Measuring the Financial Soundness of US Firms 1926-2012∗

PRELIMINARY AND INCOMPLETE

Andrew G. Atkeson,†Andrea L. Eisfeldt,‡and Pierre-Olivier Weill§

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†Department of Economics, University of California Los Angeles, NBER, and Federal Reserve Bank of Minneapolis. e-mail: andy@atkeson.net
‡Finance Area, Anderson School of Management, University of California, Los Angeles, e-mail: andrea.eisfeldt@anderson.ucla.edu
§Department of Economics, University of California Los Angeles, e-mail: poweill@econ.ucla.edu
Abstract

We develop a simple, transparent, and robust method for measuring the financial soundness of individual firms using data on their equity volatility. This method allows us to retrace the history of firms’ financial soundness during U.S. business cycles over most of the last century, and offers a useful diagnostic tool for evaluating business cycle theories based on financial frictions. In the work that we have done to date, we measure the cross-section distribution of financial soundness across publicly traded firms and financial intermediaries in the U.S., every month from 1926 to 2011. We obtain four striking results:

Finding 1: During the recessions of 1932-33, 1937, and 2008, the distribution of financial soundness collapsed relative to the distribution typically observed over the time period 1926-2011. Similar collapses in the distribution of financial soundness across firms do not occur in other recessions over this period.

Finding 2: During the recessions of 1932-33, 1937, and 2008, the timing and the magnitude of the collapse in the distribution of financial soundness is almost exactly the same for financial firms as for all firms, both financial and non-financial. This finding also holds for the recession of 2008 if we restrict attention to the distribution of financial soundness across the largest financial firms. Thus, during these three crisis episodes, there is little evidence that the financial soundness of financial firms deteriorated first, or by more. Instead, the collapse was simultaneous.

Finding 3: In the fall of 2008, the collapse in the distribution of financial soundness was mainly a result of a sudden increase in the asset volatility, or business risk, facing all firms. Contrary to many theories of financial crises, the contribution of a fall in asset values to this collapse of firms’ financial soundness was relatively small over the time period 2007-2008.

Finding 4: We also examine the distribution of financial soundness across a group of large financial firms that were at the center of attention of the recent financial crisis: the group comprised of the current set of the 18 publicly traded “Stress Test” banks together with six large financial firms that failed in the most recent crisis (AIG, Bear Stearns, Lehman Brothers, Merrill Lynch, Wachovia, and Washington Mutual). While the distribution of financial soundness across this group of government-supported large financial firms was quite similar to that for all financial firms, large and small, and to that for large firms, both financial and non-financial over the period 1997-mid 2007, the distribution of financial soundness across the survivors in this group has been significantly worse than that for all financial firms and for large firms, both non-financial and financial, over the four years that have passed since the most recent financial crisis began.
1 Introduction

A large literature in macroeconomics argues that financial frictions impair the flow of resources to and across firms and play a key role amplifying and propagating business cycle shocks. Papers in this literature include Bernanke and Gertler (1989), Carlstrom and Fuerst (1997), Kiyotaki and Moore (1997), Bernanke, Gertler, and Gilchrist (1999), Cooley and Quadrini (2001), Cooley, Marimon, and Quadrini (2004), and many others. One central theme in this literature is that the distribution of financial soundness across firms in the economy at any point in time is a state variable that has consequences for the response of the macroeconomy to a variety of aggregate shocks. In particular, in these theories, negative macroeconomic shocks are greatly amplified when they simultaneously deteriorate the distribution of financial soundness across firms.

In this paper we develop a simple, transparent, and broadly applicable procedure for measuring the distribution of financial soundness across a wide cross-section of firms in the economy at any point in time. Our procedure allows us to retrace the history of firms’ financial soundness during U.S. business cycles over most of the last century, and offers a useful diagnostic tool for evaluating business cycle theories that emphasize the role of financial frictions in shaping macroeconomic dynamics.

We use this empirical procedure to address several questions. First, we ask in which U.S. recessions since 1926 do we see a significant deterioration in the distribution of financial soundness across firms? And, in contrast, in which recessions during this time period do we not see significant changes in the distribution of financial soundness across firms?

Financial soundness collapsed during only three recessions. We find that the distribution of financial soundness across publicly traded firms deteriorated in a very significant manner in three recessions: the two recessions of the Great Depression, 1932-33 and 1937, as well as the recent recession of 2008. Basically, in these three recessions, financial soundness for almost all publicly traded firms deteriorated to a level usually associated with a junk credit rating status or worse. In contrast, we find that there are not significant deteriorations in the distribution of financial soundness across firms in other recessions outside of these three, including even the deep recessions of the late 1970’s and early 1980’s. Thus, the collapse of the distribution of financial soundness across firms in these three recessions is distinctive and is not characteristic of other recessions.

The macroeconomic literature cited above highlights the role of financial frictions facing all firms in shaping business cycles. There is also a large literature in macroeconomics
focusing on the frictions facing financial intermediaries as playing a large role in shaping the evolution of the macroeconomy. According to this literature, recessions can be caused by a deterioration in the financial soundness of financial intermediaries alone, due to their central role in reallocating resources in the economy. Important papers in this literature include Bernanke (1983), and recent surveys of theory by Gertler and Kiyotaki (2010) and of empirical experience with financial crises by Reinhart and Rogoff (2009).

One of the main virtues of our proposed method for measuring the financial soundness of firms is that it can easily be applied to financial as well as non-financial firms. In our empirical work, we apply our method to measure the distribution of financial soundness for publicly traded financial firms from 1926 through 2011. This allows us to address our second question: during the three recessions of 1932-33, 1937, and 2008, is the evolution of the distribution of financial soundness significantly different for financial firms than for other firms?

