Option-Based Pseudo Banks

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This Version: November 15, 2023

Preliminary Draft

Not for circulation

Abstract

We build a fictitious but empirically observable macroeconomy in which pseudo firms (Culp, Nozawa, and Veronesi, 2018) invest in traded assets by borrowing from fictitious pseudo banks. Pseudo banks' assets are then comprised of observable pseudo bonds, i.e. portfolios of risk-free bonds minus traded put options. All shocks in the pseudo economy are observable. We run "what if" experiments to assess the causal impact of shocks to pseudo firms' fundamentals on pseudo banks' balance sheets. The distribution of pseudo banks' asset returns is strongly negatively skewed and leptokurtic. Large shocks to fundamentals induce joint defaults of pseudo banks, even when they only make safe loans and risk concentration is limited. Countercyclical capital buffers mitigate the impact of economic shocks.

*For their comments, we thank seminar participants at the New York Fed. The views expressed herein are the authors' and do not necessarily reflect those of any institutions with which any of the authors are affiliated. Veronesi acknowledges financial support from the Fama-Miller Center for Research in Finance and by the Center for Research in Security Prices at the University of Chicago Booth School of Business. Contact information: Yoshio Nozawa: yoshio.nozawa@rotman.utoronto.ca; and Pietro Veronesi: pietro.veronesi@chicagobooth.edu.

1. Introduction

Macro-prudential regulations aim to increase the stability of the banking system, as opposed to just individual banks, by identifying policies that decrease the impact of systemic shocks on the cross-section of banks. An increase in regulatory capital and caps to the riskiness of bank loans and mortgages, for instance, increase the stability of all banks. Countercyclical capital buffers are also believed to help stabilize the banking system. Policymakers, however, must rely on complicated quantitative models to perform the proper calculations and determine regulatory capital requirements. Such models need to be calibrated to the data to provide insights on the impact of shocks to the economy on the banking system. In this paper, we study similar questions but from a different, complementary angle. Specifically, we extend the logic of "pseudo firms" introduced in Culp, Nozawa, and Veronesi (2018) to "pseudo banks" and study the impact of shocks to pseudo firms' fundamentals on the "pseudo banking system" and their channel of transmission through portfolios of loans. Our purely data-driven analysis allows us to run "what if" experiments on various proposals about capital requirements and safe lending that cannot be run using real banks, for obvious reasons. Such "what-if" experiments also allow us to trace the causal chain of events from shocks to economic fundamentals to the banking sectors and joint defaults.

But first, what are pseudo firms and pseudo banks? A pseudo firm, introduced in Culp, Nozawa, and Veronesi (2018), is a fictitious entity that invests its assets in a tradeable security, or commodity, by borrowing using zero-coupon debt. The balance sheet of a pseudo firm is fully observable at high frequency, as the asset side of the balance sheet is simply the observable value of the tradeable security, and from the classic Merton (1974) equation, the debt on the liability side of the balance sheet can be calculated from a portfolio that is long Treasuries and short a put option on the tradeable security. The difference from Merton (1974) is that we do not need a formula to compute the put option price, as we can directly use the value of traded put options to calculate the value of debt. Culp, Nozawa, and Veronesi (2018) show that these pseudo bonds – portfolios long Treasuries and short put options – have empirical features that closely mimic the ones of traded corporate bonds.

In this paper, we extend this logic to pseudo banks. A pseudo bank is another fictitious entity that makes loans to pseudo firms. As mentioned, each pseudo firm uses such loans to buy a tradeable security, say shares of individual stocks, or commodities, or other traded assets. We treat such investments in underlying traded securities as the "fundamentals" in our pseudo economy. The benefit of this assumption is that we can measure the shocks to such fundamentals. Such shocks will affect the balance sheets of the pseudo firms and thus the values of their debt. The balance sheet of the pseudo bank is nothing more than a portfolio of pseudo bonds, and thus we can study its empirical characteristics. In particular, we can now study the *causal* impact of shocks to firms' fundamentals (which are observable) onto the pseudo banks' balance sheets (which are also observable). Because then pseudo banks' assets are comprised solely of portfolios of pseudo bonds, we exploit the empirical returns on pseudo bonds to compute the empirical distribution of pseudo banks' assets and thus their default risk and minimum capital requirements. Moreover, by extending the analysis to multiple pseudo banks with random loan portfolios, we find the empirical relation between potential losses *across* pseudo banks and the shocks to pseudo-firms' fundamentals, which are observable in our setting.

Our empirical results suggest that common fundamental shocks to the individual firms' assets (which are observable for pseudo firms) are greatly amplified by the leveraged nature of bank loans, leading to severely negatively skewed and leptokurtic return distributions of pseudo banks' assets. We show that while fundamental assets' returns have mild negative skewness (-0.62) and mild excess kurtosis (1.76), returns on portfolios of pseudo loans are far more negatively skewed (-2.31) and display a very high excess kurtosis (13.56). Interestingly, when we divide the types of banks between Investment-Grade (IG) banks, which only make "safe" loans with low probability of default, and High-Yield (HY) banks, which make only risky loans, the excess kurtosis of IG banks is especially high, at over 15. That is, banks with "safe" loans are especially sensitive to fundamental shocks, which suddenly make their losses very high. That is, the right-tail of the loss distribution of IG banks is very long.

Because we can also trace the impact of common shocks to the fundamentals of pseudo firms (again, which are observable), we can correlate such shocks directly with the shock to the asset side of the balance sheet of pseudo banks. For instance, we find that a 4-standard deviation shock to fundamentals translates into an over 7-standard deviation shock to the balance sheet of pseudo banks. Indeed, for IG pseudo-banks, the impact is stronger, as a 4-standard deviation shock to fundamentals of pseudo firms translates into an over 9-standard deviation shock to their asset values.

Fundamental shocks to pseudo-firms, moreover, affect the cross-section of pseudo banks that make loans to the same universe of pseudo firms but whose portfolios are otherwise randomly assigned. Our firms have in principle thousands of types of different investment assets they can invest in (as they invest in the stocks of publicly traded companies), and with different levels of leverage. We randomly generate 1000 portfolios of pseudo loans and assign them to different pseudo banks. In essence, we randomly generate 1000 different pseudo banks month by month. We find empirically that fundamental shocks to the economy percolate through the banking sector, generating correlated losses in their portfolios. Interestingly, our pseudo-banking system does not have an interbanking sector and therefore there is no notion of a "domino effect." Yet, correlated defaults occur nonetheless from the combination of common aggregate shocks to underlying assets and the amplification effect from leverage. We show that such default occurs during recessions, with the caveat, however, that due to sample limitations, our recessions only contain the 2008 crisis and the 2020 Covid shock.

Finally, we emphasize that our fundamental shocks may be due to common discount rate shocks – that is, the increase in risk premium that investors require to hold risky securities. Such discount rate shocks affect the valuation of debt across the universe of loans, and act as a common factor in reducing the asset value of the banking system, hence inducing correlated defaults. Thus, our results highlight the discount rate channel as a key determinant of banks' risks.

We then discuss the impact of various capital requirements. We first show that the 99% VaR threshold under the normal distribution assumption using the 36-month trailing volatility to compute the capital requirement generates nearly three times as many violations as predicted by the 99% VaR. Moreover, such violations cluster in recessions and they are correlated across randomly generated pseudo banks. This finding holds for both IG banks and HY banks. Note that IG banks make only safe loans, which can be interpreted as those requiring a low loan-to-value ratio, as per recent macro-prudential regulation. Yet, the results are similar due to the extreme skewness and kurtosis of pseudo banks' asset values for IG banks.

To address the extreme skewness and kurtosis of pseudo-bank asset returns, we consider different VaR thresholds, set up to take into account the whole empirical distribution of pseudo bank assets and calibrated to match the 2008 default frequency. We find that a much higher multiple of volatility (7.15%) is required to obtain a default rate in 2008 consistent with the actual default rate in the banking sector. Using this higher threshold as the multiplier to trailing volatility, we do find a decrease in default frequencies compared to the normal distribution (not surprisingly). However, we also find that a much more conservative threshold to volatility would have not been sufficient to defend the (pseudo) banking sector from the Covid shock. In our data, the Covid shock represented a 10 standard deviation shock to the asset of the pseudo-banking sector, which would have generated correlated defaults at the staggering level of 20% in 2020. Part of this large default rate is that we ascribe "default" when the monthly decline in asset value is above the capital buffer. As we know, the monthly decline in equity in March 2020 was the largest monthly decline in history. According to our pseudo-economy, a large fraction of (pseudo) banks should have gone under. Even with this caveat, our results are consistent with the analysis by Feldman and Schmidt (2021) arguing that the impact of the 2020 Covid shock on the banking system was largely muted by the large indirect government support to the banking system.

Finally, as additional "what if" experiments, we study the impact of another proposal of macro-prudential regulation: countercyclical capital buffers and risk concentration limits. As for the former, we consider the simple strategy of requiring that the VaR threshold for capital buffers increases when volatility decreases for all simulated pseudo banks. In our calibration, which matches the average VaR volatility to the overall sample volatility, we find that the 99% VaR target hits the proper 1% of violations, as it should. However, again, such violations are concentrated in recessions. Still, the number of violations in recessions is far smaller than in the earlier case when the capital ratio depends on the trailing volatility, thereby indicating that imposing a countercyclical capital buffer may be a good macroprudential regulation policy to defend the integrity of the banking system. As for the regulation on risk concentration, our what if experiments show that while concentration in lending leads to a slightly higher frequency of joint defaults when countercyclical capital buffers use a relatively small threshold, concentration in lending actually slightly reduces the frequency of joint defaults when countercyclical capital buffers are set at a larger threshold. The reason is that risk concentration increases the impact of individual large loans, reducing pseudo banks' exposure to large common economic shocks.

We emphasize that our framework allows us to study the causal effect of economic shocks to fundamentals of (pseudo) firms on the (pseudo) banking sector by exploiting real world shocks over the last 20 years. However, our framework does not include the feedback effect from the (pseudo) banking sector back to the pseudo economy, and thus it is not equipped to answer questions about amplification effects from credit crunches. However, our empirical results may serve as benchmark for empirical work that aims at studying the feedback effect from banks back to the economy.

Our paper is related to several strands of literature. First, our framework is related to the literature that uses traded option prices to learn about the value of assets and liabilities of firms. Besides Culp, Nozawa, and Veronesi (2018) cited earlier, Kelly, Lustig, and Van Niewerburgh (2016) use option prices to estimate the value of the implicit government guarantee to the banking sectors during the 2007-2009 financial crisis; Berndt, Duffie, and Zhu (2023) assess the value of government bailout from banks' credit default swap (CDS) spreads and option prices; Coval, Jurek, and Stafford (2009) and Collin-Dufresne, Goldstein and Yang (2012) use options to study the underpricing of CDO's. Our paper is also related to the literature that studies the riskiness of banks. Recently, Nagel and Purnanandam (2020) argue that since banks' assets are mainly comprised of loans, their distribution would violate Merton's log-normal assumption, and thus propose another Merton-style model that is tailored to bank assets specificity. Their model is still analytical in nature, like other variations of Merton's models in the literature (see Sundaresan (2013) for a review), while our framework is fully empirical in nature. Begenau, Piazzesi, and Schneider (2015) use call-report data to estimate banks' sensitivity to interest rates and credit risk. Our paper gets at similar questions, but within our pseudo economy. Finally, our paper is related to the literature on macro-prudential regulation. Hanson, Kashyap, and Stein (2011) provides an overview of the micro- and macro-prudential tools and a specific proposal on how macro-prudential regulation may be designed. Aikman, Bridges, Kashyap, and Siegert (2019) review macro-prudential regulation tools in the aftermath of the 2008 crisis and studies whether these new tools would have prevented the 2008 crisis. Jeanne and Korinek (2020) studies a model of optimal macro-prudential regulation, when policymakers can also respond ex-post to a financial crisis.

The paper develops as follows: Next section introduces the pseudo economy, and along the way, briefly reviews the concept of pseudo firms from Culp, Nozawa, and Veronesi (2018). Section 3 discusses the empirical approach, and outlines the first results. Section 4 discusses capital regulations using 99% VaR, and discusses the clustering of (pseudo) bank defaults. Section 5 discusses the positive impact of macro-prudential regulation, countercyclical capital buffers, and concentration limits. Section 6 concludes. The appendix contains some additional empirical results for robustness.

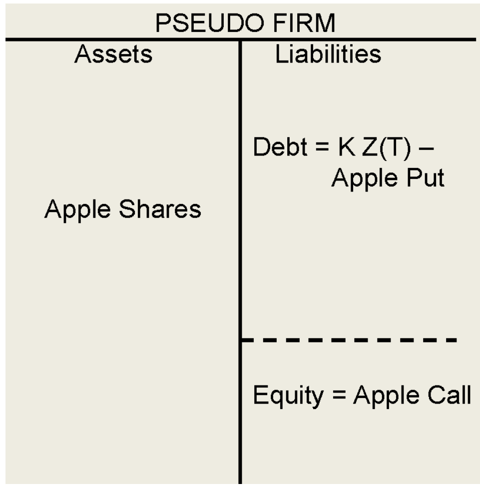
2. The Pseudo Economy

We build a "simple economy" in which a pseudo bank makes several loans to many pseudo firms, and we study the propagation of shocks to fundamentals of the pseudo firms to the pseudo banks that make the loans to them. We must first briefly describe the framework of Culp, Nozawa, and Veronesi (2018, CNV henceforth). We first review CNV's definition of pseudo firms and pseudo bonds and their characteristics.

2.1. Pseudo Firms and Pseudo Bonds

In this section, we review the notions of pseudo firms and pseudo bonds. A pseudo firm is a fictitious firm with a fully observable balance sheet. To be concrete, consider a pseudo firm that issues a zero-coupon bond and equity and uses the proceeds to purchase shares of Apple

Figure 1: The Balance Sheet of a Pseudo Firm



Notes: This diagram represents the assets of a fictitious pseudo firm investing in Apple stock. Pseudo firms are hypothetical firms that purchase shares of underlying traded firms, such as Apple, and that finance those purchases by selling equity and zero-coupon bonds. The values of these zero-coupon bonds are given by safe U.S. Treasury zero-coupon bonds minus traded put options on the underlying firms, in this case, put options on Apple. The balance sheet of pseudo firm is fully observable.

