# The Decline of Too Big to Fail

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*For globally systemically important banks (GSIBs) with U.S. headquarters, we find significant post-Lehman reductions in market-implied probabilities of government bailout, along with 50%-to-100% higher wholesale debt financing costs for these banks after controlling for insolvency risk. The data are consistent with measurable effectiveness for the official sector's post-Lehman GSIB failure-resolution intentions, laws, and rules. GSIB creditors now appear to expect to suffer much larger losses in the event that a GSIB approaches insolvency. In this sense, we estimate a major decline of "too big to fail."*

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Global financial crisis revelations of the costs of "too-big-to-fail" have lead to new legal administrative methods, globally, for resolving the insolvencies of systemically important banks. Rather than bailing out these firms with government capital injections, insolvency losses are now supposed to be allocated to wholesale creditors. As a consequence, credit rating agencies have substantially reduced or removed explicit "sovereign uplifts" to the ratings of the senior unsecured debt of the holding companies of U.S. globally systemically important banks (GSIBs). Many market participants believe, however, that these reforms have not eliminated the likelihood of government bailouts of large banks (Government Accountability Office, 2014). Our main objective is to estimate post-crisis declines in market-implied bailout probabilities, the associated increases in GSIB bond yields, and the declines in GSIB equity market values arising from reductions in debt financing subsidies associated with bailout expectations.

We show that GSIB balance sheet data and the market prices of debt and equity imply a dramatic and persistent post-crisis reduction in market-implied probabilities of government bailouts of U.S. GSIB holding companies. We also report similar but smaller effects for a set of "Other Large Banks" that are not large enough to be classified as GSIBs.[1] Our sample period is 2002–2019. Our demarcation point for measuring a change in bailout probabilities is the bankruptcy of Lehman Brothers in September 2008. We refer to the prior period as "pre-Lehman" and the subsequent period as "post-Lehman." Many market participants were surprised that the U.S. government did not bail out Lehman.[2] We cannot disentangle how much of the post-Lehman reduction in investor bailout expectations is related to the intention of the U.S. government to actually trigger its new GSIB failure resolution approach, known as "bail in" (which has not yet been tried in practice), as opposed to an

[1]European regulators officially designate their large domestically important banks. While there is no such official designation by US regulators, we label as "Other Large Bank" any non-GSIB U.S. bank holding company with $50 billion or more in total consolidated assets.

[2]See, for example, the New York Times (2014) article "Revisiting the Lehman Brothers Bailout That Never Was."

updating of beliefs by creditors about the government's intentions to simply avoid bailouts by allowing a systemically important financial firm to enter bankruptcy, as was the case with Lehman.

We exploit the fact that, for a given risk-neutral[3] probability of bailout, credit spreads are largely explained by the risk-neutral probability of insolvency and the loss given failure. The loss given failure of a debt claim is the risk-neutral expectation of the fraction of the claim lost in the event of an insolvency that is not resolved with a bailout. Fixing the risk-neutral insolvency probability and risk-neutral expected loss given failure, the credit spread of a given bond is essentially proportional to the risk-neutral probability of no bailout. For example, if the no-bailout probability given insolvency of firm $A$ is twice that of firm $B$, then the credit spreads of firm $A$ are about twice those of firm $B$, all else equal.

Variation in risk-neutral insolvency probabilities and losses given failure is largely explained by variation in "distance to default" and by firm and time fixed effects (Berndt et al., 2018). Conceptually, the distance to default of a firm is the number of standard deviations of annual growth in its stock of assets by which the current stock of assets exceeds the insolvency level of assets. Distance to default is thus a risk-adjusted measure of a firm's capital buffer, and is a strong predictor of default (Duffie, Saita, and Wang, 2007). We detect sizable post-Lehman changes in the risk-neutral (or "market-implied") probability of bank bailout given insolvency. We do this based on a change in the observed relationship between credit spreads and distance to default. By including over 550 public non-banks in our sample, we control for market-wide variation over time in corporate default risk premia. Rather than taking risk premia for non-banks and banks to be the same, we rely only on the assumption that the ratio of their risk premia did not change with the post-Lehman change in bailout probabilities.

[3] A "risk-neutral" or "market-implied" probability embeds risk premia into the probability assessment, in the sense that the market price of an asset is its risk-neutral expected future cash flows discounted at risk-free interest rates.

Our main empirical model is a non-linear panel regression that fits credit spreads to bailout probabilities and distance to default, as well as firm and time fixed effects. The non-linear dependence of distance to default on bailout probabilities is captured through a structural dynamic model of debt and equity prices that extends Leland (1994a). In the supporting structural model, at a bailout, the government injects enough capital to return the balance sheet of the bank to a given "safe" condition. At any time before insolvency, the equilibrium prices of debt and equity reflect consistent expectations regarding the likelihood of bailout and the post-bailout capital structure of the bank. Taking GSIBs for example, the data are consistent with a pre-Lehman bailout probability of 0.53 and a post-Lehman bailout probability of 0.20. Our modeled post-bailout equity market values of each bank include the market values of debt funding cost subsidies associated with the expectation by creditors of successive potential future bailouts. We find that as bailout probabilities increase, the fraction of the market value of future GSIB bailout subsidies that is associated with the first potential bailout decreases, and the fraction associated with subsequent potential bailouts increases.

We face the following identification challenge. The impact on debt and equity prices of a downward proportional shift in default risk premia can be approximately offset by the same common upward proportional shift in pre-Lehman and post-Lehman no-bailout probabilities. So, our approach is not to provide point estimates of *both* a pre-Lehman bailout probability $\pi_{\text{pre}}$ *and* a post-Lehman bailout probability $\pi_{\text{post}}$, but rather to estimate a schedule of pairs $(\pi_{\text{pre}}, \pi_{\text{post}})$ that are jointly consistent with the data. For example, as mentioned above, the data are consistent with GSIB pre-Lehman and post-Lehman bailout probabilities of 0.53 and 0.20, respectively, but are also consistent with pre-Lehman and post-Lehman bailout probabilities of 0.89 and 0.80, respectively. Schedules of data-consistent pairs of bailout probabilities are tabulated later in the paper.

We find substantial cross-GSIB variation in bailout probabilities. For instance, with a post-Lehman bailout probability of 20%, the data-implied pre-Lehman bailout probability ranges from 44% for JP Morgan & Chase to 61% for Citigroup. We also show that, relative to GSIBs, Other Large Banks (OLBs) have smaller post-Lehman declines in bailout probabilities. This is natural, given that non-GSIB banks are less likely to be viewed by regulators and creditors as too big to fail. For example, the data are consistent with a 25% pre-to-post Lehman decline in OLB bailout probabilities (from 0.45 to 0.20), compared with a 33% decline in GSIB bailout probabilities (from 0.53 to 0.20).

The post-Lehman reduction in risk-neutral GSIB bailout probabilities is associated with a 50%-to-100% increase in post-Lehman five-year senior unsecured GSIB credit spreads, relative to what these spreads would have been had there been no post-Lehman decline in bailout probability. For example, the data-consistent decline in GSIB bailout probabilities from 0.53 to 0.20 is associated with 70% higher debt financing costs. This represents a significant reduction in effective government subsidies to GSIBs. For a hypothetical scenario in which GSIB bailout probabilities are as low before Lehman failed as afterward, GSIB equity market values would have been an estimated 23% to 96% lower in the years before Lehman failed.

The remainder of the paper is structured as follows. Section I reviews related prior work. Section II is a high-level preview of our empirical identification strategy. Section III is an overview of our theoretical model of the pricing of bank debt and equity, allowing for bailout. We use this theoretical model to estimate distances to default, given our data, for each candidate bailout probability. Section IV describes the data and presents summary statistics. Section V presents our estimates of bailout probabilities and their implications for large-bank credit spreads and equity subsidies. Section VI extends our analysis to allow for bank-specific bailout probabilities and for bank franchise rents. Section VII discusses alternative interpretations of the data and then concludes. An online appendix provides additional theoretical and empirical details.

## I. Prior Related Work

Of the large empirical literature on too-big-to-fail (TBTF) subsidies, reviewed in Appendix A, relatively few research papers address the degree to which TBTF subsidies declined after the Global Financial Crisis (GFC) of 2008–2009. None of the prior studies estimate post-GFC changes in bailout probabilities. The Financial Stability Board (2019; 2020) is currently evaluating[4] whether TBTF banking reforms have been effective. Their preliminary results broadly suggest that TBTF reforms have strengthened banks' ability to absorb shocks, thus making them more resilient.

Of the body of prior research on the post-crisis decline of TBTF, the closest point of comparison to our results is Atkeson et al. (2018), who consider the extent to which TBTF subsidies are reflected in the ratio of the market value of bank equity to the book value of bank equity. In principle, a post-crisis reduction in TBTF subsidies should lower market-to-book ratios. Indeed, the authors show that the market-to-book ratio of publicly traded U.S. banks was above two, on average, between 1996 and 2007, and declined to about one after the GFC.

Sarin and Summers (2016) and Chousakos and Gorton (2017) argue, however, that the post-Lehman drop in bank market-to-book ratios is due to a loss in bank franchise value or profitability. Atkeson et al. (2018) find that a substantial reduction in bank equity market values is instead associated with the decline of TBTF. They estimate[5] the post-crisis decline of their composite-bank market-to-book ratio to be 1.05 and attribute 81% of this reduction to a decline in government guarantees. To accomplish this, they construct a detailed dynamic model of the balance sheet and income statement of a single hypothetical composite U.S. bank, based on data

[4] In November 2019, George Pennachi, an academic advisor to the Financial Stability Board on this evaluation, let us know of his preliminary work, to appear, with Maximilian Guennewig, on investor perceptions of the likelihood that bank senior and subordinated debt will be bailed-in if the bank becomes insolvent. We will compare our respective results once their work appears.

[5] Atkeson et al. (2018) estimate a pre-crisis to post-crisis reduction in the market-to-book equity ratio of $2.24-1.19=1.05$. They find that the pre-crisis contribution of government guarantees to the market-to-book ratio was 0.91 and that the post-crisis contribution was about half of 0.19, for a reduction of $0.91-0.10=0.81$.

for the aggregate U.S. banking sector, which consists of over 4,000 banks.[6] They do not distinguish systemically important banks from other banks.

Consistent with Atkeson et al. (2018), we find a significant decline in post-crisis bailout probabilities. Unlike Atkeson et al. (2018), however, we do not decompose the impact of a decline in TBTF on bank equity market value into a component due to the decline of TBTF and a component due to changes in banks' default risk or other attributes. Instead, we quantify the reduction in bailout subsidies to banks' claimants by comparing the observed market values of equity and debt to their hypothetical counterparts that would have applied in the post-crisis period had bailout probabilities not declined. When measuring the reduction in bailout subsidies we condition on banks' default risk. Thus, our estimated declines in bailout probabilities apply even if large banks are as likely to default after the GFC as before (Sarin and Summers, 2016), and likewise apply if large banks are less likely to default (Financial Stability Board, 2020) after the crisis.

Haldane (2010) estimates the reduction in TBTF subsidies implied by the post-Lehman reduction in sovereign uplifts of the credit ratings of systemically important banks. Roughly speaking, for a given bank, he assumes that the savings in its wholesale debt financing rates associated with TBTF can be estimated as the difference in average corporate bond yields associated with ratings that include and do not include the sovereign uplifts, respectively. Thus, smaller post-Lehman sovereign ratings uplifts automatically imply smaller estimated TBTF subsidies.

Acharya, Anginer and Warburton (2016) conduct an event study of the impact on GSIB credit spreads of the passage of U.S. GSIB failure resolution legislation, Title II of the Dodd-Frank Act. They find that there was no significant impact on GSIB credit default swap (CDS) rates within 60 days of the passage of Dodd-Frank Act.

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[6]The number of U.S. banks is reported by the Federal Deposit Insurance Corporation. To estimate the market value of equity of their modeled composite bank, Atkeson et al. (2018) make the simplifying assumption that there are only two possible Markov states in each time period, and that the bank chooses to default in one of these, the crisis state.

They also find that between 1990 and 2012, the bond credit spreads of the largest financial institutions are insensitive to risk, and that this is not the case for smaller financial institutions or for non-financial firms.

## II. A High-Level Outline of Our Identification Strategy

At a very high level, our empirical strategy is to exploit the fact that a given corporate credit spread $S$ can be approximated as the product of the annualized risk-neutral probability $p$ of insolvency and the risk-neutral expected fractional loss $\ell$ to creditors in the event of insolvency. For a firm subject to bailout with risk-neutral probability $\pi$, we have $\ell = (1-\pi)L$, where $L$ is the risk-neutral expected loss given insolvency with no bailout, which we call "loss given failure." The simple relationship $S = p(1-\pi)L$ implies the log-linear model

$$\log S \quad = \quad \log(1-\pi) + \log(pL). \tag{1}$$

For a large sample of U.S. public firms, Berndt et al. (2018) find that the majority of the empirical variation in $\log(pL)$ is explained by measured distance to default and firm and time fixed effects. The next section of the paper offers a structural model of the dependence of distance to default on the assumed risk-neutral bailout probability $\pi$. We let $\mathrm{DtD}_{it}(\pi_{it})$ denote the distance to default of firm $i$ at date $t$ corresponding to some assumed bailout probability $\pi_{it}$, given this firm's observed balance sheet at time $t$ and other relevant data.

So, based on the conceptual framework (1), we estimate bailout probabilities by fitting a panel model of the form

$$\log S_{it} \quad = \quad \log(1-\pi_{it}) + \beta\, \mathrm{DtD}_{it}(\pi_{it}) + \omega_{it} + \varepsilon_{it}, \tag{2}$$

where $\beta$ is a coefficient to be estimated, the term $\omega_{it}$ includes fixed effects associated with firm $i$ and date $t$, and $\varepsilon_{it}$ is an unexplained residual. The fixed effects $\omega_{it}$ allow for variation over time and across firms in the relationship between $pL$ and distance to default that are caused, for example, by time-varying default risk premia, and also allow for deviations from the pricing relationship $S = p(1-\pi)L$ caused by other effects, including market frictions. We allow for heteroskedasticity and autocorrelation in the residuals $\varepsilon_{it}$.

For simplicity, we assume that the bailout probability $\pi_{it}$ of a non-bank is zero.[7] For a GSIB bank $i$, we take $\pi_{it} = \pi^G_{\text{pre}}$ for all pre-Lehman dates and take $\pi_{it} = \pi^G_{\text{post}}$ for all post-Lehman dates, for two parameters, $\pi^G_{\text{pre}}$ and $\pi^G_{\text{post}}$, to be estimated. We treat OLBs similarly, with respective bailout probabilities $\pi^O_{\text{pre}}$ and $\pi^O_{\text{post}}$. We also estimate these pairs of data-consistent bailout probabilities for some specific GSIBs.

Using framework (2), it is challenging to identify the average level over time of the bailout probability $\pi_{it}$ for large banks. For example, a higher bank fixed effect due to higher default risk premia for large banks is observationally equivalent to a smaller average bailout probability $\pi_{it}$.[8] We can, however, use the observable post-Lehman change in the relationship between credit spreads and distance to default, caused by a regime shift in bailout expectations, to identify the *relative* change from $\pi^G_{\text{pre}}$ to $\pi^G_{\text{post}}$. Thus, as discussed in the introduction, we estimate a schedule of data-consistent pairs $(\pi^G_{\text{pre}}, \pi^G_{\text{post}})$. For example, when treating GSIBs as homogeneous, this schedule includes the pair $(0.53, 0.20)$ and also the pair $(0.89, 0.80)$. Complete schedules of estimated pairs of pre-Lehman and post-Lehman bailout probabilities for GSIBs and OLBs are shown in Section V.

Although (2) is a non-linear panel model, given the combined roles of $\beta$ and the parameters determining $\pi_{it}$, our fitting method iteratively applies linear panel regression estimation of $\beta$ in (2), based on prior-step estimates of $\pi_{it}$. Our higher-level numerical search for the parameters determining $\pi_{it}$ is based on the explicit

[7]AIG, General Motors and Chrysler were bailed out in 2008. Sjostrom Jr (2009) explains the reasons behind the collapse of AIG and details the terms of the government bailout. Faccio, Masulis and McConnell (2006) provide evidence regarding the incidence of, and the factors determining, the bailout of non-financial corporations. In the appendix, we show that our empirical findings are robust to the exclusion of insurance and car companies from our sample. Our results are also robust to allowing for non-bank bailout provided that the likelihood of non-bank bailout did not change significantly after Lehman failed.

[8]This statement assumes that $\log(1-\pi) + \beta\,\text{DtD}(\pi)$ is a decreasing function of $\pi$, which is the case in our applications.

solution of the structural model presented in the next section, which captures the dependence of distance to default on parametric bailout probabilities. For a given type of bank, data-consistent pairs $(\pi_{\text{pre}}, \pi_{\text{post}})$ are identified by ruling out interactions between firm and time fixed effects in (2). This forces the degree to which the relationship between $\log[S_{it}/(1-\pi_{it})]$ and $\text{DtD}_{it}(\pi_{it})$ differs between a non-bank and a given type of bank to be the same before and after Lehman's default.

## III. Valuation of Bank Equity and Debt with Bailout Subsidies

This section presents a simple structural model of the valuation of a bank's debt and equity, capturing the effects of a given probability of government bailout at insolvency. Additional details are provided in Appendix B. The model captures the impact of bailout on solvency, credit spreads, equity market value, and the component of equity market value associated with bailout subsidized debt. The model allows us to calibrate a data-consistent distance to default of a bank, given an assumed bailout probability, for the purpose of our panel regression, as explained in the previous section. We treat a change in the bailout regime as a shock that is not anticipated by investors.[9]

We consider a bank whose stock $V_t$ of assets in place at any time $t$ satisfies the stochastic differential equation

$$dV_t \quad = \quad V_{t-}(r-k-\lambda\eta)\,dt + V_{t-}\,dZ_t, \tag{3}$$

where $r$ is the short-term interest rate, $k$ is a constant, and $Z$ is a risk-neutral martingale Lévy process.[10] We take $Z$ to be the sum of a Brownian motion with variance parameter $\sigma^2$ and an independent compensated compound Poisson process with mean jump arrival rate $\lambda$ and exponentially distributed downward jumps with mean

[9]This is sometimes called an "MIT shock."

[10]We fix a probability space $(\Omega, \mathcal{F}, \mathbb{P})$ and a filtration $\{\mathcal{F}_t : t \geq 0\}$ of sub-$\sigma$-algebras of $\mathcal{F}$ satisfying the usual conditions. For details, see Protter (2005). All of our probabilistic statements in this section are relative to a probability measure $\mathbb{Q}$, equivalent to $\mathbb{P}$, under which the market value at time $t$ of a claim to any increasing adapted cumulative cash-flow process $C$ is $E^{\mathbb{Q}}(\int_t^\infty e^{-r(u-t)}\,dC_u \,|\, \mathcal{F}_t)$, where $r$ is the short rate and $V_{t-}$ is the left limit of the path of $V$ at $t$.

proportional jump size $\eta$, where $\eta \in (-1,0)$. The benefits of modeling $V$ as a jump diffusion rather than merely a diffusion are well documented (Leland, 2006; Chen and Kou, 2009; Sundaresan, 2013). When calibrated, our model implies substantial jump risk.

In an efficient market for bank assets, (3) and the absence of arbitrage imply that the bank has net cash outflow at the rate $kV_t$. We depart from this efficient-market assumption by assuming cash payouts at the rate $(k+\phi)V_t$, for some parameter $\phi$. For example, with $\phi > 0$, we can view $\phi V_t$ as a stream of rents (Schwert, 2020). If $\phi < 0$, for example because of overhead, salary costs or frictional costs, the bank would optimally be liquidated were it not for government subsidies or distress costs.

The bank first reaches insolvency at an endogenous random (stopping) time $\tau$ that we characterize later. At insolvency, with some risk-neutral probability $\pi$, the bank is bailed out in a manner to be described, and continues operating until the next potential time of insolvency. If, at insolvency, the bank is not bailed out, distress costs cause the stock of assets in place to drop from $V_\tau$ to $\alpha V_\tau$, for some recovery coefficient $\alpha \in (0,1)$.

An insolvency that is not resolved with a bailout is called a "failure." In practice, a failure could occur in the form of an administrative failure resolution process that involves restructuring the debt with a bail-in. Alternatively, a failure could involve a bankruptcy-style failure resolution involving reorganization or liquidation, as occurred with Lehman. Under the Dodd-Frank Act, the preferred approach to resolving an insolvent GSIB is a bankruptcy at the level of the bank holding company. If bankruptcy is judged to be likely to cause undue systemic risk, the failure is instead intended to be resolved via a Title-II administrative failure resolution process managed by the Federal Deposit Insurance Corporation (FDIC). Such a failure resolution process could result in the bail-in of non-deposit debt, likely in the form of an administratively determined swap of legacy debt claims for new equity claims in the resolved institution. For simplified modeling purposes, we will treat any failure as a terminating liquidation.

Our modeled bank has two types of debt: insured deposits and bonds. Appendix C solves an extension to three layers of debt: deposits, senior bonds and junior bonds. Deposits are of constant total size $D$ and pay interest at some constant proportional rate $d$. Because of imperfect competition in the deposit market, deposit rates are in practice often much lower than wholesale risk-free rates, and rise very sluggishly after risk-free rates rise (Driscoll and Judson, 2013; Drechsler, Savov and Schnabl, 2017). Our empirical implementation of the model simply estimates $d$ from observed deposit interest expense.

In our model, deposits are fully guaranteed, at no cost to the bank, via government guarantees. Appendix B extends the model and its explicit solution so as to accommodate FDIC deposit insurance premia and the additional FDIC assessments that were introduced after the GFC for the liabilities of "large and complex financial institutions" (FDIC, 2011). The effective level of the post-crisis FDIC assessment rates for each bank is difficult to determine and not directly observable. The post-crisis assessment rates are believed by some commenters (Whalen, 2011; Pozsar, 2016) to have ranged from ten basis points, on average, when first introduced, to around five basis points towards the end of our sample period. For simplicity, we do not include the effects of FDIC insurance assessments in our empirical estimation.

The remaining class of debt consists of bonds of constant total principal $P$, with maturities that are exponentially distributed.[11] That is, bonds mature at some aggregate proportional rate $m > 0$, so that the fraction of the original bond principal that remains outstanding at any time $t$ is $e^{-mt}$. This implies that the average bond matu-

[11] A constant exponential maturity structure can be achieved as follows, among other assumptions. There could be initially a continuum (non-atomic measure space) of different bonds with aggregate principal $P$. (The principal of each bond is "infinitesimal.") The maturity date of each bond is random and exponentially distributed with parameter $m$. The maturity dates are pairwise independent. The measurability conditions of Sun (2006) can be used to support an application of the exact law of large numbers, under which the cross-sectional distribution of maturity dates is equal to the same exponential distribution. Each time a bond matures, it pays the investor its principal and is replaced by issuing at market value a new bond of the same principal whose maturity is exponentially distributed with the same parameter $m$, again independently of all else.

rity is $1/m$. The bonds have a coupon rate $c$ per unit of principal, for a total coupon payment rate of $cP$ on all outstanding bonds. When any existing bond matures at time $t$, the same principal amount of debt is issued at its current market value, which could be at a premium or discount to par depending on $V_t$. The newly issued bonds have the original coupon rate $c$. The original exponential maturity distribution is always maintained. Interest payments are tax deductible at the corporate tax rate $\kappa$.

In summary, our model coincides with that of Leland (1994a), except that *(i)* we have two classes of debt, insured deposits and bonds, with deposits earning below-market interest rates, *(ii)* we allow for the possibility that the payout rate $(k+\phi)$ deviates from the efficient-market payout rate $k$, and *(iii)* we allow for a government bailout at default, at which the bank continues operating until its next insolvency, when it can once again be bailed out, or not, and so on.

The shareholders choose the default time $\tau$ as the time at which they are no longer willing to service the bank's debt. That is, at $\tau$ the current equity owners default, and stop participating in any cash flows, permanently. Equity ownership may be in the form of common or preferred stock. Preferred stock is modeled as a consol bond that is extinguished at $\tau$. Common stock provides a residual claim to the bank's cash flows that is junior to deposits, bonds and preferred stock. We focus on an equilibrium default time of the form $\tau = \inf\{t : V_t \leq V^*\}$, for some constant asset default boundary $V^*$ that is chosen by shareholders to maximize the total market value of the common and preferred stock.[12]

At the default time $\tau$, the bank does not necessarily go into an insolvency process, causing distress costs and lack of bond payment. The bank could instead be "bailed out" by the government. Bailout is not predictable and occurs with a

[12] Our solution concept is the equilibrium default timing model of Décamps and Villeneuve (2014), by which debt is issued at each time at a competitive market price that is consistent with correct investor conjectures of the default-time policy $\tau$. Under the assumption that the choice of the default boundary $V^*$ maximizes the total market value of common and preferred stock, $V^*$ does not depend on the preferred stock notional. If instead one were to assume that $V^*$ is chosen to maximize the market value of common stock, then $V^*$ would be a function of the pre-bailout notional and the assumed post-bailout notional of preferred stock.

given risk-neutral probability $\pi$.[13] At $\tau$, the original equity owners sever themselves from the bank permanently. If there is a bailout, the government injects new capital, becomes the new equity owner, thus avoiding any distress costs to assets, and continues to make contractual debt-servicing payments until the next time of insolvency, at which point there is another bailout, or not, and so on.