The timing and magnitude of the collapse of financial intermediaries’ financial soundness is similar to that of other firms. We find that the timing and magnitude of the deterioration in the distribution of financial soundness for financial firms in 1932-33, 1937, and 2008 is almost exactly the same as for all firms, both financial and non-financial. There is little evidence during these three recessions that the financial soundness of financial firms deteriorated first, or that it deteriorated by more. Instead, the collapse in the distribution of financial soundness across financial and non-financial firms in these episodes was simultaneous and of comparable magnitude.

In the empirical work discussed above regarding the evolution of the distribution of financial soundness across financial firms, we use a broad definition of financial firms, including all firms in the Finance, Insurance, and Real Estate sector (with SIC codes from 6000-6999). Over the last 20 years, there have been roughly 2000 such firms in our dataset each month. Ever since the Federal Deposit Insurance Corporation intervened to save Continental Illinois National Banks, large financial institutions have been deemed “Too Big to Fail” and there has been much attention in the literature to the moral hazard problems facing the managers of these large financial institutions and the critical role such institutions might play in shaping the evolution of the macroeconomy. According to this view, it is the financial soundness of large financial institutions that plays a prominent role in amplifying macroeconomic shocks. Small financial institutions are less important.

Motivated by these discussions in the literature, we also use our procedure to measure the distribution of financial soundness across large financial firms. Specifically, we examine whether we find substantial differences in the distribution of financial soundness for large...
financial firms relative to that for other financial firms and relative that for to other large non-financial firms over the period 1962-2011. We focus on the time period after 1962 as it is only after this date that we have a sufficiently large number of financial firms in our data to distinguish between large and small financial firms.

The financial soundness of large financial firms We find that the distribution of financial soundness for the 50 largest financial firms (with firm size measured by stock market capitalization) over the prior 1962-2011 is quite similar to that for all financial firms and also quite similar to that for the 50 largest firms, both non-financial and financial, with size again measured by market capitalization. Thus, we find little evidence suggesting that the distribution of financial soundness across large financial firms was significantly different than that for other financial firms or for other large non-financial firms over this period.

This finding puts some discipline on theories in which a deterioration in financial soundness impacts the real economy. In particular, our findings indicate that the transmission of a financial crisis to the real economy (if that is the direction of causation) occurs very rapidly. This empirical finding may be consistent with theories such as those put forward recently by He and Krishnamurthy (2012), Brunnermeier and Sannikov (2012) and Rampini and Viswanathan (2012) in which a deterioration in the financial soundness of financial intermediaries leads to a sudden change in the pricing of capital for all firms. Such a change in pricing might possibly lead us to measure a simultaneous deterioration in the financial soundness of non-financial firms even in the event that the driving force behind the deterioration in the financial soundness of all firms was an initial deterioration in the distribution of financial soundness of financial firms.

Alternatively, our findings may also be consistent with the models of Gabaix (2012) and Gourio (Forthcoming) in which financial crises and the recessions that accompany them are not caused by issues specific to financial intermediaries but instead are driven by the common cause of time-varying disaster risk. As we discuss below, the collapse in the distribution of financial soundness across all firms that is observed in the fall of 2008 is driven, in an accounting sense, by a substantial increase in the volatility of the value of all firms’ assets. A theory driven by a sudden increase in disaster risk has the advantage of being a very parsimonious explanation of the collapses in the distribution of financial soundness across firms observed in these three recessions. Such a theory suffers however, from the drawback that it does not account for the observation that historical events that might have objectively signaled an increase in disaster risk such as onset of World War II and the events of the Cold War such as the Cuban Missile Crisis are not associated with
similar sustained deterioration in the financial soundness of firms.

Our measure of financial soundness builds on the structural credit risk models of Merton (1974) and Leland (1994). In line with their central insight, it accounts both for leverage (how much a firm’s assets are worth relative to its liabilities) and asset volatility (also called its business risk). In particular, our measure adjusts leverage upwards when volatility is high, and vice versa, since high asset volatility decreases a firm’s effective equity cushion.

In the macroeconomic literature, it has long been recognized that leverage is likely to be a key state variable for determining the effects of financial frictions on the aggregate economy and for evaluating the current viability of the banking sector. There is a significant literature that points to the buildup of leverage as a key precursor to the start of a financial crisis (see for example Kindleberger and Aliber, 2005, and Reinhart and Rogoff, 2009). The impact of changes in asset volatility or business risk on financial soundness and financial frictions, on the other hand, has been examined more closely only recently, for example by Bloom (2009), Gilchrist, Sim, and Zakrajsek (2010), Rampini and Viswanathan (2010), Arellano, Bai, and Kehoe (2011), Christiano, Motto, and Rostagno (2010) and others.

**Leverage vs asset volatility.** To examine the role of changes in asset volatility in the most recent financial crisis, we use our measure of financial soundness together with accounting data on leverage by firm to decompose the collapse in the distribution of financial soundness across firms that occurred in the fall of 2008 into the component that was due only to an increase in asset volatility and the remainder which was due to leverage increasing. We find that the major portion of the collapse in the distribution of financial soundness that occurred in 2008 was due to an increase in asset volatility (or business risk).

