7 million, approximately 60% higher than those presented in Table II.[34] Interestingly, it is the effect that all extensions have together that changes the final result more significantly. Adding bailouts for TBTF banks to results obtained using Equation (2), for example, reduces the total benefit by USD 1.2 million approximately. In contrast, it reduces the total benefit by USD 5.2 million if it is incorporated when the other two extensions are already present. All in all, the expanded model increases fiscal costs making higher coverage levels less appealing.

VI. Conclusions

While there is ample literature that studies risks associated with DIS, design features of effective schemes have received less attention. In particular, limited coverage is recognized by practitioners as one of the key levers to contain moral hazard, but the are are not many papers that propose ways of thinking through the process of defining or changing the coverage level.

In this paper I expand the model proposed by Dávila and Goldstein (2020), and I show how to link this expanded theoretical framework to observables. By making use of a quasi-natural experiment that happened in Colombia in 2017, I calculate that the increase in the coverage level had a positive impact on welfare of USD 12.71 million. The result is sensitive to changes in some of the variables, however. Key for the Colombian case is that insured deposits are low as a percentage of total deposits in the system. Further increases in the coverage level would soon result in costs outweighing benefits.

The relevance of the analysis presented in this paper extends beyond the case studied. The framework proposed can be used to think through the benefits and costs that changing coverage levels entails elsewhere. Moreover, most of the components of the model can be calculated on an ex-ante basis. One therefore does not need to rely on a natural experiment to get a sense of benefits and costs associated with changing coverage levels. To increase or not to increase coverage levels is, and will continue to be, a relevant question for DIS going forward. This paper contributes to developing a more informed answer.

[34] Detailed results are presented in Appendix G.

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Appendix A. Detailed Derivations

Derivation of Equation (4)**:** When we apply Leibniz's rule to differentiate Equation (3) we get the following expression:

$$
\begin{aligned}
\frac{dE_s[U(C_{ti}(s))]}{d\delta} &= \int_{\underline{s}}^{\hat{s}(R_1)} U'(C_{ti}^F(s))\frac{\partial C_{ti}^F(s)}{\partial\delta}dF(s) + \pi\int_{\hat{s}(R_1)}^{s^*(\delta,R_1)} U'(C_{ti}^B(s))\frac{\partial C_{ti}^B(s)}{\partial\delta}dF(s) \\
&+ (1-\pi)\int_{\hat{s}(R_1)}^{s^*(\delta,R_1)} U'(C_{ti}^N(s))\frac{\partial C_{ti}^N(s)}{\partial\delta}dF(s) + \int_{s^*(\delta,R_1)}^{\bar{s}} U'(C_{ti}^N(s))\frac{\partial C_{ti}^N(s)}{\partial\delta}dF(s) \\
&+ [U(C_{ti}^B(s^*)) - U(C_{ti}^N(s^*))]\pi f(s^*)\frac{\partial s^*}{\partial\delta}.
\end{aligned}
$$

Since $\frac{\partial C_{ti}^N(s)}{\partial\delta} = 0$, this expression reduces to:

$$
\begin{aligned}
&= \int_{\underline{s}}^{\hat{s}(R_1)} U'(C_{ti}^F(s))\frac{\partial C_{ti}^F(s)}{\partial\delta}dF(s) + \pi\int_{\hat{s}(R_1)}^{s^*(\delta,R_1)} U'(C_{ti}^B(s))\frac{\partial C_{ti}^B(s)}{\partial\delta}dF(s) \\
&+ \left[U(C_{ti}^B(s^*)) - U(C_{ti}^N(s^*))\right]\pi f(s^*)\frac{\partial s^*}{\partial\delta}.
\end{aligned}
$$

I define $E_s^{FF} = E_s[\cdot]/q^{FF}$ and $E_s^{PF} = E_s[\cdot]/q^{PF}$, where q^{FF} is the probability of fundamental failure, and q^{PF} is the probability of a panic failure. Additionally, one can approximate the utility function around $C_{ti}^F(s)$ to move from utility functions to consumption. The derivative thus becomes:

$$
\approx q^{FF}E_s^{FF}\left[\frac{\partial C_{ti}^F}{\partial\delta}\right] + q^{PF}E_s^{PF}\left[\frac{\partial C_{ti}^B}{\partial\delta}\right] + \left[C_{ti}^B(s^*) - C_{ti}^N(s^*)\right]\pi f(s^*)\frac{\partial s^*}{\partial\delta}.
$$

Replacing $\pi f(s^*)\frac{\partial s^*}{\partial\delta} = \frac{\partial q^F}{\partial\delta}$ and reorganizing the order of some terms we get:

$$
\approx -\frac{\partial q^F}{\partial\delta}\left[C_{ti}^N(s^*) - C_{ti}^B(s^*)\right] + q^{FF}E_s^{FF}\left[\frac{\partial C_{ti}^F}{\partial\delta}\right] + q^{PF}E_s^{PF}\left[\frac{\partial C_{ti}^B}{\partial\delta}\right].
$$

The exercise will give a similar expression for taxpayers:

$$
\approx -\frac{\partial q^F}{\partial\delta}\left[C_{\tau}^N(s^*) - C_{\tau}^B(s^*)\right] + q^{FF}E_s^{FF}\left[\frac{\partial C_{\tau}^F}{\partial\delta}\right] + q^{PF}E_s^{PF}\left[\frac{\partial C_{\tau}^B}{\partial\delta}\right].
$$

Aggregating across depositors and taxpayers the expression becomes:

$$
\approx -\frac{\partial q^F}{\partial\delta}\int\left[C_j^N(s^*) - C_j^B(s^*)\right]dj + q^{FF}E_s^{FF}\left[\int\frac{\partial C_j^F}{\partial\delta}dj\right] + q^{PF}E_s^{PF}\left[\int\frac{\partial C_j^B}{\partial\delta}dj\right],
$$

which is Equation (4).