The form of bailout that we consider is roughly what happened with many of the bailouts of large European banks (Reuters, 2015).[14] In practice, a government might instead partially nationalize a bank before the market value of its equity reaches zero, as with some other European bailouts[15] and the U.S. Troubled Asset Relief Program. For simplicity, we avoid the modeling of partial nationalization.

Immediately after a bailout, the government may or may not sell its equity stake on a competitive market (this choice has no economic effect), and the bank continues to operate, following the same policy, until at least the next such insolvency time, and so on. For simplicity, the government's bailout capital injection results in the purchase of enough additional assets to bring the total market value of the bonds up to some stipulated value $B$. This total associated post-bailout asset level is $\widehat{V}$. The net government subsidy at bailout is thus $\widehat{V} - V_\tau - H(\widehat{V})$, where $H(x)$ is the equity market value of a bank with initial assets in place of $x$ and original liability structure $(D, d, P, c)$.

As mentioned above, in the event of no bailout at the insolvency time $\tau$, we assume that the bank is permanently liquidated. At liquidation, the deposits are

[13]The event of failure or bailout is revealed precisely at time $\tau$. That is, we can define the commonly observed information filtration $\{\mathcal{F}_t : t \geq 0\}$ by letting $\mathcal{F}_t = \sigma(\{Z_s : s \leq t\} \cup \{B_1, \ldots, B_n\})$, where $B_1, B_2, \ldots$ is a risk-neutrally independent sequence of Bernoulli trials corresponding to successive bailouts of the bank (one if bailout, zero otherwise), and $B_n$ is the last such trial that has occurred by time $t$. The trials are revealed each time that $V_t$ reaches $V^*$. This model implies that, at any time $t$, the conditional probability of bailout at the next insolvency time is always equal to the unconditional bailout probability $\pi$.

[14]In the aftermath of the GFC, European governments took dominant majority equity positions in ABN Amro, Anglo Irish Bank, Bank of Ireland, Dexia, Fortis, Hypo Real Estate Bank, KBC, Northern Rock, Royal Bank of Scotland, and SNS Reaal.

[15]These include the bailouts of Alpha Bank, Bankia, Commerzbank, Eurobank, ING, Lloyds, Piraeus Bank, and UBS.

redeemed in full, using if necessary funding from the government via its deposit guarantee, and the bond creditors receive any remaining liquidation value of assets, pro rata by principal amount. That is, per unit of the face value of their debt claims, the depositors receive one unit of value and the bondholders receive $(\alpha V_\tau - D)^+/P$, using the notation $x^+ = \max(0,x)$. Government deposit insurance therefore pays $(D - \alpha V_\tau)^+$. This allows for the possibility that $\alpha V^* - D > P$, in which case the bonds recover more than par. Although this case can be ruled out by reasonable parameter restrictions, bond recoveries above par are possible in practice. That said, the bond recoveries implied by our model calibrations tend to be well below par.

This simple model is time-homogeneous with Markov state variable $V_t$. The list of primitive model parameters is

$$\Theta \quad = \quad (d,D,c,P,B,m,r,k,\phi,\sigma,\lambda,\eta,\alpha,\kappa,\pi)\,. \tag{4}$$

We consider only parameters for which there is non-trivial default risk for creditors, meaning that the recovery value $(\alpha V_\tau - D)^+$ of bonds at failure is lower than the recovery $B$ at bailout, which in turn is lower than the default-risk-free market value of the bonds, $W = P(c+m)/(r+m)$. Because we have an explicit solution for $V^*$ in terms of primitive model parameters, this non-degeneracy condition is an explicit condition on these model parameters. The model can also be solved explicitly in the degenerate case, which we avoid only for simplicity of notation.

We now turn to the calculation of the optimal default boundary $V^*$, the bailout recapitalized asset level $\widehat{V}$, and the market value of the claims against the bank's cash flows. While the detailed calculations and explicit solutions are found in Appendix B, here we just provide an overview of the sequence of computations. First, we use a "smooth-pasting" condition for the market value of equity at the default boundary $V^*$ to solve explicitly for $V^*$. Second, given $V^*$, we find the recapitalization boundary $\widehat{V}$ that achieves a post-bailout market value of $B$ for bonds. Third, for any given initial asset level $V_0$, we use the previously identified constants $V^*$

and $\widehat{V}$ to compute the total market value of all cash flows available to the bank over the time period $[0,\infty)$, including the cash flows generated by assets in place, future liquidation recoveries, government tax shields, and deposit insurance claims. This total market value of available cash flows is equal to the total market value of all of the positions held by claimants against the same cash flows. These claimants are the original equity owners, the original depositors, the original bondholders, and the government as a contingent equity claimant at all future bailouts. The market values of creditor claims are explicitly solved in Appendix B, allowing us to deduce the market values of equity claims.

For an illustrative set of parameters, the left panel of Figure 1 plots the default and recapitalization asset boundaries, $V^*$ and $\widehat{V}$, showing how these boundaries depend on the assumed bailout probability $\pi$. As $\pi$ goes up, the endogenous default boundary $V^*$ goes down, reflecting the incentive of shareholders to extend the period of time over which they enjoy higher subsidies in their debt financing costs, caused by higher expectations of creditor bailout at any future default. This reflects the endogenous relationship between $\pi$ and distance to default, a key relationship that is exploited in our empirical fitting strategy. The recapitalization asset level $\widehat{V}$ also decreases as $\pi$ increases because higher bailout expectations cause higher bond prices. Thus, as $\pi$ rises, a bond price of $B$ can be achieved with a lower level $\widehat{V}$ of assets in place. As $\pi$ approaches one, the government's capital injection at bailout, $\widehat{V}-V^*$, converges to zero.[16]

The right panel of Figure 1 shows, for a given $V_0$, the market value of each type of stakeholder claim. Naturally, the market values of equity and debt are increasing in $\pi$. The market value of equity rises with increases in $\pi$ through the prospect of more heavily subsidized debt re-issuance prices that will be available if and when future asset levels decline unexpectedly. The market value of bonds increases with

[16]This results from the restriction that the market value of bonds at bailout, obtained by setting $x=\widehat{V}$ in (B5), is equal to $B$. Since $B<W$, (B5) implies $\lim_{\pi\to 1}\widehat{V}=V^*$.

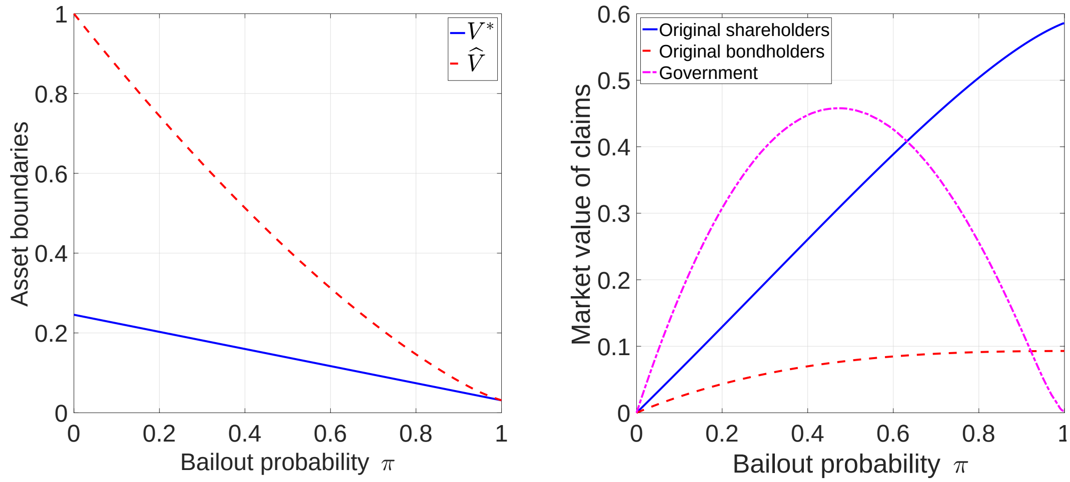


Figure 1. Effect of bailout on endogenous asset boundaries and claim valuations.

*Note:* The left panel shows the explicit solutions of the asset default boundary $V^*$ and the bailout asset level $\widehat{V}$, scaled by $\widehat{V}(\pi = 0)$, as functions of the bailout probability $\pi \in [0, 1)$. The right panel shows the increase, relative to the case where $\pi = 0$, in the market value of the claims by the original equity owners, the original bondholders and the government, scaled by $V_0(\pi = 0)$. The parameters of the model are consistent with a calibration to the case of JP Morgan & Chase on December 31, 2019: $d = 0.6\%$, $D = 0.76$, $c = 3.0\%$, $P = 0.30$, $B = 0.30$, $m = 0.29$, $r = 1.6\%$, $k = 5.7\%$, $\phi = 0$, $\sigma = 9.7\%$, $\lambda = 0.3$, $\eta = -0.2$, $\alpha = 0.50$ and $\kappa = 0.35$.

$\pi$ through higher expected bond recovery at default. The total initial market value of the equity claims received by the government at all future bailouts is a hump-shaped[17] function of $\pi$.

In prior work that incorporates government bailouts into dynamic models of endogenous default and bond pricing,[18] Albul, Jaffee and Tchistyi (2015) and Chen et al. (2017) assume that the government guarantees (with probability one) the debt principal at default.[19] Our empirical objectives obviously require a model that al-

[17]If the government never intervenes ($\pi = 0$), it has no post-bailout claim on the bank's equity. If it almost always intervenes ($\pi$ is close to one), the post-bailout asset level $\widehat{V}$ approaches the insolvency threshold $V^*$, as shown in the left panel of Figure 1, meaning $H(\widehat{V})$ approaches zero.

[18]Other variations and extensions of the Leland (1994a; 1994b) framework for financial firms include He and Xiong (2012), Harding, Liang and Ross (2013), Diamond and He (2014), Sundaresan and Wang (2014), and Auh and Sundaresan (2018). Berger et al. (2019) solve for banks' optimal capital structure under different bailout and bail-in scenarios and, given banks' capital structure responses, for socially optimal government intervention schemes. Nagel and Purnanandam (2019) find that structural credit risk models in which the asset volatility is assumed to be constant can severely understate banks' default risk in good times when asset values are high.

[19]Albul, Jaffee and Tchistyi (2015) have perpetual debt, so, once the debt is issued at time zero, the government guarantee of debt has no effect on the default boundary or on the market value of

lows variation in bailout probabilities. Taking a "macro" approach, Gandhi, Lustig and Plazzi (2020) assume that the government absorbs the aggregate losses of the entire financial sector, above a certain cap, that could be caused by a "rare disaster."

Appendix D explains how we calibrate our model parameters to the data described in the next section. The benchmark calibration assumes an efficient-market model for bank assets ($\phi = 0$). This assumption is lifted later in the paper.

## IV. Data and Descriptive Statistics

We collect data for all U.S. GSIBs identified by the Financial Stability Board, in consultation with the Basel Committee on Banking Supervision, through 2019. These are the holding companies of Bank of America, Bank of New York Mellon, Citigroup, Goldman Sachs, JP Morgan & Chase, Morgan Stanley, State Street, and Wells Fargo. The list of U.S. GSIBs has remained unchanged since it was first published in November 2011. As a separate category of large banks, we also treat those U.S. bank holding companies, beyond GSIBs, that have $50 billion or more in total consolidated assets as of December 2019. These are Ally Financial, American Express, Capital One Financial Corporation, Citizens Financial Group, Comerica, Discover Financial Services, Fifth Third Bancorp, Huntington Bancshares, KeyCorp, M&T Bank, Northern Trust, People's United Financial, PNC Financial Services Group, Regions Financial, SVB Financial Group, TRUIST,[20] and U.S. Bancorp. We refer to these additional firms as Other Large Banks (OLBs). Further details on the classification of large banks are provided in Appendix E.

We also collect data on all other public U.S. firms that can be matched unambiguously across the IHS Markit CDS, Compustat (CS) and CRSP databases. IHS Markit CDS rate observations are "at-market," meaning that they represent bids or offers of the default swap rates at which a buyer or seller of protection is propos-

equity. With Chen et al. (2017), however, there is issuance of new debt over time as in our model.

[20] TRUIST was formed in December 2019 through a merger between BB&T and SunTrust Banks, both of which had more than $50 billion in total consolidated assets prior to the merger.

ing to enter into new default swap contracts without an up-front payment. The at-market CDS rate is in theory that for which the net market value of the contract is zero, assuming no upfront and zero dealer margins. The rates provided by IHS Markit are composite CDS quotes, in that they are computed based on bid and ask quotes obtained from two or more anonymous CDS dealers.

Prior to April 8, 2009, we use CDS data based on a contractual definition of default known as "modified restructuring," and from April 8, 2009 onwards, we use CDS data based on "no restructuring." This reflects the market convention before and after the introduction of the CDS Big Bang protocol on April 8, 2009. Our CDS data apply to senior unsecured debt instruments, and are for a maturity horizon of five years. For banks, our data cover CDS for holding-company bonds.

Although IHS Markit CDS data go back as far as 2001, after cleaning the data using the protocol in Appendix F we find few 2001 observations. We therefore restrict our sample to the period from January 1, 2002 to December 31, 2019. We consider two sub-periods—the "pre-Lehman" period which ends on the date of Lehman Brothers' bankruptcy on September 15, 2008, and the "post-Lehman" period from September 16, 2008 onwards.

The accounting data that we obtain from quarterly CS files include book assets, long-term debt, short-term debt, interest expenses, book preferred equity, cash dividends on common and preferred shares, and share repurchases. When quarterly data are missing, we use annual reports to augment the data. To avoid a forward-looking bias, on any given date we use the accounting data from the last available report. For large banks—meaning GSIBs and OLBs—we augment missing CS data with CS Banks data. If there are no CS Banks data, we use quarterly 10-Q or annual 10-K Securities and Exchange Commission (SEC) disclosure filings data.[21] From

[21] We have verified that the information contained in the SEC filings of large banks closely matches that available through CS, especially for book assets, long-term debt and deposits. We use CS as our main data source because of the consistency that it offers in terms of measuring short-term debt. The SEC filings definition of short-term debt, by comparison, is inconsistent across banks and over time.

the CS Banks data (or 10-Q/K filings), we also obtain information on deposits and deposit interest expenses.

For each large bank, we hand-collect the debt maturity information provided in 10-K filings and use it to calculate a time series of notional-weighted average bond maturities. For all other firms, we approximate by treating the maturities of short-term and long-term bonds as though equal to one year and five years, respectively. Using the reported notional amounts of short-term and long-term debt, we then impute notional-weighted average bond maturities.

Equity market data, including the number of common shares outstanding and price per share, are obtained from CRSP. We filter for common equity by retaining only observations for CRSP share codes 10 and 11. Treasury yield curve data are obtained from the Federal Reserve Board.[22] Deposit rates are computed bank by bank as the ratio of the interest expense on deposits to the amount of deposits, using CS Banks or 10-Q/K data. Bond coupon rates are measured as the ratio of interest expense on short-term and long-term debt divided by the book value of short-term and long-term debt. Similarly, coupon rates on preferred equity are set equal to the ratio of dividends on preferred equity to book preferred equity.

We remove firm-date pairs with missing or incomplete information from the data.[23] The final sample includes over 1.5 million firm-date observations, representing 575 unique firms—as identified by their CS "gvkey" number—from ten industry sectors. The covered set of firms includes six of the eight GSIBs (Bank of America, Citigroup, Goldman Sachs, JP Morgan & Chase, Morgan Stanley and Wells Fargo) and six OLBs (American Express, Capital One, KeyCorp, PNC Financial Services Group, SunTrust Banks and U.S. Bancorp). Additional large banks are not included because of the lack of data or insufficient data quality. The Financials

[22] The data are based on Gurkaynak, Sack and Wright (2007), and are available at `https://www.federalreserve.gov/pubs/feds/2006/200628/200628abs.html`.

[23] We also exclude zero-leverage observations, which account for 0.3% of the data, as we require a valid distance to default estimate.

sector is comprised of GSIBs, OLBs, and insurance firms (Standard Industrial Classification (SIC) codes 6300–6499).

The range of credit qualities of the firms in our data may be judged from Appendix G, where we categorize firms according to their median Moody's credit rating over the sample period. Table G1 shows, for each rating category, the number of firms in our study with that median rating. As the table indicates, firms in the sample tend to be of medium credit quality. The fraction of investment-grade firms is highest among financial firms, and lowest for consumer services and telecommunication services firms.

Figure G1 shows the time series of median five-year CDS rates for GSIBs, OLBs, and other firms. Median CDS rates are substantially higher following WorldCom's default in July 2002, during the GFC, and during the latter half of 2011 when there were severe concerns about European peripheral sovereign debt and faltering negotiations over the U.S. government debt ceiling. The increase in CDS rates in late 2011 was particularly pronounced for GSIBs. Across all firms, CDS rates tend to be higher in the post-Lehman period than the pre-Lehman period.

Taylor and Williams (2009) point out that there was actually a significant increase in large-bank credit spreads about a year *before* the failure of Lehman. Indeed, over July 2007, the median GSIB CDS rate in Figure G1 rose by 27 basis points—a more than 160% increase over the end-of-June level—most likely on news about heightened default risks in the U.S. residential mortgage market. In the context of our model, this pre-Lehman elevation in large-bank credit spreads could be viewed as the result of an increase in the insolvency probabilities of large banks, while holding bailout probabilities at their pre-Lehman levels.

For example, at a risk-neutral pre-Lehman bailout probability $\pi_{\text{pre}}$ of 0.89 and a loss in the event of insolvency and no bailout of $L = 0.91$ (consistent with the Lehman defaulted-bond recovery rate of 9%), the risk-neutral expected loss given default is $(1-\pi)L = 0.10$. An increase in credit spreads of 27 basis points can then be interpreted as an increase in the risk-neutral annualized default probability of GSIBs in July 2007 of about 270 basis points. Berndt et al. (2018) estimate that annualized risk-neutral default probabilities in mid-2000 were roughly double actual default probabilities, for firms with five-year CDS rates near those of the largest U.S. banks at that time. At this ratio, a 2.70% increase in annualized risk-neutral default probability translates into an increase in the annualized actual default probability of GSIBs of roughly 1.35%, which seems a plausible investor reaction to the first signs of an impending mortgage crisis. Large-bank default risk is highly systematic, so two-to-one likely understates the ratio of risk-neutral default probabilities to actual default probabilities for large banks. This numerical example is not intended to be quantitatively precise, but rather to shed light on whether the July 2007 run-up in credit spreads could reasonably be related to changes in insolvency risk rather than changes in bailout expectations. We are not aware of any discussion in 2007 of changes in the perceived implicit government support of large banks. Major rating agencies maintained large sovereign uplifts in their credit ratings of large banks until after the failure of Lehman.[24]

Table G2 reports summary statistics for key accounting variables for GSIBs, OLBs, and other firms. As shown, large banks tend to have much higher accounting leverage than other firms, yet much lower market rates for CDS protection. Our leverage data include only conventional debt liabilities, and not the liabilities associated with over-the-counter derivatives, repurchase agreements, and other qualified financial contracts. Several of the GSIBs (Bank of America, Citigroup, Goldman Sachs, JP Morgan & Chase, Morgan Stanley) have substantial amounts of qualified financial contracts. For large banks, the tangible equity ratio, computed as tangible common equity divided by tangible assets, is higher on average after Lehman's default than before, while the opposite is true for other firms.

[24]We obtained sovereign uplifts to credit ratings from Moody's Investor Services.

## V. Empirical Results and Comparative Statistics

The distance to default of a generic firm in our theoretical setting is defined as

$$(5)\qquad \mathrm{DtD}_t \;=\; \frac{\log(V_t)-\log(V_t^*)}{\Sigma_t},$$

where $V_t$ denotes assets in place at time $t$, $V_t^*$ is the endogenous asset default boundary, and $\Sigma_t$ is the local variance of $\log V$. Figure G2 depicts the non-linear dependence of DtD on the bailout probability $\pi$.

Following the strategy previewed in Section II, we now describe more precisely our estimation of pre-Lehman bailout probabilities, $\pi^G_{\text{pre}}$ for GSIBs and $\pi^O_{\text{pre}}$ for OLBs, for various assumed values of the corresponding post-Lehman bailout probabilities $\pi^G_{\text{post}}$ and $\pi^O_{\text{post}}$. Our basic empirical model is

$$(6)\qquad \log\frac{S_{it}}{1-\pi_{it}} \;=\; \beta\,\mathrm{DtD}_{it}(\pi_{it})+\sum_{\text{firm } f}\delta_f D_f(i)+\sum_{\text{month } m}\delta_m D_m(t)+\varepsilon_{it},$$

where $S_{it}$ is the five-year CDS rate of firm $i$ on date $t$; $D_f(i)$ is the indicator (zero or one) that is turned on when $i=f$; $D_m(t)$ indicates whether date $t$ is in month $m$; $C_L=\left(\beta,\{\delta_f\}_{\text{firms}\,f},\{\delta_m\}_{\text{months}\,m}\right)$ are the linear-model coefficients to be estimated; and $\varepsilon_{it}$ is an uncertain residual.

We take $\pi_{it}$ to be zero if firm $i$ is not a large bank. If firm $i$ is a GSIB, we take $\pi_{it}$ to be $\pi^G_{\text{pre}}$ for any pre-Lehman date $t$ and $\pi^G_{\text{post}}$ for any post-Lehman date $t$. Likewise, if firm $i$ is an OLB, we take $\pi_{it}$ to be $\pi^O_{\text{pre}}$ for any pre-Lehman date $t$ and $\pi^O_{\text{post}}$ for any post-Lehman date $t$. We later allow for GSIB heterogeneity by taking $\pi_{i,\text{pre}}$ to be firm-specific for GSIBs.

Our model allows for variation in insolvency risk and risk premia, over time and across firms. However, (6) forces the degree to which credit spreads for GSIBs differ proportionately from those for non-banks with the same distance to default to be constant over time, except for an adjustment by a factor of $(1-\pi^G_{\text{post}})/(1-\pi^G_{\text{pre}})$ in the post-Lehman period that reflects the relative change in the likelihood that an insolvent GSIB is not bailed out. To achieve this condition, and the equivalent condition for OLBs, we use non-linear least squares estimation to identify pairs of bailout probabilities $(\pi^G_{\text{pre}}, \pi^G_{\text{post}})$ and $(\pi^O_{\text{pre}}, \pi^O_{\text{post}})$ consistent with the non-linear model (6). Holding $\pi^G_{\text{post}}$ and $\pi^O_{\text{post}}$ fixed as model parameters, we search for $\pi^G_{\text{pre}}$ and $\pi^O_{\text{pre}}$ with the property that the root mean squared error (RMSE) of the fitted version of (6) is minimized. For given bailout probability parameters, we obtain the fitted version of (6) by estimating the coefficients $C_L$ via a standard panel regression.

Figure G3 shows the RMSE estimates, as a function of various pre-Lehman bailout probabilities $\pi^G_{\text{pre}}$ and $\pi^O_{\text{pre}}$, for the special case in which the post-Lehman bailout probability for any large banks is set to 0.80. As shown, the RMSE is minimized for $\pi^G_{\text{pre}} = 0.89$ and $\pi^O_{\text{pre}} = 0.84$.

Table 1 tabulates the fitted pairs of pre-Lehman and post-Lehman bailout probabilities, for a wide range of post-Lehman bailout probabilities.[25] For each assumed level of $\pi_{\text{post}}$, the data are consistent with a significant decline of bailout probabilities from the pre-Lehman period to the post-Lehman period. As expected, this decline is more pronounced for GSIBs than OLBs.[26]

For each estimated set of bailout probability parameters, Table G3 reports the corresponding coefficient estimates and standard errors for the panel regression (6). The RMSEs for the fitted relationships are roughly 0.42. While the CDS data are noisy in this sense, the relationship between the log CDS rate and the distance to default is highly significant. Variation in distance to default, firm and month fixed effects tends to explain a sizable fraction—an $R^2$ of 0.84 or higher—of variation in log CDS rates. Table G4 reports summary statistics for the associated structural model parameters. We find that high bailout probabilities tend to imply high asset

[25]Our derivations in Appendix B are based on the assumption that bailout probabilities are less than one. As bailout probabilities approach one, the structural model calibration becomes less stable. This is because of the tension between *(i)* the assumption that the market value of bonds at bailout, $B$, is less than the default-risk-free market value of the bonds, $W$, and *(ii)* the fact that for $\pi = 1$ bonds are indeed free of default risk. To avoid such calibration issues, for each $\pi_{\text{post}} = 0, 0.1, \ldots, 0.9$, we constraint our search for $\pi^G_{\text{pre}}$ and $\pi^O_{\text{pre}}$ to the interval $[0, 0.95]$.