Inc. In what follows, we will have several pseudo firms, which we index by $i = 1, ..., N$. Let then $A_{i,t}$ be the market value of the Apple stock that pseudo firm i purchases at time t, and let $K_{i,t}$ denote the face value of the zero-coupon debt that the firm issues at t. Let $t + \tau$ be the debt's maturity.

If on date $t + \tau$, the assets of the firm are worth $A_{i,t+\tau} > K_{i,t}$, then debt holders receive the face value of debt $K_{i,t}$. Alternatively, the value of the firm's assets is inadequate to repay debt holders fully, in which case the firm defaults, debt holders take over the firm and liquidate its assets, and debt holders receive the market value of the firm's assets $A_{i,t+\tau}$. The payoff to debt holders at time $t + \tau$ is then

$$\text{Bond Payoff at } t + \tau = \min(K_{i,t}, A_{i,t+\tau}) = K_{i,t} - \max(K_{i,t} - A_{i,t+\tau}, 0) \tag{1}$$

The value at t of a τ-period zero-coupon defaultable bond is given by the value of risk-free debt minus the value of a European put option on the assets of the firm expiring on date $t + \tau$ with a strike price equal to the face value of the bond, $K_{i,t}$. Because the firm's assets are comprised solely of the Apple shares, the put option in this case is an option on Apple stock, which has an observable price $\widehat{P}_t^{Apple}(t + \tau, K_{i,t})$. Thus, denoting by $\hat{Z}_t(t + \tau)$ the observable value of a risk-free zero-coupon bond at t with maturity $t + \tau$, by no-arbitrage the value of defaultable debt is:

$$\widehat{B}_t\left(t+\tau, K_{i,t}\right) = K_{i,t}\widehat{Z}_t(t+\tau) - \widehat{P}_t^{Apple}(t+\tau, K_{i,t}). \tag{2}$$

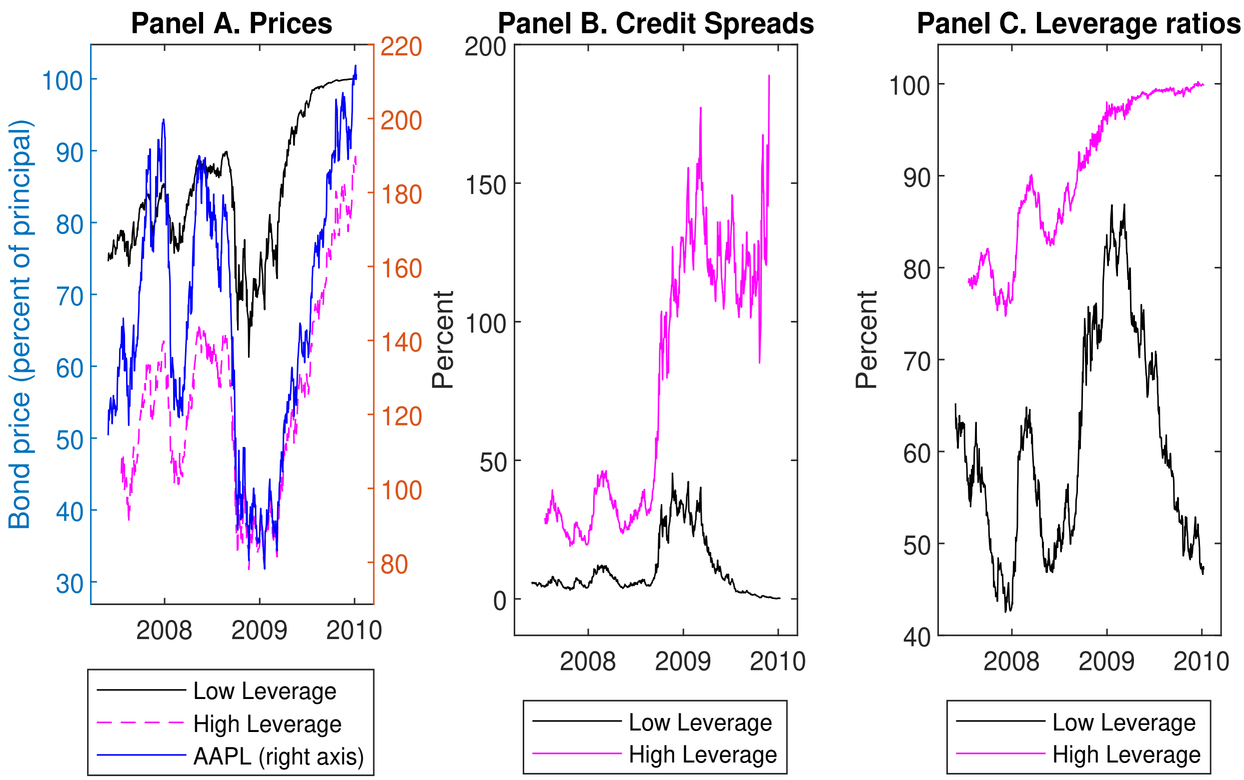
A "hat" indicates that the price is directly observable. We rely on Treasuries and Apple put option data to compute the empirical properties of pseudo bonds $\widehat{B}_t(t+\tau, K_{i,t})$. We note that the pseudo firm cannot become insolvent prior to the $t+\tau$ debt maturity date.[1] Figure 1 depicts the balance sheet of the pseudo firm that invests in Apple stocks. Both assets and liabilities are observable at high frequency.

We compute the credit spread on the pseudo bond issued by pseudo firm i at time t with time to maturity τ relative to Treasury bonds as $\widehat{cs}_{i,t}(\tau) = \widehat{y}_{i,t}(\tau) - \widehat{r}_t(\tau)$, where $\widehat{y}_{i,t}(\tau)$ and $\widehat{r}_t(\tau)$ are the semi-annually compounded zero-coupon yields for the pseudo bonds and the Treasury bond, respectively. We refer to these credit spreads as *pseudo spreads*. Similarly, we compute the returns on pseudo bonds in the same way.

To illustrate, Figure 2 shows the values of debt (i.e. pseudo bond), the credit spreads, and the leverage of two pseudo firms that invest in Apple stocks. The two pseudo firms differ in that one has low leverage and the other has high leverage. Leverage is fully determined by the strike price of the traded put option that we use in formula (2). Panel A shows the value of Apple shares (blue line, the right axis), and the two pseudo bond prices (black and purple lines), around the 2008 crisis. Again, the values of the pseudo bonds are observable as they are computed using equation (2), that is, from Treasuries and traded put option prices on Apple stock. As it can be seen, the low-leverage pseudo bond has a large drop in value around 2008, but then recovers and pays its principal in full. Instead, the high-leverage pseudo bond has an even bigger drop, but then never recovers fully and defaults at maturity. Panel B plots the corresponding credit spreads: Both credit spreads increase substantially during the 2008 crisis, but the low-leverage pseudo credit spreads then drop back to (near) zero, as the probability of default declines. In contrast, the high leverage pseudo bond has a large credit spread up to maturity, when it becomes clear that it would default. Finally, Panel C shows the leverage ratios, computed as $\widehat{B}_t\left(t+\tau, K_{i,t}\right)/A_{i,t}$, of the pseudo firms over time, with leverage shooting up during the credit crisis for both pseudo-firms. At maturity $t+\tau$, the debt of the high-leverage pseudo firms converges to $\widehat{B}_{i,t+\tau}(t+\tau, K_{i,t}) = K_{i,t} - max(K_{i,t} - A_{i,t+\tau}, 0) = A_{i,t+\tau}$ and thus leverage converges to 100%, when it defaults.

[1] In the United States, a firm is "insolvent" under the U.S. bankruptcy code in any of three situations: (i) it cannot pay its bills when they are due; (ii) it is inadequately capitalized; or (iii) the market value of its assets is less than the face value of its total outstanding debt at *or before* the dates on which the debt matures. (*See* Heaton (2007).) Following Merton (1974), we assume here that insolvency can only occur in situation (i) on the maturity date of the debt.

Figure 2: Pseudo Bond Prices and Pseudo Credit Spreads

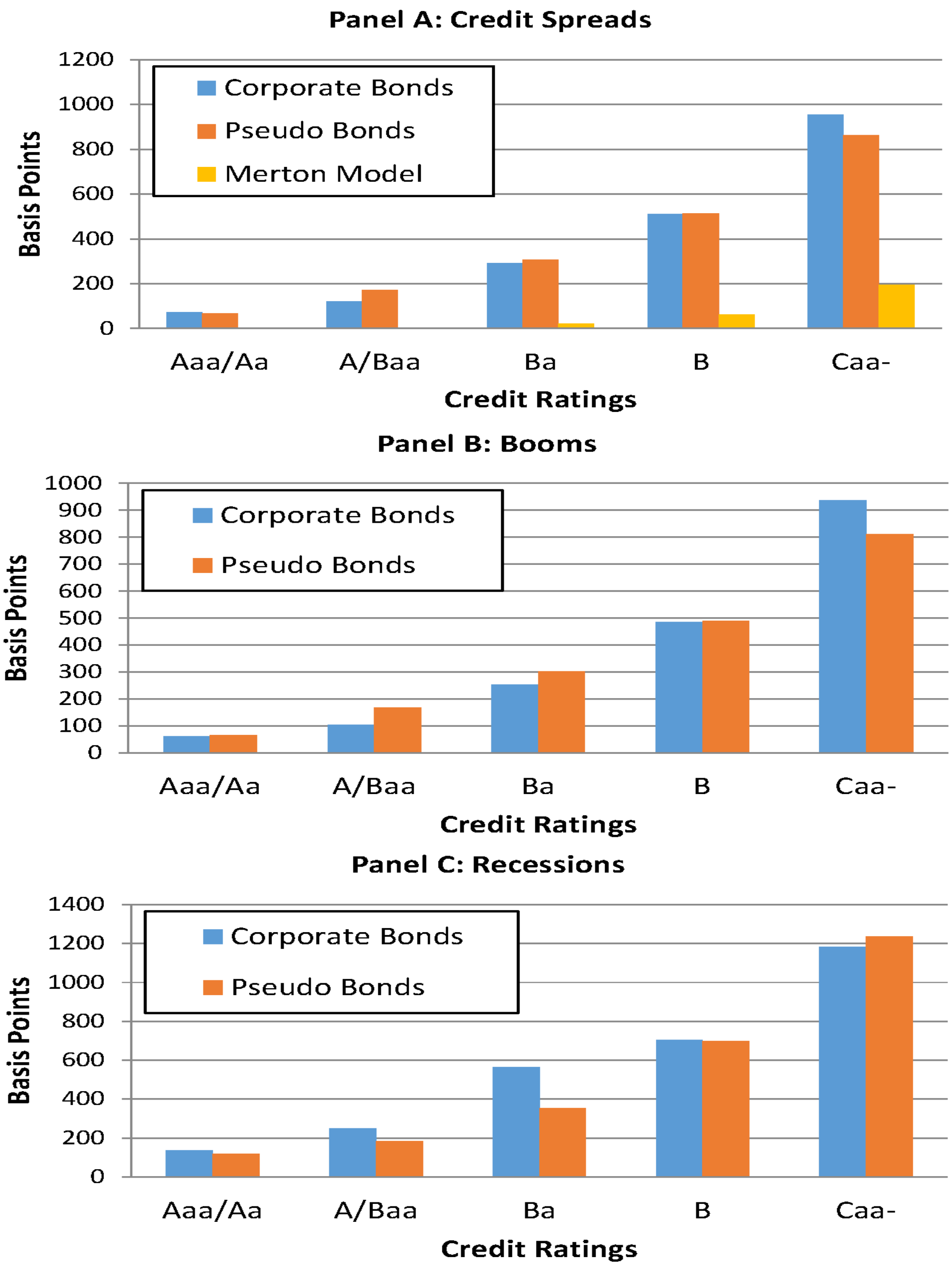


Notes: Panel A shows the value of Apple shares (right axis), and the two pseudo bond prices (left axis), around the 2008 crisis. The values of the pseudo bonds computed using $\widehat{B}_t\,(t+\tau, K_{i,t}) = K_{i,t}\widehat{Z}_t(t+\tau) - \widehat{P}_t^{Apple}(t+\tau, K_{i,t})$ where $\widehat{Z}_t(t+\tau)$ are Treasury zero-coupon bonds, and $\widehat{P}_t^{Apple}(t+\tau, K_{i,t})$ are traded put option prices on Apple stock. Panel B plots the corresponding credit spreads and Panel C plots the leverage ratios of the two pseudo firms. Data are from OptionMetrics, CRSP, and FRED.

We note that the full balance sheet of the pseudo-firms is observable, which is a critical point as we can then trace the shocks to the economy into shocks to the banks through the exact observation of what happens to the assets and liabilities of pseudo firms.

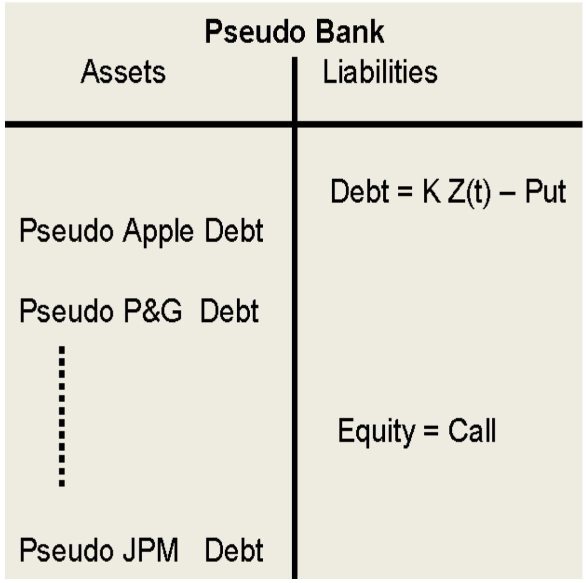
Culp, Nozawa, and Veronesi (2018) document that the pseudo-bonds' credit spreads are very similar to traded corporate bond credit spreads. Figure 3 reports the pseudo-bond credit spreads across credit ratings both on average over the sample 2001 - 2015 (Panel A) and during booms and recessions (Panels B and C, respectively). Panel A also reports the credit spreads under the log-normal assumption of the Merton model, according to which the put option in equation (2) is computed using the Black, Scholes, and Merton formula, instead of using, as we do, traded option prices. Culp, Nozawa, and Veronesi (2018) compute the credit rating of the pseudo bonds by matching the predicted default probability of a pseudo

Figure 3: Pseudo Bond and Corporate Bond Credit Spreads



Notes: Credit spreads are shown for corporate bonds, pseudo bonds, and implied by the log-normal Merton model (in panel A). For corporate bonds, the credit ratings are from Moody's. For pseudo bonds, the credit ratings are imputed by comparing their ex ante default probabilities to Moody's default frequencies in booms and in recessions. For each pseudo bond, we compute its default probability from the empirical distribution of asset returns. For the Merton model, the default probability is obtained from its implied log-normal distribution. The sample is 1990–2015 for real corporate bonds, and 1996–2015 for pseudo bonds.