This finding stands in contrast to the assumption in most macroeconomic theories of financial frictions cited above that it is an increase in firms’ leverage due to a decline in asset values that leads to financial crises. Moreover, we find it striking that our measure of the distribution of financial soundness across firms both financial and non-financial rose to historically high levels of soundness in advance of the crisis of 2008 despite the increase in leverage that occurred over this period. Hence, our empirical work thus suggests that measures of leverage and a measure of financial soundness that adjusts for volatility behave very differently over time and that it is important to account for changes in asset volatility (or business risk) over and above changes in leverage to understand financial crises.
In our empirical work, we have found little evidence that the evolution of the distribution of financial soundness across financial firms is significantly different from that for all firms, both financial and non-financial, even if we focus attention on the largest financial firms. There is a large literature, however, that points to a particular subset of financial intermediaries, often termed “banks”, as playing a particularly important role in financial crises and in shaping the impact of such crises on the macroeconomy (see, for example, Corrigan (1983), Financial Crisis Inquiry Commission (2011) and Gorton (2012)). The new financial regulatory framework that has emerged in the wake of the most recent crisis is built in large part on the premise that it is possible to identify a set of such systemically important financial institutions (SIFI) ex-ante and prevent further financial crises by subjecting these special institutions to greater regulatory scrutiny and higher standards of safety and soundness.

Motivated by this regulatory approach, we use our empirical procedure to uncover whether there indeed is a set of financial institutions for which the distribution of financial soundness evolved in a distinctive manner either in advance or after this most recent crisis. Specifically, we use our procedure for measuring the financial soundness of a narrower set of large financial firms that we term the government-backed large financial firms over the period 1997-2011. We define this set of government-backed large financial firms as the 18 publicly traded firms currently on the list of the 19 largest bank holding companies subject to the most stringent annual “stress test” by the Federal Reserve together with the six large financial firms that failed during the crisis: AIG, Bear Stearns, Lehman, Merrill Lynch, Wachovia, and Washington Mutual. We compare the distribution of financial soundness for this set of government-backed large financial firms to that for all financial firms and for the 50 largest firms, both non-financial and financial.

The financial soundness of government-backed large financial firms We find that over the period 1997 - summer 2007 leading up to the crisis the distribution of financial soundness across these government-backed large financial firms was quite similar to that for all financial firms and for the 50 largest firms, both non-financial and financial. Moreover, this distribution of financial financial soundness for these firms improved steadily over the period 2002- summer 2007. Thus, our evidence does not indicate that the government-backed large financial firms looked unsound in the years leading up to the crisis, either in comparison to their peers or in absolute terms compared to history. In contrast, we find that starting in the summer of 2007 and over the four years that have followed, the distribution of financial soundness for these government backed large financial firms has looked significantly worse than that for all financial firms and for the
One might interpret this finding that the government-backed large financial firms looked unsound relative to all financial firms and to all large firms, non-financial and financial for the period Aug 2007 to September 2008 in one of two ways. On the one hand, one might argue that this finding is simply the result of selection ex-post: six of the 24 firms in this group failed by September of 2008, at least two others received explicit bailouts, and many claim that many other firms in this group would have failed without extraordinary government intervention. On the other hand, one might argue that indeed it was this set of firms that was “systemically important” ex-ante and it was their failure that led to the collapse in the distribution of financial soundness across all firms in September of 2008. We cannot resolve which interpretation is correct with the methods presented here.

We do, however, see the finding that the distribution of financial soundness across these government-backed large financial institutions has been substantially worse than that for all financial firms and that for all large firms as striking. Basically, the stress test banks and AIG have looked substantially less sound than their peers despite the attention that they have received from regulators in the years following the crisis. In this regard, our findings are consistent with the theories of Diamond and Rajan (2011) and Admati et al. (2012) arguing that these increased regulatory efforts have not overcome the problems of debt overhang and moral hazard due to government support that hinder the incentives of bank owners and managers to take the steps needed to restore their banks to financial health after a crisis.

The remainder of this paper is organized as follows. In section 2, we describe the theory underlying our measurement procedure, in section 3 we compare the empirical performance of our measure of financial soundness to other measures of financial soundness, and in section 4 we present our empirical results. We conclude with a discussion of the implications of these findings for business cycle research.

2 The Theory Underlying our Measurement

Our empirical work is based on a specific theoretical one-dimensional index of a firm’s financial soundness which we term Distance to Insolvency.\footnote{Our concept of Distance to Insolvency is closely related to but distinct from the concept of Distance to Default defined in structural models of firms’ credit risk pioneered by Merton (1974) and Leland (1994).} To define terms, we say that a firm is solvent if its underlying assets are worth more than its liabilities and insolvent if this is not the case. More specifically, we define the firm’s leverage as the percentage gap
between the value of the firm’s underlying assets and the firm’s liabilities, and we define
the volatility of the firm’s underlying assets as the (instantaneous) percentage standard
deviation of innovations to the value of these assets. A firm’s distance to insolvency is
defined as the ratio of our measure of leverage to our measure of asset volatility, both
dated at a point in time \(t\). Thus, a firm’s distance to insolvency is the drop in asset
value that would render the firm insolvent, measured in units of the firm’s asset standard
deviation.