[26]For $\pi_{\text{post}} = 0.9$, extrapolation of fitted RMSEs beyond the $\pi_{\text{pre}} = 0.95$ limit yields $\pi^O_{\text{pre}} = 0.966$ and $\pi^G_{\text{pre}} \approx 1$.

Table 1—Data-consistent pairs of bailout probabilities.

| | $\pi^G_{\text{pre}}$ | | $\pi^O_{\text{pre}}$ | | | $\pi^G_{\text{pre}}$ | | $\pi^O_{\text{pre}}$ | |
|---|---|---|---|---|---|---|---|---|---|
| $\pi_{\text{post}}$ | Est. | SE | Est. | SE | $\pi_{\text{post}}$ | Est. | SE | Est. | SE |
| 0.0 | 0.420 | (0.002) | 0.309 | (0.003) | 0.5 | 0.708 | (0.001) | 0.701 | (0.002) |
| 0.1 | 0.480 | (0.002) | 0.359 | (0.003) | 0.6 | 0.732 | (0.001) | 0.727 | (0.002) |
| 0.2 | 0.528 | (0.002) | 0.446 | (0.002) | 0.7 | 0.813 | (0.001) | 0.804 | (0.001) |
| 0.3 | 0.608 | (0.001) | 0.508 | (0.002) | 0.8 | 0.890 | (0.001) | 0.838 | (0.001) |
| 0.4 | 0.665 | (0.001) | 0.591 | (0.002) | 0.9 | 0.950 | (0.000) | 0.950 | (0.000) |

*Note:* This table reports the estimates for $\pi^G_{\text{pre}}$ and $\pi^O_{\text{pre}}$ that minimize the RMSE of the non-linear model (6), at various values for $\pi^G_{\text{post}} = \pi^O_{\text{post}}$. Asymptotic standard error (SE) estimates are reported in parentheses, and are based on the computations detailed in Appendix H. The data include 575 firms over 2002–2019. For each estimated set of bailout probability parameters, we report the results for the fitted version of (6) in Table G3 and for the structural model parameter estimates in Table G4.

volatilities and high payout rates.

While Table 1 reports the results for cases in which $\pi^G_{\text{post}} = \pi^O_{\text{post}}$, we have confirmed that the estimated pairs of bailout probabilities $(\pi^G_{\text{pre}}, \pi^G_{\text{post}})$ and $(\pi^O_{\text{pre}}, \pi^O_{\text{post}})$ remain nearly unchanged when $\pi^G_{\text{post}}$ and $\pi^O_{\text{post}}$ are allowed to differ. For each assumed combination of $\pi^G_{\text{post}}$ and $\pi^O_{\text{post}}$, the data-consistent pre-Lehman bailout probabilities closely resemble those reported in Table 1 and are consistent with a significant post-Lehman decline in bailout probabilities.

Variation in insolvency risk is explained, to a close approximation, by variation in distance to default, and by firm and time fixed effects (Duffie, Saita, and Wang, 2007). Thus, by holding the variables on the right-hand side of (6) fixed, we condition on a given level of insolvency risk. In that sense, $(1-\pi_{\text{post}})/(1-\pi_{\text{pre}})$ measures the ratio of fitted post-Lehman credit spreads to hypothetical credit spreads for the same firm with the same insolvency risk that would have applied after Lehman's default had bailout probabilities not declined. For GSIBs, this ratio ranges between 1.5 and 2.0, depending on the assumed $\pi^G_{\text{post}}$, whereas for OLBs it ranges from 1.2 to 2.0.

To further illustrate this post-Lehman increase in large-bank debt financing costs, Figure 2 plots the fitted credit spread (five-year CDS rate) for GSIB holding company senior unsecured bonds at a distance to default of 2.0. As shown by the solid

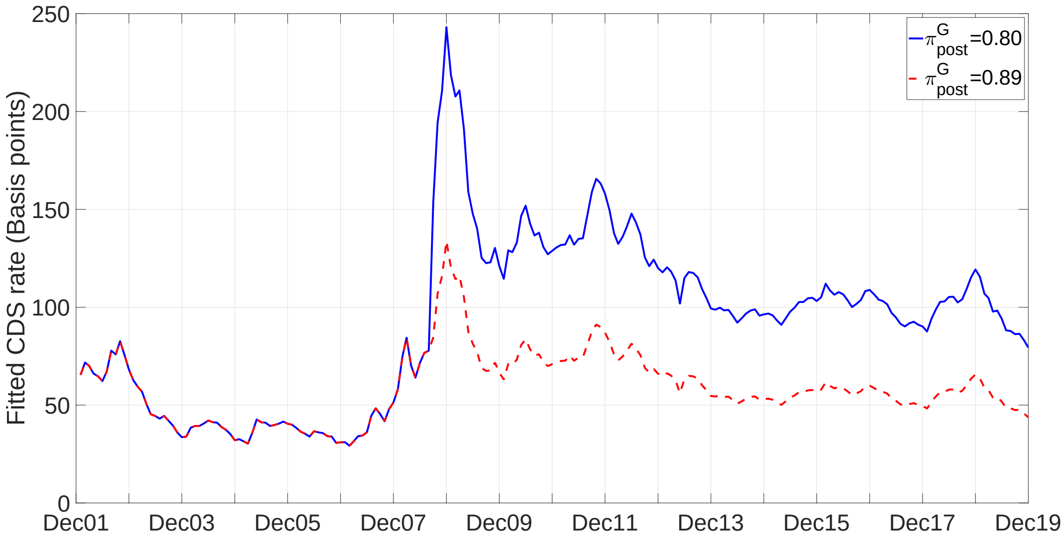


Figure 2. Fitted CDS rates.

*Note:* This figure shows fitted credit spreads (five-year CDS rates) for GSIBs at a distance to default of two standard deviations. The solid blue line is based on the fitted pre-Lehman bailout probability of $\pi^G_{\text{pre}} = 0.89$ reported in Table 1 for an assumed post-Lehman bailout probability $\pi^G_{\text{post}} = 0.8$. The firm fixed effect is set equal to the median GSIB fixed effect in Table G3. The dashed red line is based on the counterfactual assumption that there is no post-Lehman change in bailout probability, taking $\pi^G_{\text{post}} = 0.89$.

blue line, the cost of debt financing for GSIBs at this fixed distance to default is on average much higher in the post-Lehman than the pre-Lehman period. The dashed red line in Figure 2 indicates that some of this increase in debt financing costs is caused by a general post-Lehman re-pricing of credit risk, at a fixed distance to default. That is, the red line is the fitted GSIB credit spread for the counterfactual case in which bailout probabilities did not go down after the GFC. The remaining post-Lehman increase in GSIB debt financing costs, which is the difference between the blue and red lines, reflects a substantial post-Lehman drop in the fitted bailout probability. As shown, at a fixed distance to default, post-Lehman credit spreads were nearly double what they would have been had pre-Lehman bailout probabilities been maintained in the post-Lehman period.

Table 2 shows, for fitted pairs of pre-Lehman and post-Lehman bailout probabilities, the average across GSIBs of the bank asset level and insolvency threshold, as

Table 2—Market value of bank cash flows and stakeholder claims for GSIBs.

| | $\pi$ | $V_0$ | $V^*$ | $Y_0$ | $v_3$ | $y_G$ | $\frac{y_{G,n}}{y_G}$ | $\frac{y_{G,f}}{y_G}$ | $H_s$ | $H_{s,1}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Pre-Lehman bailout probability is calibrated to data* | | | | | | | | | | |
| Pre | 0.95 | 2.49 | 1.01 | 8.38 | 1.75 | 3.55 | 0.18 | 0.82 | 0.23 | 0.12 |
| Post | 0.90 | 2.90 | 1.49 | 14.46 | 4.79 | 7.63 | 0.19 | 0.81 | – | – |
| Pre | 0.89 | 3.61 | 2.19 | 8.45 | 1.81 | 2.94 | 0.29 | 0.71 | 0.53 | 0.20 |
| Post | 0.80 | 5.51 | 4.11 | 13.46 | 3.89 | 5.38 | 0.32 | 0.68 | – | – |
| Pre | 0.81 | 4.90 | 3.63 | 8.31 | 1.68 | 2.13 | 0.40 | 0.60 | 0.71 | 0.22 |
| Post | 0.70 | 7.12 | 5.91 | 13.15 | 3.71 | 4.48 | 0.43 | 0.57 | – | – |
| Pre | 0.73 | 5.70 | 4.58 | 8.24 | 1.62 | 1.74 | 0.49 | 0.51 | 0.77 | 0.22 |
| Post | 0.60 | 8.23 | 7.14 | 12.82 | 3.50 | 3.87 | 0.53 | 0.47 | – | – |
| Pre | 0.71 | 5.91 | 4.83 | 8.21 | 1.60 | 1.63 | 0.52 | 0.48 | 0.88 | 0.33 |
| Post | 0.50 | 8.98 | 7.90 | 12.62 | 3.35 | 3.56 | 0.62 | 0.38 | – | – |
| Pre | 0.66 | 6.23 | 5.19 | 8.16 | 1.55 | 1.49 | 0.56 | 0.44 | 0.91 | 0.40 |
| Post | 0.40 | 9.32 | 8.23 | 12.53 | 3.30 | 3.49 | 0.70 | 0.30 | – | – |
| Pre | 0.61 | 6.40 | 5.45 | 8.23 | 1.63 | 1.52 | 0.62 | 0.38 | 0.94 | 0.43 |
| Post | 0.30 | 9.74 | 8.62 | 12.18 | 3.07 | 3.20 | 0.79 | 0.21 | – | – |
| Pre | 0.53 | 6.68 | 5.77 | 8.22 | 1.64 | 1.50 | 0.69 | 0.31 | 0.94 | 0.43 |
| Post | 0.20 | 10.05 | 8.94 | 11.40 | 2.32 | 2.41 | 0.86 | 0.14 | – | – |
| Pre | 0.48 | 6.89 | 6.00 | 8.15 | 1.80 | 1.40 | 0.72 | 0.28 | 0.96 | 0.49 |
| Post | 0.10 | 10.36 | 9.27 | 10.23 | 1.29 | 1.32 | 0.93 | 0.07 | – | – |
| Pre | 0.42 | 7.06 | 6.19 | 8.08 | 1.82 | 1.35 | 0.76 | 0.24 | 0.96 | 0.52 |
| Post | 0.00 | 10.90 | 9.80 | 8.87 | 0.00 | 0.00 | – | – | – | – |
| *Panel B: Pre-Lehman bailout probability is set to zero* | | | | | | | | | | |
| Pre | 0.00 | 7.46 | 6.63 | 6.36 | 0.00 | 0.00 | – | – | 0.00 | 0.00 |
| Post | 0.00 | 10.90 | 9.80 | 8.87 | 0.00 | 0.00 | – | – | – | – |

*Note:* This table reports the average, across GSIBs and within-period dates, of the bank asset level ($V_0$); endogenous insolvency threshold ($V^*$); and market value of total bank cash flows ($Y_0$), government claims ($v_3$), all potential future bailout injections by the government ($y_G$), potential future bailout injections associated with the next bailout ($y_{G,n}$), and potential future bailout injections associated with subsequent events of insolvency ($y_{G,f}$). $H_s$ is the difference between the pre-Lehman market value of equity and the market value of equity in the counterfactual pre-Lehman economy where bailout probabilities are as low as post-Lehman bailout probabilities. $H_{s,1}$ is the difference between the pre-Lehman market value of equity and the hypothetical market value of equity that would have applied, at the same asset insolvency boundary, had bailout probabilities been as low before Lehman's default as after Lehman's default. All variables are computed as fractions of the market value of common and preferred equity. Results are reported for each of the data-consistent pairs of bailout probabilities in Table 1. The data include 575 firms over 2002–2019.

well as the market values of total future bank cash flows and government bailout subsidies, as fractions of the market value of equity. Appendix Table G5 reports similar results for OLBs. As the assumed post-Lehman bailout probability $\pi_{\text{post}}$ increases, the fitted bank asset levels and insolvency thresholds tend to be lower.

Table 2 reports that in the pre-Lehman period of high bailout expectations, the total market value of government bailout subsidies,[27] as a multiple of the current market value of equity, ranges from $-0.2$ to 1.8 as the bailout probability $\pi^G_{\text{pre}}$ ranges from zero to 0.9. In the post-Lehman period, the total market value of bailout subsidies ranges from zero to 2.8 times the market value of equity as $\pi^G_{\text{post}}$ increases from zero to 0.9.

We also estimate the difference $H_s$ between the market value of equity in the pre-Lehman period and the market value of equity in the counterfactual pre-Lehman economy in which the bailout probability is equal to the post-Lehman bailout probability. Table 2 reports that these relative pre-Lehman subsidies range from 23% to 96% of the market value of equity. (These relative subsidy estimates are higher when post-Lehman bailout probabilities are assumed to be lower.) The estimated counterfactual reductions in the pre-Lehman market value of equity for OLBs are lower than those for GSIBs, as shown in Table G5.

For the case in which post-Lehman bailout probabilities are set to 0.80, Table 2 reports that in a hypothetical scenario in which GSIB bailout probabilities are the same in the pre-Lehman period as in the post-Lehman period, equity market values would have been an estimated 53% lower than in the data-consistent scenario in which GSIB bailout probabilities declined from 0.89 to 0.80, on average across GSIBs and pre-Lehman dates. Of the estimated 53% decline in the market value of equity, 20% is due to an increase in debt financing costs stemming from lower

[27]For a generic bank, the modeled market value $y_G(V_t)$ of all potential future bailout injections by the government is determined by

$$y_G(V_t) \quad = \quad \pi_t E\left[e^{-r(\tau-t)}(\widehat{V}-V_\tau)\middle|V_t\right]+\pi_t E\left[e^{-r(\tau-t)}y_G(\widehat{V})\middle|V_t\right].$$

In return for all of its successive potential future bailout injections, the government has a claim on bank cash flows with a market value of $v_3(V_t)$, as defined in (B7). The total market value of all potential future bailout subsidies provided by the government is thus $y_G - v_3$. The first component of $y_G(V_t)$ in the equation above, which we label $y_{G,n}$, is the market value of government bailout injections associated with the first potential bailout. The second component, denoted $y_{G,f}$, is the market value of all subsequent bailouts. As assumed post-Lehman bailout probabilities increase, the fitted fraction of the market value of all potential future bailouts stemming from the next bailout, $y_{G,n}/y_G$, declines, and the fraction stemming from subsequent bailouts, $y_{G,f}/y_G$, increases.

expected bond recoveries at the same insolvency threshold.[28] The remaining 33% is due to the optimal reaction by GSIBs to a reduced bailout probability of raising the level of assets at which they would default.

Appendix I shows that our findings are robust to alternative specifications of the price of non-deposit debt at bailout, of the market value of preferred shares, and of cash payout rates, and to even stricter data cleaning filters.

## VI. Extensions

We now extend our analysis to allow for *(i)* bank-specific bailout probabilities or *(ii)* elevated market discount rates applied to GSIB earnings in the post-Lehman period. We show that our main finding of a sizable post-Lehman reduction in market-implied bailout probabilities is robust to these extensions.

### *VI.1. Bank-specific bailout probabilities*

In Table 3, we show how data-consistent pre-Lehman and post-Lehman bailout probabilities vary across GSIBs. For each bank, we find a sizable post-Lehman decline in bailout probability. For example, the bank-level estimates of pre-Lehman bailout probabilities range across banks from 44% to 61% at an assumed post-Lehman default probability of $\pi_{\text{post}} = 0.20$. At higher assumed post-Lehman bailout probabilities, however, there is not as much dispersion across banks in pre-Lehman fitted bailout probabilities.

### *VI.2. Bank asset payout rates that deviate from efficient-market levels*

Sarin and Summers (2016) report that half of the GSIBs in our sample experienced a decrease in their price-to-earnings ratio from the pre-Lehman period to the

[28]The difference $H_s$ between the pre-Lehman market value of equity and the hypothetical market value of equity that would have applied if the pre-Lehman bailout probability would have been as low as the assumed post-Lehman bailout probability consists of two components: $H_s = H_{s,1} + H_{s,2}$. The first component, $H_{s,1}$, is the difference between the pre-Lehman market value of equity and the hypothetical market value of equity that would have applied, *at the same asset insolvency boundary*, had bailout probabilities been as low before Lehman's default as after Lehman's default. The second component, $H_{s,2}$, measures the decline in the market value of equity due to banks optimally adjusting their insolvency thresholds to higher asset-to-debt levels in response to a decrease in bailout probability. Higher insolvency thresholds translate into a greater likelihood of bank insolvency.

Table 3—Data-consistent pairs of GSIB-specific bailout probabilities.

| $\pi_{\text{post}}$ | 0.0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | $\pi_{\text{pre}}$ | | | | | |
| BAC | 0.54 | 0.57 | 0.60 | 0.62 | 0.70 | 0.71 | 0.76 | 0.84 | 0.91 | 0.95 |
| C | 0.57 | 0.60 | 0.61 | 0.66 | 0.70 | 0.71 | 0.74 | 0.81 | 0.89 | 0.95 |
| GS | 0.34 | 0.38 | 0.59 | 0.62 | 0.69 | 0.72 | 0.80 | 0.82 | 0.90 | 0.94 |
| JPM | 0.31 | 0.40 | 0.44 | 0.51 | 0.61 | 0.65 | 0.70 | 0.79 | 0.82 | 0.93 |
| MS | 0.42 | 0.43 | 0.47 | 0.53 | 0.70 | 0.72 | 0.80 | 0.82 | 0.90 | 0.95 |
| WFC | 0.34 | 0.41 | 0.46 | 0.56 | 0.61 | 0.70 | 0.72 | 0.80 | 0.90 | 0.95 |

*Note:* This table reports our estimates for GSIB-specific pre-Lehman bailout probabilities $\pi_{i,\text{pre}}$, at various values for $\pi_{\text{post}}$. For each assumed value of $\pi_{\text{post}}$, we use the panel regression coefficient estimates for distance to default and month fixed effects reported in Table G3 and, for each GSIB $i$ separately, find that $\pi_{i,\text{pre}}$ and bank fixed effect that minimize the RMSE of the non-linear model (6) for this bank. Results are reported for Bank of America (BAC), Citigroup (C), Goldman Sachs (GS), JP Morgan & Chase (JPM), Morgan Stanley (MS), and Wells Fargo (WFC).

post-Lehman period. They conclude that the market discounted the future earnings of these banks at a higher rate after the GFC than before. We allow for the effect of a higher post-GFC discount factor on GSIB earnings by assuming that, after Lehman failed, the total proportional payout rate $k_{it} + \phi_{it}$ on bank assets is below the efficient-market level $k_{it}$. In effect, a given amount of bank assets is assumed to produce net income at a lower rate after the GFC than before the GFC, holding interest rates constant, reflecting some form of heightened frictional cost of intermediation or reduction in rents. Specifically, we report results for the case in which, for any large bank $i$, $\phi_{it}$ is set to zero in the pre-Lehman period, whereas in the post Lehman period, $\phi_{it} = \rho_\phi\, k_{it}$, where $\rho_\phi$ is set to either $-0.2$ or $-0.4$. (For any non-bank, we keep $\phi_{it}$ at zero across all dates.)

Consistent with the benchmark findings in Table 1, and independent of the assumed post-Lehman bailout probability, Table 4 reports a sizable decline in bailout probabilities from the pre-Lehman period to the post-Lehman period. For example, for the case in which post-Lehman asset payout rates are reduced proportionately by 40% relative to their efficient-market level, the fitted post-Lehman declines in GSIB bailout probabilities are similar to those reported in Table 1 for the benchmark model with no post-Lehman deviations from efficient-market asset payout rates.

Table 4—Bailout probabilities and equity subsidies when post-Lehman large-bank asset payout rates are below efficient-market levels.

| $\pi_{\text{post}}$ | 0.0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A:* $\rho_\phi = -0.2$ *in post-Lehman period* | | | | | | | | | | |
| $\pi^G_{\text{pre}}$ | 0.50 | 0.52 | 0.60 | 0.62 | 0.68 | 0.71 | 0.74 | 0.81 | 0.89 | 0.95 |
| $\pi^O_{\text{pre}}$ | 0.31 | 0.36 | 0.45 | 0.51 | 0.59 | 0.70 | 0.72 | 0.80 | 0.84 | 0.95 |
| $H^G_s$ | 0.98 | 0.97 | 0.96 | 0.94 | 0.92 | 0.88 | 0.79 | 0.71 | 0.53 | 0.23 |
| $H^O_s$ | 0.59 | 0.54 | 0.54 | 0.49 | 0.45 | 0.44 | 0.27 | 0.19 | 0.06 | 0.05 |
| *Panel B:* $\rho_\phi = -0.4$ *in post-Lehman period* | | | | | | | | | | |
| $\pi^G_{\text{pre}}$ | 0.55 | 0.61 | 0.62 | 0.66 | 0.71 | 0.72 | 0.75 | 0.82 | 0.89 | 0.95 |
| $\pi^O_{\text{pre}}$ | 0.32 | 0.37 | 0.45 | 0.51 | 0.60 | 0.70 | 0.73 | 0.80 | 0.84 | 0.95 |
| $H^G_s$ | 0.98 | 0.98 | 0.97 | 0.95 | 0.93 | 0.88 | 0.81 | 0.72 | 0.53 | 0.23 |
| $H^O_s$ | 0.60 | 0.56 | 0.55 | 0.48 | 0.47 | 0.44 | 0.27 | 0.19 | 0.06 | 0.05 |

*Note:* This table reports data-consistent pairs of bailout probabilities when, for large banks $i$, $\phi_{it} = 0$ on pre-Lehman dates $t$ and $\phi_{it} = \rho_\phi k_{it}$ on post-Lehman dates $t$, where $\rho_\phi \in \{-0.2, -0.4\}$. For non-banks $i$, $\phi_{it} = 0$ for all $t$. $H_s$ is the difference between the pre-Lehman market value of equity and the market value of equity in the counterfactual pre-Lehman economy where bailout probabilities are as low as post-Lehman bailout probabilities. $H^G_s$ and $H^O_s$ are reported as fractions of the market value of equity, averaged across pre-Lehman dates and, respectively, GSIBs and OLBs.

(For small post-Lehman bailout probabilities, the fitted decline in bailout probabilities is somewhat greater than in the benchmark case.) In particular, with this model extension that allows for heightened frictional costs for banks after Lehman failed, it is still the case that post-Lehman credit spreads, fitted at a fixed distance to default, are much higher than what they would have been had bailout probabilities not declined—at a multiple of 1.6 to 2.3 times their hypothetical levels at pre-Lehman bailout probabilities. For OLBs, the fitted pairs of bailout probabilities are nearly unchanged from those reported in Table 1. In particular, fitted post-Lehman OLB credit spreads are 1.2 to 2.0 times what they would have been had bailout probabilities remained at pre-Lehman levels.

Table 4 reports the average difference, across GSIBs and post-Lehman dates, between the market value of equity and its hypothetical counterpart when the pre-Lehman bailout probability is assumed to be as low as the post-Lehman bailout probability. This difference ranges from 23% to 98% of the market value of equity, both for $\rho_\phi = -0.2$ and $\rho_\phi = -0.4$. These figures are similar to those reported for the benchmark model in Table 2. The same observation applies to OLBs. Thus, even when expected future earnings of large banks are more heavily discounted after Lehman's default than before, the data are consistent with sizable pre-Lehman subsidies to the market value of equity stemming from higher bailout expectations. This finding holds independent of the assumed post-Lehman bailout probability. As the post-Lehman $\rho_\phi$ decreases, the pre-Lehman equity subsidies are estimated to be slightly larger.

## VII. Discussion and Concluding Remarks

As we have shown, market prices and financial statement data are consistent with a significant post-Lehman decrease in bailout probabilities, and an associated increase in the debt financing costs of large banks, and with a significant reduction in the market value of their equity per unit of assets in place. This result holds independent of the assumed post-Lehman likelihood of government intervention.

Our strategy is to quantify data-consistent *changes* in bailout probabilities, not their absolute levels. To identify the level of bailout probabilities, additional assumptions must be made. For example, one could impose the additional assumption that the credit spreads implied by our structural model match observed credit spreads, at least on average. According to the results reported in Table G4, this would suggest a post-Lehman bailout probability slightly above 0.8 for GSIBs, and between 0.6 and 0.7 for OLBs. While these bailout probability estimates are subject to model misspecification, they are roughly consistent with an April 2020 survey of about 350 financial economists,[29] who were asked "Going forward, what is your subjective probability that the U.S. government would bail out a U.S. systematically important financial institution?" Over 62% of the participants responded with a bailout probability estimate of 80% or higher. These subjective probability estimates likely exceed their risk-neutral counterparts, given the positive risk premium

[29] The survey was carried out during a virtual finance seminar presentation of this paper hosted by the University of California, Los Angeles, on April 8, 2020.