Figure 4: The Balance Sheet of a Pseudo Bank



Notes: This diagram represents the assets of a fictitious pseudo bank that lends money to the pseudo firms. Pseudo firms are hypothetical firms that purchase shares of underlying traded firms, and that finance those purchases by selling equity and zero-coupon bonds. The values of these zero-coupon bonds are given by safe U.S. Treasury zero-coupon bonds minus traded put options on the underlying firms. In the figure, the pseudo bank purchases the pseudo bonds, which then form its loan asset portfolio, and finances the acquisition of its portfolio by issuing equity and short-term zero-coupon debt. The value of the asset sides of the pseudo bank is fully observable.

bond with the average default frequencies from Moody's. The matching of the pseudo credit spreads and corporate credit spreads, and their large increase during recessions, provide confidence that the valuation of pseudo bonds is in line with those of corporate bonds, and thus that our empirical analysis below on their impact on pseudo banks' balance sheets is empirically relevant.

2.2. The Pseudo Bank

Culp, Nozawa, and Veronesi (2018) document that pseudo bonds and real corporate bonds are quite similar along many dimensions and demonstrate how pseudo bonds can be utilized to study questions related to credit spreads. In this section, we show we can exploit the pseudo firms to study the source and the size of tail risk in bank lending, its impact on bank default risks, systemic risk, and macro-prudential regulation.

Consider a hypothetical bank that makes zero-coupon commercial loans to our single-stock pseudo firms. Equivalently, the "pseudo bank" purchases pseudo bonds from the pseudo firms to which it extends credit. Figure 4 shows a schematic representation of the pseudo bank's balance sheet, which is comprised of several pseudo bonds that are issued from the various pseudo firms. Each pseudo bond value is observable and given by equation (2). The asset side of the balance sheet of the pseudo bank is fully observable at a relatively high frequency, from the observed risk-free rates and put option prices. There is no modeling required for this calculation.

The pseudo bank defaults if the market value of its assets is below the face value of the bank's debt when that debt matures. We assume the pseudo bank finances itself by issuing short-term liabilities, such as commercial paper or demand deposits. For every t, default of the pseudo bank thus occurs if

$$A_t^{Bank} < K_{t-1}^{Bank},$$

where K_{t-1}^{Bank} is the total face value of short-term debt issued by the pseudo bank in previous month $t-1$. Given that the bank's assets are a portfolio of pseudo bonds issued by the bank's pseudo firm borrowers, we have $A_t^{Bank} = A_{t-1}^{Bank}(1 + R_{t-1,t}^{Port})$, where $R_{t-1,t}^{Port}$ is the return on the portfolio of bonds between $t-1$ and t. Therefore, the requirement for one-month survival for the bank is

$$R_{t-1,t}^{Port} > -(1 - \frac{K_{t-1}^{Bank}}{A_{t-1}^{Bank}}) = -(1 - L_{t-1}^{Bank}),$$

where L_{t-1}^{Bank} is the bank's leverage ratio at $t-1$. All the quantities in this equation are observable. In particular, by choosing K_{t-1}^{Bank}, we can study the impact of various capital requirements on the frequency and correlation of defaults of banks, through its impact on bank leverage $L_{t-1}^{Bank} = \frac{K_{t-1}^{Bank}}{A_{t-1}^{Bank}}$.

2.3. The Pseudo Economy and Shock Propagation

Putting everything together, we can now look at Figure 5. On the left-hand-side of the figure are the set of pseudo firms' fundamental investment assets, namely, the stocks of publicly traded firms. Like any investment assets, their values depend on the gyrations of the economy. The difference between real firms and pseudo firms is that we can fully observe the value of the investment assets of pseudo firms. Moreover, as shown in the middle and discussed earlier, we can also fully observe the value of the liabilities of pseudo firms, and especially the value of their loans obtained from the pseudo banks. Lastly. the right-hand-side has (one) pseudo bank that makes such pseudo loans. The value of the assets of the pseudo-banks is also fully observable.

The figure also highlights that shocks to fundamental assets propagate through the system to the balance sheet of pseudo banks. Because we can observe the value of fundamental assets, we will be able to compare *empirically* shocks to fundamental assets, on the left-hand-side of the figure, with shocks to the pseudo bank's assets, on the right-hand-side of the figure.

3. Empirical Analysis

3.1. Data

We rely on data from the Center for Research in Security Prices (CRSP) for individual stock prices. Our daily prices on options on individual stocks from January 4, 1996, through December 31, 2022, are from the OptionMetrics Ivy database. To filter our data, we generally follow the approach of Constantinides, Jackwerth, and Savov (2013) for SPX options in order to minimize the effects of quotation errors and the methodology of Frazzini and Pedersen (2012) for individual equity options. In addition, we obtain our risk-free rate from the Federal Reserve Economic Data (FRED) database.

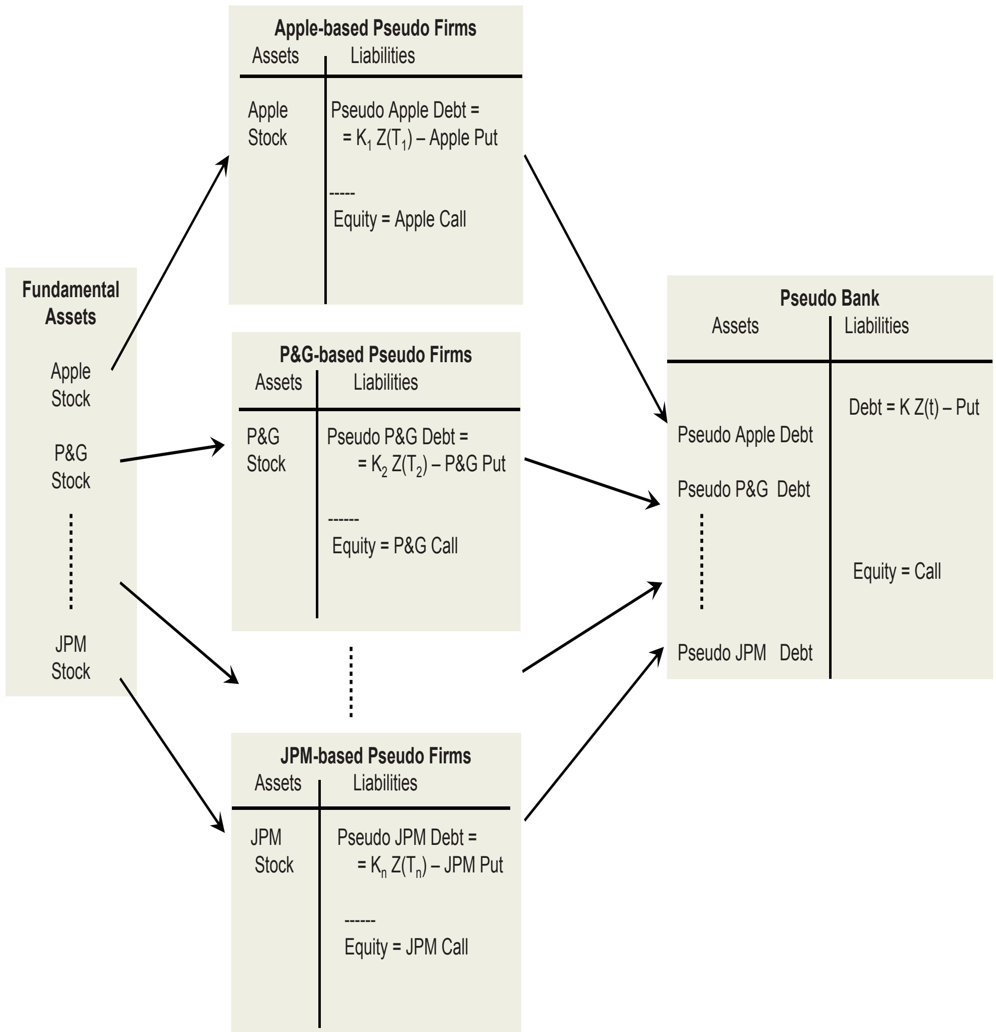
3.2. 1,000 Random Pseudo Banks

In this section, we use the data described in the previous section to construct returns on the bond portfolios of pseudo banks. We consider three types of pseudo bond portfolios that comprise the assets of a pseudo bank. The first is an "ALL " portfolio consisting of pseudo bonds diversified by maturity and credit rating. In addition, we consider IG and HY portfolios that contain only pseudo bonds with credit ratings above (and equal to) or below Baa, respectively. Although the IG and HY portfolios are distinguished by credit quality, we assume that both portfolios are diversified across maturities. The pseudo bank only extends one loan to each pseudo firm.

We construct pseudo bank loan portfolios to have approximately constant characteristics across our sample. We draw the maturities of our pseudo bonds from only three maturity bins – up to 273 days, 274 to 548 days, and 549 days or longer.[2] We also choose a minimum portfolio size $N = 20$ to ensure some diversification benefits for the pseudo bank. For every month t, for each firm and rating category, we randomly choose one maturity bin per pseudo

[2]We choose these three maturity bins because they are equally well-populated across the overall sample.

Figure 5: The Pseudo-Economy and Shock Propagation



Notes: This diagram represents the pseudo-economy comprised of fundamental assets on the left-hand-side, whose value is observable, the pseudo-firms that invest in such assets by borrowing from banks in the middle, and the pseudo-banks that lend to the pseudo-firms on the right-hand-side. As all values of fundamental assets are observable, shocks to the economy on the left hand side propagate through the individual pseudo firms to the pseudo-banks on the right-hand-side. Pseudo firms are hypothetical firms that purchase shares of underlying traded firms, and that finance those purchases by selling equity and zero-coupon bonds. The values of these zero-coupon bonds are given by safe U.S. Treasury zero-coupon bonds minus traded put options on the underlying firms. In the figure, the pseudo bank purchases the pseudo bonds, which then form its loan asset portfolio, and finances the acquisition of its portfolio by issuing equity and short-term zero-coupon debt.

Table 1: Distribution of Portfolio Returns

	Mean	Std	Skew	Excess Kurtosis	Percentiles Min	1	5	25	50	75	90	99	Max
	Panel A. Returns on Portfolios of Pseudo Bonds												
IG	0.23	0.63	-2.27	15.83	-6.21	-1.57	-0.72	-0.02	0.24	0.56	0.87	1.60	2.61
HY	0.48	1.83	-1.93	10.31	-12.08	-4.77	-2.49	-0.12	0.64	1.39	2.18	4.79	6.11
ALL	0.30	1.23	-2.31	13.56	-10.98	-3.64	-1.60	-0.12	0.42	0.93	1.44	2.93	6.73
	Panel B. Returns on Portfolios of Underlying Assets												
IG	0.42	3.74	-0.68	1.23	-19.48	-9.48	-6.48	-1.63	0.89	2.90	4.68	7.75	17.87
HY	0.59	5.00	-0.40	1.45	-20.24	-11.40	-8.74	-1.88	1.04	3.58	5.91	13.57	18.15
ALL	0.37	4.43	-0.62	1.76	-24.44	-11.56	-7.85	-1.86	0.87	3.09	5.18	10.36	21.91

This table reports the summary statistics of the panel data of pseudo bond portfolio returns and underlying asset returns. IG is for pseudo banks that invest only in IG-rated bonds, HY is for those that invest only in HY-rated bonds, and ALL is for those that split their portfolio into IG and HY-rated bonds. The sample is monthly from January 2003 to December 2022.

firm (borrower) and select one pseudo bond as the bank's loan to that firm. Some firms may have no pseudo bonds with the selected maturity/rating combination, in which case such firms are not part of the portfolio. For the IG and HY portfolios, if the number of firms with the selected pseudo bonds is more than N, we average them and record the portfolio returns. Otherwise, we have missing data for that month. For the "ALL" portfolio, if the number of IG firms is more than $N/2$, we randomly pick the same number of HY bonds as IG bonds and compute returns for the overall portfolio. This methodology ensures that the "All" portfolio has an equal representation of IG and HY pseudo bonds.

We repeat this procedure for every month in the 2003 – 2022 sample period. The sample before 2003 does not have a sufficient number of IG bonds for this analysis. In addition, we simulate this procedure 1,000 times to construct a wide variety of portfolios. Note that the simulation only pertains to the *choice of the portfolio* at any month t. The portfolio return itself is not simulated and is the actual market return for the chosen pseudo bonds. Because we consider 1,000 random portfolios, our results can be interpreted as representing 1,000 different random pseudo banks.