Derivation of Equation (14)**:** A time lag between payout and recoveries will not affect depositors, but conditions need to be expressed in terms of $\phi_k(s)$. Thus, for early and late depositors at bank k, aggregate change in consumption will be given by:

$$\int_0^{\overline{D}_k} (C^N_{1i,k}(s) - C^F_{1i,k}(s))dG(i) = \begin{cases} (R_k - \chi_k(s)\rho_{1,k}(s))D_{0,k} & \text{if } \phi_k(s) = T_k(s) \\ \int_0^{\overline{D}_k} \max\{D_{0i,k}R_k - \delta\}dG(i) & \text{if } \phi_k(s) < T_k(s), \end{cases}$$

for early depositors and,

$$\int_0^{\overline{D}_k} (C^N_{2i,k}(s) - C^F_{2i,k}(s))dG(i) =$$
$$\begin{cases} (\alpha_{N,k}(s)R_k - \chi_k(s)\rho_{1,k}(s))D_{0,k} & \text{if } \phi_k(s) = T_k(s) \\ (\alpha_{N,k}(s) - 1)D_{0,k}R_k + \int_0^{\overline{D}_k} \max\{D_{0i,k}R_k - \delta\}dG(i) & \text{if } \phi_k(s) < T_k(s), \end{cases}$$

for late depositors, where $\alpha_{N,k}(s)$ is the rate of recovery of non-insured depositors at bank k, $\alpha_{N,k}(s) = \rho_{2,k}(s)\frac{\rho_{1,k}(s)-\lambda R_k}{(1-\lambda)R_k}$. Thus, aggregate change in consumption for depositors will be:

$$\begin{cases} \lambda(R_k - \chi_k(s)\rho_{1,k}(s))D_{0,k} + (1-\lambda)(\alpha_{N,k}(s)R_k - \chi_k(s)\rho_{1,k}(s))D_{0,k} & \text{if } \phi_k(s) = T_k(s) \\ (1-\lambda)(\alpha_{N,k}(s) - 1)D_{0,k}R_k + \int_0^{\overline{D}_k} \max\{D_{0i,k}R_k - \delta, 0\}dG(i) & \text{if } \phi_k(s) < T_k(s). \end{cases}$$

Including the change in consumption for taxpayers due to a failure at bank k, $C^N_{\tau,k} - C^F_{\tau,k} = T_k + \kappa_k(\cdot) - \phi_k(s)$, and replacing $\alpha_{N,k}(s)$ and $\phi(s)$ in this equation, the aggregate change in consumption becomes:

$$\int \left[C^N_{j,k}(s) - C^F_{j,k}(s)\right] dj = (\rho_{2,k}(s) - 1)(\rho_{1,k}(s) - \lambda R_k)D_{0,k} + (1 - \chi_k(s))\rho_{1,k}(s)D_{0,k} + \kappa_k(T_k),$$

which is the same as Equation (14), in that case evaluated at $s = s^*_k$. Thus, the equation that represents term 1c for non-systemic banks does not change. The results vary, however, because T_k has changed and $\kappa_k(T_k)$ too.

Consumption in Bailouts: Consumption for late depositors when the bank is bailed out will be given by:

$$C^B_{ti,k}(s) = [\alpha_{B,k}(s) + (1 - \zeta_k)]D_{0i,k}R_k + \frac{B_k(s)}{1-\lambda} + Y_{2i}(s),$$

where the first term corresponds to the return of funds left at the bank until $t = 2$ and the second term to those funds that depositors take out at $t = 1$. $B_k(s)$ are the funds given by taxpayers and $Y_{2i}(s)$ is other depositors' wealth. The return of funds left at the bank will be given by:

$$\alpha_{B,k}(s) = \frac{\rho_{2,k}(s)\left[\rho_{1,k}(s) - \lambda R_k - (1-\lambda)(1-\zeta_k)R_k\right]}{(1-\lambda)R_k}.$$

The difference in consumption between non-failure and bailout states for late depositors will thus be given by:

$$\begin{aligned} C^N_{ti,k}(s) - C^B_{ti,k}(s) = &\left\{\frac{\rho_{2,k}(s)\left[\rho_{1,k}(s) - \lambda R_k\right]}{(1-\lambda)R_k} - \frac{\rho_{2,k}(s)\left[\rho_{1,k}(s) - \lambda R_k - (1-\lambda)(1-\zeta_k)R_k\right]}{(1-\lambda)R_k}\right\} D_{0i,k}R_k \\ &- (1-\zeta_k)D_{0i,k}R_k - \frac{B_k(s)}{1-\lambda}, \end{aligned}$$

which will be equal to $(\rho_{2,k}(s)-1)(1-\zeta_k)D_{0i,k}R_k - \frac{B_k(s)}{1-\lambda}$. Aggregating all late depositors:

$$C^N_{j,k}(s) - C^B_{j,k}(s) = (1-\lambda)(\rho_{2,k}(s)-1)(1-\zeta_k)D_{0,k}R_k - B_k(s). \tag{A1}$$

The change in consumption for late depositors because of a change in coverage will be:

$$\begin{aligned} \frac{\partial C^B_{ti,k}(s)}{\partial \delta} &= -(1-\rho_{2,k}(s))D_{0i,k}R_k \frac{\partial \zeta_k(\delta, R_k)}{\partial \delta} + \frac{1}{(1-\lambda)}\frac{\partial B_k(s)}{\partial \delta} \\ &= (\rho_{2,k}(s)-1)D_{0i,k}R_k \frac{\partial \zeta_k(\delta, R_k)}{\partial \delta} + \frac{1}{(1-\lambda)}\frac{\partial B_k(s)}{\partial \delta}. \end{aligned}$$

Similarly, aggregating all late depositors:

$$\frac{\partial C^B_{j,k}(s)}{\partial \delta} = (\rho_{2,k}(s)-1)(1-\lambda)D_{0,k}R_k \frac{\partial \zeta_k(\delta, R_k)}{\partial \delta} + \frac{\partial B_k(s)}{\partial \delta}.$$

Finally, the aggregate change in consumption, for both taxpayers and depositors will be:

$$\begin{aligned} \int \frac{\partial C^B_{j,k}}{\partial \delta}(s)dj &= -\frac{\partial((\kappa_k)B_k(s))}{\partial \delta} + (\rho_{2,k}(s)-1)(1-\lambda)D_{0,k}R_k \frac{\partial \zeta_k(\delta, R_k)}{\partial \delta} \\ &= \kappa'_k(\cdot)(1-\lambda)D_{0,k}R_k \frac{\partial \zeta_k(\delta, R_k)}{\partial \delta} + (\rho_{2,k}(s)-1)(1-\lambda)D_{0,k}R_k \frac{\partial \zeta_k(\delta, R_k)}{\partial \delta} \\ &= ((\rho_{2,k}(s)-1) + \kappa'_k(\cdot))(1-\lambda)D_{0,k}R_k \frac{\partial \zeta_k(\delta, R_k)}{\partial \delta}. \end{aligned} \tag{A2}$$