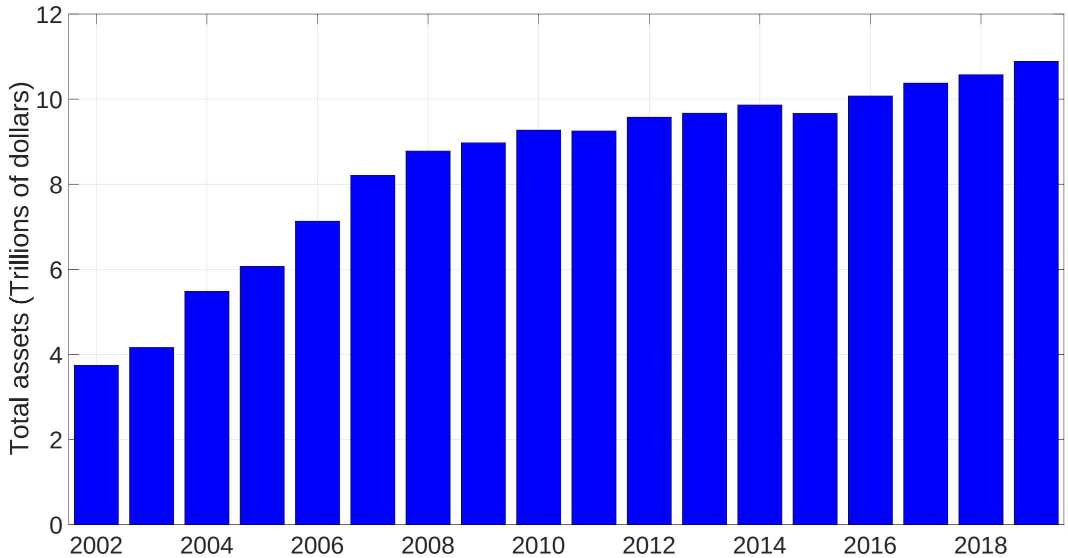


Figure 3. Total assets of six GSIBs.

*Note:* This figure shows the sum of total book assets across the six GSIBs in our sample—Bank of America, Citigroup, Goldman Sachs, JP Morgan & Chase, Morgan Stanley and Wells Fargo. Data on book assets are sourced from CS.

for bank failure.

In the post-Lehman period, we find that the reduced bailout prospects of GSIBs increased their cost of debt financing by 50% to 100%, at a given level of solvency. This in turn reduced the incentives of these firms to grow large balance sheets (Andersen, Duffie and Song, 2019). As shown in Figure 3, the post-Lehman growth rate of large-bank assets is much more muted than the pre-Lehman growth rate. Asset growth was also discouraged after the GFC by large increases in regulatory capital requirements. From the viewpoint of legacy shareholders, equity is a more costly source of financing than debt.

Figure 4 shows significant improvements after 2008 in the asset-weighted average solvency ratios of the largest U.S. financial institutions, the same firms whose assets are depicted in Figure 3. We define the solvency ratio of a firm to be the firm's accounting tangible common equity, measured as a fraction of tangible assets, divided by the estimated standard deviation of annualized asset growth. The improved solvency of large banks is due to significantly higher regulatory bank capital require-

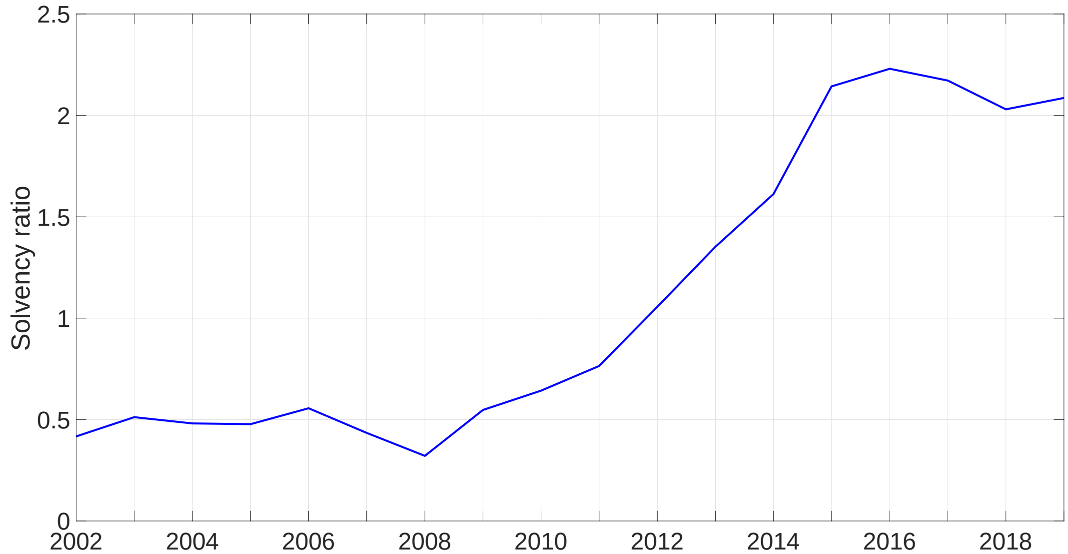


Figure 4. Solvency ratios of six GSIBs.

*Note:* The figure shows the asset-weighted average solvency ratio across the six GSIBs in our sample—Bank of America, Citigroup, Goldman Sachs, JP Morgan & Chase, Morgan Stanley and Wells Fargo. The solvency ratio is computed as the ratio of tangible equity to tangible assets, divided by an estimate of the annualized asset volatility. The tangible equity and asset data are sourced from CS. Asset volatility is estimated as the standard deviation of the proportional change in book asset values, using quarterly data over a trailing five-year rolling window period.

ments, especially for GSIBs. Carney (2014), Rosengren (2014) and Tucker (2014) describe the dramatic increases in capital buffers of the largest banks that were induced by the post-GFC reform of bank capital regulations.

The post-crisis improvement in GSIB solvency is consistent with the decrease in actual probability of large-bank failure depicted in Figure G4. The figure shows the time series of the actual likelihood that a bankruptcy, missed payment or materially adverse debt restructuring event occurs for a given GSIB over the next year, averaged across the six GSIBs in our sample. The underlying failure probability data are provided by the Risk Management Institute at the National University of Singapore. They imply that the average GSIB failure probability declined from 92 basis points in the pre-Lehman period to 53 basis points in the post-Lehman period.[30] Similarly, the Financial Stability Board (2020) reports a post-TBTF-reform

[30] A closer look at the data underlying Figure G4 reveals significantly lower post-Lehman failure probabilities for Goldman Sachs, JP Morgan & Chase and Morgan Stanley, fairly similar failure

decline in the average one-year Moody's Expected Default Frequency for GSIBs from 90 to 60 basis points. Barring a post-Lehman increase in the likelihood of government intervention, a post-Lehman decline in failure probabilities implies lower post-Lehman large-bank insolvency risk.

Overall, the data suggest that wholesale credit spreads of large banks were significantly higher after the GFC than before *despite* an overall improvement in large-bank solvency. Heightened GSIB credit spreads over the decade following the GFC are thus due to some combination of increased expected losses to wholesale creditors in the event of insolvency and increased default risk premia, rather than higher probabilities of insolvency. In contrast, Sarin and Summers (2016) suggest that the high credit spreads of large U.S. banks that prevailed in 2015 reflect high levels of default risk at that time, and that these firms were then about as likely to default as they were before the GFC. Their argument runs counter to the significant improvements by 2015 in the solvency ratios of the largest U.S. financial institutions, and the decrease in large-bank failure probability estimates.

Our primary hypothesis is that a decline of TBTF, meaning a lower reliance by large-bank creditors on the prospect of a government bailout, has resulted in a significant post-Lehman increase in large-bank debt financing costs at a given level of insolvency risk. An alternative, behavioral, explanation for high post-GFC large-bank credit spreads is that, before the GFC, large-bank creditors had little awareness that these banks could actually fail (Gennaioli and Shleifer, 2018). By this line of reasoning, once Lehman failed and several other large banks had close calls, creditors could have become much more aware of risks of failure that were already elevated well before the GFC, but had been badly under-estimated. This would have caused wholesale bank credit spreads to remain elevated after the GFC. This story does not rely on changes in the likelihood of bailout, but rather changes in the

probabilities before and after Lehman's default for Bank of America and Citigroup, and significantly higher post-Lehman failure probabilities for Wells Fargo. On average across the six GSIBs, failure probabilities decreased by nearly 40 basis points in the post-Lehman period.

behaviorally perceived likelihood of insolvency.

If this alternative story applies, then the fact that large-bank credit spreads have remained high relative to their pre-Lehman levels would imply that the GFC-induced increase in the behavioral perception of bank insolvency risk would need to have persisted for some years after the crisis. Historically, however, we are not aware of previous financial crises in which a large crisis-induced jump in wholesale large-bank credit spreads persisted well beyond the end of the crisis. For example, Gorton and Tallman (2016) use the "currency premium" as a gauge of wholesale bank (Clearinghouse) obligations, around nineteenth century banking crises. Regarding the banking panic of 1893, for example, they write: "As gold inflows helped to restore reserve levels following suspension of convertibility on August 3, reports of redeposit of funds in New York Clearing House banks (presumably by interior correspondents) all contributed to an improvement to the financial setting. The key indicators for the banking system—the reserve deficit and the currency premium—become noticeably benign in newspaper articles. By August 31, the currency premium was less than one percent (0.625% in New York Tribune page 3, column 1). We find evidence from both the stock and bond markets that is consistent with the hypothesis." This quote and the data analysis supporting it, shown in Figures 7 and 8 of Gorton and Tallman (2016), suggest that credit spreads jumped up during the 1893 crisis and then quickly went back down again within weeks after the panic.

In the setting of our research, were it not for a post-Lehman drop in the creditor-perceived probability $\pi$ of a government bailout, we might expect large-bank wholesale credit spreads to have returned to closer to their pre-GFC levels, at a given level of solvency, given the general improvement in the economy and in large-bank solvency. That is not what we find. It seems that the simplest explanation for the data is that, after the GFC, wholesale creditors to large U.S. banks substantially lowered their expectations of a bailout the next time that a large bank approaches insolvency.

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**FOR ONLINE PUBLICATION**

**APPENDIX**

## A. Prior Work on Too Big to Fail

Years before the Great Recession, Stern and Feldman (2004) stressed the importance of the TBTF problem, arguing that a safety net provided by the government lowers creditors' incentive to monitor and banks' incentive to act prudently. Mishkin (2006), however, argue that Stern and Feldman (2004) overstate the importance of the TBTF problem. Using international data, Mäkinen, Sarno and Zinna (2020) find a risk premium associated with implicit government guarantees. They suggest that the risk premium is tied to sovereign risk, meaning guaranteed banks inherit the guarantor's risk. Gandhi, Lustig and Plazzi (2020) also provide empirical evidence consistent with the idea that stock-market investors price in the implicit government guarantees that protect shareholders of the largest banks in developed countries. Minton, Stulz and Taboada (2019), on the other hand, find no evidence that large banks are valued more highly than other firms.

O'Hara and Shaw (1990) find positive wealth effects accruing to TBTF banks, with corresponding negative effects accruing to less systemically important banks. Kelly, Lustig and Van Nieuwerburgh (2016) use options data to show that a collective government guarantee for the financial sector lowers index put prices far more than those of individual banks and explains the increase in the basket-index put spread observed during the GFC. Schweikhard and Tsesmelidakis (2012) investigate the impact of government guarantees on the pricing of default risk in credit and stock markets and, using a Merton-type credit model with exogenous default boundary, provide evidence of a structural break in the valuation of U.S. bank debt in the course of the GFC, manifesting in a lowered default boundary, or, under the pre-GFC regime, in higher stock-implied credit spreads.

Balasubramnian and Cyree (2011) claim that the TBTF discount on bond yield spreads is absent prior to the Long-Term Capital Management (LTCM) bailout. They find a paradigm shift in determinants of yield spreads after the LTCM bailout. Santos (2014) demonstrates that the additional discount that bond investors offer the largest banks compared with the return they demand from the largest non-banks and non-financial corporations is consistent with the idea that investors perceive the largest U.S. banks to be too big to fail. The impact of subsidies on firms' borrowing cost has also been analyzed for European banks (Neuberg et al., 2018; Lindstrom and Osborne, 2020), and studied in sectors other than the banking industry (see, for example, Anginer and Warburton (2014) for the auto industry).

Begenau and Stafford (2019) propose that the reliance of banks on high leverage, presumably in the supply of liquidity, appears to generate costs of financial distress that are not offset with other benefits. Gündüz (2020) documents a temporary increase in CDS rates when a bank holding company is added to the list of GSIBs or assigned to a GSIB bucket with a higher capital surcharge, and concludes that in the short run higher capital surcharges and more stringent regulation outweigh any implicit TBTF advantages. Covas and Fernandez-Dionis (2020) show that GSIB credit spreads widened relative to non-GSIB spreads during the early stages of the 2020 coronavirus pandemic, and take this as evidence that GSIBs benefitted from a TBTF status in the post-GFC period. Buch, Dominguez-Cardoza and Völpel (2020) comprehensively review studies on the impact of TBTF reforms on banks' funding costs.

Similar to Haldane (2010), Ueda and Weder di Mauro (2013) provide estimates of the value of the subsidy to systemically important financial institutions in terms of their credit ratings. They report that a one-unit increase in government support for banks in advanced economies has an impact equivalent to 0.55–0.90 notches on the overall long-term credit rating at the end of 2007. This effect increased to 0.80–1.23 notches by the end of 2009. Rime (2005) also examines the possible effects of

TBTF expectations on issuer ratings and finds that proxies of the TBTF status of a bank have a significant, positive impact on bank issuer ratings.

## B. Model Solution

This appendix provides explicit solutions for the asset default boundary $V^*$ and the valuation of bank debt and equity claims.

### *B.1. Characterization of the joint distribution of $\tau$ and $V_\tau$*

Kou and Wang (2003) show that the joint distribution of $\tau$ and $V_\tau$ depends on the three roots of the polynomial $G(x) = \theta$, where $\theta > 0$, $\eta = -1/(1+\xi)$ and

$$\text{(B1)} \qquad G(x) \equiv -\left(r - k - \frac{\sigma^2}{2} - \lambda\eta\right)x + \frac{\sigma^2}{2}x^2 + \lambda\left(\frac{\xi}{\xi - x} - 1\right).$$

The three roots of $G(x) = \theta$ are denoted $\gamma_{1,\theta}$, $\gamma_{2,\theta}$ and $-\gamma_{3,\theta}$, where $0 < \gamma_{1,\theta} < \xi < \gamma_{2,\theta}$ and $0 < \gamma_{3,\theta}$. Explicit formulas for $\gamma_{1,\theta}$, $\gamma_{2,\theta}$ and $\gamma_{3,\theta}$ are provided in Appendix B of Kou, Petrella and Wang (2005).[31] Define

$$c_{1,\theta} = \frac{\xi - \gamma_{1,\theta}}{\gamma_{2,\theta} - \gamma_{1,\theta}} \frac{\gamma_{2,\theta} + 1}{\xi + 1}, \qquad c_{2,\theta} = \frac{\gamma_{2,\theta} - \xi}{\gamma_{2,\theta} - \gamma_{1,\theta}} \frac{\gamma_{1,\theta} + 1}{\xi + 1},$$
$$d_{1,\theta} = \frac{\xi - \gamma_{1,\theta}}{\gamma_{2,\theta} - \gamma_{1,\theta}} \frac{\gamma_{2,\theta}}{\xi}, \qquad d_{2,\theta} = \frac{\gamma_{2,\theta} - \xi}{\gamma_{2,\theta} - \gamma_{1,\theta}} \frac{\gamma_{1,\theta}}{\xi}.$$

Using similar calculations as for Theorem 3.1 and Corollary 3.3 in Kou and Wang (2003), we obtain

$$\text{(B2)} \qquad \begin{aligned} U_\theta(V_t) &\equiv E[e^{-\theta(\tau-t)}|V_t] = d_{1,\theta}\left(\frac{V^*}{V_t}\right)^{\gamma_{1,\theta}} + d_{2,\theta}\left(\frac{V^*}{V_t}\right)^{\gamma_{2,\theta}}, \\ L_\theta(V_t) &\equiv \frac{E[e^{-\theta(\tau-t)}V_\tau|V_t]}{V^*} = c_{1,\theta}\left(\frac{V^*}{V_t}\right)^{\gamma_{1,\theta}} + c_{2,\theta}\left(\frac{V^*}{V_t}\right)^{\gamma_{2,\theta}}. \end{aligned}$$

Given assets in place of $V_0 = x$, the time-0 market value of all future liquidation recoveries is given by

$$\begin{aligned} y_1(x) &= (1-\pi)E\left(e^{-r\tau}\alpha V_\tau \middle| V_0 = x\right) + \pi U_r(x) y_1(\widehat{V}) \\ &= (1-\pi)L_r(x)\alpha V^* + \pi U_r(x) y_1(\widehat{V}), \end{aligned}$$

[31] In the notation of Appendix B of Kou, Petrella and Wang (2005), $a = 0$, $b = \sigma^2$, $c = -(\sigma^2\xi + 2\mu)$, $d = 2(\mu\xi - \lambda - \theta)$ and $e = 2\theta\xi$, where $\mu = r - k - \sigma^2/2 - \lambda\eta$.

where, solving for the special case of $x = \widehat{V}$, we have

$$y_1(\widehat{V}) = \frac{L_r(\widehat{V})(1-\pi)\,\alpha V^*}{1-\pi U_r(\widehat{V})}.$$

The market value of all future tax shields, making the basic tax assumptions of Leland (1994), is

$$y_2(x) = \kappa\frac{cP+dD}{r}(1-U_r(x)) + \pi U_r(x) y_2(\widehat{V}),$$

where

$$y_2(\widehat{V}) = \frac{\kappa\frac{cP+dD}{r}(1-U_r(\widehat{V}))}{1-\pi U_r(\widehat{V})}.$$

The liquidation deposit guarantee requires cash flows from the government with a current market value of

$$y_3(x) = (1-\pi)\,E\left[e^{-r\tau}(D-\alpha V_\tau)^+ \middle| V_0 = x\right] + \pi U_r(x) y_3(\widehat{V}),$$

where

$$y_3(\widehat{V}) = \frac{(1-\pi)\,E\left[e^{-r\tau}(D-\alpha V_\tau)^+ \middle| V_0 = x\right]}{1-\pi U_r(\widehat{V})}.$$

Banks earn cash flows from assets in place at the total rate $(k+\phi)V_t$. The current market value of these cash flows is

$$\begin{aligned} y_4(x) &= q(x) - E\left[e^{-r\tau} q(V_\tau) \middle| V_0 = x\right] + \pi U_r(x) y_4(\widehat{V}) \\ &= q(x) - \frac{k+\phi}{k} L_r(x) V^* + \pi U_r(x) y_4(\widehat{V}), \end{aligned}$$

where

$$\text{(B3)} \qquad q(x) = E\left[\int_0^\infty e^{-rt}(k+\phi)V_t\,dt \middle| V_0 = x\right] = \frac{k+\phi}{k} x$$

and

$$y_4(\widehat{V}) = \frac{q(\widehat{V}) - L_r(\widehat{V}) q(V^*)}{1-\pi U_r(\widehat{V})}.$$

The total market value of all cash flows available to the bank's current claimants is thus

$$Y(x) = y_1(x) + y_2(x) + y_3(x) + y_4(x). \tag{B4}$$

On the liability side, the total value of the claims of all current depositors is

$$v_1(x) = D\frac{d}{r}(1 - U_r(x)) + U_r(x)\left[\pi v_1(\widehat{V}) + (1-\pi)D\right],$$

where

$$v_1(\widehat{V}) = \frac{D\frac{d}{r}(1 - U_r(\widehat{V})) + (1-\pi)DU_r(\widehat{V})}{1 - \pi U_r(\widehat{V})}.$$

Extending the integration-by-parts argument of Leland (1994), the market value of the claims of current bondholders is

$$\begin{aligned} v_2(x) &= W(1 - U_{r+m}(x)) + U_{r+m}(x)\pi B \\ &\quad + (1-\pi)E\left[e^{-(r+m)\tau}(\alpha V_\tau - D)^+ \middle| V_0 = x\right], \end{aligned} \tag{B5}$$

where

$$W = P\frac{c+m}{r+m} \tag{B6}$$

is the market value of bonds that are default free but otherwise equivalent to those issued by the bank.

In return for all of its successive potential future bailout injections, the government has a claim with a market value of

$$v_3(x) = U_r(x)\pi\left[H(\widehat{V}) + v_3(\widehat{V})\right], \tag{B7}$$

where

$$v_3(\widehat{V}) = \frac{\pi U(\widehat{V})H(\widehat{V})}{1 - \pi U(\widehat{V})}.$$

The total market value of all claims on the bank's future cash flows is equal to the market value of total cash flows available, so the market value of the bank's equity is

$$H(x) = Y(x) - v_1(x) - v_2(x) - v_3(x), \quad x \geq V^*. \tag{B8}$$

Substituting in the definition of each asset and liability term, we obtain

$$\begin{aligned} H(x) &= -W + \left(\kappa \frac{cP+dD}{r} - \frac{dD}{r}\right) + \frac{k+\phi}{k}x - \frac{k+\phi}{k}V^* L_r(x) \\ &\quad + \left(\pi B - \kappa \frac{cP+dD}{r} + \frac{dD}{r}\right) U_r(x) + (W-\pi B)\, U_{r+m}(x) \\ &\quad + (1-\pi)\, E\left[e^{-r\tau}(\alpha V_\tau - D)^+ \middle| V_0 = x\right] \\ &\quad - (1-\pi)\, E\left[e^{-(r+m)\tau}(\alpha V_\tau - D)^+ \middle| V_0 = x\right], \end{aligned}$$

for $x \geq V^*$. By definition, $H(x) = 0$ for $x < V^*$.

*B.2. Solving for $V^*$*

The smooth-pasting condition implies that

$$H'(x)\Big|_{x=V^*} = 0. \tag{B9}$$

This condition will be used to solve for $V^*$ in explicit forms.