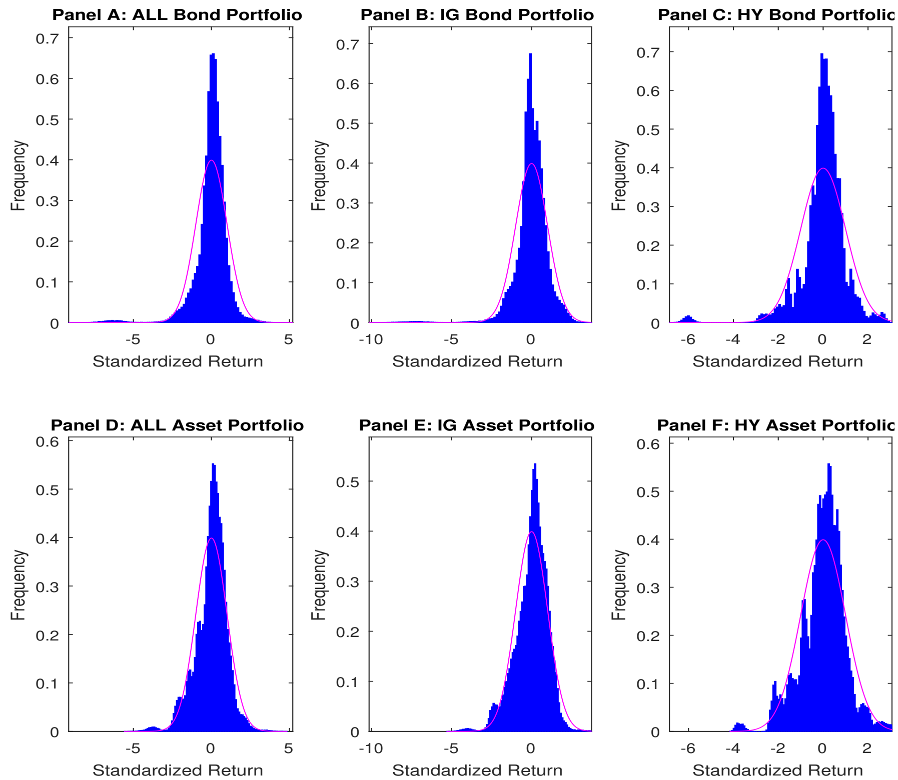
Table 1 reports the empirical distribution of both pseudo-bond portfolio returns and the underlying fundamental investment assets' returns. First, note that the portfolio of pseudo-bonds has a far lower standard deviation than the underlying assets. For instance, for the All portfolios, underlying assets have monthly standard deviation of 4.43% while pseudo bonds portfolios have standard deviation of only 1.23%. This is expected, given that these are bonds, and a large component of bonds is made up of very safe Treasuries. Moreover, the standard deviation of IG pseudo bond portfolios (0.63%) is much smaller than the standard deviation of HY pseudo bond portfolios (1.83%). Again, this is intuitive as IG pseudo bonds are less information sensitive and more insulated from shocks to fundamentals.

The critical distinction between pseudo bond portfolios and underlying fundamental assets is however in the skewness and kurtosis of the two types of return distributions. In essence, pseudo bond portfolios, aka pseudo bank assets, have a distribution of returns that is far more negatively skewed and leptokurtic than the distribution of underlying assets. For instance, while for the ALL portfolios, underlying assets have mild negative skewness (-0.62) and excess kurtosis (1.76), the pseudo bond portfolios have strong negative skewness (-2.31) and very high excess kurtosis (13.56). Indeed, the difference is even larger for the IG portfolios: While for the underlying assets the excess kurtosis of IG assets is just 1.23, the excess kurtosis for the corresponding pseudo bonds is 15.83, a huge tail risk, especially considering that IG pseudo bond portfolios are comprised of safe loans, i.e., those that have very low probability of default (above Baa) at inception.

Moreover, recall that in our pseudo economy, shocks to underlying investments assets *cause* the shocks to the pseudo bank assets, and therefore, the size of the amplification effect is clear from the observation of the tails of the distribution.

Panels A to C of Figure 6 show the return distributions of our pseudo bond portfolios. For comparison, Panels D to E show the return distributions of the portfolios of assets underlying the pseudo bond portfolios. All distributions are normalized to have a zero mean and unitary standard deviation for ease of comparison. Several results are apparent. First, the distributions of pseudo bonds (top row) are always more dispersed than the corresponding distributions of assets that underlie the pseudo bonds (bottom row) – *i.e.*, the diversification benefit in a portfolio of bonds is not as strong as for the portfolio of underlying assets inasmuch as diversification does not curtail the tails by the same amount. Second, the difference is large for all three portfolios, and especially for the IG and ALL banks. For the former, for instance, the underlying assets have a maximum negative standardized return of about four standard deviations below the mean, whereas the pseudo bond portfolio reaches ten standard deviations below the mean. Recalling that IG pseudo banks only make "safe loans" with low probability of default, these results show that such banks are especially prone to "Black Swans" (*i.e.*, low-frequency, high-severity events) even if the underlying individual asset distributions do not demonstrate such risks.

Figure 6: Pseudo Banks' Asset Returns and Fundamental Asset Returns



Notes: Panels A, B, and C show the distribution of bond returns that make up pseudo-bank assets, for all pseudo-banks, the ones that only make IG loans, and those that only make HY loans, respectively. Panels D, E, and F show the distribution of underlying asset returns – i.e. the corresponding stock returns that are the assets of the pseudo-firms – that correspond to the respective three panels. The distributions have been normalized to have zero-mean and unit standard deviations. The random portfolios are constructed as follows: For every month t, we consider all potential available pseudo bonds for all the firms with traded options. We group such bonds in credit rating / maturity bins. We consider only two credit ratings: Investment Grade (i.e. Aaa/Aa and A/Baa) or High Yield (i.e. Ba, B, Caa-) and only three maturity ranges (0,273), (274,548), (549, ∞). For each firm and for each rating, we randomly choose one maturity bin per firm, when available. For "All" portfolio (Panel A), if the number of IG firms is more than 10, then we randomly pick the same number of HY bonds as the IG bonds, and then compute the average across all the bonds. For the IG and HY portfolios, if the number of firms is more than 20, then we average them and record the portfolio returns. In either case, if the minimum number of firms condition is not met, we record a missing observation for the portfolio return in the month. This procedure is performed for every month t in the sample, and repeated 1,000 times to obtain return distributions.

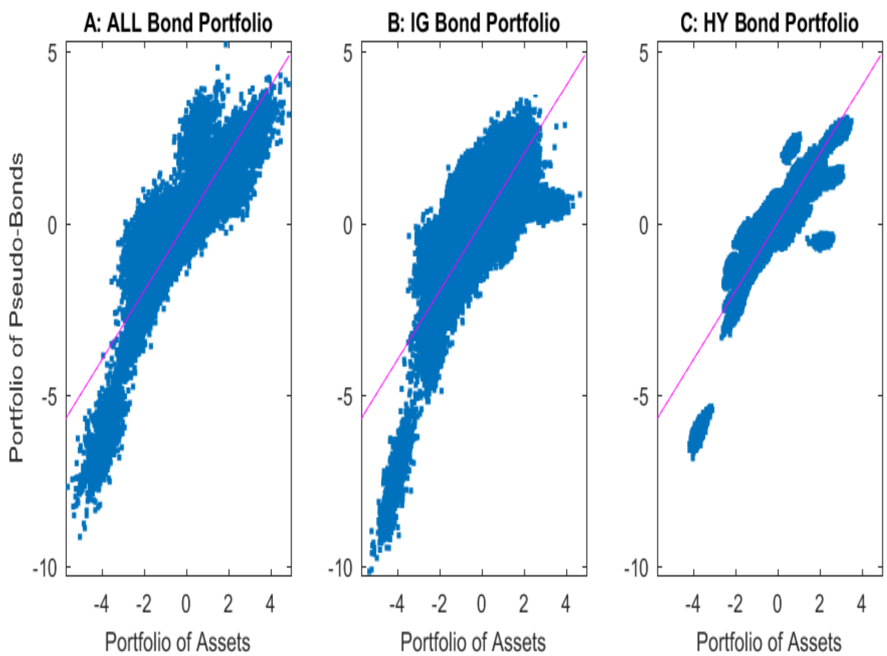
3.3. The Causal Impact of Shocks to Fundamentals on Pseudo Banks' Assets

We are interested in investigating both the tails of the distributions of the banks' assets, as well as the amplification effect of any shocks to the pseudo firms' fundamentals (*i.e.*, the assets of the pseudo firms, which are observable to us), on the values of pseudo bank assets. Both quantities can be gleaned by looking at Figure 7, which plots the distribution of standardized returns of the pseudo banks' portfolios against the standardized returns of the assets of the pseudo firms. Specifically, Panel A considers loans to ALL firms, while Panel B and C consider loans only to IG and HY firms, respectively. The ALL loan portfolios, recall, have equal representation of IG and HY loans. This latter case is one in which pseudo banks afford the most diversification, as they lend to both risky and less risky firms.

Focusing on Panel A, the scatter plot clearly shows the amplification of fundamental shocks to the assets of the pseudo firms on the assets of the pseudo banks. A three standard deviation shock to fundamentals (the $x-$axis) may easily translate into a five standard deviation shock to pseudo banks' assets (the $y-$axis), and a five standard deviation fundamental shock into an nine standard deviation shock to bank assets. Recall, moreover, that our loan portfolios are randomly assigned to the pseudo banks, which implies that these random portfolios would all lose value at the same time and thus may be considered a symptom of systemic risk. Indeed, the extreme negative realizations visible on the bottom left corner are due to just two dates (*i.e.*, October 2008 and March 2020), and several points on the scatter plot illustrate different combinations of returns across different random portfolios (pseudo banks) on that date. In other words, even if pseudo banks' loan portfolios are well-diversified across credit ratings and borrowers, the leverage of the pseudo bond portfolios and the comovements in the values of assets of pseudo firms are sufficient to generate a potential "Black Swan" scenario that could have a devastating effect on the bank itself (or, in fact, the banking sector as a whole).

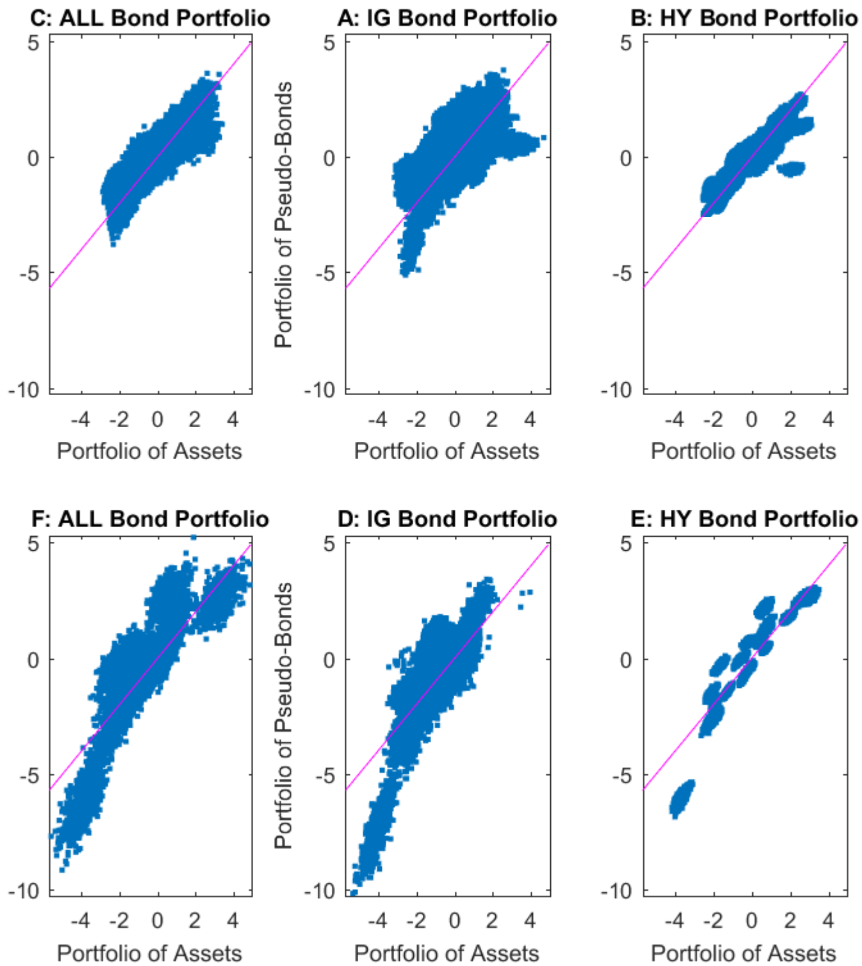
The reason for this amplification effect is that, although the standard deviation of the loan portfolios is normally very low (*i.e.*, bonds/pseudo bonds have normally low volatility), common negative shocks to fundamentals generate correlation *across* pseudo bonds. As is well known, higher bonds' default correlation strongly increases the tails of the banks' asset distributions. Finally, note that such common shocks to fundamentals are not likely driven by shocks to the cash flows across pseudo firms. Rather, they are more likely joint discount rate shocks that affect the valuation of the assets of all of the pseudo firms, thereby

Figure 7: Scatterplot of Pseudo Banks' Asset Returns versus Fundamental Asset Returns



Notes: Panels A, B, and C show the scatter-plot of pseudo bond portfolio returns versus underlying asset portfolio returns. The distributions have been normalized to have zero-mean and unit standard deviations. The random portfolios are constructed as follows: For every month t, we consider all potential available pseudo bonds for all firms with valid option data. We group such bonds in credit rating / maturity bins. We consider only two credit ratings: Investment Grade (i.e. Aaa/Aa and A/Baa) or High Yield (i.e. Ba, B, Caa-) and only three maturity ranges (0,273), (274,548), (549, ∞). For each firm and for each rating, we randomly choose one maturity bin per firm, when available. For "All" portfolio (Panel A), if the number of IG firms is more than 10, then we randomly pick the same number of HY bonds as the IG bonds, and then compute the average across all the bonds. For the IG and HY portfolios, if the number of firms is more than 20, then we average them and record the portfolio returns. In either case, if the minimum number of firms condition is not met, we record a missing observation for the portfolio return in the month. This procedure is performed for every month t in the sample, and repeated 1,000 times to obtain return distributions.