Derivation of Equation (16)**:** Aggregate consumption for depositors in the case of bank failure does not change when we include a time lag between payout and recoveries. Thus, when we add this to taxpayers consumption we get the following expression:

$$\begin{aligned} \int_0^{\overline{D}_k} C^F_{ti,k}(\delta, R_k)dG(i) + C^F_{\tau,k} = \max&\left\{\chi_k(s)\rho_{1,k}(s)D_{0,k}, \int_0^{\overline{D}_k} \min\{D_{0i,k}R_k, \delta\}dG(i)\right\} \\ &- T_k - \kappa_k(T_k) + \phi_k(s) + \overline{Y}_j(s), \end{aligned}$$

where $\overline{Y}_j(s) = \int_0^{\overline{D}} Y_{ti}(s)dG(i) + Y_\tau(s)$. Replacing $\phi_k(s)$ in this equation:

$$\int_0^{\overline{D}_k} C^F_{ti,k}(\delta, R_k)dG(i) + C^F_{\tau,k} = \chi_k(s)\rho_{1,k}(s)D_{0,k} - \kappa_k(T_k) + \overline{Y}_{j,k}(s),$$

which is Equation (16).

Appendix B. Detailed Statistics per Bank

Table III. Relevant Variables for Each Bank

	μ_k	σ_k	χ_k	R_k	$\zeta_{k,t}$	$\zeta_{k,t+1}$	ψ_k	$D_{0,k}$
1	0.156	0.037	0.676	1.061	0.082	0.116	0.052	17.167
2	0.182	0.049	0.803	1.068	0.092	0.124	0.057	5.103
3	0.122	0.066	0.738	1.069	0.051	0.083	0.021	6.309
4	0.131	0.021	0.752	1.060	0.192	0.251	0.111	26.405
5	0.126	0.028	0.685	1.048	0.092	0.136	0.046	2.813
6	0.139	0.042	0.473	1.059	0.039	0.062	0.016	4.034
7	0.168	0.023	0.743	1.066	0.103	0.149	0.057	14.435
8	0.158	0.040	0.757	1.065	0.056	0.091	0.022	7.133
9	0.193	0.025	0.772	1.043	0.414	0.513	0.267	3.394
10	0.157	0.020	0.767	1.061	0.149	0.207	0.077	15.681
11	0.172	0.035	0.763	1.063	0.084	0.137	0.039	5.842
12	0.252	0.039	0.644	1.042	0.198	0.222	0.235	4.822
13	0.167	0.013	0.731	1.051	0.211	0.284	0.115	3.184
14	0.129	0.050	0.836	1.066	0.289	0.442	0.157	0.750
15	0.082	0.026	0.815	1.077	0.096	0.187	0.048	0.665
16	0.252	0.072	0.803	1.086	0.026	0.063	0.0001	0.648

Note: This table reports data for each bank. The data set consists of 16 banks that account for 95.9% of deposits and 94.5% of assets within Colombia's banking sector at t (March 2017). μ_k is the median return over equity (ROE) for each bank from Jan 2010 - March 2017; σ_k is the standard deviation of the ROE for this same time frame. χ_k is the recovery rate of bank assets in a failed scenario. R_k is the implied interest rate at March 2017, calculated as total interest rate expenses by total interest-bearing liabilities; to match the way this is used in the derivations it is presented gross (one plus the rate). $\zeta_{k,t}$ is insured deposits / total deposits as of March 2017 and $\zeta_{k,t+1}$ is the same ratio one month after. ψ_k is the percentage of fully-covered deposits at March 2017. $D_{0,k}$ corresponds to total deposits for this date as well; this amount is presented in USD billion.

Appendix C. Estimation of Parameters

The Merton model: Structural models for modeling default probabilities usually go back to the seminal work done by Merton (1974). The model presented there builds on the option pricing theory developed by Black and Scholes (1973). It delivers the probability of default of a firm using market information and a simple structure. Several authors have studied this framework and documented some of its strengths and limitations. Vassalou and Xing (2004) highlight some of the benefits of using it since it contains forward-looking information. Duffie, Saita, and Wang (2007) show that it has predictive power, while Bharath and Shumway (2008) conclude that most of its predicting capability comes from its functional form which they replicate with a naive model.[35]

Despite its simplicity, or because of it, the Merton model continues to be a relevant theoretical framework and is used regularly by practitioners. Regarding the latter, a well known application of it was developed by KMV, a firm later bought by Moodys in 2002. A more recent version has been developed by Bloomberg.[36]

The model presented by Merton begins with a simple capital structure, where assets are equal to the sum of equity and liabilities. The model links the probability of a firm defaulting to the possibility that the market value of assets is reduced to less than the value of liabilities. To estimate this probability, the market value of assets is assumed to follow a geometric Brownian motion:

$$dA = \mu_A A dt + \sigma_A A dB,$$

where A corresponds to the market value of the assets, μ to its drift and σ_A to its volatility. B is a standard Brownian motion, where $dB \sim N(0, dt)$. Our interest is in determining the probability that assets are less than liabilities (D) at a certain point in time. Taking logs and rearranging terms, this probability (q^F_{Merton}) can be expressed as:

$$q^F_{Merton} = N\left(-\frac{ln(A_t/D_t) + (\mu_A - \sigma_A^2/2)dt}{\sigma_A\sqrt{dt}}\right), \tag{C1}$$

where $N(\cdot)$ is the cumulative distribution for a standardized normal distribution. The right hand side of Equation (C1) is commonly presented as $N(-DD)$, where the distance to default DD is:

$$DD = \frac{ln(A_t/D_t) + (\mu_A - \sigma_A^2/2)dt}{\sigma_A\sqrt{dt}}. \tag{C2}$$

In order to calculate Equation (C2), however, we need to have an estimate of both the market value of the assets (A) and its volatility (σ_A), both of which are unobserved. To estimate this, the framework incorporates two additional equations.