**Case 1.** Suppose $\alpha V^* < D$. Then $(\alpha V_\tau - D)^+ = 0$ and

$$\begin{aligned} H'(x) &= \frac{k+\phi}{k} - \frac{k+\phi}{k} V^* L_r'(x) \\ &\quad + \left(\pi B - \kappa \frac{cP+dD}{r} + \frac{dD}{r}\right) U_r'(x) + (W - \pi B)\, U_{r+m}'(x). \end{aligned}$$

Note that $U_\theta'(V^*) = -(\gamma_{1,\theta} d_{1,\theta} + \gamma_{2,\theta} d_{2,\theta})/V^*$ and $L_\theta'(V^*) = -(\gamma_{1,\theta} c_{1,\theta} + \gamma_{2,\theta} c_{2,\theta})$ $/V^*$, meaning (B9) can be solved for

$$\begin{aligned} V^* &= \frac{k}{k+\phi} \frac{1}{1 + \gamma_{1,r} c_{1,r} + \gamma_{2,r} c_{2,r}} \\ &\quad \times \left[ \left(\pi B - \kappa \frac{cP+dD}{r} + \frac{dD}{r}\right) (\gamma_{1,r} d_{1,r} + \gamma_{2,r} d_{2,r}) \right. \\ &\quad \left. + (W - \pi B)(\gamma_{1,r+m} d_{1,r+m} + \gamma_{2,r+m} d_{2,r+m}) \right]. \end{aligned} \tag{B10}$$

**Case 2.** Suppose $\alpha V^* \geq D$. We need to calculate the expectations $E[e^{-\theta\tau}(\alpha V_\tau - D)^+ | V_0 = x]$, for $\theta = r$ and $\theta = r+m$. Dropping the "conditioned on $V_0 = x$" notation, we have

$$E\left[e^{-\theta\tau}(\alpha V_\tau - D)^+\right] = E\left[e^{-\theta\tau}\alpha V_\tau \mathbf{1}_{\{\alpha V_\tau \geq D\}}\right] - DE\left(e^{-\theta\tau}\mathbf{1}_{\{\alpha V_\tau \geq D\}}\right)$$

$$
\begin{aligned}
&= E\left[e^{-\theta\tau}\alpha V_\tau \mathbf{1}_{\{\alpha V_\tau \geq D\}}\left(\mathbf{1}_{\{V_\tau = V^*\}} + \mathbf{1}_{\{V_\tau < V^*\}}\right)\right] - DE\left(e^{-\theta\tau}\mathbf{1}_{\{\alpha V_\tau \geq D\}}\right) \\
&= \alpha V^* E\left(e^{-\theta\tau}\mathbf{1}_{\{V_\tau = V^*\}}\right) + \alpha E\left(e^{-\theta\tau} V_\tau \mathbf{1}_{\{\alpha V_\tau \geq D\}}\mathbf{1}_{\{V_\tau < V^*\}}\right) \\
&\quad - DE\left(e^{-\theta\tau}\mathbf{1}_{\{\alpha V_\tau \geq D\}}\right),
\end{aligned}
$$

where the second equality follows from $\mathbf{1}_{\{V_\tau = V^*\}} + \mathbf{1}_{\{V_\tau < V^*\}} = 1$. Using the notation

$$
\begin{aligned}
K_1(x,\theta) &= \alpha V^* E\left[e^{-\theta\tau}\mathbf{1}_{\{V_\tau = V^*\}} \middle| V_0 = x\right] \\
K_2(x,\theta) &= \alpha E\left[e^{-\theta\tau} V_\tau \mathbf{1}_{\{\alpha V_\tau \geq D\}}\mathbf{1}_{\{V_\tau < V^*\}} \middle| V_0 = x\right] \\
K_3(x,\theta) &= DE\left[e^{-\theta\tau}\mathbf{1}_{\{\alpha V_\tau \geq D\}} \middle| V_0 = x\right],
\end{aligned}
$$

we have $E\left[e^{-\theta\tau}(\alpha V_\tau - D)^+\right] = K_1(x,\theta) + K_2(x,\theta) - K_3(x,\theta)$ and

$$
\text{(B11)} \quad \frac{\partial}{\partial x} E\left[e^{-\theta\tau}(\alpha V_\tau - D)^+ \middle| V_0 = x\right] = \frac{\partial}{\partial x} K_1(x,\theta) + \frac{\partial}{\partial x} K_2(x,\theta) - \frac{\partial}{\partial x} K_3(x,\theta).
$$

From Proposition 2.1 and Theorem 3.1 in Kou and Wang (2003), we can derive

$$
\begin{aligned}
K_1(x,\theta) &= \alpha V^*\left[\frac{\xi - \gamma_{1,\theta}}{\gamma_{2,\theta} - \gamma_{1,\theta}}\left(\frac{V^*}{x}\right)^{\gamma_{1,\theta}} + \frac{\gamma_{2,\theta} - \xi}{\gamma_{2,\theta} - \gamma_{1,\theta}}\left(\frac{V^*}{x}\right)^{\gamma_{2,\theta}}\right] \\
K_2(x,\theta) &= \alpha \frac{1}{\xi + 1}\frac{(\xi - \gamma_{1,\theta})(\gamma_{2,\theta} - \xi)}{(\gamma_{2,\theta} - \gamma_{1,\theta})} V^*\left[\left(\frac{V^*}{x}\right)^{\gamma_{1,\theta}} - \left(\frac{V^*}{x}\right)^{\gamma_{2,\theta}}\right] \\
&\quad \times \left[1 - \left(\frac{\alpha V^*}{D}\right)^{-(\xi+1)}\right] \\
K_3(x,\theta) &= D\left\{\frac{\xi - \gamma_{1,\theta}}{\xi}\frac{\gamma_{2,\theta}}{\gamma_{2,\theta} - \gamma_{1,\theta}}\left(\frac{V^*}{x}\right)^{\gamma_{1,\theta}} + \frac{\gamma_{2,\theta} - \xi}{\xi}\frac{\gamma_{1,\theta}}{\gamma_{2,\theta} - \gamma_{1,\theta}}\left(\frac{V^*}{x}\right)^{\gamma_{2,\theta}}\right. \\
&\quad \left. - \left(\frac{\alpha V^*}{D}\right)^{-\xi}\frac{(\xi - \gamma_{1,\theta})(\gamma_{2,\theta} - \xi)}{\xi(\gamma_{2,\theta} - \gamma_{1,\theta})}\left[\left(\frac{V^*}{x}\right)^{\gamma_{1,\theta}} - \left(\frac{V^*}{x}\right)^{\gamma_{2,\theta}}\right]\right\},
\end{aligned}
$$

and

$$
\begin{aligned}
\frac{\partial}{\partial x} K_1(x,\theta)\Big|_{x=V^*} &= \alpha(\xi - \gamma_{1,\theta} - \gamma_{2,\theta}) \\
\frac{\partial}{\partial x} K_2(x,\theta)\Big|_{x=V^*} &= \alpha \frac{1}{\xi + 1}(\xi - \gamma_{1,\theta})(\gamma_{2,\theta} - \xi)\left[1 - \left(\frac{\alpha V^*}{D}\right)^{-(\xi+1)}\right]
\end{aligned}
$$

$$\frac{\partial}{\partial x}K_3(x,\theta)\Big|_{x=V^*} = -\frac{D}{V^*}\left\{\frac{\gamma_{1,\theta}\gamma_{2,\theta}}{\xi}+\left(\frac{\alpha V^*}{D}\right)^{-\xi}\frac{(\xi-\gamma_{1,\theta})(\gamma_{2,\theta}-\xi)}{\xi}\right\}.$$

Evaluating (B11) at $x = V^*$, we obtain

$$\begin{aligned}\frac{\partial}{\partial V_0}E\left[e^{-\theta\tau}(\alpha V_\tau - D)^+\right]\Big|_{V_0=V^*} &= \alpha\left[\xi-\gamma_{1,\theta}-\gamma_{2,\theta}+\frac{(\xi-\gamma_{1,\theta})(\gamma_{2,\theta}-\xi)}{\xi+1}\right] \\ &\quad +\frac{\gamma_{1,\theta}\gamma_{2,\theta}}{\xi}\frac{D}{V^*}+\alpha\left(\frac{\alpha V^*}{D}\right)^{-\xi-1}\frac{(\xi-\gamma_{1,\theta})(\gamma_{2,\theta}-\xi)}{\xi(\xi+1)}.\end{aligned}$$

As a result, the smooth-pasting condition (B9) can be rewritten as

$$\begin{aligned}\text{(B12)}\quad 0 &= \frac{k+\phi}{k}(1+\gamma_{1,r}c_{1,r}+\gamma_{2,r}c_{2,r}) \\ &\quad -\left(\pi B-\kappa\frac{cP+dD}{r}+\frac{dD}{r}\right)(\gamma_{1,r}d_{1,r}+\gamma_{2,r}d_{2,r})\frac{1}{V^*} \\ &\quad -(W-\pi B)(\gamma_{1,r+m}d_{1,r+m}+\gamma_{2,r+m}d_{2,r+m})\frac{1}{V^*} \\ &\quad +(1-\pi)\left\{\alpha\left[\xi-\gamma_{1,r}-\gamma_{2,r}+\frac{(\xi-\gamma_{1,r})(\gamma_{2,r}-\xi)}{\xi+1}\right]\right. \\ &\quad \left.+\frac{\gamma_{1,r}\gamma_{2,r}}{\xi}\frac{D}{V^*}+\alpha\left(\frac{\alpha V^*}{D}\right)^{-\xi-1}\frac{(\xi-\gamma_{1,r})(\gamma_{2,r}-\xi)}{\xi(\xi+1)}\right\} \\ &\quad -(1-\pi)\left\{\alpha\left[\xi-\gamma_{1,r+m}-\gamma_{2,r+m}+\frac{(\xi-\gamma_{1,r+m})(\gamma_{2,r+m}-\xi)}{\xi+1}\right]\right. \\ &\quad \left.+\frac{\gamma_{1,r+m}\gamma_{2,r+m}}{\xi}\frac{D}{V^*}+\alpha\left(\frac{\alpha V^*}{D}\right)^{-\xi-1}\frac{(\xi-\gamma_{1,r+m})(\gamma_{2,r+m}-\xi)}{\xi(\xi+1)}\right\}.\end{aligned}$$

Equation (B12) provides a closed-form expression for $V^*$. For special values of $\xi$, we can express $V^*$ in simpler terms. For example, for $\xi = 1$ the above expression reduces to an equation that is quadratic in $V^*$. More generally, the solution to (B12) can be easily obtained numerically.

### *B.3. Existence and uniqueness of $V^*$*

We now present conditions for the existence and uniqueness of $V^*$.

PROPOSITION B.1: *There exists a unique solution $V^* > 0$ to (B9) as long as*

$$
\text{(B13)} \qquad 0 < \left(\pi B - \kappa \frac{cP + dD}{r} + \frac{dD}{r}\right)(\gamma_{1,r} d_{1,r} + \gamma_{2,r} d_{2,r}) + (W - \pi B)(\gamma_{1,r+m} d_{1,r+m} + \gamma_{2,r+m} d_{2,r+m}).
$$

*Moreover, this solution satisfies $\alpha V^* - D \geq (\leq) 0$ if*

$$
\text{(B14)} \qquad \frac{D}{\alpha}\frac{k+\phi}{k}\left[1 + \gamma_{1,r} c_{1,r} + \gamma_{2,r} c_{2,r}\right] \leq (\geq) \left(\pi B - \kappa \frac{cP + dD}{r} + \frac{dD}{r}\right)(\gamma_{1,r} d_{1,r} + \gamma_{2,r} d_{2,r}) + (W - \pi B)(\gamma_{1,r+m} d_{1,r+m} + \gamma_{2,r+m} d_{2,r+m}).
$$

*A sufficient condition for (B13) is $\kappa \frac{cP+dD}{r} < \pi B + \frac{dD}{r}$.*

To prove the proposition, we introduce the following notation:

$$
\begin{aligned}
\mathcal{C}_1 &= \frac{k+\phi}{k}(1 + \gamma_{1,r} c_{1,r} + \gamma_{2,r} c_{2,r}) \\
\mathcal{C}_2 &= -\left(\pi B - \kappa \frac{cP + dD}{r} + \frac{dD}{r}\right)(\gamma_{1,r} d_{1,r} + \gamma_{2,r} d_{2,r}) \\
&\quad - (W - \pi B)(\gamma_{1,r+m} d_{1,r+m} + \gamma_{2,r+m} d_{2,r+m}) \\
\mathcal{C}_3 &= (1-\pi)\alpha \left\{ \left[\xi - \gamma_{1,r} - \gamma_{2,r} + \frac{(\xi - \gamma_{1,r})(\gamma_{2,r} - \xi)}{\xi + 1}\right] \right. \\
&\quad \left. - \left[\xi - \gamma_{1,r+m} - \gamma_{2,r+m} + \frac{(\xi - \gamma_{1,r+m})(\gamma_{2,r+m} - \xi)}{\xi + 1}\right] \right\} \\
\mathcal{C}_4 &= (1-\pi)\alpha \left(\frac{\gamma_{1,r}\gamma_{2,r}}{\xi} - \frac{\gamma_{1,r+m}\gamma_{2,r+m}}{\xi}\right) \\
\mathcal{C}_5 &= (1-\pi)\alpha \left[\frac{(\xi - \gamma_{1,r})(\gamma_{2,r} - \xi)}{\xi(\xi+1)} - \frac{(\xi - \gamma_{1,r+m})(\gamma_{2,r+m} - \xi)}{\xi(\xi+1)}\right] \\
&= (1-\pi)\alpha \left[\frac{\xi(\gamma_{1,r} + \gamma_{2,r}) - \gamma_{1,r}\gamma_{2,r} - \xi(\gamma_{1,r+m} + \gamma_{2,r+m}) + \gamma_{1,r+m}\gamma_{2,r+m}}{\xi(\xi+1)}\right].
\end{aligned}
$$

Next, we derive a number of conditions that are satisfied by $\mathcal{C}_1$–$\mathcal{C}_5$, using the properties of the function $G(x)$ defined in (B1):

LEMMA B.1: *$\gamma_{1,r} < \gamma_{1,r+m}$ and $\gamma_{2,r} < \gamma_{2,r+m}$*

PROOF:

For $x \in [0,\xi)$, $G''(x) = \sigma^2 + 2\lambda \frac{\xi}{(\xi-x)^3} > 0$, meaning $G(x)$ is convex on $x \in [0,\xi)$. This, together with $G(0) = 0$ and $\gamma_{1,\theta} < \xi$ being the smallest positive root of $G(x) = \theta$, implies $\gamma_{1,r} < \gamma_{1,r+m}$.

Next, the function $-(r-k-\sigma^2/2-\lambda\eta)x + (\sigma^2/2)x^2$ has two roots. One root is zero; we will refer to the other root as $x_0$. Set $\bar{x} = \max\{x_0, \xi\}$. Both $-(r-k-\sigma^2/2-\lambda\eta)x + (\sigma^2/2)x^2$ and $\xi/(\xi-x)$ increase monotonically for $x > \bar{x}$. Also, $\gamma_{2,r}, \gamma_{2,r+m} > \bar{x}$. This is trivially true when $\bar{x} = \xi$. And when $\bar{x} > \xi$, then $-(r-k-\sigma^2/2-\lambda\eta)x + (\sigma^2/2)x^2 < 0$ and $\frac{\xi}{\xi-x_0} < 0$, and thus $G(x) \leq 0$, for all $x \in (\xi, \bar{x}]$. The monotonicity of $G(x)$ on $x > \bar{x}$ implies that $\gamma_{2,r} < \gamma_{2,r+m}$.

LEMMA B.2: *$\mathcal{C}_1 > 0$, $\mathcal{C}_3 > 0$, $\mathcal{C}_4 < 0$, $\mathcal{C}_3 + \mathcal{C}_4 + \mathcal{C}_5 = 0$ and $\mathcal{C}_4 + (1+\xi)\mathcal{C}_5 < 0$.*

PROOF:

The statement $\mathcal{C}_1 > 0$ is true by definition. The fact that $\mathcal{C}_4 < 0$ follows directly from Lemma B.1. Note that

$$\mathcal{C}_4 + (1+\xi)\mathcal{C}_5 = (1-\pi)\alpha\left[(\gamma_{1,r} + \gamma_{2,r}) - (\gamma_{1,r+m} + \gamma_{2,r+m})\right] < 0,$$

where the last inequality holds because of Lemma B.1. Straightforward algebra shows that $\mathcal{C}_3 + \mathcal{C}_4 + \mathcal{C}_5 = 0$. If $\mathcal{C}_5 < 0$, then $\mathcal{C}_4 + \mathcal{C}_5 = -\mathcal{C}_3 < 0$. If $\mathcal{C}_5 \geq 0$, then $-\mathcal{C}_3 = \mathcal{C}_4 + \mathcal{C}_5 \leq \mathcal{C}_4 + (1+\xi_d)\mathcal{C}_5 < 0$. Thus, $\mathcal{C}_3 > 0$.

PROOF OF PROPOSITION B.1: We define functions $F_1(x)$ and $F_2(x)$ as

$$F_1(x) = \mathcal{C}_1 + \mathcal{C}_2 \frac{1}{x},$$

$$F_2(x) = F_1(x) + \mathcal{C}_3 + \mathcal{C}_4 \frac{D}{\alpha x} + \mathcal{C}_5 \left(\frac{D}{\alpha x}\right)^{\xi+1}.$$

With this notation, Equations (B10) and (B12) can be rewritten as $F_1(V^*) = 0$ and $F_2(V^*) = 0$, respectively. Thus, $V^* > 0$ solves (B9) if and only if the following condition holds:

CONDITION B.1: (i) $F_1(V^*) = 0$ *and* $0 < V^* < D/\alpha$, *or* (ii) $F_2(V^*) = 0$ *and* $V^* \geq D/\alpha$.

Observe that, for $x > 0$,

$$F_1(x) \quad \leq (\geq) \quad 0 \quad \text{if} \quad x \leq (\geq) -\frac{\mathcal{C}_2}{\mathcal{C}_1} \tag{B15}$$

and, whenever $\mathcal{C}_2 < 0$,

$$F_1'(x) \quad = \quad -\frac{\mathcal{C}_2}{x^2} > 0. \tag{B16}$$

Lemma B.2 implies $F_1(D/\alpha) = F_2(D/\alpha)$ and, for $x \in [\frac{D}{\alpha}, \infty)$, $\mathcal{C}_4 + \mathcal{C}_5(\xi+1)\left(\frac{D}{\alpha x}\right)^{\xi} < 0$, meaning

$$F_2'(x) \quad = \quad -\mathcal{C}_2\frac{1}{x^2} - \frac{D}{\alpha x^2}\left[\mathcal{C}_4 + \mathcal{C}_5(\xi+1)\left(\frac{D}{\alpha x}\right)^{\xi}\right] > 0 \tag{B17}$$

whenever $\mathcal{C}_2 < 0$.

Suppose (B13) holds, meaning $\mathcal{C}_2 < 0$ is true. Then Condition B.1 holds, and $V^* > 0$ is unique and has the property described in (B15). To see why this is true, consider the following three scenarios:

**Case A.** Suppose $-\mathcal{C}_2/\mathcal{C}_1 < D/\alpha$. Then $F_1(D/\alpha) > 0$ and Part *(i)* of Condition B.1 holds for $V^* = -\mathcal{C}_2/\mathcal{C}_1$. The solution is unique because both $F_1(x)$ and $F_2(x)$ are monotonically increasing in $x$, with $F_1(D/\alpha) = F_2(D/\alpha)$.

**Case B.** Suppose $-\mathcal{C}_2/\mathcal{C}_1 = D/\alpha$. Then $F_1(D/\alpha) = F_2(D/\alpha) = 0$, and the unique solution is given by $V^* = D/\alpha$.

**Case C.** Suppose $-\mathcal{C}_2/\mathcal{C}_1 > D/\alpha$. Then $F_1(x) \leq F_1(D/\alpha) < 0$ for all $x \in (0, D/\alpha]$. On the other hand, $F_2(D/\alpha) = F_1(D/\alpha) < 0$ and, according to Lemma B.2, $\lim_{x\to\infty} F_2(x) = \mathcal{C}_1 + \mathcal{C}_3 > 0$. Thus, by continuity and monotonicity of $F_2$, we can find exactly one $V^* > D/\alpha$ such that $F_2(V^*) = 0$.

A sufficient condition for $\mathcal{C}_2 < 0$ is that $\pi B - \kappa\frac{cP+dD}{r} + \frac{dD}{r} > 0$.

### B.4. Special case where assets in place follow pure diffusion process

We now provide explicit solutions for the optimal default boundary $V^*$ for the special no-jump case of Equation (3). In this case, assets in place, $V_t$, at any time $t$ before default, satisfy the stochastic differential equation $dV_t = V_t(r-k)\,dt + V_t\sigma\,dZ_t$, and the function $G(x)$ in (B1) reduces to

$$G(x) \equiv -\left(r-k-\frac{\sigma^2}{2}\right)x + \frac{\sigma^2}{2}x^2.$$

The unique positive solution to $G(x) = \theta$ is given by

$$\gamma_\theta = \frac{r-k-\frac{\sigma^2}{2} + \sqrt{\left(r-k-\frac{\sigma^2}{2}\right)^2 + 2\sigma^2\theta}}{\sigma^2}.$$

Equation (B2) reduces to

$$U_\theta(V_t) = E[e^{-\theta(\tau-t)}|V_t] = \left(\frac{V^*}{V_t}\right)^{\gamma_\theta}.$$

Without jumps, the condition $v_2(\widehat{V}) = B$ implies that

$$\text{(B18)} \qquad \widehat{V} = h(V^*) \equiv V^*\left(\frac{W-B}{W-\pi B-(1-\pi)(\alpha V^*-D)^+}\right)^{-\frac{1}{\gamma_{r+m}}}.$$

We can rewrite Equation (B8) as

$$\text{(B19)} \qquad H(x) = \frac{k+\phi}{k}x + a + b(V^*)U_{r+m}(x) + g(V^*)U_r(x), \quad x \geq V^*,$$

where

$$\begin{aligned}
a &= \kappa\frac{cP+dD}{r} - \frac{dD}{r} - W \\
b(V^*) &= W - \pi B - (1-\pi)(\alpha V^* - D)^+ \\
g(V^*) &= \pi B + (1-\pi)(\alpha V^* - D)^+ - \kappa\frac{cP+dD}{r} + \frac{dD}{r} - \frac{k+\phi}{k}V^*.
\end{aligned}$$

The endogenous insolvency boundary level of assets $V^*$ that maximizes shareholder value can be conjectured and then verified from the smooth-pasting condition (B9), which reduces to

$$\text{(B20)} \qquad 0 = \frac{k+\phi}{k}V^* - \gamma_{r+m}b(V^*) - \gamma_r g(V^*).$$

Rewriting Equation (B20) yields

$$\text{(B21)} \quad (1+\gamma_r)\frac{k+\phi}{k}V^* = \gamma_{r+m}\left[W-\pi B-(1-\pi)(\alpha V^*-D)^+\right] + \gamma_r\left[(1-\pi)\left(\alpha V^*-D\right)^+ - \kappa\frac{cP+dD}{r}+\frac{dD}{r}+\pi B\right].$$

Expression (B21) provides an equation for the default boundary $V^*$ that can be solved explicitly for $V^*$ and, in turn, $\widehat{V}$ and all of the contingent claim market valuation functions $y_1, y_2, y_3, y_4, v_1, v_2, v_3$ and $H$ that we have considered.

There are two cases to consider when solving for $V^*$:

**Case 1.** Suppose $\alpha V^* - D < 0$. Then Equation (B21) can be re-written as

$$\text{(B22)} \quad V^* = \frac{\gamma_{r+m}(W-\pi B)+\gamma_r\left(-\kappa\frac{cP+dD}{r}+\frac{dD}{r}+\pi B\right)}{(1+\gamma_r)\frac{k+\phi}{k}}.$$

We obtain a solution $V^* \in (0, D/\alpha)$ in (B22) if and only if

$$\text{(B23)} \quad 0 < \gamma_{r+m}(W-\pi B)+\gamma_r\left(-\kappa\frac{cP+dD}{r}+\frac{dD}{r}+\pi B\right) < \frac{D}{\alpha}(1+\gamma_r)\frac{k+\phi}{k}.$$

**Case 2.** Suppose $\alpha V^* - D \geq 0$. Then Equation (B21) yields

$$\text{(B24)} \quad V^* = \frac{\gamma_{r+m}(W-\pi B)+\gamma_r\left(-\kappa\frac{cP+dD}{r}+\frac{dD}{r}+\pi B\right)}{(1+\gamma_r)\frac{k+\phi}{k}-\alpha(1-\pi)(\gamma_r-\gamma_{r+m})} - \frac{(1-\pi)(\gamma_r-\gamma_{r+m})D}{(1+\gamma_r)\frac{k+\phi}{k}-\alpha(1-\pi)(\gamma_r-\gamma_{r+m})}.$$

We obtain a solution $V^* \geq D/\alpha$ in (B24) as long as

$$\text{(B25)} \quad \frac{\gamma_{r+m}(W-\pi B)+\gamma_r\left(-\kappa\frac{cP+dD}{r}+\frac{dD}{r}+\pi B\right)}{(1+\gamma_r)\frac{k+\phi}{k}-\alpha(1-\pi)(\gamma_r-\gamma_{r+m})} - \frac{(1-\pi)(\gamma_r-\gamma_{r+m})D}{(1+\gamma_r)\frac{k+\phi}{k}-\alpha(1-\pi)(\gamma_r-\gamma_{r+m})} \geq \frac{D}{\alpha}.$$

Note that $(1+\gamma_r)\frac{k+\phi}{k} > 0$ and, because of $\gamma_r < \gamma_{r+m}$, $(1+\gamma_r)\left(1+\frac{\phi}{k}\right) - \alpha(1-\pi)(\gamma_r-\gamma_{r+m}) > 0$. Condition (B25) can therefore be re-written as

$$\text{(B26)} \quad \gamma_{r+m}(W-\pi B)+\gamma_r\left(-\kappa\frac{cP+dD}{r}+\frac{dD}{r}+\pi B\right) \geq \frac{D}{\alpha}(1+\gamma_r)\frac{k+\phi}{k}.$$

We observe that (B23) and (B26) are mutually exclusive. As a results, there exists a unique solution for $V^*$ if and only if

$$\gamma_{r+m}(W-\pi B)+\gamma_r\left(-\kappa\frac{cP+dD}{r}+\frac{dD}{r}+\pi B\right) \;>\; 0.$$

*B.5. Liability insurance assessments*

Our model can accommodate deposit and other liability insurance premia, as follows. We suppose a deposit insurance rate $i_D$ and an insurance assessment rate $i_P$ on other liabilities. Given $V^*$, the total market value of future insurance premia is

$$y_5(x) \;=\; \frac{i_P P+i_D D}{r}(1-U_r(x))+U_r(x)\pi y_5(\widehat{V}).$$

As with the other value components, $y_5(\widehat{V})$ can be expressed as a function of $U_r(\widehat{V})$, which implies an explicit solution for $y_5(x)$ at any $x$. The valuation of total available bank cash flows is now extended from (B4) to

$$Y(x) \;=\; y_1(x)+y_2(x)+y_3(x)+y_4(x)-y_5(x).$$

From this point, the solution method for the boundary $V^*$ and, from that, all of the value components, is just as for the benchmark model. The solution is again explicit.