Figure 8: Scatterplot of Pseudo Banks' Asset Returns versus Fundamental Asset Returns: Booms and Busts



Notes: The top panels show the scatter-plot of pseudo bond portfolio returns versus underlying asset portfolio returns for the three types of pseudo banks during booms, and the bottom panles show the same during recessions. The distributions have been normalized to have zero-mean and unit standard deviations. The random portfolios are constructed as follows: For every month t, we consider all potential available pseudo bonds for all firms with valid option data. We group such bonds in credit rating / maturity bins. We consider only two credit ratings: Investment Grade (i.e. Aaa/Aa and A/Baa) or High Yield (i.e. Ba, B, Caa-) and only three maturity ranges (0,273), (274,548), (549, ∞). For each firm and for each rating, we randomly choose one maturity bin per firm, when available. For "All" portfolio (Panel A), if the number of IG firms is more than 10, then we randomly pick the same number of HY bonds as the IG bonds, and then compute the average across all the bonds. For the IG and HY portfolios, if the number of firms is more than 20, then we average them and record the portfolio returns. In either case, if the minimum number of firms condition is not met, we record a missing observation for the portfolio return in the month. This procedure is performed for every month t in the sample, and repeated 1,000 times to obtain return distributions.

generating a large tail event to pseudo banks that is attributable to discount rate shocks.[3]

Figure 8 plots the same scatterplots as in Figure 7, but we divide the sample in booms (top panels) and recessions (bottom panels). As it can be seen, the distributions are quite different in the two periods, showing the severe impact of recessions on the returns of bank assets. We note that in our sample (2003 - 2022), the only two recessions were the 2008 financial crisis and the 2020 Covid crisis, which had large impacts on the valuation of stocks, which comprise the assets of our pseudo firms. Still, the amplification effect of leverage is visible by comparing the range of the x-axis to the the range of the y-axis in the bottom panels. Note in particular that the IG bond portfolios is especially sensitive to large negative shocks of fundamentals.

Figure A1 in the appendix shows that a similar amplification effect occurs when we limit the number of pseudo bonds that each of the 1000 pseudo banks can buy to $N = 20$, 30, 50, 100. By limiting the number of pseudo bonds that pseudo banks can invest in, we greatly limit the overlap of pseudo banks' investments and increase the idiosyncratic risk of their assets. The effects are similar, and in fact, the tails of pseudo banks' assets become even more extended when N is small, due to a reduction in diversification opportunities.

4. 99% VaR and Correlated Defaults

In this section, we translate the distributions of portfolios of pseudo bonds in the previous section into default frequencies. Starting with the standard 99% Value-at-Risk normal assumption, we first assume that a pseudo bank is considered to be in default if its pseudo bond portfolio return goes below the threshold value determined by 3 standard deviation below the average.

Table 2 reports the percentage of observations that fall below the threshold from January 2003 to December 2022. We calculate the mean and standard deviation on the rolling 36-month basis. "IG" refers to banks that only invest in IG-rated pseudo bonds, while "HY" refers to banks that only invest in HY-rated bonds. "ALL" banks split their portfolio equally between IG and HY bonds.

There are two key observations: the number of violations is three times as big as it should according to the 99% VaR rule. This indicates that big shocks (e.g. 2008) occur after relatively calm periods, in which the standard deviation computed using the trailing average

[3] See e.g. Vuolteenaho (2002) on the role of discount rate shocks on individual stocks.

Table 2: Percentage of Defaulted Banks That Set Equity Following 1% VaR Rule

	Threshold = 3 σ_{t-1}			Threshold = 5 σ_{t-1}		
	IG	HY	All	IG	HY	All
Full sample	2.52	3.45	3.58	0.88	0.98	1.16
Booms	0.82	1.55	1.37	0.00	0.00	0.00
Recessions	22.00	19.16	24.46	10.91	9.09	12.08
2008 Financial Crisis	4.67	11.66	14.17	0.24	5.26	6.31
2020 Covid Shock	99.35	66.67	72.01	58.51	33.33	38.79

A pseudo bank is considered to be in default if its pseudo bond portfolio return goes below the threshold value determined by 3 (columns 1 through 3) or 5 (columns 4 through 6) standard deviation below the average. The table reports the percentage of observations that fall below the threshold from January 2003 to December 2022. We calculate the mean and standard deviation on the rolling 36-month basis. "IG" refers to banks that only invest in IG-rated pseudo bonds, while "HY" refers to banks that only invest in HY-rated bonds. "All" banks split their portfolio equally between IG and HY bonds.

is especially low.

Second, the VaR violations (defaults) are not iid, and they occur during the NBER recessions, which in our sample are unfortunately restricted to essentially the 2008 financial crisis and the 2020 Covid crisis, two "outliers" in terms of recession severity. From Column 3, 24% of all pseudo banks would have violated the VaR constraint and considered "failed". Interestingly, among IG banks the percentage is 22% (Column 1) while among HY banks the percentage is 19% (Column 2). The reason is that the standard deviation of assets of IG firms is smaller ahead of the crisis, and therefore the highly negative shock of 2008 and the Covid shock in 2020 are especially severe for these pseudo banks.

The last two lines of Table 2 break down the recessions in the 2008 financial crisis and the 2020 Covid shock. As it is apparent, the number of defaults under the Covid shock is very large, due to the severity of the stock price declines (and hence pseudo bonds) during that event.

Increasing the threshold for default to 5 standard deviations (Columns 4 through 6) clearly reduces the total number of defaults, and in fact, they are in line now with the 99% VaR requirement. This highlights the fact that returns are strongly negatively skewed and leptokurtic, a point we pick up again in the next section. However, we still have a large number of correlated defaults in recessions. Interestingly, the percentage of defaults during the 2020 Covid shock even under the 5-standard deviation threshold is still very high, ranging from 33% to 59%. The reason is that the Covid shock represented an 8 to 10 standard deviation event for the pseudo bank assets, i.e. far larger than 5-standard deviations. Hence, the number of violations in the month of March 2020 remains elevated.

4.1. Capital Requirement under Historical Return Distribution

The 2008 financial crisis highlighted that the standard 99% VaR threshold for capital requirement, defined at the bank level, is not sufficient as a buffer. As shown Table 2, this is also true in our pseudo economy: using the standard 3-year trailing volatility to compute VaR capital requirement generates too many violations, and clustering during recessions. Part of the reason is also the fact that the distribution of returns is negatively skewed and leptokurtic, and thus the standard 99% (normal) VaR threshold may not be sufficient.

In this section, we first consider capital requirements that take into account the full distribution of returns on loans in order to set capital requirements. That is, move away from the normal distribution assumption to define the threshold and calibrate the threshold to a number that takes into account the whole distribution of asset returns. In particular, consider a bank whose asset value is A_t, and its mean return and volatility are μ_t and σ_t, respectively. The bank sets the face value of debt K_t^{Bank} following the α-% VaR rule. Then, the face value of debt satisfies:

$$Pr\left[A_{t+1} < K_t^{Bank}\right] = 1 - \alpha/100 \tag{3}$$

$$Pr\left[\frac{A_{t+1}}{A_t} < \frac{K_t^{Bank}}{A_t}\right] = 1 - \alpha/100 \tag{4}$$

$$Pr\left[\frac{r_{t+1} - \mu_t}{\sigma_t} < d_t\right] = 1 - \alpha/100 \tag{5}$$

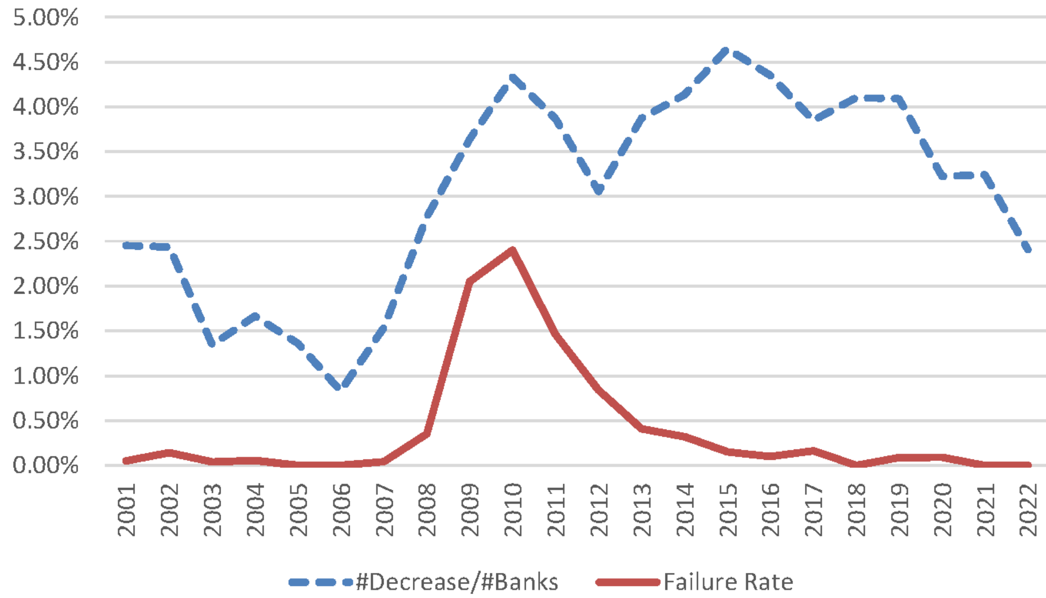
where $d_t = (\log(K_t^{Bank}/A_t) - \mu_t)/\sigma_t$.

We now impose that the cutoff d_t (and thus the amount of debt K_t^{Bank}) is set by a bank to satisfy equation (5), taking the shape of the distribution of r_{t+1} into account.

To calibrate its value, we set d_t such that the fraction of banks defaulted after the financial crisis starting in 2008 equals $1-\alpha/100$. Thus, our pseudo bank knows the asset distribution that is highly negatively skewed, and set the risk capital to mimic the outcome of the financial crisis. Figure 9 shows the number of banks that fail in the U.S. divided by the number of banks in the previous year. Since actual failure occurs with a lag, the failure rate peaks in 2010 (as opposed to 2008) at 2.4%. Since poorly performing banks do not necessarily "fail" in a legal sense but are purchased by other banks, we also calculate the decrease in the number of banks scaled by the lagged number of banks. In 2010, this decrease rate is 4.3%, which can be considered as an upper bound for the real failure rate.

Therefore, we set d_t such that the fraction of pseudo bond portfolio returns that fall below d_t is 2.4% or 4.3% in 2008. The return distribution is empirical distribution (rather

Figure 9: Historical Rate of Bank Failure in the U.S.



Source: FDIC, Statista.

than normal), obtained from standardized returns where mean and standard deviation are estimated with the 36-month rolling windows using the data up to the previous month. We then keep the rule and evaluate the percentage of (standardized) returns that fall below the threshold since 2011, that is, after the crisis.

Table 3 presents the results. Since the observations for "IG" banks are scarce in 2008, we use the threshold value estimated using "ALL" banks for all three types of banks. If we set the failure rate to 2.4%, the default threshold is -7.15 standard deviation while if the failure rate is 4.3%, then the threshold is -6.31, which are both far lower than the value implied from the normal distribution (-3.14, which is the 1/12-th percentile). Thus, using the empirical distribution from 2008 makes our pseudo banks more conservative in setting leverage K_t^{Bank}.

The first three rows of Table 3 show the percentage of standardized returns that fall below the threshold during the post-crisis period. Being more conservative indeed helps reduce the fraction of returns that "fail". However, the percentage of bank failure is still high for the Covid-shock subsample of the 2020 recession (February 2020-April 2020) compared to the data, which show nearly no failures (see Figure 9). Indeed, Figure 10 replicates Figure 9 using pseudo bond portfolio returns with $d_t = -7.15$ instead of actual bank failure. While the model matches the 2008 fail rate (by construction), it generates the very high fail rate

Table 3: Percentage of Defaulted Banks: Post Financial Crisis

	2008 Default Rate = 2.4			2008 Default Rate = 4.3			Normal Distribution 99%VaR		
	IG	HY	All	IG	HY	All	IG	HY	All
Full sample	0.95	0.69	0.79	0.97	0.69	0.81	2.55	2.96	2.91
Booms	0.00	0.00	0.00	0.00	0.00	0.00	0.67	1.61	1.34
Recessions	49.38	33.33	35.54	50.32	33.33	36.11	98.75	66.67	71.87
d_t	-7.15	-7.15	-7.15	-6.31	-6.31	-6.31	-3.14	-3.14	-3.14

A pseudo bank is considered to be in default if its pseudo bond portfolio return goes below the threshold value d_t. The table reports the percentage of observations that fall below the threshold during the time period from January 2011 to December 2022. In the left panel, we set the default threshold such that the percentage of observations that fall below d_t is 2.4%, while the middle panel uses 4.3%. In the right panel, we use the fixed rule based on the normal distribution. Specifically, the threshold is set to the 0.083-percentile (1/12) of the normal distribution. We calculate the mean and standard deviation on the rolling 36-month basis to standardize returns. "IG" refers to banks that only invest in IG-rated pseudo bonds, while "HY" refers to banks that only invest in HY-rated bonds. "All" banks split their portfolio equally between IG and HY bonds.

of 20% in 2020 for the ALL banks, which did not occur in the data.[4]

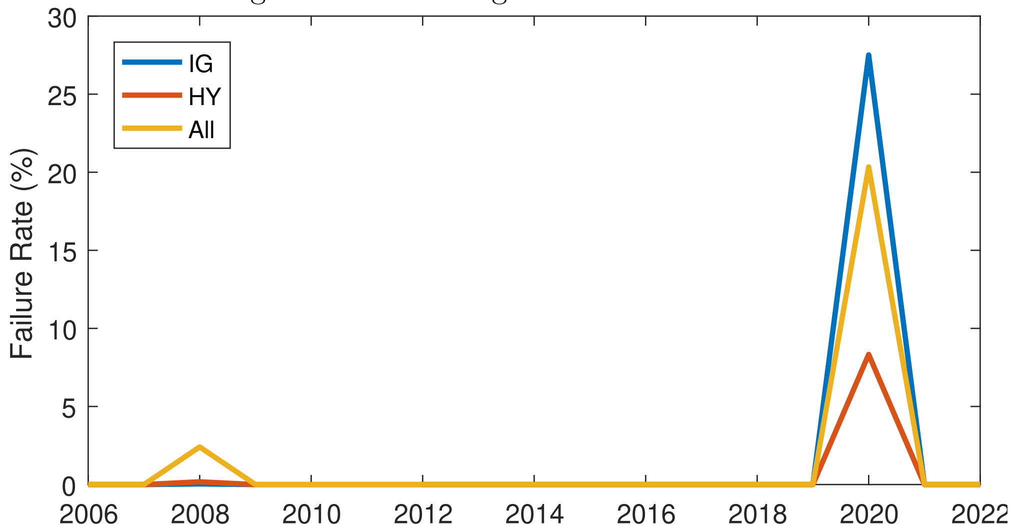
There are two reasons for the high default rate in our pseudo banks in 2020: *i*) the Covid shock was an 8 to 10 sigma event for pseudo bond portfolios (see Figure 8), so even above-7 sigma threshold is not enough to cover pseudo-banks; *ii*) there may not be enough heterogeneity across pseudo banks in our setting due to our restriction of only looking at investment assets in shares of publicly traded securities. This implies that when a bank fails, all other banks fail, which may change if we expand the set of underlying assets.