First, equity can be understood as a call option with the market value of the asset as the

[35] Other relevant papers include Hillegeist, Keating, Cram, and Lundstedt (2004) and Campbell, Hilscher, and Szilagyi (2008).

[36] Documentation about this can be found under the DRSK model.

underlying. Thus, it can be priced using option pricing:

$$E = AN(d_1) - De^{-rdt}N(d_2),$$

where E is the value of equity, r is the risk free rate, and

$$d_1 = \frac{ln(A_t/D_t) + (\mu_A - \sigma_A^2/2)dt}{\sigma_A\sqrt{dt}},\ d_2 = d_1 - \sigma_A dt.$$

The second equation makes use of the assumption that both the market value of assets and the equity follow a geometric Brownian motion. The ratio of their volatilities can be expressed as:

$$\frac{\sigma_E}{\sigma_A} = N(d_1)\frac{A_t}{E_t},$$

where σ_E is the volatility of equity. One can solve both equations simultaneously to get estimates for A and σ_A. These can then be incorporated into Equation (C2) to obtain an estimate of the distance to default.

The GMM: The GMM is a generalization of the method of moments, where we estimate moments of a population based on the moments from a particular sample. In the case of the GMM, there are more moments than variables to estimate so we need to minimize a weighted function of the moments. Mathematically, one needs to minimize the following expression:

$$Q_g(\theta; y_{1:T}) = [g(\theta; y_{1:T}]' W_T [g(\theta; y_{1:T}], \tag{C3}$$

where W_T is the weighting matrix for the moments, y_t is an (h x 1) vector of variables observed at time t, and $y_{1:T} = (y_T^\top, y_{T-1}^\top, ..., y_1^\top)$ is the (Th x 1) vector with all the observations.

For the case that interest us, where $\theta = (\lambda, \pi)$, $g(\theta; y_{1:T})$ in Equation (C3) will be given by:

$$g(\theta; y_{1:T}) = \frac{1}{T}\sum_{t=1}^{T}\mathbb{E}\left[q_{Merton,t}^F - q_t^F(\theta)\right], \tag{C4}$$

where q_{Merton}^F can be calculated using Equation (C1), and $q^F(\theta)$ by Equation (9).

Following Hansen and Singleton (1982), including lagged values of the variables as instruments allows us to work with unconditional rather than conditional moments. Instruments need to be variables with finite second moments that are in agents' information set, so a priori, any of the variables or a function of them could be used. Expanding Equation (C4) to include instruments gives us a new f function:

$$f(\theta; y_{1:T}, z_t) = g(\theta; y_{1:T}) \otimes z_t,$$

where z_t is a matrix with a vector of ones in the first column and the instruments in the following columns; $\otimes$ corresponds to the Kronecker product between $g(\theta; y_{1:T})$ and z_t. Thus, when we include instruments the minimization to estimate θ needs to be done over a new function Q_f:

$$Q_f(\theta; y_{1:T}) = [f(\theta; y_{1:T}]' \, W_T \, [f(\theta; y_{1:T}] \, . \tag{C5}$$

Putting it All Together: To estimate A_t and σ_A for $t = (1, \ldots, 96)$ I use data from Bloomberg[37]. Using these estimates I am able to calculate the distance to default (DD) for each bank at each point in time per Equation (C2).

Although the original Merton model transforms these DD using a normal distribution, as presented earlier in Equation (C1), this approach might underestimate the default probabilities for firms with high DD values. This is argued by Crosbie and Bohn (2003) and is a fact that practitioners have embedded in their frameworks. Thus, both the methodologies developed by KMV and Bloomberg make use of their own databases of defaults to calibrate an exponential function instead of using the normal distribution.[38]

Since the exact functions these companies use are not public information, I take a practical approach to address this. I use Bloomberg's information regarding DD and probabilities of default, as calculated per their own methodology, and I find an exponential function that fits the data. Thus, I calculate my own DD for each bank, but I leverage on their database for the non-linear function that relates them to probabilities.

In order to transform DD to probabilities of default I fit the following equation to the data:

$$PD = y_f + (y_0 - y_f)e^{-DD \times t}, \tag{C6}$$

where PD is the probability of default and DD is the distance to default. Both are taken from Bloomberg information for a Colombian bank. The coefficients found and the resulting function are presented in Table IV and Figure 4 respectively. Detailed results for the most relevant variables used to calculate the DD are presented in Figure 5.

Table IV. Fitted Coefficients for Equation (C6)

	Estimate	Std. Error	t value	Pr(>|t|)
y_f	4.70E-05	6.32E-07	74	<2e-16 ***
y_0	1.96E-02	7.16E-06	2739	<2e-16 ***

Note: This table presents estimated coefficients when I fit Equation (C6) to Bloomberg data for a Colombian bank. Significance is presented as: ***0.1%.

With these probabilities as inputs I am able to calculate $g(\theta; y_{1:T})$ per Equation (C4). I include two lagged values as instruments and minimize Equation (C5) using a two-step procedure, where for the first step I used an identity matrix and for the second one I use S^{-1} calculated using the Newey-West estimate with two lags (Newey and West (1987)). Adding more instruments or lags did not reduce the variance and after some point made the results unstable. I use a constrained

[37] BCOLO CB Equity and BOGOTA CB Equity.

[38] See Nazeran and Dwyer (2015) and Bloomberg's DRSK methodological framework.

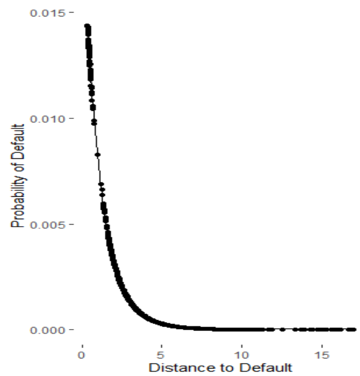

Figure 4. Exponential Function for Mapping DD to PD
Note: This figure shows the fitted exponential function and the data from Bloomberg used to map distances to default to probabilities of default.

optimization routine for this, with initial values for $\theta = (0.05, 0.15)$ as proposed by Dávila and Goldstein (2020).