## C. A Model With Senior Bonds and Bail-In Junior Bonds

This appendix generalizes our benchmark model to allow for senior and junior bonds, with the objective of separate identification of the risk-neutral probabilities $\pi$ of bailout, $\psi$ of bail-in, and $1-\pi-\psi$ of liquidation at insolvency. The dynamic Equation (3) for $V_t$ is maintained. We have the same non-bond parameters $d, D, r, k, \phi, \sigma, \lambda, \eta, \alpha$ and $\kappa$ as for the benchmark version of the model. The senior and junior bonds have the same maturity parameter $m$. As with the benchmark model, the senior bonds have principal $P$ and coupon rate $c$.

At a bailout, the assets in place are increased to some level $\widehat{V}$ by a capital injection that increases the market value of the senior bonds to $B$, as before. The junior bonds have principal $J$, coupon rate $j$, and at a bailout have whatever market value is implied by the capital injection. At a bail-in, the junior bonds are given all of the equity in the bank. For tractability, we assume that the government ensures that junior bondholders receive $H(V^*)$, by increasing assets in place by $V^* - V_\tau \geq 0$. After a bail-in, for simplicity, we assume that the bank emerges with only its original senior bonds, and that only bailout and liquidation are possible. The values of all elements of the capital structure are then given by the benchmark version of the model without junior debt. The default boundary for the benchmark model will therefore apply after a bail-in. This is different from the default boundary $V^*$ that initially applies when there is bail-in junior debt. An alternative and more complicated version of the model would have a bail-in design that restructures the liabilities so as to introduce after bail-in a given new amount of senior and junior bonds.

When any existing bond matures at time $t$, the same principal amount of the same type of debt is issued at its current market value, which could be at a premium or discount to par depending on $V_t$. Newly issued senior and junior bonds have the original coupon rates $c$ and $j$, respectively. The original exponential maturity distribution is always maintained.

The vector of primitive model parameters is

$$(d, D, c, P, B, j, J, m, r, k, \phi, \sigma, \lambda, \eta, \alpha, \kappa, \pi, \psi).$$

In what follows, we take the default boundary $V^*$ and first bailout level $\widehat{V}$ for assets in place as given and provide formulas for the contingent claim market valuation functions. Later, we derive the associated smooth-pasting and value-consistency conditions determining $V^*$ and $\widehat{V}$. As before, we use $y_1(\cdot), \ldots, y_4(\cdot)$ to denote the solution for the market value of all future liquidation recoveries, tax shields, deposit guarantees and cash flows from assets in place for a bank with parameters $d, D, c, P, B, m, r, k, \phi, \sigma, \lambda, \eta, \alpha, \kappa$ and $\pi$.

Given assets in place of $V_0 = x$, the time-0 market value of all future liquidation recoveries, including those associated with potential subsequent insolvencies, is

$$y_{1b}(x) \;=\; (1-\pi-\psi)L_r(x)\alpha V^* + \pi U_r(x) y_{1b}(\widehat{V}) + \psi U_r(x) y_1(V^*).$$

This equation implies an explicit solution for $y_{1b}(\widehat{V})$.

The market value of all future tax shields is

$$y_{2b}(x) \;=\; \kappa \frac{cP + dD + jJ}{r}(1 - U_r(x)) + U_r(x)\left[\pi y_{2b}(\widehat{V}) + \psi y_2(V^*)\right].$$

This implies an explicit solution for $y_{2b}(\widehat{V})$.

The liquidation deposit guarantee requires cash flows from the government with a current market value of

$$y_{3b}(x) \;=\; U_r(x)\left[(1-\pi-\psi)(D-\alpha V^*)^+ + \pi y_{3b}(\widehat{V}) + \psi y_3(V^*)\right].$$

Again, we have an explicit solution for $y_{3b}(\widehat{V})$.

The current market value of cash flows earned by banks is

$$y_{4b}(x) \;=\; q(x) - \frac{k+\phi}{k} L_r(x) V^* + U_r(x)\left[\pi y_{4b}(\widehat{V}) + \psi y_4(V^*)\right],$$

where $q(x)$ is defined as in (B3).

The total market value of all cash flows available to the bank's current claimants is

$$Y_b(x) \;=\; y_{1b}(x) + y_{2b}(x) + y_{3b}(x) + y_{4b}(x).$$

The total market value of the claims of all current depositors is

$$v_{1b}(x) \;=\; D\frac{d}{r}(1 - U_r(x)) + U_r(x)\left[(1-\pi-\psi)D + \pi v_{1b}(\widehat{V}) + \psi v_1(V^*)\right].$$

We can solve explicitly for $v_{1b}(\widehat{V})$.

The market value of all claims by current senior bondholders is

$$\begin{aligned} v_{2b}(x) \;=\; & W(1 - U_{r+m}(x)) + (1-\pi-\psi)E\left[e^{-(r+m)\tau}(\alpha V_\tau - D)^+ \middle| V_0 = x\right] \\ & + U_{r+m}(x)\left[\pi B + \psi v_2(V^*)\right]. \end{aligned}$$

We have the consistency condition

$$v_{2b}(\widehat{V}) \quad = \quad B, \tag{C1}$$

which determines $\widehat{V}$ uniquely given $V^*$.

In return for all of its future successive bailout injections, the government has a claim with a market value of

$$v_{3b}(x) \quad = \quad U_r(x)\left[\pi H_b(\widehat{V}) + \pi v_{3b}(\widehat{V}) + \psi v_3(V^*)\right],$$

where $H_b(x)$ is the equity value of the original bank with assets in place of $x$.

The market value of all claims by current junior bondholders is

$$\begin{aligned} v_{4b}(x) \quad = \quad & J\frac{j+m}{r+m}(1-U_{r+m}(x)) \\ & +(1-\pi-\psi)E\left[e^{-(r+m)\tau}(\alpha V_\tau - D - P)^+ \middle| V_0 = x\right] \\ & +U_{r+m}(x)\left[\pi v_{4b}(\widehat{V}) + \psi H(V^*)\right]. \end{aligned}$$

By definition, $H_b(x) = 0$ for $x < V^*$. The total market value of all claims on the bank's future cash flows is equal to the market value of total cash flows available. So,

$$H_b(x) \quad = \quad Y_b(x) - v_{1b}(x) - v_{2b}(x) - v_{3b}(x) - v_{4b}(x), \quad x \geq V^*.$$

Given the assets in place $\widehat{V}$ after the first bailout, the default boundary $V^*$ that maximizes shareholder value can be conjectured and then verified from the smooth-pasting condition, namely that the market value of equity is continuously differentiable at $V^*$, implying that

$$\mathcal{H}(V^*, \widehat{V}) \quad \equiv \quad H_b'(x)\Big|_{x=V^*} = 0. \tag{C2}$$

We can calculate $\mathcal{H}(V^*, \widehat{V})$ explicitly as a function of the default and recapitalization boundaries $V^*$ and $\widehat{V}$. We have reduced the solution of the equilibrium for the model to the two equations (C1) and (C2) to solve for $V^*$ and $\widehat{V}$.

## D. Model Calibration

Although every model is mis-specified to some extent, there is a significant tension between our restrictive theoretical assumption that the structural model parameters are treated by agents as though constant over time and the practical need in our non-stationary setting to allow some of these parameters to vary across observation dates for the purpose of calibrating the model to the data. This appendix is a summary of how each of the model parameters in (4), other than $\pi$, is chosen.

The proportional asset recovery $\alpha$ at failure and the corporate tax rate $\kappa$ are fixed for the entire panel study at 50% and 35%, respectively, common to all firms. For bank $i$ on date $t$, the quantity $D_{it}$ of deposits, if any, and the notional-weighted average deposit interest rate $d_{it}$ are obtained from quarterly accounting statements. Of course, non-banks have no deposits. The total principal of short-term and long-term non-deposit debt $P_{it}$, and the notional-weighted average bond maturity $1/m_{it}$ are also obtained from quarterly public firm disclosure. The risk-free rate $r_{it}$ used as a theoretical model input for firm $i$ on date $t$ is the constant-maturity Treasury rate for the average maturity $1/m_{it}$ of the firm's non-deposit debt.

For each firm, the non-deposit debt coupon rate $c_{it}$ is computed as the ratio of annualized interest expenses for non-deposit debt and $P_{it}$. (Interest expense is obtained from quarterly accounting statements.) For large banks, the market value $B_{it}$ of non-deposit debt immediately after a bailout is chosen to achieve a given post-bailout bond yield spread $s$, by setting $B_{it} = P_{it}(c_{it} + m_{it})/(r_{it} + s + m_{it})$. This is based on the idea that a government bailout would target a given level of creditworthiness of a large bank as judged in wholesale credit markets. We set $s = 100$ basis points, which is reasonable but still somewhat arbitrary. In Appendix I, we consider an alternative specification in which $B_{it}$ is set equal to par. The corresponding results are qualitatively similar to those for the base case.

Motivated by Chen et al. (2017), we calibrate our model on a grid of jump parameters $(\lambda, \eta)$, taking $\lambda \in \{0.1, 0.2, 0.3, 0.4, 0.5\}$ and $-\eta \in \{0.2, 0.15, 0.1, 0.05\}$.

For each grid point $(\lambda, \eta)$, the local variance of the driving Lévy noise process (variance per unit of time)[32] of $\log V_{it}$ is $\Sigma_{it}^2 = \sigma_{it}^2 + 2\lambda\eta^2/(1+\eta)^2$. The Brownian volatility parameter $\sigma_{it}$ of a given firm $i$ on a given date $t$ is assumed to be constant across dates within the pre-Lehman period, and to be constant at a different level in the post-Lehman period. The theoretical model is solved by assuming for simplicity that the change in parameters at the default of Lehman is completely unanticipated by investors, a so-called "MIT shock." Within each of these two periods, $\sigma_{it}$ is set to the annualized sample standard deviation of first differences of the logarithm of the model-implied asset level $V_{it}$ of firm $i$ within that sub-period, after excluding jumps. We identify as jumps the $N_i$ most negative asset returns, where $N_i$ is the product of the expected number of jumps per year, $\lambda$, and the length of the sample sub-period of firm $i$, in years. The model-implied asset level $V_{it}$ is the asset level at which the model-implied market value of common equity is equal to its observed counterpart. This calibration depends in turn on $\sigma_{it}$, so involves an iterative joint search for $\sigma_{it}$ and $V_{it}$.

The asset drift parameter $k_{it}$ is set at some positive multiple $\rho_{it}$ of the risk-free rate $r_{it}$. We impose the over-identifying restriction that $\rho_{it}$ is constant within each of the pre-Lehman and post-Lehman periods. For firm $i$, the constant level of $\rho_{it}$ within a given period (whether pre-Lehman or post-Lehman) is chosen to match the within-period average of the cash payout rate $k_{it} + \phi_{it}$ to the within-period average ratio of annualized cash payouts to model-implied asset levels $V_{it}$. Payouts are obtained from quarterly public firm disclosures and include dividends on common and preferred equity, share repurchases, and interest expenses on deposits and non-deposit debt. The model-implied asset level $V_{it}$ depends in turn on $\rho_{it}$, again necessitating a joint iterative search for $\sigma_{it}$, $\rho_{it}$, and $V_{it}$. In the main part of the paper, we set the cash payout parameter $\phi_{it}$ to zero, consistent with an efficient-market model for

[32] That is, $\mathrm{var}(\log V_{is} \mid \mathcal{F}_t) = (s-t)\Sigma_{it}^2$, for any $t \leq s$ in the same sub-period, whether pre-Lehman or post-Lehman.

bank assets. In Section VI and Appendix I, we report results for cases in which the bank payout rate $k_{it}+\phi_{it}$ deviates from the efficient-market level $k_{it}$, because of franchise rents, overhead, and expenses.

For each firm and sub-period, we choose the jump-model parameters $(\lambda,\eta)$ by minimizing, across all dates in the sub-period, the root mean squared error (RMSE) between the model-implied and observed log CDS rate.

Table D1 describes the key input variables of the model calibration, and also lists the model outputs and the restrictions through which they are identified.

Table D1—Model inputs and outputs.

| | Definition | Source/Value/Identifying assumption |
|---|---|---|
| *Panel A: Model inputs* | | |
| $H$ | MV of equity | Sum of MVs of common and preferred equity, $H=H_C+H_P$. |
| $H_C$ | MV of common equity | CRSP |
| $F$ | BV of preferred equity | Compustat |
| $f$ | Preferred equity coupon rate | Ratio of dividends on preferred equity from Compustat and $F$. |
| $H_P$ | MV of preferred equity | Valued as a consol bond with notional $F$, coupon rate $f$, and zero recovery at insolvency $\tau$: $H_P=F(f/r)[1-U_r(V)]$. |
| $D$ | Deposit notional | Compustat Banks or 10-Q/K filings |
| $P$ | Bond notional | Compustat. Computed as short-term debt plus long-term debt. |
| $BVA$ | BV of assets | Compustat |
| $CD$ | Cash dividends on common equity, dividends on preferred equity, share repurchases | Compustat |
| $IE$ | Interest expense on deposits and non-deposit debt | Compustat |
| $m$ | Inverse of notional-weighted bond maturity | Compustat, 10-K filings (large banks) |
| $r$ | Risk-free rate | Treasury yield, linearly interpolated at notional-weighted bond maturity. |
| $d$ | Deposit rate | Compustat Banks. Computed as the ratio of the deposit interest expense and the deposit notional. |

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Table D1 – Continued from previous page

| | Definition | Source/Value/Identifying assumption |
|---|---|---|
| $c$ | Coupon rate | Compustat. Computed as total interest expense minus deposit interest expense, divided by notional of short-term plus long-term debt. |
| $B$ | MV of bonds at bailout | In benchmark case, $B = P(c+m)/(r+s+m)$, where $s$ is set to 100 basis points. |
| $\alpha$ | One minus fractional bankruptcy cost at failure | 0.50 |
| $\kappa$ | Corporate tax rate | 0.35 |
| $\rho_\phi$ | Parameter linking $\phi$ to $k$ | $\phi = \rho_\phi k$. In benchmark case, $\rho_\phi = 0$. |
| $\pi^G_{\text{post}}$ $\pi^O_{\text{post}}$ | Risk-neutral bailout probabilities for GSIBs and OLBs in post-Lehman period | $\pi^G_{\text{post}}, \pi^O_{\text{post}} \in \{0, 0.1, \ldots, 0.9\}$ |
| $S$ | Five-year at-market CDS rate | IHS Markit |
| $L$ | Fractional loss of bond notional at failure | One minus the recovery rate estimate reported by IHS Markit. |
| *Panel B: Model outputs* | | |
| $V$ | Assets in place | Model-implied MV of common equity equals observed MV of common equity. |
| $V^*$ | Asset insolvency threshold | Smooth-pasting condition (B9) |
| $\widehat{V}$ | Asset recapitalization level | Value-consistency condition $v_2(\widehat{V}) = B$ in (B5) |
| $U_r(V)$ | MV of receiving \$1 at default | (B2) |
| $DtD$ | Distance to default | (5) |
| $S^m$ | Five-year model CDS rate | (D1) |
| $\sigma$ | Brownian asset volatility parameter | For period $p$, $\sigma_p = \text{StdDev}\left(\log(V_{t+h}/V_t)\middle\vert t \in p, \text{excl jumps}\right)/\sqrt{h}$, for daily time steps $h$. |
| $\lambda$ $\eta$ | Jump arrival rate / Mean proportional jump size | For each period, choose $(\lambda, \eta)$ so that log CDS RMSE is minimized. |
| $\Sigma$ | Local variance of $\log V$ | $\Sigma^2 = \sigma^2 + 2\lambda\eta^2/(1+\eta)^2$ |
| $\phi$ | Cash flow parameter | Exogenous |
| $k$ | Asset drift parameter | For period $p$, set $k = \rho r$. Choose $\rho$ so that period-$p$ mean of $k+\phi$ equals period-$p$ mean of payout rate $(CD+IE)/V$. |
| $\rho$ | Parameter linking $k$ to $r$ | $k = \rho r$ |

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Table D1 – Continued from previous page

| | Definition | Source/Value/Identifying assumption |
|---|---|---|
| $\pi^G_{\text{pre}}$ $\pi^O_{\text{pre}}$ | Risk-neutral bailout probabilities for GSIBs and OLBs in pre-Lehman period | Find $\pi^G_{\text{pre}}, \pi^O_{\text{pre}} \in [0, 0.95]$ such that RMSE in (6) is minimized. |

*Note:* The table describes the input and output variables of the model calibration, and explains how they are sourced, parameterized or identified. MV and BV stand for market value and book value, respectively.

For firm $i$, period $p$, and bailout probabilities $\pi_{it} = \pi_{ip}$ for $t \in p$, the calibration proceeds as follows:

1) Specify a pair of jump parameters $(\lambda, \eta)$, where $\lambda \in \{0.1, 0.2, 0.3, 0.4, 0.5\}$ and $-\eta \in \{0.2, 0.15, 0.1, 0.05\}$.

2) Make an initial guess of $\rho_{ip}$, which determines the asset drift parameter $k_{it}$ via $k_{it} = \rho_{ip} r_{it}$, and of the Brownian asset volatility parameter $\sigma_{ip}$, using accounting data.[33] Set $\rho_{it} = \rho_{ip}$ and $\sigma_{it} = \sigma_{ip}$ for all $t \in p$.

3) For each date $t \in p$, we find the default threshold $V^*_{it}$ as the solution to (B9).

4) For each date $t \in p$, find $V_{it}$ such that $H_C(V_{it}) = H(V_{it}) - H_P(V_{it})$ matches the observed market value of common equity, where $H(V_{it})$ is computed according to (B8) and $H_P(V_{it}) = F_{it}(f_{it}/r_{it})[1 - U_r(V_{it})]$.

5) Re-compute $\rho_{ip}$ and $\sigma_{ip}$ as

$$\begin{aligned}
\rho_p &= \frac{\text{Mean}\left\{(\text{CD}_t + \text{IE}_t)/\text{V}_\text{t} \middle| t \in p\right\}}{(1 + \rho_{\phi,p})\text{Mean}\left\{r_t \middle| t \in p\right\}} \\
\sigma_p &= \frac{1}{\sqrt{h}} \text{StdDev}\left\{\log(V_{i,t+h}) - \log(V_{it}) \middle| t \in p,\ \text{excluding jumps}\right\},
\end{aligned}$$

after dropping the firm subscript $i$. If $\rho_{ip}$ or $\sigma_{ip}$ have changed, return to Step 3. Otherwise, move on to Step 6.

[33] For a given firm, the initial input parameters $\rho_p$ and $\sigma_p$ are computed from accounting data as $\rho_p = \text{Mean}\left\{(\text{CD}_t + \text{IE}_t)/\text{BVA}_\text{t} \middle| t \in p\right\}/\text{Mean}\left\{r_t \middle| t \in p\right\}$ and $\sigma_p = \text{StdDev}\left\{\log(\text{BVA}_{t+h}) - \log(\text{BVA}_t) \middle| t \in p\right\}/\sqrt{h}$, where $h$ measures daily time steps. The firm subscript $i$ has been dropped from the notation.

6) For each $t \in p$, compute the model-implied CDS rate $S^m_{it}$:

(D1) $$S^m = \frac{(1-\pi)4LX}{\sum_{k=1}^{20} e^{-r_k \frac{k}{4}} \left[1 - \mathbb{Q}\left(\tau < \frac{k}{4}\right)\right] + \frac{1}{2}X},$$

where

$$X = \sum_{k=1}^{20} e^{-r_{k-0.5} \frac{k-0.5}{4}} \left[\mathbb{Q}\left(\tau < \frac{k}{4}\right) - \mathbb{Q}\left(\tau < \frac{k-1}{4}\right)\right],$$

$\mathbb{Q}$ is the risk-neutral probability measure, and $r_k$ is the $k$-quarter risk-free rate. The subscripts $i$ and $t$ have been dropped from the notation. $S^m$ is computed as the no-bailout CDS rate in Bai, Goldstein and Yang (2020) times the likelihood $1-\pi$ of failure given insolvency. This computation assumes that a CDS credit event is triggered at the first instance of insolvency, whether the government decides to intervene or not. The assumption that a CDS credit event is triggered at bailout is consistent with the determination made by the International Swaps and Derivatives Association (2017) following the bailout of Monte dei Paschi. We rule out perverse incentives in CDS markets by setting net settlement payments at bailout to zero. Like Bai, Goldstein and Yang (2020), we use an exogenous rather than model-implied loss-given-failure rate $L$. In our applications, we set $L_{it}$ equal to one minus the recovery rate estimate reported by IHS Markit for firm $i$ on date $t$.

7) Compute the root mean squared log CDS pricing error:

$$\text{RMSE}_i(\lambda, \eta) = \sqrt{\text{Mean}\left\{\left[\log(S^m_{it}) - \log(S_{it})\right]^2 \middle| t \in p\right\}}.$$

8) Complete Steps 1-7 for all twenty pairs of jump parameters $(\lambda, \eta)$. Choose the pair $(\lambda, \eta)$ with the lowest $\text{RMSE}_i(\lambda, \eta)$.

## E. Large Banks

U.S. GSIBs are identified by the Financial Stability Board, in consultation with the Basel Committee on Banking Supervision. The list of GSIBs[34] is updated and published annually, typically in November, and is based on previous-year-end data and on the updated assessment methodology published by the Basel Committee on Banking Supervision (2013). The list of U.S. GSIBs has remained unchanged since it was first published in November 2011.

As a separate category of large banks, we also treat those U.S. bank holding companies, beyond GSIBs, that have \$50 billion or more in total consolidated assets as of December 2019. Total consolidated assets are available from the Federal Reserve Board's website.[35] The December 2019 list of non-GSIB U.S. bank holding companies with at least \$50 billion in total consolidated assets includes all the non-GSIB bank holding companies that require stress tests in 2020 under the Federal Reserve Board's Comprehensive Capital Analysis and Review and the Dodd-Frank Act stress test,[36] plus Comerica, People's United Financial, and SVB Financial Group. The Economic Growth, Regulatory Relief, and Consumer Protection Act enacted in May 2018 reduced the supervisory stress-testing requirements, particularly for bank holding companies with less than \$250 billion in total assets. There are also three banks with more than \$50 billion in total consolidated assets that do not have a bank holding company parent: First Republic Bank, Signature Bank, and Zions Bank. None of these three banks meet the data availability thresholds for sample inclusion. The group of OLBs includes TRUIST which was formed in December 2019 through a merger between BB&T and SunTrust Banks, each of which had more than \$50 billion in total consolidated assets prior to the merger.

[34]For example, the November 2019 list of GSIBs is available from the Financial Stability Board's website at https://www.fsb.org/2019/11/fsb-publishes-2019-g-sib-list/.

[35]The December 2019 consolidated assets statistics, for example, can be downloaded from https://www.federalreserve.gov/releases/lbr/20191231/lrg_bnk_lst.txt.

[36]The list of banks requiring stress tests in 2020 can be accessed from the Federal Reserve Board's website at https://www.federalreserve.gov/publications/comprehensive-capital-analysis-and-review-summary-instructions-2020.htm.

## F. CDS Data Cleaning

Prior to April 8, 2009, we use CDS data based on a contractual definition of default known as "modified restructuring," and from April 8, 2009 onwards, we use CDS data based on "no restructuring." This reflects the market convention before and after the introduction of the CDS Big Bang protocol on April 8, 2009. The "modified restructuring" definition allows for CDS protection against losses not only in the event of a bankruptcy or missed payment, but also in the event of an out-of-court restructuring that results in a material failure by the obligor to make payments on its debt. The "no restructuring" definition does not cover such out-of-court debt restructurings. Berndt, Jarrow and Kang (2007) show that the likelihood of a restructuring event is substantially smaller than that of a bankruptcy or missed payment, and that the difference in CDS rates with and without restructuring clauses tends to be small.

We only use CDS quotes for which IHS Markit rates the data quality of the quotes as "BB" or higher. If a quote-quality rating is not available, we require a composite level of "CcyGrp," "DocAdj" or "Entity Tier." Although IHS Markit CDS data go back as far as 2001, after cleaning the data we find few 2001 observations. We therefore restrict our sample to the period from January 1, 2002 to December 31, 2019. We exclude firms until they have at least one year of valid CDS observations.

The CDS data for Capital One are spotty and extremely volatile throughout 2002 and the first half of 2003. Capital One therefore enters our sample only on July 1, 2003. In July 2002, Capital One disclosed that it was in discussions with regulators about adding to its reserves for bad loans, which sent Capital One shares tumbling 40 percent the next day (Wall Street Journal, 2003). In March 2003, Capital One's chief financial officer became the subject of an SEC insider trading investigation and resigned abruptly (Bloomberg, 2004). In July 2003, a new chief financial officer was instated and tasked with strengthening the company's risk management practices (Capital One, 2003).