To test the second explanation, we set the maximum number of pseudo bonds each bank can have to 30, 50, and 100. If a bank is assigned more than the limit, we randomly select the pseudo bonds to satisfy the cap. Then, for each value of the caps, we compute the percentage of pseudo banks that default in 2020. Table 4 reports the default rate. If we set the maximum number of loans per bank to 30, the default rate drops from 20% in the main result with no cap (Figure 10) to 18%. This decrease is modest, so the high default rate is not a mechanical result of overlapping loan holdings of the 1000 pseudo banks.

An alternative explanation is also the fact that the banking system in reality did not fail thanks to the \$100 to \$300 billion indirect government support to the banking industry (see Fedlman and Schmidt (2021)). Such indirect government support is not taken into account

[4]The fail rate in Figure 10 is 20% in 2020 for All banks while it is 35.54% in Table 3 for the Covid recession. The reason of the difference is that the Covid recession was only in March 2020, while the plot in the future is for the overall year 2020.

Figure 10: Percentage of Defaulted Banks



The figure plots the fraction of pseudo bond portfolio returns that fall below threshold value $d_t = -7.15$, which corresponds to the failure rate of 2.4% in 2008 for "All" banks.

Table 4: Default Rate in 2020 Using Different Maximum Number of Loans Per Bank

Max Number of Loans	IG	HY	All
20	24.48	6.67	17.55
30	25.56	7.04	18.17
50	26.45	7.20	18.79
100	27.54	7.58	20.07
∞	27.51	8.33	20.34

The table reports the percentage of pseudo bond portfolio returns that fall below threshold value $d_t = -7.15$ in 2020. We simulate 1,000 banks under the constraint that the maximum number of loans is 20, 30, 50, 100, and infinity.

in our calculations in Table 4.1.. That is, in our analysis, the pseudo-banks failure rate depends on our monthly horizon of the underlying shocks. Thus, the large decline in asset prices in March 2020 would not take into account the ex-post indirect government support that took place after the initial shock, which indeed led to a large recovery of asset prices.

5. Macro-Prudential Regulation

Macro-prudential regulation aims at imposing a set of requirements for the banking sector to mitigate the impact of large economic shocks to the banking sectors. We already explored one of such regulations, namely, the limit to the riskiness of loans, such as require a low loan-to-value ratio. The IG banks only make loans to pseudo firms with very low probability of default, namely, below 0.1%. As we have seen in Table 2 such "IG" banks are still very sensitive to large shocks to the economy, and in fact, their default rate (i.e. VaR violations) are close to the ALL banks. This is especially visible around the Covid shock, when the IG banks would have been the most affected by the decline of the value of pseudo firms' investment assets.

We now investigate the impact of proposals of macro-prudential regulation, namely, countercyclical capital buffers and risk concentration limits.

5.1. Countercyclical Capital Buffer

In this final section, we study the impact on default from countercyclical capital buffers. In particular, we consider a few simple rules. The simplest rule is to have the threshold d_t to increase when the trailing volatility is low, and decrease when the trailing volatility is high

$$d_t = \frac{d_1}{\sigma_{t-1}} \tag{6}$$

We set $d_1 = -3\ \overline{\sigma}$ or $d_1 = -5\ \overline{\sigma}$ where $\overline{\sigma}$ is the average volatility of asset returns across the overall sample. The second rule is to make the threshold related to variance as opposed to standard, by setting

$$d_t = \frac{d_2}{\sigma_{t-1}^2} \tag{7}$$

where $d_2 = -3\ \overline{\sigma^2}$ and $\overline{\sigma^2}$ is the average variance of asset returns across the overall sample. We see that this second rule implies a higher reactivity of d_t to σ_{t-1} unless σ_{t-1} is already high. Denoting $d(\sigma_{t-1})$ and $d(\sigma_{t-1}^2)$ the thresholds in Equations (6) and (7), respectively, we find

$$\frac{\partial d(\sigma_{t-1}^2)}{\partial \sigma_{t-1}} > \frac{\partial d(\sigma_{t-1})}{\partial \sigma_{t-1}} \text{ if and only if } \sigma_{t-1} < 2\ \overline{\sigma} \tag{8}$$

Thus, the thresholds adjusts more quickly under the second rule to variation in volatility, unless the volatility is already higher than twice the sample average.

Table 5 contains the results. Consider the first three columns first. The total number of defaults is 1.07%, which is in line with the expectation from a 99% VaR rule. Like in other cases, the defaults however still occur mostly in recessions, at 14%. Notably, however, this percentage is far smaller than the corresponding one in Table 2 (24%) under the assumption that the threshold is calculated as 3 standard deviations from the 36-month trailing volatility. That is, a countercyclical capital buffer is indeed able to dampen the number of defaults in

Table 5: Percentage of Defaulted Banks Under Countercyclical Buffer

	$d_t = -3\ \overline{\sigma}/\sigma_{t-1}$			$d_t = -5\ \overline{\sigma}/\sigma_{t-1}$			$d_t = -3\ \overline{\sigma^2}/\sigma^2_{t-1}$		
	IG	HY	All	IG	HY	All	IG	HY	All
Full sample	0.91	0.87	1.07	0.52	0.83	0.82	1.01	1.98	1.27
Booms	0.24	0.00	0.01	0.00	0.00	0.00	0.01	0.84	0.05
Recessions	12.18	9.48	14.36	9.18	9.09	11.17	12.42	11.49	12.74
2008 Financial Crisis	3.33	5.72	9.50	0.09	5.26	5.81	4.02	8.04	7.76
2020 Covid Shock	51.62	33.33	36.80	49.73	33.33	35.97	49.93	33.33	35.79

A pseudo bank is considered to be in default if its pseudo bond portfolio return goes below the threshold value d_t. The table reports the percentage of observations that fall below the threshold during the time period from January 2011 to December 2022. In the left panel, we set the default threshold such that the percentage of observations that fall below d_t is 2.4%, while the middle panel uses 4.3%. In the right panel, we use the fixed rule based on the normal distribution. Specifically, the threshold is set to the 0.083-percentile (1/12) of the normal distribution. We calculate the mean and standard deviation on the rolling 36-month basis to standardize returns. "IG" refers to banks that only invest in IG-rated pseudo bonds, while "HY" refers to banks that only invest in HY-rated bonds. "All" banks split their portfolio equally between IG and HY bonds.

bad times (and in good times). Interestingly, when the threshold is 5 times the standard deviation (Columns 4 to 6 in both Tables 2 and 5), the gain from countercyclical capital buffer is smaller: The number of defaults in recession under countercyclical capital buffer is 11% against 12% in the traditional case.

In both cases, the gain occurs in the 2008 Financial Crisis, however. We can see that the number of defaults in the 2020 Covid shock is in fact independent of whether we are in the traditional case (Table 2) or the countercyclical capital buffer case (Table 5). The severity of the Covid shock makes these differences immaterial.

The rule that sets the threshold as the inverse of variance, instead of volatility, also improves upon the case with the standard trailing average, but not as much.

5.2. Risk Concentration Limits

In this section, we consider the impact to systemic risk when banks' bond holdings are concentrated. In the previous sections, all loans were given equal weights in each bank's portfolio. As such, there was no risk concentration. In this section, we now assign different weights to each pseudo bond in the portfolio. Specifically, risk concentration occurs when a bank has a higher weight for some bonds than for others. In order to guide the analysis, we set a target Gini coefficient, which measures bond concentration for the portfolio weights. The coefficient of 0 is perfect equality (i.e., no concentration, as in previous sections), while that of 1 is perfect concentration. It is known that if the portfolio weight follows a lognormal distribution $LN(\mu, \sigma)$, then the Gini coefficient G is given by

$$G = 2\Phi(\sigma/\sqrt{2}) - 1, \tag{9}$$

We target a Gini coefficient G, and we back out the value of σ given G. We then draw random numbers from the lognormal distribution and use them as weights for the bonds.

Figure 11 shows the relationship between the returns of pseudo-bond portfolios and the returns of the underlying asset when $G = 0.5$. As expected, concentrated bond ownership inflates tail risk, and we observe more pseudo-bond portfolio returns closer to -12 standard deviations. However, we also notice that the scatterplot is more sparse around the extreme tails, indicating fewer "joint" defaults.

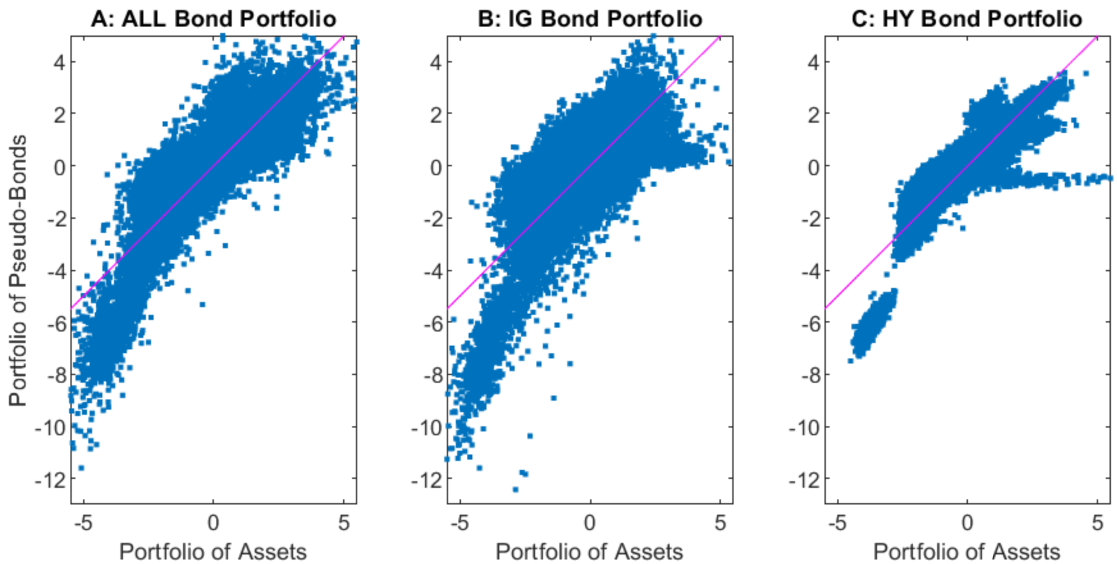
To further investigate, Table 6 reproduces the case with countercyclical capital buffers but for the case in which $G = 0.5$ (as opposed to 0 as in Table 5). As it can be seen, when the threshold is $d_t = -3\overline{\sigma}/\sigma_t$, concentration risk shows itself into a higher fraction of defaults, especially during recessions, although the increase is modest. Interestingly, in the case with a higher (more negative) threshold, $d_t = -5\overline{\sigma}/\sigma_t$, the case with $G = 0.5$ produces fewer defaults than $G = 0$. This result is due to the higher importance of single big loans when $G = 0.5$ and thus the less likely correlation of such big loans defaulting at the same time across banks. Indeed, Table A5 in the Appendix shows that if we limit the number of loans permitted for each pseudo bank to $N = 20$, 30, 50, 100, the number of joint defaults during bad times decreases. Again, this is due to the higher importance of idiosyncratic shocks and the lower likelihood of large correlated losses across pseudo banks, even when we look at large shocks to pseudo firms' fundamentals. The appendix provides additional results for default correlations for this case as well.

6. Conclusions

In this paper, we use the pseudo firms of Culp, Nozawa, and Veronesi (2018) to build a fictitious, but empirically observable, macroeconomy to investigate the nature of tail risk in bank loan portfolios and the effectiveness of macro-prudential policies to stabilize the (pseudo) banking sector. Specifically, we look at the empirical distribution of several random loan portfolios made by random pseudo banks to pseudo firms. We find that the tails of the distribution around severe shocks, such as the 2008 crisis and the 2020 Covid crisis, induce a large correlation in default rates across pseudo banks, in the sense that the loan portfolio of such pseudo banks all drop at the same time. The tails of the distribution of loan

Figure 11: Scatterplot of Pseudo Banks' Asset Returns versus Fundamental Asset Returns: Concentrated Bond Holdings

All Bonds, Gini Coefficient = 0.5



Notes: Panels A, B, and C show the scatter-plot of pseudo bond portfolio returns versus underlying asset portfolio returns. The distributions have been normalized to have zero-mean and unit standard deviations. The random portfolios are constructed as follows: For every month t, we consider all potential available pseudo bonds for all firms with valid option data. We group such bonds in credit rating / maturity bins. We consider only two credit ratings: Investment Grade (i.e. Aaa/Aa and A/Baa) or High Yield (i.e. Ba, B, Caa-) and only three maturity ranges (0,273), (274,548), (549, ∞). For each firm and for each rating, we randomly choose one maturity bin per firm, when available. For "All" portfolio (Panel A), if the number of IG firms is more than 10, then we randomly pick the same number of HY bonds as the IG bonds, and then compute the average across all the bonds. For the IG and HY portfolios, if the number of firms is more than 20, then we average them and record the portfolio returns. In either case, if the minimum number of firms condition is not met, we record a missing observation for the portfolio return in the month. To compute the average, we value-weight using the weights drawn from the lognormal distribution that generates the target value of the Gini coefficient. In particular, given the Gini coefficient G, parameter σ of the lognormal distribution is calculated as $\sigma = \sqrt{2}\Phi^{-1}(0.5 \times (G+1))$. This procedure is performed for every month t in the sample, and repeated 1,000 times to obtain return distributions.

portfolios are far larger than the distribution of the underlying fundamental assets due to the natural negative skewness of bond returns and thus the inability of standard diversification arguments to reduce the size of the tails of the distribution.