### 2.1 Distance to Insolvency: definition

To define terms, we make use of the following notation. The firm has on the left-hand
side of its balance sheet assets which yield at time \(t \geq 0\) a stochastic cash flow denoted
by \(y_t\). Let \(V_{At}\) the market value of these cash flow, where market values are measured
using state-contingent prices to value the future cash flows derived from the firm’s lines
of business. On the right-hand side of its balance sheet, the firm has liabilities which we
model as a deterministic sequence of cash flows \(\{c_t, t \geq 0\}\) which the equity holders of
the firm are contractually obligated to pay if they should wish to continue as owners of
the firm. Let \(V_{Bt}\) the market value of the firm’s liabilities, valued as if it were default
free. Of course, since the firm may default on its liabilities, \(V_{Bt}\) is larger than the market
value of the firm’s debt. We say that a firm is **solvent** if its underlying assets are worth
more than its liabilities, \(V_{At} \geq V_{Bt}\), and **insolvent** otherwise. Let the **asset volatility**, \(\sigma_{At}\),
be the (instantaneous) percentage standard deviation of innovations to \(V_{At}\), representing
the business risk that the firm faces. Let the **leverage** be the percentage gap between the
value of the firm’s underlying assets and the firm’s liabilities, \((V_{At} - V_{Bt})/V_{At}\). A firm’s
distance to insolvency is defined as

\[
DI_t = \left(\frac{V_{At} - V_{Bt}}{V_{At}}\right) \frac{1}{\sigma_{At}},
\]

the ratio of our measure of leverage to our measure of asset volatility, both dated at a
point in time \(t\). Thus, \(DI_t\) is the drop in asset value that would render the firm insolvent,
measured in units of the firm’s asset standard deviation.

We illustrate these concepts graphically in Figure 1. The solid blue line in the figure
denotes the evolution of the value of the firm’s assets, \(V_{At}\), over time. The solid blue line
ends at the current time \(t\). The solid red line denote the value of the firm’s liabilities \(V_{Bt}\).
The black arrow denotes the distance between \(V_{At}\) and \(V_{Bt}\) at time \(t\). The dashed blue
lines denote standard error bands around the evolution of \(V_{At+s}\) going forward at different
time horizons \( s > 0 \). The likelihood that the firm becomes insolvent in the near term depends both on the distance between \( V_{At} \) and \( V_{Bt} \), measured here in percentage terms by the firm’s leverage, and the volatility in percentage terms of innovations to the value of the firm’s assets. We combine these two factors into Distance to Insolvency which serves as simple one-dimensional index of the firm’s financial soundness.

Calculating a firm’s distance to insolvency may be challenging because, in principle, it requires one to measure the market value and volatility of a firm’s underlying assets, \( V_{At} \) and \( \sigma_{At} \), and the value of its liabilities, \( V_{Bt} \). The former are not directly observable, and the latter is subject to deficiencies and inconsistencies in accounting measures of firms’ liabilities across countries, time, and industries. To circumvent these difficulties, we use a straightforward extension of Leland (1994) structural model of credit risk in order to derive two approximation results that dramatically simplify measurement relative to what has been done in the academic literature and in commercial applications.\(^2\) Specifically, we show that one can approximate a firm’s Distance to Insolvency simply with the inverse of the firm’s equity volatility. This approach has several strengths: it appears to be robust to a variety of model specifications, it does not require the use of accounting data, and it can be implemented over long time periods and across many countries.

### 2.2 Distance to Insolvency in a simple structural model

Using Leland (1994) structural model of credit risk, we derive two theoretical approximation results. First, if equity is a claim with limited liability to the cash flow from the assets of the firm, then the inverse of the (instantaneous) standard deviation of innovations to the firm’s equity value at time \( t \) is an upper bound on the firm’s distance to insolvency at time \( t \). Second, if the firm’s creditors are aggressive in forcing the equity holders to file for bankruptcy as soon as the firm is insolvent, then this upper bound is tight.\(^3\) We argue that because these findings rely on just a few elementary properties of the value of equity, they are likely to hold in a broad class of models.

**The Leland Model.** Let interest rates and the market price of risk be constant. On the left–hand side of the firm’s balance sheet, the cash flows derived from the firm’s underlying assets (lines of business) follow a geometric Brownian motion with constant volatility. In this case, the market value of the firm’s asset, \( V_{At} \), also follows a geometric

\(^2\)Moody’s has implemented and marketed a structural model of firm’s credit risk for the past decade. One of our contributions relative to the work done at Moody’s is to propose a method that allows us to measure credit risk back to 1926.

\(^3\)Black and Cox (1976) pioneered the study of structural models of credit risk in which creditors add bond provisions to force equity to exercise their right to limited liability when the firm becomes insolvent.
Brownian motion with constant volatility $\sigma_A$. In particular, fluctuations in $V_{At}$ are driven entirely by fluctuations in the firm’s projected cash flows. On the right-hand side of its balance sheet, the firm has liabilities given by a perpetual constant flow of payments $c > 0$. Hence, the present value of these payment is constant and equal to $V_B = c/r$, where $r > 0$ denotes the interest rate.

Equity holders have limited liability, in that they can choose to stop making the contractual liability payments, in which case they default and assets are transferred to creditors. Creditors are protected by covenants, allowing them to force equity holders into default if the value $V_{At}$ of the assets fall below some exogenously given threshold, which we assume is lower than $V_B$. Using standard argument, one can show that, when the value of assets falls below some endogenous threshold $V^*_A \leq V_B$, either equity holders exercise their right to default or creditors exercise their protective covenant. The value of equity can be written as $V_{Et} = w(V_{At})$, for some continuous function $w(V_A)$ with key properties illustrated in Figure 2.

Lemma 1. In Leland (1994) structural model, the value of equity, $w(V_A)$, is greater than $\max\{0, V_A - V_B\}$, non-decreasing, convex, and satisfies $w'(V_A) \leq 1$ as well as $w(V^*_A) = 0$.