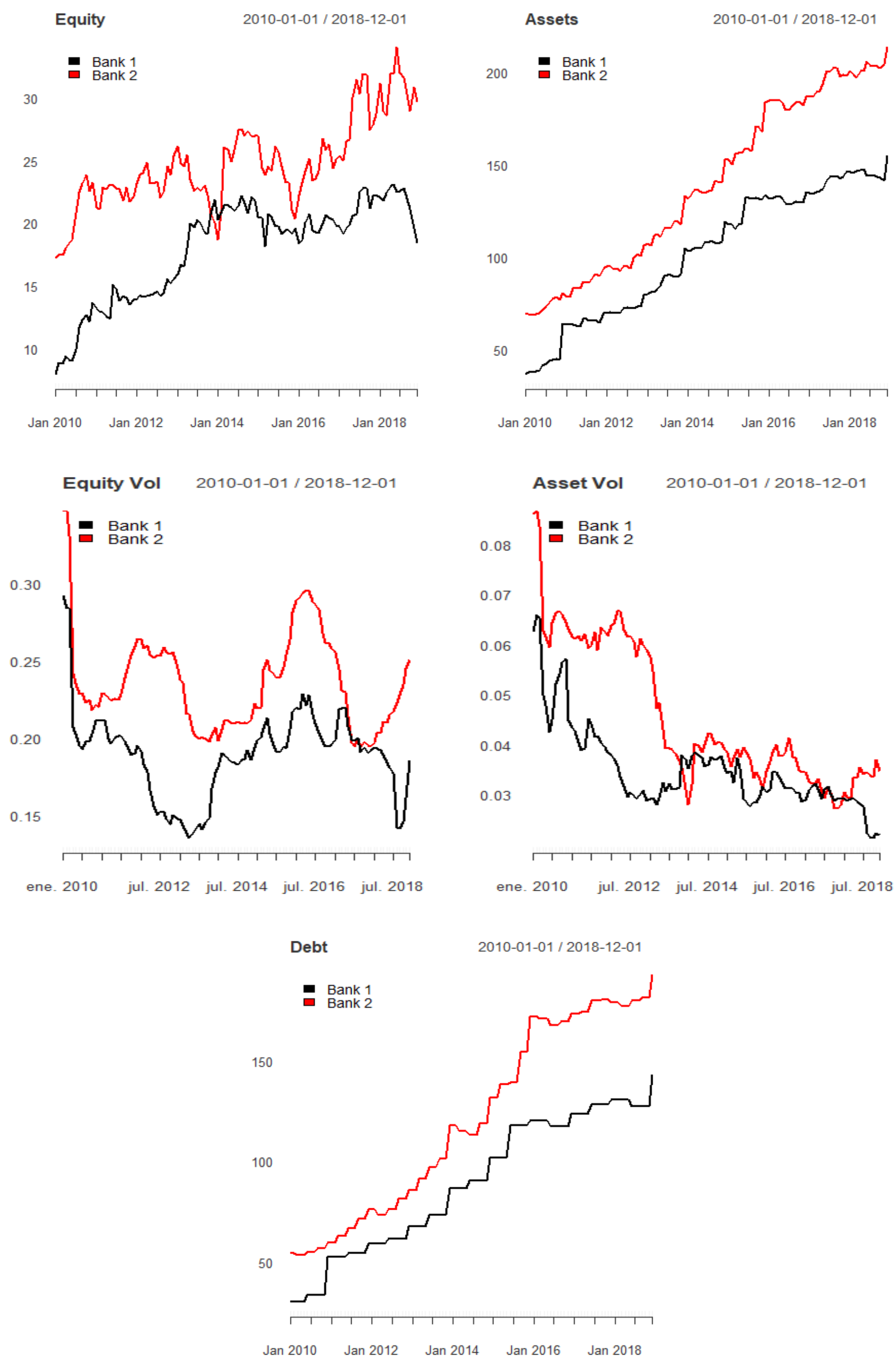

Figure 5. Variables Used to Calculate DD

Note: The panels in this figure show the variables used to calculate the distance to default (DD) of the banks used to estimate π and λ. The top panel shows the value of equity and assets in USD million. The middle panel presents the volatility of equity and of assets. The bottom panel shows the value of debt in USD million.

Appendix D. Calculating the Impact on Rates

In order to estimate the impact that the change in coverage had on rates, I use a fixed-effects model with banks' risk variables and the monetary interest rate as controls. The model is the following:

$$r_{it} = \mu_i + \alpha_t + \eta_t + \beta' BankInd_{i,t-j} + e_{it}, \tag{D1}$$

where i corresponds to the individual bank, $i = 1, \ldots, N$ and t corresponds to the time script, $t = 1, \ldots, T$. The dependent variable, r_{it}, is the interest rate paid by bank i at time t. μ_i represents fixed effects for bank. η_t corresponds to the rate set by the monetary authority at t, and α_t is a dummy that equals 1 when the coverage level has increased to COP 50 million and zero otherwise. $BankInd_{i,t-j}$ is a $N \times T$ by k matrix and β is a $1 \times k$ vector, where k is the number of banks' risk variables included in the analysis. e_{it} is the standard error. $BankInd_{i,t-j}$ is included with a lag of $j = 3$ months because data are usually available with this lag.

For r_{it} I use an implicit rate calculated by dividing the total interest rate expenses by the total interest-bearing liabilities (IR). Regarding $BankInd_{i,t-j}$, I use three variables for capturing banks' risk: a) for capital adequacy (C) I use a leverage ratio, calculated as total capital divided by total assets; b) my second variable, a proxy for asset quality (A), is the ratio of non-performing loans (minus provisions) divided by total capital; c) finally, for earnings (E) I use net income divided by equity (return on equity). To estimate Equation (D1) I use monthly data from 2010 until 2018 for all banks for which there was information available. Summary statistics for the data used are presented in Table (V).

Table V. Summary Statistics of Relevant Variables

Statistic	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
IR	0.056	0.016	0.026	0.043	0.055	0.067	0.086
C	0.232	0.208	0.082	0.109	0.140	0.243	0.849
A	−0.001	0.086	−0.145	−0.050	−0.006	0.020	0.224
E	0.071	0.139	−0.313	0.024	0.112	0.160	0.252
η	0.046	0.013	0.030	0.035	0.045	0.052	0.078

Note: This table reports the summary statistics of the variables used in Equation (D1). IR is calculated as total interest rate expenses divided by total interest-bearing liabilities. The capital adequacy variable (C) is the leverage ratio, calculated as total capital divided by total assets. For asset quality (A), I use the ratio of non-performing loans (minus provisions) divided by total capital. Earnings (E) is equal to net income divided by equity (ROE). η is the interest rate set by the monetary authority. All relevant data are winsorized at a 95% level.