# G. Additional Figures and Tables

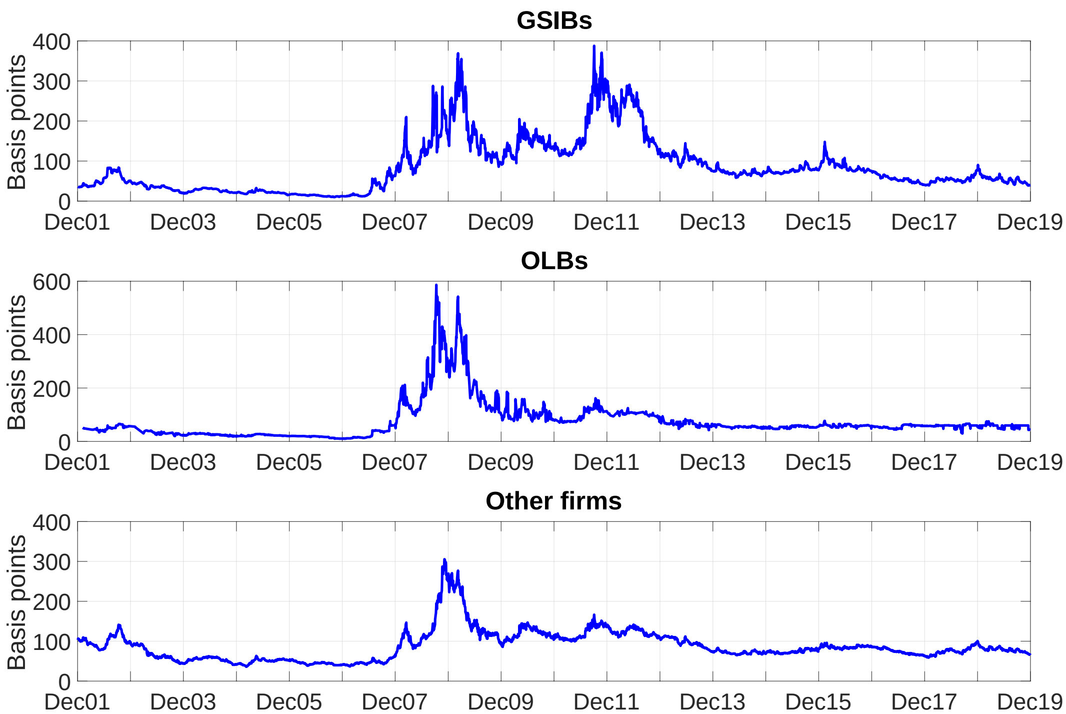


Figure G1. Median five-year CDS rates.

*Note:* The figure shows the daily times series of median five-year CDS rates. The data include 575 firms over 2002–2019. For GSIBs and OLBs, only those days on which CDS rates are available for four or more banks are shown. For other firms, only days on which CDS rates are available for 50 or more firms are shown.

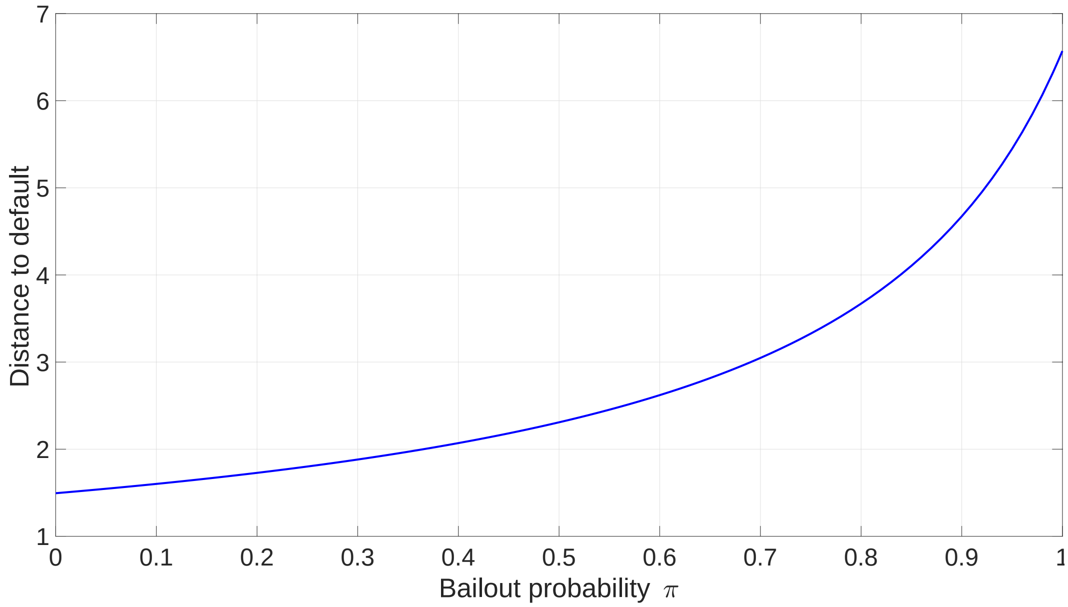


Figure G2. Effect of bailout probability on distance to default.

*Note:* The figure shows the distance to default implied by the structural model in Section III, as a function of the bailout probability $\pi$. As in Figure 1, the model parameters are consistent with a calibration to the case of JP Morgan & Chase on December 31, 2019.

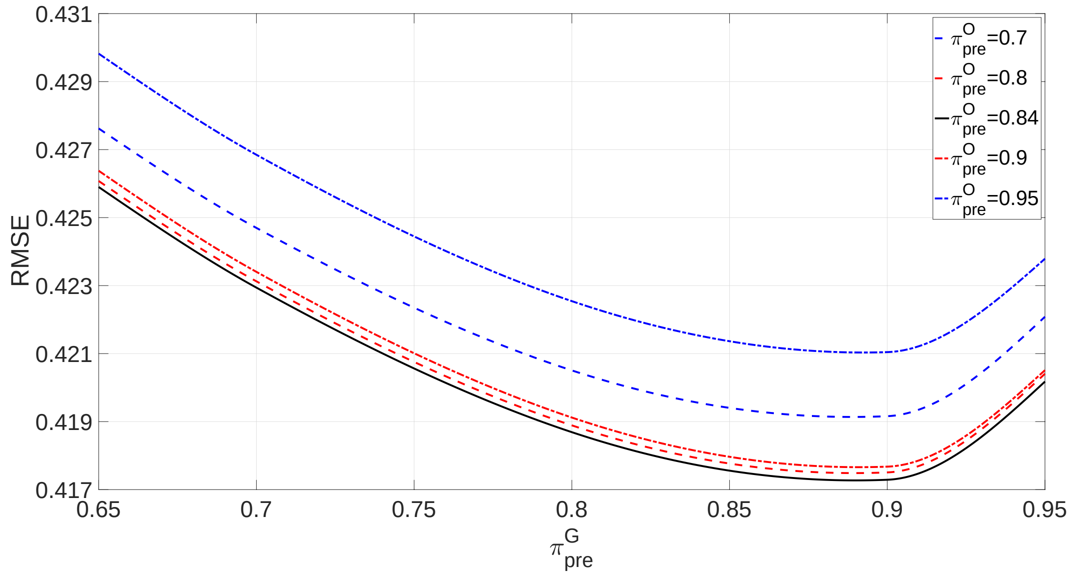


Figure G3. Non-linear least squares fit.

*Note:* The figure shows the RMSE estimates for the non-linear model (6), as a function of the pre-Lehman bailout probabilities $\pi_{\text{pre}}^{G}$ and $\pi_{\text{pre}}^{O}$. The post-Lehman bailout probabilities for large banks are set to 0.8. The RMSE is minimized at pre-Lehman bailout probability estimates of $\pi_{\text{pre}}^{G} = 0.89$ and $\pi_{\text{pre}}^{O} = 0.84$.

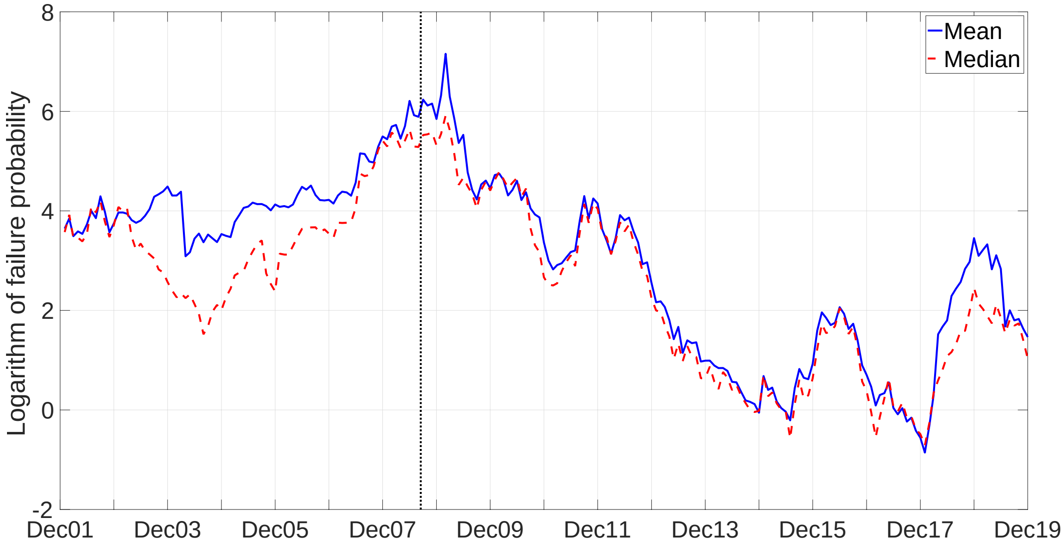


Figure G4. GSIB failure probabilities.

*Note:* The solid blue line shows the monthly times series of the logarithm of the average one-year failure probability across the six GSIBs in our sample—Bank of America, Citigroup, Goldman Sachs, JP Morgan & Chase, Morgan Stanley and Wells Fargo. The dashed red line shows the logarithm of the median one-year failure probability. Failure probabilities are sourced from the Risk Management Institute at the National University of Singapore, and are reported in basis points. They are based on the methodology developed by Duan, Sun and Wang (2012), and measure the likelihood that a bankruptcy, missed payment or materially adverse debt restructuring event occurs over the next twelve months. The dotted vertical line marks the Lehman default date.

Table G1—Distribution of firms across sectors and by credit quality.

| | Aaa | Aa | A | Baa | Ba | B | Caa | Ca–C | NR | All |
|---|---|---|---|---|---|---|---|---|---|---|
| Basic Materials | 0 | 0 | 8 | 21 | 10 | 5 | 0 | 0 | 5 | 49 |
| Consumer Goods | 0 | 4 | 14 | 37 | 16 | 10 | 2 | 0 | 9 | 92 |
| Consumer Services | 0 | 1 | 11 | 29 | 18 | 15 | 7 | 1 | 11 | 93 |
| Energy | 1 | 1 | 6 | 20 | 12 | 8 | 1 | 0 | 6 | 55 |
| Financials | 1 | 1 | 20 | 19 | 4 | 2 | 0 | 0 | 7 | 54 |
| Healthcare | 1 | 0 | 11 | 16 | 6 | 5 | 1 | 0 | 15 | 55 |
| Industrials | 0 | 3 | 15 | 29 | 12 | 8 | 4 | 0 | 8 | 79 |
| Technology | 0 | 1 | 5 | 10 | 3 | 4 | 0 | 0 | 8 | 31 |
| Telecomm. Services | 0 | 0 | 3 | 4 | 7 | 3 | 3 | 0 | 2 | 22 |
| Utilities | 0 | 0 | 2 | 24 | 6 | 6 | 0 | 0 | 7 | 45 |
| Total | 3 | 11 | 95 | 209 | 94 | 66 | 18 | 1 | 78 | 575 |

*Note:* The table reports the distribution of firms across sectors and by median Moody's senior unsecured issuer ratings. The data include 575 public U.S. firms, over the period 2002–2019.

Table G2—Accounting measures.

| | GSIBs | | OLBs | | Other firms | |
|---|---|---|---|---|---|---|
| | Pre | Post | Pre | Post | Pre | Post |
| Book assets | 949 | 1631 | 138 | 255 | 26 | 39 |
| Book non-deposit debt | 363 | 482 | 37 | 46 | 7 | 10 |
| Deposits | 306 | 734 | 65 | 158 | 0 | 0 |
| Market common equity | 119 | 146 | 36 | 49 | 18 | 30 |
| Book preferred equity | 1.2 | 14.9 | 0.1 | 1.7 | 0.0 | 0.1 |
| Share dividends, repurchases | 7.3 | 10.8 | 1.9 | 3.0 | 0.7 | 1.7 |
| Total interest expense | 23.9 | 13.1 | 2.9 | 2.6 | 0.4 | 0.4 |
| Tangible equity | 0.04 | 0.06 | 0.07 | 0.08 | 0.19 | 0.17 |
| CDS rates | 41 | 114 | 52 | 87 | 151 | 197 |
| Rating | Aa2 | A3 | A1 | A3 | Baa2 | Baa3 |
| Non-deposit debt maturity | 2.6 | 3.2 | 3.4 | 4.1 | 4.5 | 4.6 |
| Risk-free rate | 3.2 | 1.3 | 3.6 | 1.6 | 3.8 | 1.6 |
| Deposit rate | 1.7 | 0.6 | 2.3 | 0.9 | 0.0 | 0.0 |
| Coupon rate | 4.4 | 2.0 | 4.4 | 3.7 | 6.0 | 5.2 |
| Number of firms | 6 | 6 | 6 | 6 | 522 | 407 |

*Note:* This table reports average statistics for the pre-Lehman (Pre) and post-Lehman (Post) period for book assets, book non-deposit debt computed as book short-term debt plus book long-term debt, deposits, market capitalization of common equity, book preferred equity, sum of cash dividends on common shares, dividends on preferred shares and share repurchases, and total interest expense on deposits and non-deposit debt, in billions of U.S. dollars. Tangible equity is the ratio of book tangible common equity to book tangible assets. Sample-average five-year CDS rates are reported in basis points. Moody's senior unsecured issuer ratings are reported as median alphanumeric ratings. Notional-weighted average bond maturities are shown in years. The risk-free rate is reported as the debt-maturity-interpolated risk-free rate, and deposit interest rates and non-deposit debt coupon rates are computed from accounting data, all expressed as averages across firms and within-period dates and reported in percent. The data include 575 public U.S. firms, over the period 2002–2019.

Table G3—Panel regression results.

| $\pi_{\text{post}}$ | $\beta$ | Firm fixed effects C | GS | JPM | MS | WFC | $R^2$ | RMSE |
|---|---|---|---|---|---|---|---|---|
| 0.0 | -0.258 | 0.012 | 0.276 | -0.091 | 0.291 | 0.169 | 0.839 | 0.418 |
| | (0.002) | (0.009) | (0.015) | (0.017) | (0.015) | (0.016) | | |
| 0.1 | -0.258 | -0.009 | 0.258 | -0.110 | 0.268 | 0.182 | 0.839 | 0.418 |
| | (0.002) | (0.009) | (0.015) | (0.016) | (0.015) | (0.015) | | |
| 0.2 | -0.258 | 0.001 | 0.475 | -0.104 | 0.257 | 0.220 | 0.839 | 0.418 |
| | (0.002) | (0.009) | (0.010) | (0.016) | (0.015) | (0.015) | | |
| 0.3 | -0.258 | -0.006 | 0.473 | -0.088 | 0.239 | 0.356 | 0.840 | 0.418 |
| | (0.002) | (0.009) | (0.010) | (0.016) | (0.015) | (0.014) | | |
| 0.4 | -0.259 | 0.008 | 0.401 | -0.164 | 0.314 | 0.327 | 0.840 | 0.417 |
| | (0.002) | (0.010) | (0.010) | (0.014) | (0.012) | (0.011) | | |
| 0.5 | -0.259 | 0.018 | 0.398 | -0.164 | 0.294 | 0.355 | 0.841 | 0.417 |
| | (0.002) | (0.010) | (0.011) | (0.014) | (0.013) | (0.010) | | |
| 0.6 | -0.260 | -0.018 | 0.362 | -0.204 | 0.240 | 0.257 | 0.842 | 0.417 |
| | (0.002) | (0.010) | (0.011) | (0.014) | (0.014) | (0.010) | | |
| 0.7 | -0.260 | 0.002 | 0.323 | -0.090 | 0.169 | 0.057 | 0.844 | 0.417 |
| | (0.002) | (0.013) | (0.011) | (0.019) | (0.015) | (0.009) | | |
| 0.8 | -0.259 | -0.002 | 0.248 | -0.031 | 0.134 | -0.012 | 0.847 | 0.417 |
| | (0.002) | (0.010) | (0.012) | (0.022) | (0.015) | (0.008) | | |
| 0.9 | -0.259 | -0.064 | 0.051 | -0.072 | 0.051 | 0.078 | 0.857 | 0.418 |
| | (0.002) | (0.009) | (0.016) | (0.016) | (0.017) | (0.008) | | |

*Note:* This table reports the results for the panel data regression (6), for the data-consistent pairs of bailout probabilities reported in Table 1. CDS rates are measured in basis points. The benchmark firm is Bank of America and the benchmark month is December 2019. Firm fixed effects are included for all firms, and reported for Citigroup (C), Goldman Sachs (GS), JP Morgan & Chase (JPM), Morgan Stanley (MS), and Wells Fargo (WFC). Driscoll-Kraay standard errors that are robust to heteroskedasticity, autocorrelation and cross-sectional dependence are shown in parentheses. The data include 575 firms over 2002–2019.

Table G4—Parameter estimates and structural model fit.

| | $\pi$ | $k$ | $\sigma$ | $\lambda$ | $\eta$ | $\Sigma$ | DtD | $U_r$ | $S^m$ | $S$ |
|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: GSIBs* | | | | | | | | | | |
| Pre | 0.95 | 0.12 | 0.20 | 0.47 | -0.17 | 0.30 | 3.23 | 0.74 | 32 | 41 |
| Post | 0.90 | 0.07 | 0.18 | 0.50 | -0.20 | 0.31 | 2.86 | 0.88 | 59 | 114 |
| Pre | 0.89 | 0.08 | 0.12 | 0.27 | -0.13 | 0.17 | 3.44 | 0.72 | 58 | 41 |
| Post | 0.80 | 0.04 | 0.11 | 0.35 | -0.14 | 0.18 | 2.64 | 0.87 | 113 | 114 |
| Pre | 0.81 | 0.06 | 0.09 | 0.15 | -0.08 | 0.11 | 3.47 | 0.71 | 98 | 41 |
| Post | 0.70 | 0.03 | 0.08 | 0.17 | -0.15 | 0.14 | 2.26 | 0.86 | 172 | 114 |
| Pre | 0.73 | 0.05 | 0.08 | 0.13 | -0.08 | 0.10 | 3.07 | 0.70 | 152 | 41 |
| Post | 0.60 | 0.03 | 0.06 | 0.12 | -0.15 | 0.11 | 2.05 | 0.85 | 238 | 114 |
| Pre | 0.71 | 0.05 | 0.08 | 0.12 | -0.08 | 0.09 | 2.98 | 0.70 | 170 | 41 |
| Post | 0.50 | 0.02 | 0.06 | 0.13 | -0.13 | 0.12 | 1.94 | 0.85 | 323 | 114 |
| Pre | 0.66 | 0.05 | 0.07 | 0.10 | -0.08 | 0.09 | 2.81 | 0.70 | 203 | 41 |
| Post | 0.40 | 0.02 | 0.07 | 0.17 | -0.12 | 0.13 | 1.79 | 0.85 | 424 | 114 |
| Pre | 0.61 | 0.05 | 0.07 | 0.10 | -0.13 | 0.10 | 2.35 | 0.71 | 248 | 41 |
| Post | 0.30 | 0.02 | 0.07 | 0.17 | -0.15 | 0.14 | 1.50 | 0.86 | 534 | 114 |
| Pre | 0.53 | 0.04 | 0.07 | 0.12 | -0.13 | 0.11 | 2.10 | 0.71 | 316 | 41 |
| Post | 0.20 | 0.02 | 0.07 | 0.20 | -0.17 | 0.16 | 1.30 | 0.86 | 642 | 114 |
| Pre | 0.48 | 0.04 | 0.07 | 0.12 | -0.13 | 0.11 | 1.99 | 0.71 | 361 | 41 |
| Post | 0.10 | 0.02 | 0.08 | 0.18 | -0.20 | 0.17 | 1.02 | 0.86 | 763 | 114 |
| Pre | 0.42 | 0.04 | 0.07 | 0.13 | -0.13 | 0.11 | 1.84 | 0.72 | 418 | 41 |
| Post | 0.00 | 0.02 | 0.08 | 0.18 | -0.20 | 0.17 | 0.96 | 0.86 | 880 | 114 |
| *Panel B: OLBs* | | | | | | | | | | |
| Pre | 0.95 | 0.08 | 0.17 | 0.50 | -0.20 | 0.31 | 4.14 | 0.60 | 10 | 52 |
| Post | 0.90 | 0.08 | 0.19 | 0.50 | -0.20 | 0.32 | 4.96 | 0.79 | 18 | 88 |
| Pre | 0.84 | 0.06 | 0.15 | 0.38 | -0.16 | 0.23 | 4.21 | 0.58 | 31 | 52 |
| Post | 0.80 | 0.07 | 0.16 | 0.50 | -0.20 | 0.30 | 4.20 | 0.80 | 50 | 88 |
| Pre | 0.80 | 0.06 | 0.14 | 0.31 | -0.14 | 0.21 | 4.20 | 0.58 | 39 | 52 |
| Post | 0.70 | 0.06 | 0.14 | 0.36 | -0.20 | 0.25 | 3.92 | 0.80 | 80 | 88 |
| Pre | 0.73 | 0.06 | 0.13 | 0.20 | -0.12 | 0.17 | 4.24 | 0.56 | 52 | 52 |
| Post | 0.60 | 0.05 | 0.12 | 0.22 | -0.15 | 0.17 | 4.18 | 0.78 | 97 | 88 |
| Pre | 0.70 | 0.05 | 0.12 | 0.28 | -0.10 | 0.15 | 4.25 | 0.56 | 58 | 52 |
| Post | 0.50 | 0.04 | 0.11 | 0.21 | -0.12 | 0.14 | 4.09 | 0.78 | 129 | 88 |
| Pre | 0.59 | 0.05 | 0.12 | 0.21 | -0.07 | 0.13 | 4.07 | 0.56 | 91 | 52 |
| Post | 0.40 | 0.04 | 0.11 | 0.16 | -0.08 | 0.13 | 4.00 | 0.78 | 171 | 88 |
| Pre | 0.51 | 0.05 | 0.11 | 0.16 | -0.07 | 0.12 | 3.83 | 0.56 | 129 | 52 |
| Post | 0.30 | 0.04 | 0.11 | 0.10 | -0.12 | 0.13 | 3.69 | 0.78 | 221 | 88 |
| Pre | 0.45 | 0.05 | 0.11 | 0.12 | -0.09 | 0.12 | 3.61 | 0.56 | 159 | 52 |
| Post | 0.20 | 0.03 | 0.10 | 0.15 | -0.12 | 0.13 | 3.48 | 0.78 | 280 | 88 |

Continued on next page

Table G4 – Continued from previous page

| | $\pi$ | $k$ | $\sigma$ | $\lambda$ | $\eta$ | $\Sigma$ | DtD | $U_r$ | $S^m$ | $S$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Pre | 0.36 | 0.04 | 0.11 | 0.12 | -0.09 | 0.12 | 3.44 | 0.56 | 208 | 52 |
| Post | 0.10 | 0.03 | 0.10 | 0.13 | -0.11 | 0.13 | 3.36 | 0.78 | 345 | 88 |
| Pre | 0.31 | 0.04 | 0.11 | 0.12 | -0.09 | 0.12 | 3.33 | 0.56 | 240 | 52 |
| Post | 0.00 | 0.03 | 0.10 | 0.13 | -0.14 | 0.14 | 3.12 | 0.79 | 408 | 88 |
| *Panel C: Other firms* | | | | | | | | | | |
| Pre | 0.00 | 0.05 | 0.20 | 0.36 | -0.18 | 0.28 | 5.41 | 0.45 | 162 | 151 |
| Post | 0.00 | 0.05 | 0.20 | 0.34 | -0.18 | 0.28 | 5.07 | 0.75 | 234 | 197 |

*Note:* This table reports averages, across firms and within-period dates, for the calibrated model parameters $k$, $\sigma$, $\lambda$, $\eta$, and the local asset volatility $\Sigma = \sqrt{\sigma^2 + 2\lambda\eta^2/(1+\eta)^2}$. It also shows the average model-implied distance to default (DtD), market value of receiving \$1 at default ($U_r$), model-implied five-year CDS rate in basis points ($S^m$, defined in (D1)), and observed five-year CDS rate in basis points ($S$). The data-consistent pairs of bailout probabilities are as reported in Table 1. The data include 575 firms over 2002–2019.