Because all shocks of our macroeconomy are fully observable, we can trace the *causal*

Table 6: Percentage of Defaulted Banks Under Countercyclical Buffer, Concentrated Bond Holdings

	$d_t = -3\ \overline{\sigma}/\sigma_{t-1}$			$d_t = -5\ \overline{\sigma}/\sigma_{t-1}$			$d_t = -3\ \overline{\sigma^2}/\sigma^2_{t-1}$		
	IG	HY	All	IG	HY	All	IG	HY	All
Gini = 0.5									
Full sample	0.96	0.95	1.13	0.52	0.83	0.73	1.11	1.93	1.34
Booms	0.26	0.00	0.06	0.02	0.00	0.00	0.08	0.80	0.12
Recessions	12.67	10.31	14.59	8.96	9.07	9.98	12.99	11.25	12.87
2008 Financial Crisis	3.48	6.67	9.56	0.48	5.26	4.87	4.71	7.76	8.14
2020 Covid Shock	53.67	33.37	37.85	46.78	33.20	33.62	49.93	33.33	34.71

A pseudo bank is considered to be in default if its pseudo bond portfolio return goes below the threshold value d_t. The table reports the percentage of observations that fall below the threshold during the time period from January 2011 to December 2022. In the left panel, we set the default threshold such that the percentage of observations that fall below d_t is 2.4%, while the middle panel uses 4.3%. In the right panel, we use the fixed rule based on the normal distribution. Specifically, the threshold is set to the 0.083-percentile (1/12) of the normal distribution. We calculate the mean and standard deviation on the rolling 36-month basis to standardize returns. "IG" refers to banks that only invest in IG-rated pseudo bonds, while "HY" refers to banks that only invest in HY-rated bonds. "All" banks split their portfolio equally between IG and HY bonds. The banks have a value-weighted portfolio of pseudo bonds, where the weights are drawn from a lognormal distribution and its parameter is calibrated to the Gini coefficient.

impact of shocks to fundamentals onto shocks to the balance sheets of pseudo banks. We can observe the amplification effect that, for instance, translates a 3 standard deviation shock to the fundamentals of the pseudo economy onto a 5 standard deviation shock to the balance sheet of pseudo banks. As an example, while the Covid shock represented a 5 standard deviation shock to fundamentals, it translated into a 10 standard deviation shock of pseudo banks, even those that specialize in safe (investment grade) loans.

Such experiments allow us also to capture the variation in debt valuations arising from discount rate movements, as opposed to just shocks to cash flows. Those variations in discount rates generate significant changes in the mark-to-market values of assets that impact the market values of debt in a systematic fashion. That is, the valuation of loans jointly declines simply because a market-wide increase in risk premia, for instance, is taking place. This systematic variation in debt valuation increases the need for higher capital requirements. In our framework, the threshold doubles compared to the standard 99% VaR approach.

Finally, we show that macro-prudential regulation that focuses on imposing banks to concentrate on safer loans has only a mild impact on the stability of banks, as their asset returns become even more leptokurtic and therefore more sensitive to large shocks. Countercyclical capital buffers, on the other hand, also help in reducing the number of defaults, but we do still find a concentration of (pseudo) bank defaults in recession, although this empirical result is also due to the unprecedented severity of the 2020 Covid shock.

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Appendix

In this appendix, we collect some additional results about the impact of pseudo banks' portfolio composition. In particular, we consider the case in which pseudo banks are limited in the number of pseudo bonds they can have on their assets.

Figure A1 shows the relationship between the returns on pseudo-bond portfolios and the returns on the underlying asset, when the maximum number of bonds per bank is set to 20, 30, 50, and 100. For HY banks, there is one outlier in the stock returns, which is Gamestop Corporation (Secid = 113993) in January 2021, where the monthly stock return in the CRSP database is 1625%, which is about a 40 standard deviation change. As seen in Figure A2, this observation obscures the visibility of the remaining data points. Therefore, in Figure A1, we limit the x-axis to -5.5 to 5.5 standard deviations. This limit does not affect the figures for the All and IG banks.

Figure A1 shows that the left tail of the pseudo-bond portfolios becomes more pronounced as we reduce the number of bonds per bank. This is especially visible for IG banks. When the number of bonds is capped at 20, there is less diversification benefit for the portfolio, and there are a significant number of observations near -12 standard deviations. These left tail events are somewhat mitigated when we increase the number of bonds to 30, 50, and 100.

Tables A1, A3, A5 replicate Tables 2, 3, and 5, respectively, using different caps on the number of bonds. The resulting percentage of defaulted banks is similar to the main results, suggesting that the clustering of bank defaults is not due to overlapping bond holdings.

Figure A1: Scatterplot of Pseudo Banks' Asset Returns versus Fundamental Asset Returns: Imposing Caps on the Number of Loans

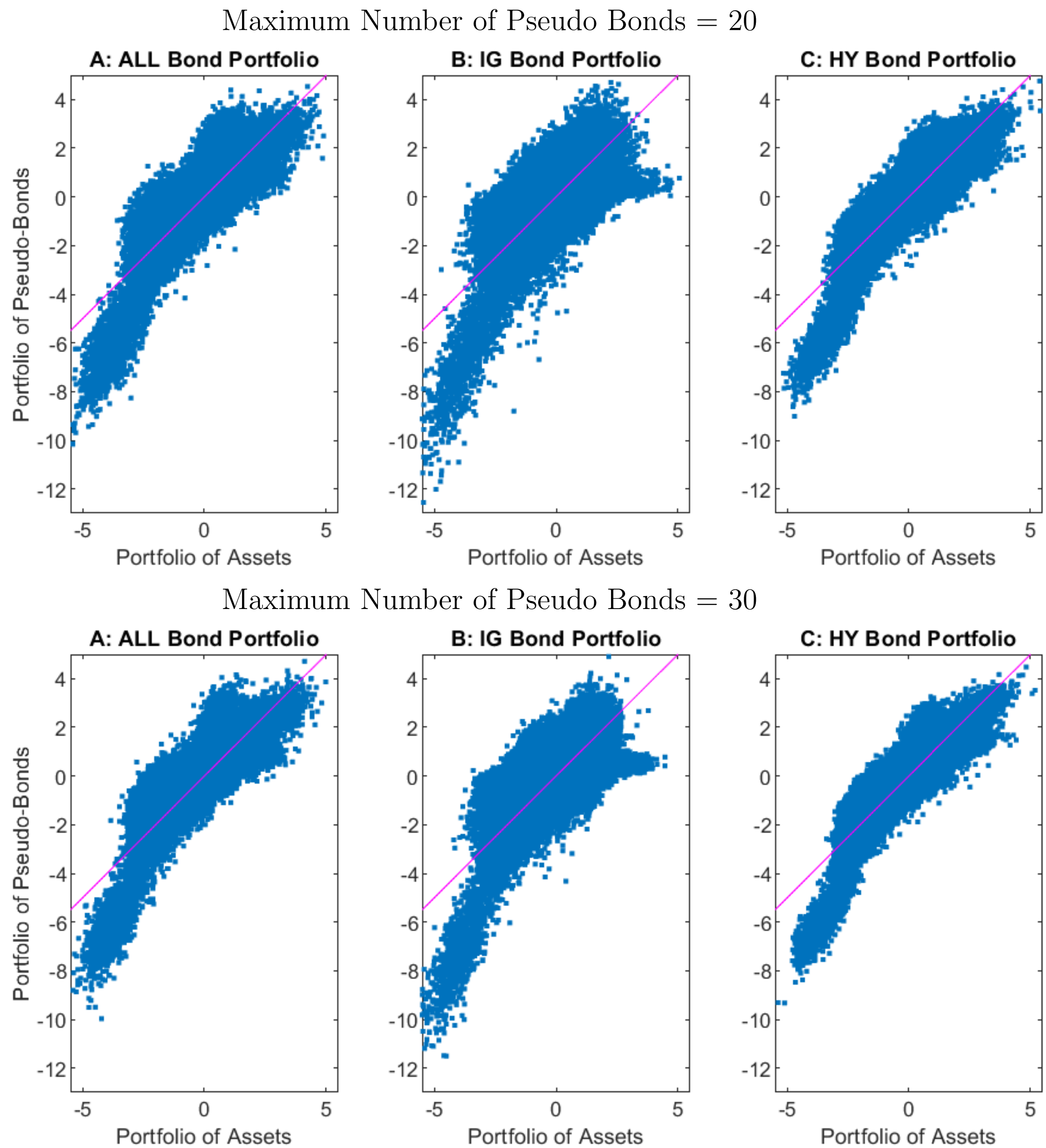
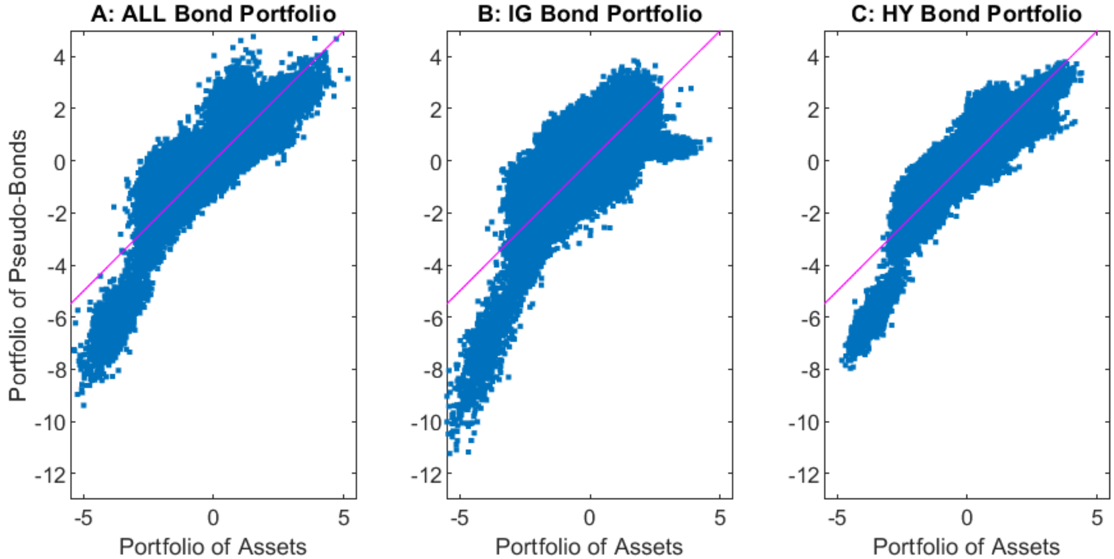
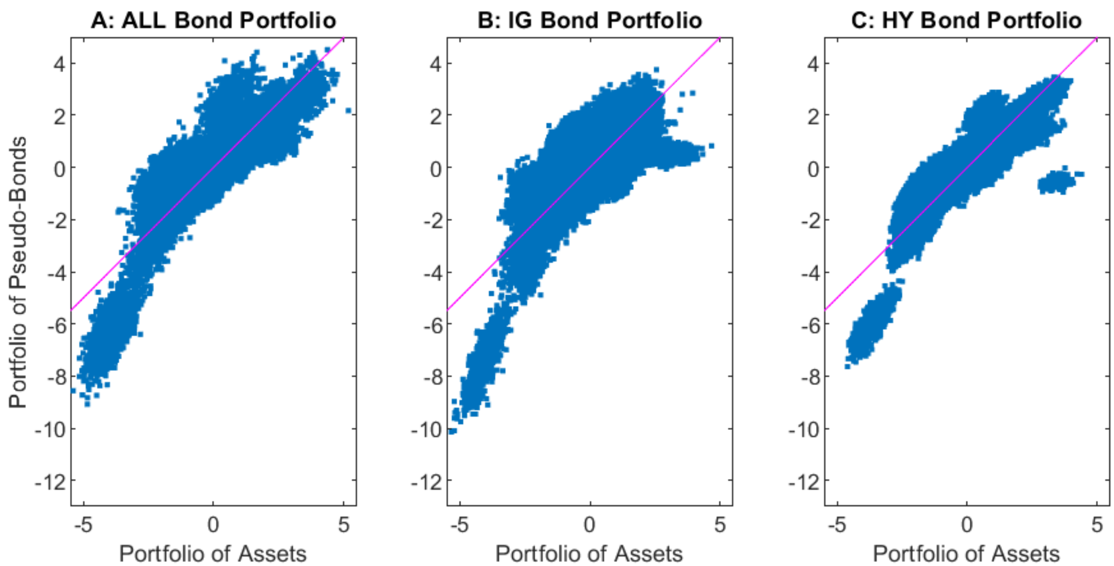


Figure A1, Continued.