The lower bound, $\max\{0, V_A - V_B\}$, follows from limited liability assumption: the value of equity has to be greater than zero, and it also has to be greater than $V_A - V_B$, its value under unlimited liability. Moreover, in line with Merton (1974) original insights, the value of equity inherits standard convexity properties of call options. Note in particular that $w'(V_A) \leq 1$, which follows from the fact that the option value of limited liability falls as the value of the firm’s assets rises. Finally, the value of equity must be zero at the default point, $V^*_A$.

Measuring distance to insolvency. As mentioned above, measuring $DI_t$ is challenging because, typically, one does not have data with which to directly measure the firm’s asset value and volatility, $V_{At}$ and $\sigma_A$, nor the value of its liabilities, $V_{Bt}$. The approach pioneered by Merton and Leland is to use a specific structural model of the kind above to model the value of the firm’s equity at $t$, which we denote, $V_{Et}$, and the standard deviation of the innovations to the logarithm of $V_{Et}$, denoted by $\sigma_{Et}$, as functions of the asset value and volatility and the firm’s liabilities. Armed with a model of this kind, one can measure a firm’s distance to insolvency at $t$ using data on its equity value, equity volatility, and its liabilities by inverting the specified structural model to uncover the unobserved asset value $V_{At}$ and asset volatility $\sigma_{At}$. The complexity in measuring a firm’s credit risk in this way stems from the fact that the equity typically has limited liability and hence has an
option to not pay the firm’s liabilities. Because equity has limited liability, the value of
equity is the value of a call option on the assets of the firm, where the specifics of the
option value depend on the details of the model specification.

One leading example of a structural credit risk model is implemented by Moody’s
Analytics (a subsidiary of the credit rating agency) which has sold the model results under
the brand name Expected Default Frequency or EDF for over a decade. The specification
of their specific model together with method that they use to implement this model is
described in Sun, Munves, and Hamilton (2012).

We simplify the approach taken in this literature with the following two approximation
results.

**Proposition 1.** In a Leland (1994) structural model, Distance to Insolvency, $DI_t$, is
bounded above by the inverse of equity volatility.

$$ DI_t \leq \frac{1}{\sigma_{Et}}. $$

*Proof.* To prove this result, note first that, by Ito’s formula, the volatility of equity solves:

$$\sigma_{Et} = \frac{w'(V_{At})}{w(V_{At})} \sigma_A V_{At} \implies \frac{1}{\sigma_{Et}} = \frac{w(V_{At})}{w'(V_{At})} \frac{1}{\sigma_A V_{At}}. $$

By Lemma 1 we have that $w(V_{At}) \geq V_{At} - V_{Bt}$, and $w'(V_{At}) \leq 1$, and the results follow. 

Next, consider the question of whether this upper bound on the firm’s distance to
insolvency is tight. To do this, recall that $V^*_A$ is be the threshold asset value at $t$ at
which equity exercises its option of limited liability to give up control of the firm’s assets
in exchange for abandoning the firm’s liabilities. We use $V^*_A$ to define the concept of
Distance to Default as

$$ DD_t = \left( \frac{V_{At} - V^*_A}{V_{At}} \right) \frac{1}{\sigma_A}. $$

Note that default is distinct from insolvency in our theory and that quite generally a
firm’s distance to default exceeds its distance to insolvency. This is because equity may
not walk away immediately from an insolvent firm, but will not choose default if the firm
is solvent. With this definition we have our second proposition:

**Proposition 2.** In a Leland (1994) structural model, the inverse of a firm’s equity volatil-
ity lies between its Distance to Insolvency and its Distance to Default.

\[ DI_t \leq \frac{1}{\sigma_{Et}} \leq DD_t \]

**Proof.** This proposition follows from the convexity of the value of the firm’s equity as a function of the value of the firm’s assets at each time \( t \) and because \( w(V_A^*) = 0 \).

We illustrate the proof of these two propositions in Figure 2. At time \( t \), the value of the firm’s equity as a function of the value of its assets is a convex function with slope less than or equal to one that lies above the horizontal axis (exceeds zero) and the line \( V_{At} - V_{B} \) giving the value of the firm’s equity under unlimited liability. The value of the firm’s equity hits the horizontal axis at the default point \( V_{At}^* \). Define \( X_t \) to be the point at which the tangent line to the the value of equity \( V_{Et} \) at the current asset value \( V_{At} \) hits the x-axis. All these lines and points are drawn in this figure.

By the convexity of \( w(V_A) \), we have \( V_{At}^* \leq X_t \leq V_{Bt} \). Simple algebra then delivers that

\[
\frac{1}{\sigma_{Et}} = \left( \frac{V_{At} - X_t}{V_{At}} \right) \frac{1}{\sigma_A}
\]

which proves the result.

With these two results, we have that the inverse of a firm’s equity volatility is an accurate measure of its distance to insolvency if the firm’s distance to default is close to its distance to insolvency. That is, the bound is tight if creditors quickly force insolvent firms into default. Proving that a firm’s distance to default will be close to its distance to insolvency as a theoretical matter relies on the specifics of the model. As an empirical matter however, the economics of creditors’ incentives to force a firm that is insolvent into bankruptcy as soon as possible to avoid further costs of financial distress suggest that firms with alert and aggressive creditors should satisfy this condition.

While we have established our approximations in the context of a simple model, our results rely on just a few elementary properties of the value of equity, which are likely to hold in a broad class of models used in applied work. First, the proof requires that the value of equity be a convex function of the value of assets with slope less than one, a property that is typical of structural credit risk models. Second, the proof requires that the value of equity is the only state variable following a diffusion. Thus our results hold if there are others state variables, for interest rate, market price of risk, or liability payments, as long as these are “slower moving”, in the sense of being continuous time Markov processes.