Table G5—Market value of bank cash flows and stakeholder claims for OLBs.

| | $\pi$ | $V_0$ | $V^*$ | $Y_0$ | $v_3$ | $y_G$ | $\frac{y_{G,n}}{y_G}$ | $\frac{y_{G,f}}{y_G}$ | $H_s$ | $H_{s,1}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Pre-Lehman bailout probability is calibrated to data* | | | | | | | | | | |
| Pre | 0.95 | 2.02 | 0.65 | 4.32 | 0.32 | 1.01 | 0.22 | 0.78 | 0.05 | 0.03 |
| Post | 0.90 | 1.67 | 0.41 | 6.27 | 1.16 | 2.01 | 0.21 | 0.79 | – | – |
| Pre | 0.84 | 2.42 | 1.10 | 4.74 | 0.69 | 1.10 | 0.43 | 0.57 | 0.06 | 0.02 |
| Post | 0.80 | 1.88 | 0.62 | 7.16 | 1.92 | 2.63 | 0.34 | 0.66 | – | – |
| Pre | 0.80 | 2.53 | 1.24 | 4.80 | 0.74 | 1.09 | 0.47 | 0.53 | 0.19 | 0.06 |
| Post | 0.70 | 2.21 | 0.94 | 7.25 | 1.92 | 2.47 | 0.45 | 0.55 | – | – |
| Pre | 0.73 | 2.79 | 1.56 | 4.77 | 0.68 | 0.90 | 0.55 | 0.45 | 0.27 | 0.08 |
| Post | 0.60 | 2.73 | 1.48 | 6.80 | 1.44 | 1.80 | 0.55 | 0.45 | – | – |
| Pre | 0.70 | 2.87 | 1.66 | 4.76 | 0.67 | 0.86 | 0.58 | 0.42 | 0.44 | 0.12 |
| Post | 0.50 | 3.17 | 1.92 | 6.60 | 1.20 | 1.43 | 0.63 | 0.37 | – | – |
| Pre | 0.59 | 3.17 | 2.02 | 4.75 | 0.62 | 0.70 | 0.67 | 0.33 | 0.45 | 0.12 |
| Post | 0.40 | 3.57 | 2.31 | 6.43 | 0.98 | 1.12 | 0.71 | 0.29 | – | – |
| Pre | 0.51 | 3.34 | 2.23 | 4.74 | 0.59 | 0.63 | 0.73 | 0.27 | 0.48 | 0.12 |
| Post | 0.30 | 3.81 | 2.59 | 6.35 | 0.86 | 0.94 | 0.79 | 0.21 | – | – |
| Pre | 0.45 | 3.40 | 2.33 | 4.76 | 0.61 | 0.63 | 0.78 | 0.22 | 0.54 | 0.14 |
| Post | 0.20 | 4.05 | 2.84 | 6.14 | 0.62 | 0.66 | 0.86 | 0.14 | – | – |
| Pre | 0.36 | 3.55 | 2.50 | 4.71 | 0.55 | 0.54 | 0.83 | 0.17 | 0.54 | 0.14 |
| Post | 0.10 | 4.31 | 3.10 | 5.88 | 0.33 | 0.35 | 0.93 | 0.07 | – | – |
| Pre | 0.31 | 3.63 | 2.60 | 4.67 | 0.50 | 0.48 | 0.86 | 0.14 | 0.59 | 0.17 |
| Post | 0.00 | 4.35 | 3.18 | 5.59 | 0.00 | 0.00 | – | – | – | – |
| *Panel B: Pre-Lehman bailout probability is set to zero* | | | | | | | | | | |
| Pre | 0.00 | 3.93 | 2.96 | 4.20 | 0.00 | 0.00 | – | – | 0.00 | 0.00 |
| Post | 0.00 | 4.35 | 3.18 | 5.59 | 0.00 | 0.00 | – | – | – | – |

*Note:* This table reports the average, across OLBs and within-period dates, of the bank asset level ($V_0$); endogenous insolvency threshold ($V^*$); and market value of total bank cash flows ($Y_0$), government claims ($v_3$), all potential future bailout injections by the government ($y_G$), potential future bailout injections associated with the next bailout ($y_{G,n}$), and potential future bailout injections associated with subsequent events of insolvency ($y_{G,f}$). $H_s$ is the difference between the pre-Lehman market value of equity and the market value of equity in the counterfactual pre-Lehman economy where bailout probabilities are as low as post-Lehman bailout probabilities. $H_{s,1}$ is the difference between the pre-Lehman market value of equity and the hypothetical market value of equity that would have applied, at the same asset insolvency boundary, had bailout probabilities been as low before Lehman's default as after Lehman's default. All variables are computed as fractions of the market value of common and preferred equity. Results are reported for each of the data-consistent pairs of bailout probabilities in Table 1. The data include 575 firms over 2002–2019.

## H. Standard Error of $\pi_{\text{pre}}$

We re-write (6) as

$$\text{(H1)} \qquad \log(S_{it}) = \log(1-\pi_{it}) + \beta\,\text{DtD}(\pi_{it}, z_{it}) + \sum_{\text{firm } f} \delta_f D_f(i) + \sum_{\text{month } m} \delta_m D_m(t) + \varepsilon_{it},$$

where $z_{it}$ is the list of variables for observation $(i,t)$ for firm $i$ and date $t$ that determine the distance to default, given $\pi$. For an assumed value of $\pi^G_{\text{post}} = \pi^O_{\text{post}}$, (H1) can be expressed in compact form as

$$\log(S_{it}) = h(\theta, x_{it}) + \varepsilon_{it},$$

where $\theta = (\pi^G_{\text{pre}}, \pi^O_{\text{pre}}, \beta, \{\delta_f\}, \{\delta_m\}) \in \mathbb{R}^p$, with $p$ denoting the dimension of $\theta$, and $x_{it} = (z_{it}, \{D_f(i)\}, \{D_m(t)\})$.

Standard errors for $\widehat{\theta}$ are obtained by exploiting the asymptotic distribution of the non-linear least squares estimator $\widehat{\theta}$ (Ruckstuhl, 2010), as follows. Let $n$ denote the number of observations $(i,t)$, and $F$ the number of firms $i$. The $n \times p$ Jacobian matrix $A(\theta)$ is defined, at some data point $(i,t)$, by

$$A_{it,j}(\theta) = \frac{\partial h(\theta, x_{it})}{\partial \theta_j}.$$

In particular,

$$A_{it,1}(\theta) = \begin{cases} -\frac{1}{1-\pi^G_{\text{pre}}} + \beta \frac{\partial d(\pi^G_{\text{pre}}, z_{it})}{\partial \pi^G_{\text{pre}}}, & \text{firm } i \text{ is GSIB, } t \text{ is pre-Lehman} \\ 0, & \text{otherwise} \end{cases}$$

$$A_{it,2}(\theta) = \begin{cases} -\frac{1}{1-\pi^O_{\text{pre}}} + \beta \frac{\partial d(\pi^O_{\text{pre}}, z_{it})}{\partial \pi^O_{\text{pre}}}, & \text{firm } i \text{ is OLB, } t \text{ is pre-Lehman} \\ 0, & \text{otherwise} \end{cases}$$

$$A_{it,3}(\theta) = d(\pi_{it}, z_{it})$$

$$A_{it,3+f}(\theta) = D_f(i), \text{ for all firms } f$$

$$A_{it,3+F+m}(\theta) = D_m(t), \text{ for all months } m.$$

The asymptotic covariance matrix of estimator $\widehat{\theta}$ is $\widehat{\sigma}^2\left(A(\widehat{\theta})^\top A(\widehat{\theta})\right)^{-1}$, where

$$\widehat{\sigma}^2 = \frac{1}{n-p}\sum_{it}\left(\log(S_{it}) - h(\widehat{\theta}, x_{it})\right)^2.$$

The standard errors $\widehat{\sigma}_{\pi^G_{\text{pre}}}$ and $\widehat{\sigma}_{\pi^O_{\text{pre}}}$ of $\widehat{\pi}^G_{\text{pre}}$ and $\widehat{\pi}^O_{\text{pre}}$ are computed as

$$\widehat{\sigma}^2_{\pi^G_{\text{pre}}} = \widehat{\sigma}^2\left(A(\widehat{\theta})^\top A(\widehat{\theta})\right)^{-1}_{11} \quad \text{and} \quad \widehat{\sigma}^2_{\pi^O_{\text{pre}}} = \widehat{\sigma}^2\left(A(\widehat{\theta})^\top A(\widehat{\theta})\right)^{-1}_{22}.$$

## I. Robustness Checks

We show that our main findings are qualitatively robust to *(i)* an alternative specification of the market value of bonds at bailout, *(ii)* an alternative computation of the market value of preferred shares, *(iii)* allowing large banks' asset payout rates to deviate from efficient-market levels throughout the entire sample period, *(iv)* stricter data cleaning procedures, and *(v)* taking into consideration major bank mergers. The results are reported in Table I1. They reveal that for each of these alternative settings the data are consistent with a dramatic post-Lehman decline in fitted bailout probabilities, and that this decline is more pronounced for GSIBs than OLBs.

Table I1—Robustness checks: Data-consistent bailout probabilities and equity subsidies.

| | | $\pi_{\text{post}}$ | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 0.0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| (A) | $\pi^G_{\text{pre}}$ | 0.42 | 0.49 | 0.53 | 0.60 | 0.64 | 0.71 | 0.74 | 0.81 | 0.90 | 0.95 |
| | $\pi^O_{\text{pre}}$ | 0.31 | 0.38 | 0.46 | 0.52 | 0.59 | 0.65 | 0.72 | 0.81 | 0.86 | 0.95 |
| | $H^G_s$ | 0.85 | 0.84 | 0.80 | 0.78 | 0.75 | 0.71 | 0.60 | 0.52 | 0.42 | 0.26 |
| | $H^O_s$ | 0.46 | 0.44 | 0.44 | 0.38 | 0.34 | 0.27 | 0.21 | 0.16 | 0.08 | 0.06 |
| (B) | $\pi^G_{\text{pre}}$ | 0.42 | 0.47 | 0.53 | 0.61 | 0.67 | 0.71 | 0.73 | 0.81 | 0.89 | 0.95 |
| | $\pi^O_{\text{pre}}$ | 0.31 | 0.36 | 0.45 | 0.51 | 0.59 | 0.70 | 0.73 | 0.80 | 0.84 | 0.95 |
| | $H^G_s$ | 0.96 | 0.96 | 0.94 | 0.94 | 0.92 | 0.88 | 0.79 | 0.72 | 0.53 | 0.23 |
| | $H^O_s$ | 0.59 | 0.54 | 0.54 | 0.48 | 0.45 | 0.44 | 0.28 | 0.19 | 0.06 | 0.05 |

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Table I1 – Continued from previous page

| | | $\pi_{\text{post}}$ | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 0.0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| (C) | $\pi^G_{\text{pre}}$ | 0.45 | 0.51 | 0.53 | 0.61 | 0.63 | 0.70 | 0.73 | 0.81 | 0.88 | 0.95 |
| | $\pi^O_{\text{pre}}$ | 0.30 | 0.34 | 0.43 | 0.51 | 0.59 | 0.70 | 0.73 | 0.80 | 0.84 | 0.95 |
| | $H^G_s$ | 0.97 | 0.96 | 0.94 | 0.94 | 0.90 | 0.88 | 0.77 | 0.72 | 0.54 | 0.24 |
| | $H^O_s$ | 0.64 | 0.55 | 0.54 | 0.50 | 0.47 | 0.44 | 0.28 | 0.19 | 0.06 | 0.05 |
| (D) | $\pi^G_{\text{pre}}$ | 0.43 | 0.50 | 0.52 | 0.60 | 0.64 | 0.70 | 0.74 | 0.81 | 0.88 | 0.95 |
| | $\pi^O_{\text{pre}}$ | 0.31 | 0.35 | 0.44 | 0.51 | 0.60 | 0.70 | 0.73 | 0.80 | 0.84 | 0.95 |
| | $H^G_s$ | 0.97 | 0.96 | 0.94 | 0.94 | 0.90 | 0.88 | 0.79 | 0.72 | 0.53 | 0.24 |
| | $H^O_s$ | 0.62 | 0.56 | 0.55 | 0.49 | 0.47 | 0.44 | 0.28 | 0.19 | 0.06 | 0.05 |
| (E) | $\pi^G_{\text{pre}}$ | 0.45 | 0.51 | 0.54 | 0.61 | 0.64 | 0.71 | 0.73 | 0.81 | 0.88 | 0.95 |
| | $\pi^O_{\text{pre}}$ | 0.31 | 0.36 | 0.45 | 0.51 | 0.59 | 0.70 | 0.72 | 0.80 | 0.84 | 0.95 |
| | $H^G_s$ | 0.96 | 0.95 | 0.93 | 0.93 | 0.88 | 0.86 | 0.73 | 0.67 | 0.50 | 0.23 |
| | $H^O_s$ | 0.55 | 0.50 | 0.50 | 0.45 | 0.44 | 0.43 | 0.27 | 0.19 | 0.06 | 0.05 |
| (F) | $\pi^G_{\text{pre}}$ | 0.49 | 0.51 | 0.54 | 0.60 | 0.63 | 0.70 | 0.72 | 0.81 | 0.89 | 0.95 |
| | $\pi^O_{\text{pre}}$ | 0.28 | 0.33 | 0.42 | 0.51 | 0.61 | 0.70 | 0.73 | 0.80 | 0.84 | 0.95 |
| | $H^G_s$ | 0.87 | 0.83 | 0.80 | 0.79 | 0.72 | 0.74 | 0.58 | 0.59 | 0.48 | 0.22 |
| | $H^O_s$ | 0.42 | 0.39 | 0.40 | 0.40 | 0.42 | 0.41 | 0.26 | 0.19 | 0.06 | 0.05 |
| (G) | $\pi^G_{\text{pre}}$ | 0.43 | 0.50 | 0.54 | 0.61 | 0.68 | 0.71 | 0.74 | 0.81 | 0.89 | 0.95 |
| | $\pi^O_{\text{pre}}$ | 0.31 | 0.37 | 0.46 | 0.51 | 0.60 | 0.70 | 0.73 | 0.80 | 0.84 | 0.95 |
| | $H^G_s$ | 0.97 | 0.96 | 0.95 | 0.94 | 0.92 | 0.88 | 0.78 | 0.71 | 0.53 | 0.23 |
| | $H^O_s$ | 0.59 | 0.55 | 0.55 | 0.49 | 0.47 | 0.44 | 0.28 | 0.19 | 0.06 | 0.05 |
| (H) | $\pi^G_{\text{pre}}$ | 0.42 | 0.46 | 0.53 | 0.61 | 0.66 | 0.71 | 0.73 | 0.81 | 0.87 | 0.95 |
| | $\pi^O_{\text{pre}}$ | 0.31 | 0.36 | 0.45 | 0.51 | 0.59 | 0.70 | 0.73 | 0.80 | 0.84 | 0.95 |
| | $H^G_s$ | 0.99 | 0.98 | 0.98 | 0.97 | 0.96 | 0.93 | 0.86 | 0.80 | 0.60 | 0.26 |
| | $H^O_s$ | 0.59 | 0.54 | 0.54 | 0.48 | 0.45 | 0.44 | 0.27 | 0.19 | 0.06 | 0.05 |

*Note:* This table reports data-consistent pairs of bailout probabilities, for various robustness specifications. Panel (A) reports results when $B = \min\{P, W_-\}$, with $W_-$ as in (I1); Panel (B) reports results when the market value of preferred equity is set equal to book preferred equity; Panels (C) through (F) show the results when $\phi_{it} = \rho_\phi k_{it}$ for all large banks $i$ and dates $t$, where $\rho_\phi = 0.4$ in Panel (C), $\rho_\phi = 0.2$ in (D), $\rho_\phi = -0.2$ in (E) and $\rho_\phi = -0.4$ in (F), and $\phi_{it} = 0$ for all other firms; Panel (G) reports the results after removing insurance and car companies from the sample; and Panel (H) shows the results when accounting for major bank mergers. As in Table 4, $H_s$ is the difference between the pre-Lehman market value of equity and the market value of equity in the counterfactual pre-Lehman economy where bailout probabilities are as low as post-Lehman bailout probabilities. $H^G_s$ and $H^O_s$ are reported as fractions of the market value of equity, averaged across pre-Lehman dates and, respectively, GSIBs and OLBs.

Table I1 also reports the fraction of the pre-Lehman large-bank market value of equity that can be ascribed to the subsidies to debt financing costs stemming from bailout expectations being higher before Lehman's default than after Lehman's default. Independent of the assumed post-Lehman bailout probability, for each robustness specification we find a sizable subsidy to the market value of equity stemming from higher pre-Lehman bailout probabilities. As in the benchmark specification (Tables 2 and G5), the estimated percentage subsidy to the pre-Lehman market value of equity is greater for GSIBs than OLBs.

Panel (A) of Table I1 shows the results when the market value of bonds at bailout, $B$, is set to the par value of bonds, $P$. In rare occasions, large-bank interest expenses are so small that the par value $P$ of bonds exceeds the market value $W$, introduced in (B6), of bonds that are default free but otherwise equivalent to those issued by the bank. We therefore cap $B$ at a value $W_-$ just below $W$: $B = \min\{P, W_-\}$, where

$$W_- = P\frac{c+m}{r+m+0.0001}. \tag{I1}$$

Table panel (B) reports the results when the market value of preferred equity is set equal to its book value. Panels (C) through (F) tabulate results when large banks' payout rates $k_{it} + \phi_{it}$ deviate from efficient-market levels $k_{it}$ throughout the sample period. For large banks $i$, we set $\phi_{it} = \rho_\phi k_{it}$ for all dates $t$, where $\rho_\phi \in \{0.4, 0.2, -0.2, -0.4\}$. For all other firms and dates, $\phi_{it} = 0$. Note that marginal pre-Lehman subsidies to large-bank equity are estimated to be greater when $\rho_\phi$ is assumed to be higher. When $\rho_\phi$ is high, large banks collect extra rents that they can enjoy for longer when bailout probabilities are higher.

Wholesale creditors of large insurance companies (such as AIG) and car companies (such as General Motors, Ford and Chrysler) may have non-zero bailout expectations. In Panel (G), we re-estimate bailout probabilities after removing insurance and car companies from our sample, and find that the results remain nearly unchanged. Insurance companies are identified as firms with SIC codes 6300–6499, and car companies as firms with SIC codes 3700–3799.

In our benchmark empirical estimation, we have not captured the effects of some significant bank mergers. During our sample period, JP Morgan & Chase acquired Bank One (2004) and Bear Stearns (2008), Bank of America acquired Merrill Lynch (2008), and Wells Fargo acquired Wachovia (2008). To ensure the robustness of our findings, we build pro-forma merged datasets for these banks. Specifically, we construct pro-forma estimates of CDS rates as weighted averages of the pre-merger CDS rates of the constituent firms, weighting by principal amounts $P$ of non-deposit debt. Pro-forma market values of equity and accounting data are constructed by adding the relevant data items for the acquirer and the acquired bank prior to the merger. In Panel (H) of Table I1, we confirm that accounting for these mergers has relatively little impact on our estimates of bailout probabilities and subsidies to the market value of equity.

For each alternative specification (A)–(H) in Table I1, Table I2 shows the corresponding measured distances to default and model-implied CDS rates for GSIBs. The reported statistics are close to their counterparts in Table G4. Note, however, that fitted distances to default tend to be higher, and model CDS rates tend to be lower, when $\phi$ is assumed to be more negative. As a result, the post-Lehman bailout probability for which average model credit spreads match their observed counterparts decreases when expected future earnings of large banks are discounted more heavily because of high overhead or frictional costs. Similar results apply to OLBs, and are available upon request.

Table I2—Robustness checks: GSIB distances to default and model CDS rates.

| | $\pi_{\text{post}}$ | (A) | (B) | (C) | (D) | (E) | (F) | (G) | (H) |
|---|---|---|---|---|---|---|---|---|---|
| *Panel A: DtD* | | | | | | | | | |
| Pre | | 3.92 | 3.23 | 3.23 | 3.23 | 3.24 | 3.24 | 3.23 | 3.03 |
| Post | 0.90 | 3.71 | 2.91 | 2.86 | 2.86 | 2.87 | 2.88 | 2.86 | 2.86 |
| Pre | | 3.49 | 3.42 | 3.39 | 3.40 | 3.41 | 3.47 | 3.35 | 3.36 |
| Post | 0.80 | 2.79 | 2.78 | 2.60 | 2.61 | 2.60 | 2.65 | 2.64 | 2.64 |
| Pre | | 3.02 | 3.54 | 3.40 | 3.44 | 3.55 | 3.63 | 3.47 | 3.32 |
| Post | 0.70 | 2.35 | 2.40 | 2.16 | 2.20 | 2.39 | 2.57 | 2.26 | 2.25 |

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Table I2 – Continued from previous page

| | $\pi_{\text{post}}$ | (A) | (B) | (C) | (D) | (E) | (F) | (G) | (H) |
|---|---|---|---|---|---|---|---|---|---|
| Pre | | 2.94 | 3.08 | 2.94 | 3.01 | 3.23 | 3.47 | 3.06 | 2.85 |
| Post | 0.60 | 2.03 | 2.11 | 1.72 | 1.98 | 2.23 | 2.41 | 2.05 | 2.05 |
| Pre | | 2.79 | 2.97 | 2.83 | 2.88 | 3.14 | 3.58 | 2.99 | 2.60 |
| Post | 0.50 | 1.71 | 1.95 | 1.53 | 1.62 | 2.12 | 2.52 | 1.94 | 1.94 |
| Pre | | 2.34 | 2.70 | 2.32 | 2.37 | 2.80 | 3.41 | 2.86 | 2.34 |
| Post | 0.40 | 1.58 | 1.81 | 1.35 | 1.46 | 1.91 | 2.42 | 1.79 | 1.79 |
| Pre | | 2.29 | 2.35 | 2.22 | 2.26 | 2.71 | 3.31 | 2.36 | 1.99 |
| Post | 0.30 | 1.34 | 1.68 | 1.23 | 1.25 | 1.95 | 2.30 | 1.50 | 1.50 |
| Pre | | 1.96 | 2.09 | 1.96 | 2.01 | 2.51 | 2.89 | 2.12 | 1.77 |
| Post | 0.20 | 1.15 | 1.32 | 1.04 | 1.05 | 1.81 | 2.41 | 1.30 | 1.30 |
| Pre | | 1.86 | 1.97 | 1.79 | 1.96 | 2.41 | 2.94 | 2.02 | 1.64 |
| Post | 0.10 | 1.00 | 1.02 | 0.97 | 0.98 | 1.71 | 2.49 | 1.02 | 1.01 |
| Pre | | 1.71 | 1.84 | 1.65 | 1.64 | 2.28 | 2.91 | 1.85 | 1.56 |
| Post | 0.00 | 0.93 | 0.96 | 0.92 | 0.93 | 1.65 | 2.45 | 0.96 | 0.95 |
| *Panel B: $S^m$* | | | | | | | | | |
| Pre | | 21 | 32 | 32 | 32 | 32 | 32 | 32 | 34 |
| Post | 0.90 | 42 | 55 | 59 | 59 | 59 | 58 | 59 | 59 |
| Pre | | 50 | 58 | 62 | 62 | 61 | 59 | 58 | 71 |
| Post | 0.80 | 107 | 107 | 116 | 115 | 113 | 110 | 113 | 113 |
| Pre | | 106 | 97 | 101 | 99 | 96 | 94 | 99 | 108 |
| Post | 0.70 | 175 | 162 | 182 | 177 | 167 | 153 | 172 | 172 |
| Pre | | 148 | 149 | 161 | 150 | 145 | 140 | 150 | 165 |
| Post | 0.60 | 254 | 225 | 251 | 248 | 224 | 197 | 238 | 238 |
| Pre | | 179 | 168 | 182 | 178 | 162 | 151 | 168 | 183 |
| Post | 0.50 | 378 | 305 | 335 | 333 | 297 | 248 | 323 | 323 |
| Pre | | 234 | 197 | 237 | 229 | 211 | 196 | 194 | 217 |
| Post | 0.40 | 481 | 400 | 433 | 429 | 374 | 305 | 424 | 424 |
| Pre | | 272 | 242 | 265 | 262 | 233 | 216 | 247 | 262 |
| Post | 0.30 | 618 | 512 | 550 | 543 | 471 | 367 | 534 | 534 |
| Pre | | 341 | 313 | 341 | 339 | 288 | 254 | 310 | 329 |
| Post | 0.20 | 733 | 618 | 669 | 662 | 577 | 426 | 642 | 642 |
| Pre | | 379 | 363 | 359 | 357 | 317 | 274 | 347 | 399 |
| Post | 0.10 | 787 | 725 | 811 | 791 | 667 | 488 | 763 | 763 |
| Pre | | 458 | 414 | 408 | 424 | 367 | 287 | 413 | 442 |
| Post | 0.00 | 899 | 837 | 972 | 932 | 760 | 540 | 880 | 880 |

*Note:* This table reports averages, across GSIBs and within-period dates, of measured distances to default and model CDS rates, for the robustness scenarios (A)–(H) and associated data-consistent pairs of bailout probabilities in Table I1. Model CDS rates are computed as in (D1) and reported in basis points.

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