Nominal interest rates have a mean of 5.6% and range roughly from 2% to 8%. Mean values for capital are 23% of equity, non-performing loans are equal to provisions and ROE is on average 7.1%. The policy interest rate is 4.6%, on average.

Columns 1-4 of Table VI present regression results per Equation (D1). I use different combinations of bank and time fixed effects, but since I am interested in estimating the effect of coverage through α the relevant columns are the first two; including time fixed effects does not allow me to get an estimate for α. For estimating the fiscal externality due to the change in the coverage level I use results from column 2, which includes bank fixed effects. Per Table VI, the impact that the change in coverage had on deposit rates was 0.008. This value is significant at a 1% level. Risk variables and the monetary interest rate are significant at this level as well. All results presented include heteroskedasticity and auto-correlated adjusted errors.

Table VI. Regression Results

	Dep variable: IR			
	(1)	(2)	(3)	(4)
C	-0.014^{***}	-0.017^{***}	-0.014^{***}	-0.018^{***}
	(0.001)	(0.002)	(0.001)	(0.001)
A	0.003	0.012^{***}	0.002	0.010^{***}
	(0.003)	(0.002)	(0.002)	(0.002)
E	-0.043^{***}	-0.017^{***}	-0.042^{***}	-0.014^{***}
	(0.002)	(0.002)	(0.002)	(0.001)
α	0.006^{***}	0.008^{***}		
	(0.001)	(0.0003)		
η	0.170^{***}	0.195^{***}		
	(0.016)	(0.009)		
Bank effects	No	Yes	No	Yes
Time effects	No	No	Yes	Yes
Adjusted R^2	0.190	0.251	0.124	0.028

Note: This table reports results for Equation (D1). The four columns differ in their inclusion of fixed effects: no fixed effects (column 1), including fixed effects for banks (column 2), including fixed effects for time (column 3) and both fixed effects for time and bank (column 4). Estimators for time dummies, fixed effects and the constant term are not included in the table but were included in the regression. (C) is the leverage ratio, calculated as total capital divided by total assets, (A) is asset quality, the ratio of non-performing loans (minus provisions) divided by total capital and (E) is the ROE. η is the monetary interest rate and α is a dummy for the level of coverage: it is 0 for months before coverage was increased and 1 afterwards. Errors are adjusted for autocorrelation and heteroskedasticity. Significance is presented as: ***1%, **5%, *10%.

Appendix E. Detailed Results

Table VII. Primary Terms in Equation (7)

	Term 1a (%)	Term 1b (%)	Term 1c (USD M)	Term 2a (USD)	Term 2b (USD)	Term 3 (USD)
1*	0.05	0.0007	930	-2	2	-63.37
2	0.15	0.0003	1456	-2	-1	-2.71
3	9.83	0.0001	2218	-99	-10	-20.35
4*	0.00	0.0042	1120	-0	0	-1.41
5	0.02	0.0011	1069	-0	-0	-0.26
6	0.58	0.0002	2496	-3	-1	-2.12
7*	0.00	0.0049	819	-0	0	-0.02
8	0.12	0.0006	2339	-2	-1	-1.90
9	0.00	0.0025	1083	-0	-0	-0.00
10*	0.00	0.0065	740	-0	0	-0.00
11	0.01	0.0016	1873	-0	-0	-0.24
12	0.00	0.0004	2133	-0	-0	-0.00
13	0.00	0.0186	1100	-0	-0	-0.00
14	2.92	0.0004	183	-19	-2	-7.55
15	6.96	0.0009	182	-3	-2	-1.68
16	0.22	0.0004	200	-1	-0	-0.15
M	1.30	0.0027	1246	-8	-1	-6.4
Md	0.04	0.0008	1091	-0	-0	-0.8
Tot			19941	-131	-15	-101.7

Note: This table reports results for the primary components of Equation (7). Each row corresponds to a bank; the last three rows are the mean, the median and the sum of each column respectively. Totals are not shown for columns that correspond to percentages. With regards to columns, the first three columns corresponds to terms 1a, 1b and 1c. Term 1b is negative for all banks; it is presented in absolute value. The first two terms are shown in percentage terms, the third one in thousands of USD. Columns 4 to 5 present terms 2a and 2b. They are presented in USD. Finally, column 6 presents term 3; it is also shown in USD.

Appendix F. Sensitivity Analysis[39]