In our empirical work, we use data from the CRSP database on daily equity returns
to measure a firm’s equity volatility $\sigma_{Et}$, and we use this measure to approximate the firms’ true Distance to Insolvency. For the remainder of this paper, in a slight abuse of terminology, we will refer to this equity volatility-based approximation directly as the firm’s Distance to Insolvency.

3 Distance to Insolvency and Financial Soundness

We now compare Distance to Insolvency, our measure of financial soundness, empirically to other measures of financial soundness available over this time period so as to establish benchmarks for interpreting the level of a firm’s Distance to Insolvency.

3.1 Distance to Insolvency and credit ratings

We first compare the inverse of firms’ equity volatility to their credit ratings as reported quarterly in COMPUSTAT. We pool all the firm-month observations since 1985 for which we simultaneously have a credit rating from COMPUSTAT and daily stock return data from CRSP. We find that there is a clear systematic relationship between firms’ credit ratings and firms’ Distance to Insolvency. In particular, when we compute the cross-section distribution of Distance to Insolvency conditional on S&P credit rating in the pooled data, we find that this conditional distribution declines monotonically (in the sense of first-order stochastic dominance) with a decline in credit rating. We also find that this relationship between credit ratings and firms’ Distance to Insolvency is nearly identical for financial firms as it is for all firms, financial and non-financial combined.

In Figure 3, we plot the median of the cross-section distribution of firms’ Distance to Insolvency conditional on S&P credit rating. As shown in the figure, for highly rated firms (AAA and similar ratings), the median distance to insolvency is 4, for firms at the margin between investment grade and speculative grade (BBB- vs. BB+), the median distance to insolvency is 3, while for firms with a rating of C or D (indicating that they have filed for bankruptcy and/or have defaulted on a bond) the median distance to insolvency is 1.

We identify financial firms in our data as those firms with an SIC code ranging from 6000-6999. These SIC codes cover the industries of Finance, Insurance, and Real Estate (FIRE). In Figure 4 we compare the median of firms’ Distance to Insolvency conditional on S&P credit rating for financial firms shown in the blue line and compare it to the median of firms’ Distance to Insolvency conditional on S&P credit rating for all firms shown in the red line. As shown in the figure we find that the relationship between the inverse of a firm’s equity volatility and its credit rating using the same pooled data since
1985 is nearly identical for financial firms as it is for all firms.

Using the results in these two charts as guidelines for interpreting the preliminary empirical work that follows, we find that, according to their credit rating, firms with a Distance to Insolvency over 4 have low credit risk, firms with a Distance to Insolvency near 1 have very high credit risk, and firms with a Distance to Insolvency near 3 are at the borderline of investment grade versus junk status. Moreover, these numerical benchmarks are the same for non-financial and financial firms with a credit rating.

To give a sense of the dispersion of the distribution of Distance to Insolvency by credit rating, we show the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles of the cross-section distribution of Distance to Insolvency conditional on S&P credit rating from the pooled data in Figure 5. We find that over 95 percent of highly rated firms (AAA and similar ratings) have a Distance to Insolvency over 2 and that over 95 percent of very low rated firms have a Distance to Insolvency under 4. Hence we can say that firms with a Distance to Insolvency below 2 are extremely unlikely to also have a high credit rating and firms with a Distance to Insolvency over 4 are extremely unlikely to have a very low credit rating. For values of Distance to Insolvency between 2 and 4, no such sharp statistical statements can be made.

3.2 Distance to Insolvency and bankruptcy

We have also examined Distance to Insolvency as an indicator of a firm’s subsequent probability of bankruptcy. To do so, we merged two data sets on bankruptcy filings by publicly traded firms collected by Chava and Jarrow (2004) and the UCLA-LoPucki bankruptcy database. The results that we find are consistent with the results found on the conditional distribution of distance to insolvency for firms with a credit rating of C or D (indicating that they have already filed for bankruptcy and/or defaulted on a bond). Specifically, a Distance of Insolvency near 1 is a strong indicator that a firm will file for bankruptcy in the near term (less than six months). The relationship is weaker at longer horizons.

Moreover, we find that the distribution of insolvency for those firms that do end up filing for bankruptcy deteriorates steadily in the months prior to bankruptcy. In figure 6, we show the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles of the distribution of the distance to insolvency for those firms that end up filing for bankruptcy in the sixty months prior to filing for bankruptcy or being delisted. As one can see, these percentiles decline monotonically as bankruptcy approaches. Twelve months prior to bankruptcy, these percentiles are all roughly half the corresponding percentiles of the pooled cross-
section distribution of distance to insolvency for all firms. We see in this figure that nearly all firms that end up filing for bankruptcy have a distance to insolvency under two immediately prior to filing, a distance to insolvency under three three months prior to filing, and a distance to insolvency under four 18 months prior to filing.

We interpret these results as being consistent with the view that firms with a Distance to Insolvency over 4 have low risk of bankruptcy in the near term and that firms with a Distance to Insolvency near 1 have very high bankruptcy risk in the near term.

In the empirical work below, we also examine, as a case study, the evolution of Distance to Insolvency for six firms that failed in the financial crisis of 2007-2008: AIG, Bear Stearns, Lehman, Merrill Lynch, Wachovia, and Washington Mutual. As we discuss below, we find that distance to insolvency for these firms declined to very low levels in advance of failure in a manner consistent with the general pattern shown in figure 6.