Maximum Number of Pseudo Bonds = 50



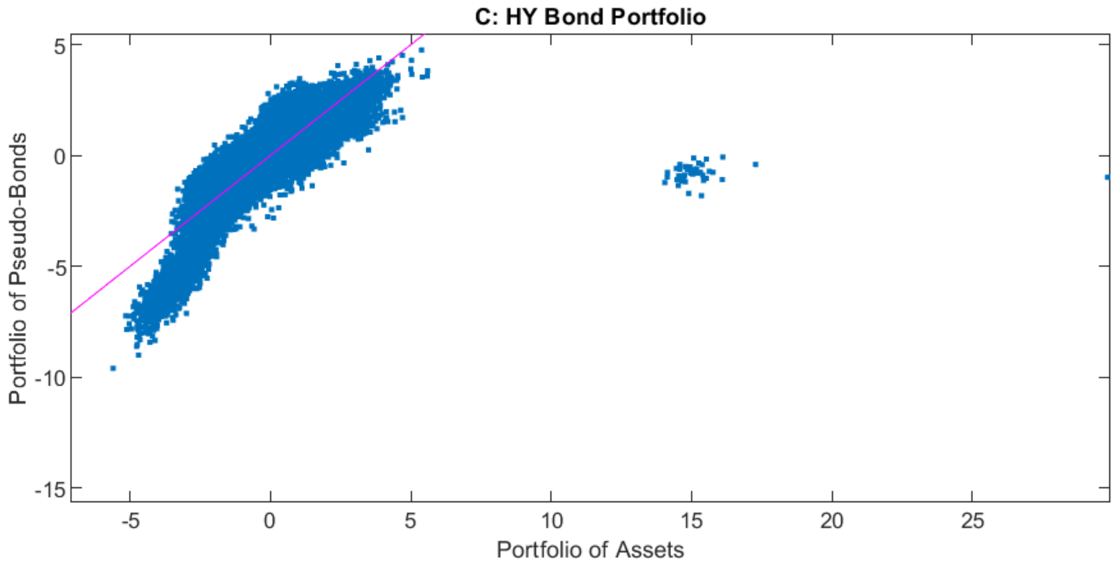
Maximum Number of Pseudo Bonds = 100



Notes: Panels A, B, and C show the scatter-plot of pseudo bond portfolio returns versus underlying asset portfolio returns. The distributions have been normalized to have zero-mean and unit standard deviations. The random portfolios are constructed as follows: For every month t, we consider all potential available pseudo bonds for all firms with valid option data. We group such bonds in credit rating / maturity bins. We consider only two credit ratings: Investment Grade (i.e. Aaa/Aa and A/Baa) or High Yield (i.e. Ba, B, Caa-) and only three maturity ranges (0,273), (274,548), (549, ∞). For each firm and for each rating, we randomly choose one maturity bin per firm, when available. For "All" portfolio (Panel A), if the number of IG firms is more than 10, then we randomly pick the same number of HY bonds as the IG bonds, and then compute the average across all the bonds. For the IG and HY portfolios, if the number of firms is more than 20, then we average them and record the portfolio returns. In either case, if the minimum number of firms condition is not met, we record a missing observation for the portfolio return in the month. This procedure is performed for every month t in the sample, and repeated 1,000 times to obtain return distributions.

Figure A2: Scatterplot of HY Pseudo Banks' Asset Returns versus Fundamental Asset Returns with a Cap on the Number of Loans

Maximum Number of Pseudo Bonds = 20



Notes: This figure shows the scatter-plot of pseudo bond portfolio returns versus underlying asset portfolio returns for the HY portfolio when the number of pseudo bonds in the pseudo bank portfolio is exactly 20. This figure is the same as Panel C in Figure A1 except that the $x-$axis is not restricted between -5.5 and 5.5. The scatter of observations visible at 15 standard deviations (and one observation at 30 standard deviations) are all due to one single outlier in the stock returns, Gamestop Corporation (Secid = 113993) in January 2021, where the monthly stock return in the CRSP database is 1625%, which is about a 40 standard deviation change. The procedure to build random portfolio is in the notes of Figure A1.

Table A1: Percentage of Defaulted Banks That Set Equity Following 1% VaR Rule, Imposing Caps on the Number of Pseudo Bonds

	Threshold = $3\sigma_{t-1}$			Threshold = $5\sigma_{t-1}$		
	IG	HY	All	IG	HY	All
Max = 20						
Full sample	2.39	2.85	3.11	0.91	0.97	1.14
Booms	0.89	1.09	1.12	0.05	0.03	0.04
Recessions	19.59	17.35	21.96	10.79	8.78	11.49
2008 Financial Crisis	4.41	10.58	12.64	0.49	4.57	5.43
2020 Covid Shock	87.32	60.20	65.01	56.71	35.43	39.51
Max = 30						
Full sample	2.42	3.00	3.27	0.90	1.00	1.15
Booms	0.83	1.18	1.20	0.04	0.01	0.03
Recessions	20.66	18.02	22.88	10.77	9.19	11.70
2008 Financial Crisis	4.72	10.99	13.12	0.15	4.98	5.69
2020 Covid Shock	91.76	62.57	68.00	58.16	35.83	39.47
Max = 50						
Full sample	2.40	3.15	3.45	0.87	1.01	1.17
Booms	0.77	1.28	1.29	0.01	0.00	0.01
Recessions	21.07	18.63	23.84	10.76	9.33	12.12
2008 Financial Crisis	4.26	11.29	13.80	0.11	5.19	6.20
2020 Covid Shock	96.06	65.13	70.24	58.26	35.57	39.51
Max = 100						
Full sample	2.52	3.31	3.53	0.88	1.00	1.17
Booms	0.82	1.38	1.35	0.00	0.00	0.00
Recessions	21.99	19.29	24.12	10.92	9.25	12.17
2008 Financial Crisis	4.66	11.84	13.78	0.25	5.28	6.27
2020 Covid Shock	99.35	66.47	71.90	58.51	34.40	39.44

A pseudo bank is considered to be in default if its pseudo bond portfolio return goes below the threshold value determined by 3 (columns 1 through 3) or 5 (columns 4 through 6) standard deviation below the average. The table reports the percentage of observations that fall below the threshold from January 2003 to December 2022. We calculate the mean and standard deviation on the rolling 36-month basis. "IG" refers to banks that only invest in IG-rated pseudo bonds, while "HY" refers to banks that only invest in HY-rated bonds. "All" banks split their portfolio equally between IG and HY bonds.

Table A2: Percentage of Defaulted Banks That Set Equity Following 1% VaR Rule, Concentrated Bond Holdings

	Threshold = $3\sigma_{t-1}$			Threshold = $5\sigma_{t-1}$		
	IG	HY	All	IG	HY	All
Gini = 0.5						
Full sample	2.41	3.39	3.40	0.93	0.98	1.17
Booms	0.79	1.45	1.25	0.04	0.00	0.03
Recessions	20.92	19.45	23.67	11.06	9.13	11.95
2008 Financial Crisis	4.48	11.99	13.58	0.72	5.27	5.93
2020 Covid Shock	94.26	66.63	70.31	57.21	33.57	39.80

A pseudo bank is considered to be in default if its pseudo bond portfolio return goes below the threshold value determined by 3 (columns 1 through 3) or 5 (columns 4 through 6) standard deviation below the average. The table reports the percentage of observations that fall below the threshold from January 2003 to December 2022. We calculate the mean and standard deviation on the rolling 36-month basis. "IG" refers to banks that only invest in IG-rated pseudo bonds, while "HY" refers to banks that only invest in HY-rated bonds. "All" banks split their portfolio equally between IG and HY bonds. The banks have a value-weighted portfolio of pseudo bonds, where the weights are drawn from a lognormal distribution and its parameter is calibrated to the Gini coefficient.

Table A3: Percentage of Defaulted Banks: Post Financial Crisis, Imposing Caps on the Number of Pseudo Bonds

	2008 Default Rate = 2.4			2008 Default Rate = 4.3			Normal Distribution 99%VaR		
	IG	HY	All	IG	HY	All	IG	HY	All
Max = 20									
Full sample	0.86	0.56	0.69	1.01	0.68	0.80	2.34	2.17	2.33
Booms	0.02	0.00	0.00	0.03	0.01	0.01	0.73	0.98	0.95
Recessions	43.93	26.67	30.66	50.67	32.33	35.21	84.37	58.27	62.91
Default Threshold	-6.46	-6.46	-6.46	-5.57	-5.57	-5.57	-3.14	-3.14	-3.14
Max = 30									
Full sample	0.89	0.59	0.71	1.00	0.67	0.79	2.41	2.35	2.47
Booms	0.00	0.00	0.00	0.02	0.00	0.00	0.70	1.11	1.01
Recessions	45.88	28.17	31.74	50.92	32.13	35.07	89.87	60.60	66.34
Default Threshold	-6.58	-6.58	-6.58	-5.81	-5.81	-5.81	-3.14	-3.14	-3.14
Max = 50									
Full sample	0.91	0.60	0.73	0.97	0.67	0.79	2.42	2.52	2.68
Booms	0.00	0.00	0.00	0.00	0.00	0.00	0.62	1.21	1.16
Recessions	47.48	28.80	32.83	50.47	32.27	35.39	94.56	64.00	69.19
Default Threshold	-6.87	-6.87	-6.87	-6.15	-6.15	-6.15	-3.14	-3.14	-3.14
Max = 100									
Full sample	0.95	0.63	0.78	0.97	0.69	0.80	2.55	2.69	2.86
Booms	0.00	0.00	0.00	0.00	0.00	0.00	0.67	1.34	1.29
Recessions	49.43	30.30	35.07	50.32	32.97	35.97	98.80	66.13	71.65
Default Threshold	-7.04	-7.04	-7.04	-6.31	-6.31	-6.31	-3.14	-3.14	-3.14

A pseudo bank is considered to be in default if its pseudo bond portfolio return goes below the threshold value d_t. The table reports the percentage of observations that fall below the threshold during the time period from January 2011 to December 2022. In the left panel, we set the default threshold such that the percentage of observations that fall below d_t is 2.4%, while the middle panel uses 4.3%. In the right panel, we use the fixed rule based on the normal distribution. Specifically, the threshold is set to the 0.083-percentile (1/12) of the normal distribution. We calculate the mean and standard deviation on the rolling 36-month basis to standardize returns. "IG" refers to banks that only invest in IG-rated pseudo bonds, while "HY" refers to banks that only invest in HY-rated bonds. "All" banks split their portfolio equally between IG and HY bonds.

Table A4: Percentage of Defaulted Banks: Post Financial Crisis, Concentrated Bond Holdings

	2008 Default Rate = 2.4			2008 Default Rate = 4.3			Normal Distribution 99%VaR		
	IG	HY	All	IG	HY	All	IG	HY	All
Gini = 0.5									
Full sample	0.87	0.68	0.72	0.98	0.69	0.81	2.46	2.79	2.65
Booms	0.01	0.00	0.00	0.02	0.00	0.01	0.71	1.43	1.14
Recessions	44.93	32.47	32.36	50.27	33.33	36.08	91.96	66.57	68.83
Default Threshold	-7.07	-7.07	-7.07	-5.97	-5.97	-5.97	-3.14	-3.14	-3.14

A pseudo bank is considered to be in default if its pseudo bond portfolio return goes below the threshold value d_t. The table reports the percentage of observations that fall below the threshold during the time period from January 2011 to December 2022. In the left panel, we set the default threshold such that the percentage of observations that fall below d_t is 2.4%, while the middle panel uses 4.3%. In the right panel, we use the fixed rule based on the normal distribution. Specifically, the threshold is set to the 0.083-percentile (1/12) of the normal distribution. We calculate the mean and standard deviation on the rolling 36-month basis to standardize returns. “IG” refers to banks that only invest in IG-rated pseudo bonds, while “HY” refers to banks that only invest in HY-rated bonds. “All” banks split their portfolio equally between IG and HY bonds. The banks have a value-weighted portfolio of pseudo bonds, where the weights are drawn from a lognormal distribution and its parameter is calibrated to the Gini coefficient.

Table A5: Percentage of Defaulted Banks Under Countercyclical Buffer, Imposing Caps on the Number of Pseudo Bonds

	$d_t = -3\ \overline{\sigma}/\sigma_{t-1}$			$d_t = -5\ \overline{\sigma}/\sigma_{t-1}$			$d_t = -3\ \overline{\sigma^2}/\sigma^2_{t-1}$		
	IG	HY	All	IG	HY	All	IG	HY	All
Max = 20									
Full sample	1.02	1.12	1.13	0.46	0.64	0.68	1.26	1.68	1.38
Booms	0.30	0.02	0.05	0.01	0.00	0.00	0.15	0.57	0.13
Recessions	13.18	12.00	14.74	7.88	7.01	9.27	13.96	10.85	13.23
2008 Financial Crisis	3.66	8.15	9.42	0.37	4.19	5.17	6.04	7.83	8.78
2020 Covid Shock	55.67	36.43	39.36	41.39	24.90	28.21	49.28	29.97	33.80
Max = 30									
Full sample	1.01	1.08	1.10	0.46	0.70	0.73	1.18	1.73	1.34
Booms	0.28	0.01	0.04	0.00	0.00	0.00	0.09	0.62	0.10
Recessions	13.21	11.69	14.48	8.18	7.69	9.91	13.71	10.90	13.01
2008 Financial Crisis	3.60	7.87	9.27	0.06	4.59	5.49	5.60	7.62	8.26
2020 Covid Shock	56.07	35.87	38.57	44.43	27.27	30.37	49.93	31.63	34.96
Max = 50									
Full sample	0.94	1.04	1.07	0.49	0.77	0.79	1.07	1.78	1.30
Booms	0.23	0.00	0.02	0.00	0.00	0.00	0.04	0.67	0.07
Recessions	12.73	11.32	14.32	8.73	8.36	10.68	12.92	11.02	12.92
2008 Financial Crisis	3.31	7.59	9.23	0.06	4.92	5.85	4.59	7.59	8.04
2020 Covid Shock	54.77	34.97	37.85	47.43	30.17	33.01	50.07	32.70	35.46
Max = 100									
Full sample	0.91	1.00	1.07	0.52	0.81	0.81	1.01	1.88	1.26
Booms	0.24	0.00	0.01	0.00	0.00	0.00	0.01	0.77	0.05
Recessions	12.18	10.96	14.42	9.18	8.88	11.07	12.42	11.13	12.74
2008 Financial Crisis	3.33	7.32	9.54	0.09	5.19	5.80	4.02	7.64	7.80
2020 Covid Shock	51.62	34.00	36.94	49.73	32.20	35.46	49.93	33.27	35.61

A pseudo bank is considered to be in default if its pseudo bond portfolio return goes below the threshold value d_t. The table reports the percentage of observations that fall below the threshold during the time period from January 2011 to December 2022. In the left panel, we set the default threshold such that the percentage of observations that fall below d_t is 2.4%, while the middle panel uses 4.3%. In the right panel, we use the fixed rule based on the normal distribution. Specifically, the threshold is set to the 0.083-percentile (1/12) of the normal distribution. We calculate the mean and standard deviation on the rolling 36-month basis to standardize returns. “IG” refers to banks that only invest in IG-rated pseudo bonds, while “HY” refers to banks that only invest in HY-rated bonds. “All” banks split their portfolio equally between IG and HY bonds.