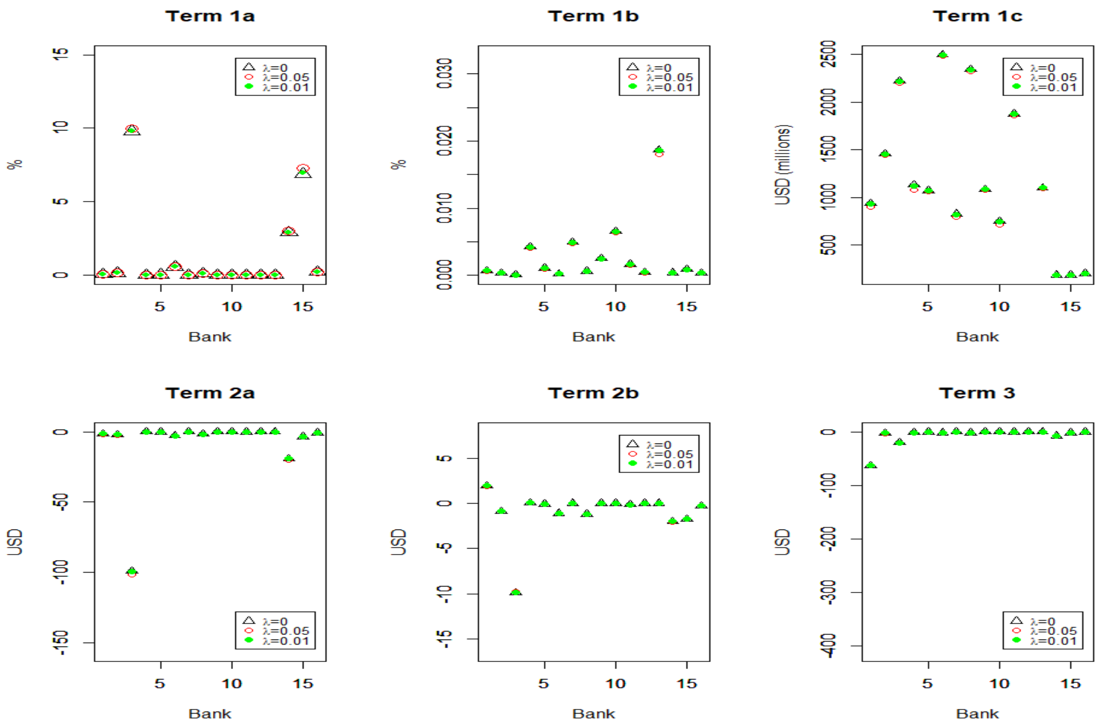

Figure 6. Sensitivity Analysis: Varying λ.
Note: The panels in this figure show how individual terms in Equation (7) change for each bank when λ varies between 0 and 0.05. Results for $\lambda = 0.01$ are also included in the plots.

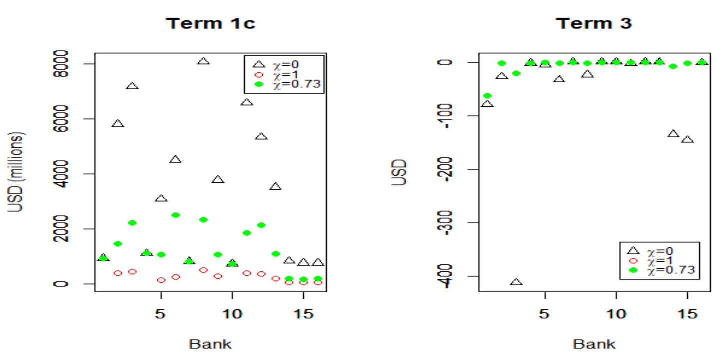

Figure 7. Sensitivity Analysis: Varying χ
Note: The panels in this figure show how individual terms in Equation (7) change for each bank when χ varies between 0 and 100%. Results for $\chi = 73\%$ are included in the plots.

[39] Term 1b is negative for all banks, it is presented in absolute value in all figures.

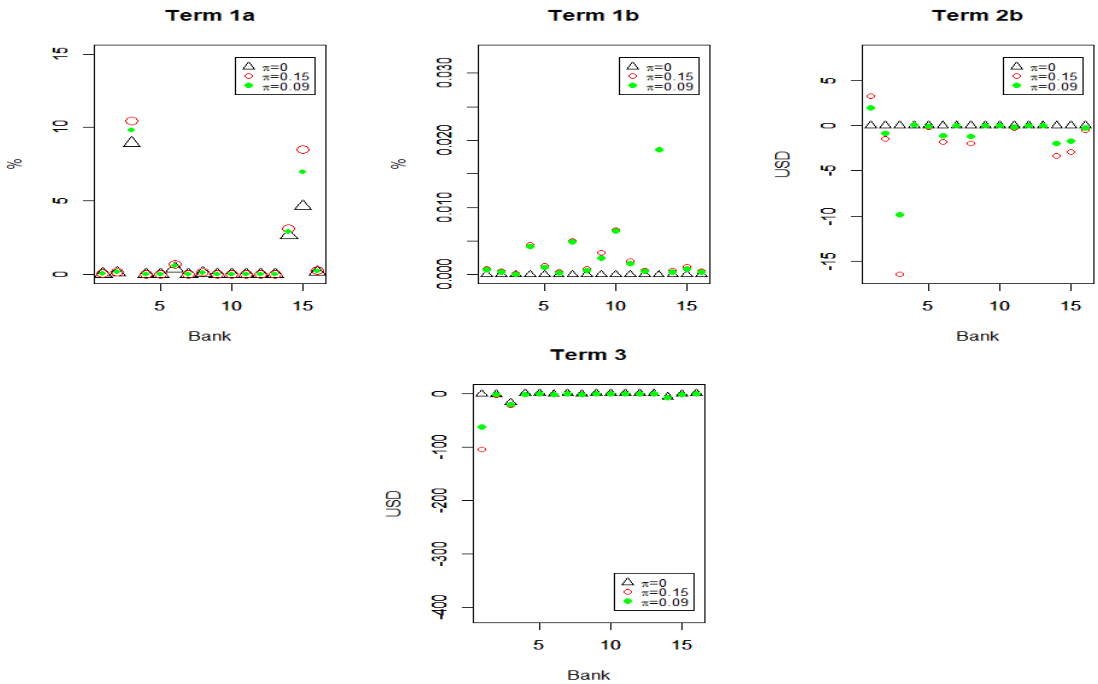

Figure 8. Sensitivity Analysis: Varying π.

Note: The panels in this figure show how individual terms in Equation (7) change for each bank when π varies between 0 and 0.15. Results for $\pi = 0.09$ are also included in the plots.