4 Financial soundness during U.S. Business Cycles

We now use our measure of Distance to Insolvency to retrace the history of U.S. firms’ financial soundness, from 1926 to now. We use data from the CRSP database on daily equity returns to calculate $\sigma_{Et}$ for each firm and each month from 1926 to 2012.\footnote{The CRSP daily dataset on equity returns includes NYSE daily data beginning December 1925, Amex (formerly AMEX) daily data beginning July 1962, NASDAQ daily data beginning December 1972, and ARCA daily data beginning March 2006.} Precisely, we approximate $\sigma_{Et}$ by the square root of the average squared daily returns in the month.\footnote{One could also compute volatility using a range of alternative methods including a rolling window of returns, the latent-variable approach of stochastic volatility models, or using option-implied equity volatilities as measures of $\sigma_{Et}$. We have chosen our measure primarily to ensure that it does not use overlapping daily data and for the convenience of correspondence with the monthly calendar. Moody’s uses a much longer window to compute equity volatility in its KMV model.} We annualize this standard deviation by multiplying by $\sqrt{252}$ where 252 is the average number of trading days in a year. We then plot, for each month, the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles, of the cross-sectional distribution of $1/\sigma_{Et}$. We break our plots into 15 year long time periods so that fluctuations in the distribution of Distance to Insolvency across firms can be seen in the graphs.

4.1 Financial soundness collapsed during only three recessions

Figure 7 starts with a plot of the evolution of the distribution of Distance to Insolvency across firms over the period 1926-1940 by plotting the time series of the percentile cutoffs for firms’ Distance to Insolvency. The vertical scale on this plot (and all of our subsequent
plots) runs from 0 to 10 where, again, our measure of Distance to Insolvency is in units of annualized standard deviations of the gap between the value of a firm's assets and the value of its liabilities. As we saw above, a value of Distance to Insolvency over 4 corresponds to a high credit rating or a very low credit risk. A value of Distance to Insolvency of 1 corresponds to a very low credit rating and a very high credit risk. A value of Distance to Insolvency of 3 corresponds to the borderline between an investment grade and a speculative grade credit rating and hence corresponds to a moderately high credit risk.

In Figure 7 covering the period 1926 to 1940, we see two collapses in the distribution of Distance to Insolvency during the Great Depression: in the recession of 1932-33 and in the recession of 1937. In both of these recessions, the median Distance to Insolvency (shown in bright red and labeled perc50) falls from 4 (safe) to 1 (very high credit risk) and the Distance to Insolvency for the 95th percentile (shown in dark blue and labeled perc95) falls from a very high level to 3 (borderline junk). Thus, in both of these recessions, we have that the financial soundness of the median firm fell to near bankruptcy and the financial soundness of the 95th percentile firm fell to borderline junk status.

Next, compare the Great Depression to the recent recession of 2008. Figure 8 below shows the evolution of the distribution of Distance to Insolvency over the time period 1997 to 2008. In this figure we clearly see a collapses in the distribution of Distance to Insolvency in the fall of 2008. Just as during the Great Depression, in this recession, the median Distance to Insolvency (shown in bright red and labeled perc50) falls from 4 (safe) to 1 (very high credit risk) and the Distance to Insolvency for the 95th percentile (shown in dark blue and labeled perc95) falls from a very high level to 3 (borderline junk). Again, in this recession, we have that the financial soundness of the median firm fell to near bankruptcy and the financial soundness of the 95th percentile firm fell to borderline junk status.

These two figures document our first result that during the recessions of 1932-33, 1937, and 2008 there was a significant collapse of the distribution of financial soundness across firms.

We find that this collapse in the distribution of financial soundness across firms in these three recessions did not happen in other recessions. To illustrate this result, we show the evolution of the distribution of financial soundness across firms in other recessions. In the figure covering the period 1997-2011, we have shaded the months of the recession of 2001 in grey. There is no similar collapse in the distribution of financial soundness across firms in this recession.

To further illustrate this point, in Figure 9, we show the evolution of the distribution
of Distance to Insolvency across firms for the period 1979-1996. In this figure, we have shaded in grey the months of the three recessions in this time period. As one can clearly see in this figure, the distribution of the Distance to Insolvency across firms in these three recessions does not collapse significantly. In contrast, one of the striking features of the data in this figure is the stability in the cross-section distribution of Distance to Insolvency across firms over time outside of the stock market crash of October 1987. This dramatic decline in the stock market in October 1987 clearly appears in the figure, but note that it does not occur during a recession.

In Figures 10 and 11 we show the evolution of the distribution of Distance to Insolvency across firms for the periods 1962-1978 and 1941-1961. Again, in these figures we do not see a substantial collapse in the distribution of insolvency across firms during recessions, with the possible exception of the recession in 1970. In these two figures, we also see a number of instances in which the distribution of distance to insolvency collapses briefly as it did in October 1987. These episodes include September 1939, May 1940, December 1941, August 1946, and May 1970. Each of these episodes was associated with a sudden large drop in the overall stock market that was not associated with a recession.

4.2 Financial intermediaries financial soundness

A large literature in macroeconomic and finance argues that, when financial intermediaries are financially unsound, they amplify and propagate negative shocks to the real economy. In fact, a commonly held view is that the weak financial soundness of financial intermediaries caused the large recession of 1932-33, 1937, and 2008. Our Distance to Insolvency measure does not lend strong support to this view: the timing and magnitude of the collapse is similar during the three recessions when comparing all firms to financials. We find similar results when we focus simply on the largest financial intermediaries, where we measure size by stock market capitalization.