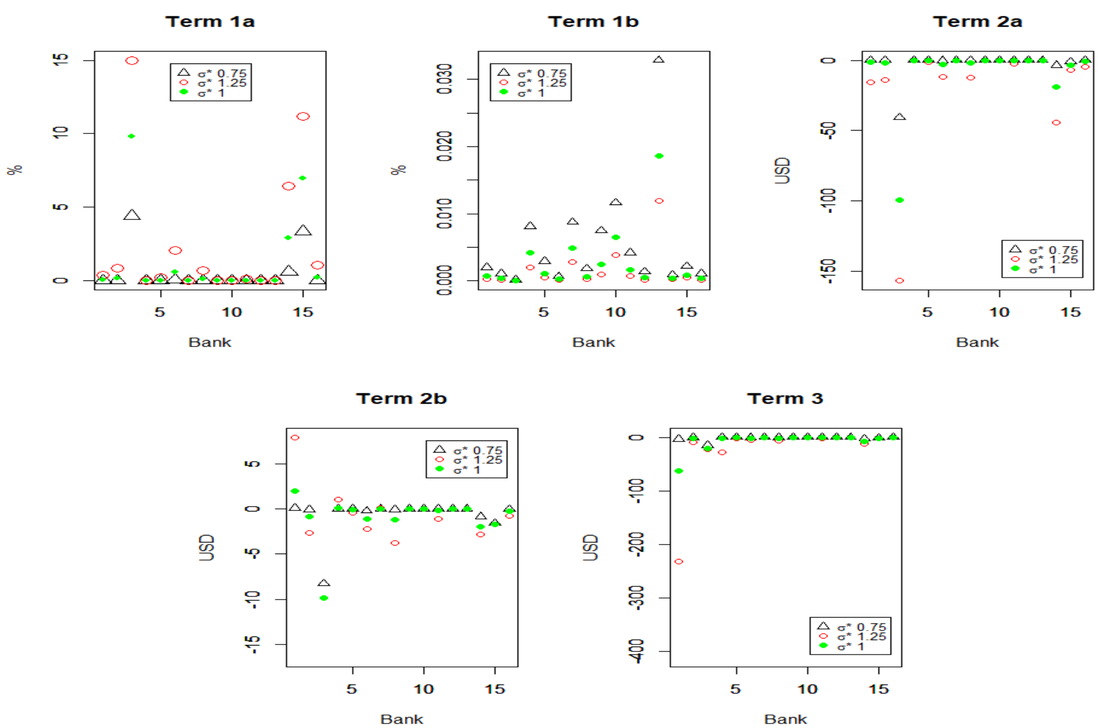

Figure 9. Sensitivity Analysis: Varying σ

Note: The panels in this figure show how individual terms in Equation (7) change for each bank when σ varies between 75% and 125% of its actual value per the data. Results for $\sigma = 1$ are also included.

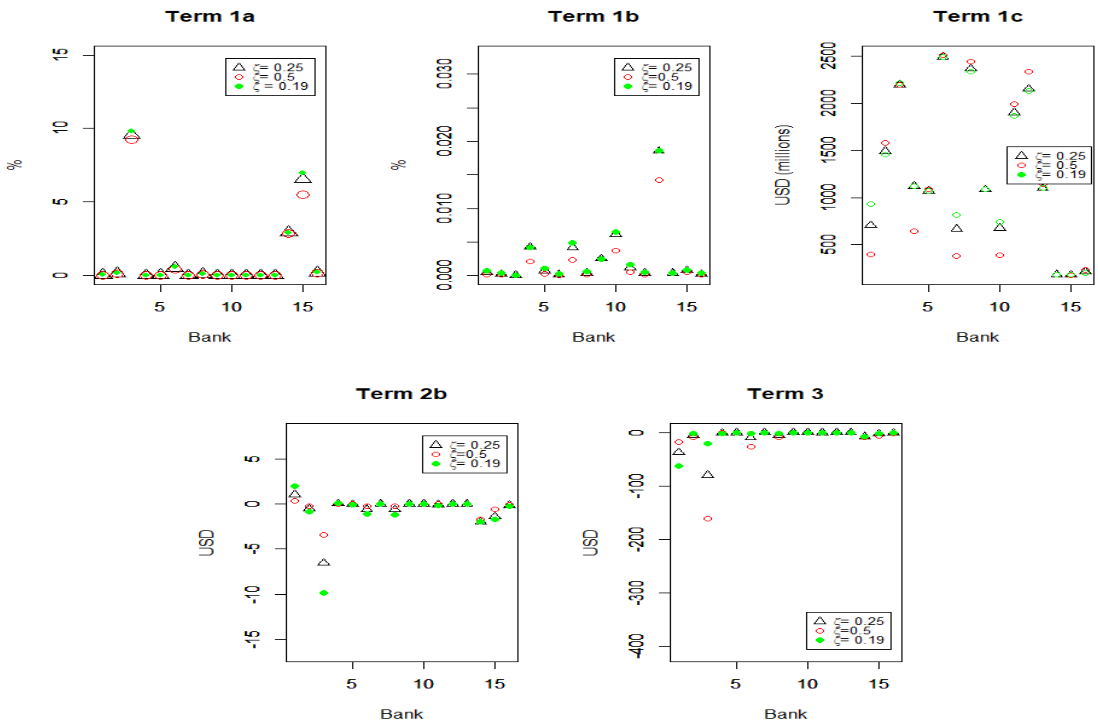

Figure 10. Sensitivity Analysis: Varying ζ

Note: The panels in this figure show how individual terms in Equation (7) change for each bank when ζ varies from 25% to 50%. Results for insured deposits per the data ($\zeta = 0.19$) are also shown.

Appendix G. Results per D&G Model

Table VIII. Costs, Benefits and Net Impact on Wealth

	Marginal benefit (USD)	Marginal cost (USD)	Agg impact (USD)	Total impact (TI) (USD M)	TI / Assets (%)
1	24.6	-2.8	21.8	1.40	0.005
2	7.3	-3.0	4.4	0.24	0.003
3	147.0	-109.3	37.7	3.09	0.030
4	1.1	-0.0	1.1	0.08	0.000
5	2.7	-0.2	2.5	0.20	0.005
6	32.6	-3.9	28.7	2.07	0.030
7	0.0	-0.0	0.0	0.00	0.000
8	17.4	-2.8	14.6	0.92	0.008
9	0.0	-0.0	0.0	0.00	0.000
10	0.0	-0.0	0.0	0.00	0.000
11	2.1	-0.2	1.9	0.11	0.001
12	0.0	-0.0	0.0	0.00	0.000
13	0.0	-0.0	0.0	0.00	0.000
14	18.5	-21.2	-2.7	-0.21	-0.018
15	109.6	-5.2	104.3	12.79	1.197
16	1.5	-1.1	0.5	0.02	0.002
M	22.8	-9.4	13.4	1.29	0.079
Md	2.4	-0.7	1.5	0.10	0.002
Tot	364.4	-149.7	214.7	20.70	0.011

Note: This table reports results for aggregate benefits and costs per Equation (2). Each row corresponds to a bank. The last three rows are the mean, the median and the sum of each column, respectively. With regards to columns, the first column is term 1 (the marginal benefit). The second column is term 2 (the marginal cost). Column 3 is the aggregate impact on wealth per unit of increase of coverage, $\frac{dW_k}{d\delta}$. All these columns are in USD. The fourth column is column 3 capitalized at the ROE of each bank times the increase in coverage (USD 10,000 approx); it is presented in millions of USD. Column 5 is column 4 divided by the assets of each bank.