4.2.1 Financials, 1926-2011

To address intermediaries’ financial soundness with the longest possible time series, we identify financial firms as those firms in CRSP with an SIC code in the range of 6000-6999. We measure the Distance to Insolvency for these financial firms in exactly the same way that we do for all firms. Namely, we construct, every month, the percentiles of the cross-section distribution of Distance to Insolvency across these financial firms.

Consider first the two recessions of the Great Depression. In Figure 12 below we show the 50th and 90th percentiles of the cross-section distributions of Distance to Insolvency
across all firms and across only financial firms for the time period 1926 to 1940. As is evident in this figure, the evolution of these percentiles of the distribution of Distance to Insolvency for financial firms over this time period is almost exactly the same as the evolution of the corresponding percentiles of the distribution of Distance to Insolvency for all firms. Hence, we conclude that the timing and the magnitude of the collapse of the distribution of Distance to Insolvency across financial firms is almost exactly the same as that for all firms in the two recessions of the Great Depression.

Consider now the recession of 2008. In Figure 13 below we show the 50th and 95th percentiles of the cross-section distribution of Distance to Insolvency across all firms and across only financial firms for the time period 1997-2011. In contrast to the data for the Great Depression, in the data for the period 1997-2011, it appears that the distribution of Distance to Insolvency across financial firms is higher, in the sense of first order stochastic dominance, than that for all firms. We show in Figure 14, however, that the median, or 50th percentile of the distribution of Distance to Insolvency across financial firms (shown in light red) matches up almost exactly with the 75th percentile of the distribution of Distance to Insolvency across all firms (shown in orange-yellow) over the same time period.\(^6\) Hence, we conclude that the timing and the magnitude of the collapse of the distribution of Distance to Insolvency across financial firms is almost exactly the same as that for all firms in the 2008 recession.

4.2.2 Large financials, 1962-2011

We now examine the evolution of the distribution of financial soundness for large financial firms. We focus on the time period after 1962 as it is only after this date that we have a sufficiently large number of financial firms in our data to distinguish between large and small financial firms. Every month over this time period, we calculate the distribution of Distance to Insolvency for the top 50 financial firms, as measured by market capitalization. As shown in Tables 1 and 2, these top firms can be banks (such as Wells Fargo), investment firms (such as Berkshire Hathaway), or insurance companies (such as United Healthcare).

We see in Figure 15 that the evolution over the 1962-2012 time period, of the median Distance to Insolvency for the largest 50 financial firms (by market capitalization) is quite similar to that for the median Distance to Insolvency for all financial firms, particularly since the late 1990’s. We see little evidence here for the hypothesis that large financial

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\(^6\) The distribution of Distance to Insolvency for financial firms shifted up relative to the distribution of Distance to Insolvency for all firms in a gradual process that started in the early 1970s and was complete in the mid 1990s. This may have occurred as a result of financial regulation or, alternatively, as a result of the opening up of NASDAQ as a market for the shares of less creditworthy non-financial firms.
firms look systematically different from financial firms as a whole in terms of their Distance to Insolvency.

Figure 16 illustrates that the median Distance to Insolvency for these 50 large financial firms is not much different from that for the largest 50 firms by market capitalization, both non-financial and financial. As clear from the figure, the two time series are again very similar. Hence, we also see little evidence here for the hypothesis that large financial firms look systematically different from large firms as a whole in terms of their Distance to Insolvency.

4.3 Leverage vs asset volatility

Next we consider the source of the collapse of the cross-section distribution of Distance to Insolvency in the fall of 2008. Given the definition of Distance to Insolvency, this distribution can collapse for two reasons: one due to an increase in leverage (a drop in \((V_{At} - V_{Bt})/V_{At}\)) and the other due to an increase in asset volatility (an increase in business risk, \(\sigma_{At}\)). Most of the current literature on financial frictions in macroeconomics envisions that the shock that drives a deterioration in the distribution of financial soundness across firms is a decline in asset values \(V_{At}\) and hence an increase in leverage. Moreover, most models of agency costs focus on the effects of leverage alone on managerial and equity holder decisions.

To examine whether such an increase in leverage occurred in the fall of 2008, we conduct a model-based decomposition of the decline in the distribution of Distance to Insolvency to determine the extent to which the decline occurred due to an increase in leverage or an increase in asset volatility. To do so, we use data from COMPUSTAT to construct a measure of firm liabilities \(V_{Bt}\) (here simply the book value of liabilities) and use the simplest structural model in which equity has unlimited liability to construct the following decomposition. For October 2007 and October 2008, we construct \(V_{Bt}\) from COMPUSTAT data on total liabilities and construct \(V_{At}\) from \(V_{At} = V_{Et} + V_{Bt}\) where \(V_{Et}\) is the firm’s market value of equity from CRSP. We then construct the corresponding terms for leverage and asset volatility \(\sigma_{At} = (V_{Et}/V_{At})\sigma_{Et}\) by direct calculation. We then compare the percentiles of the cross-section distribution of Distance to Insolvency in October 2008, to the cross-section distribution of Distance to Insolvency in October 2008 that would have occurred if leverage for each firm had remained at its level from October 2007 and only asset volatility had risen to its level in October 2008.

These percentiles are shown in Figure 17. The first column of colored bars shows the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles of the cross section distribution
of distance to insolvency in October 2007. The second column of colored bars shows the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles of the cross section distribution of distance to insolvency in October 2008. The third column of colored bars shows the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles of the cross section distribution of distance to insolvency computed firm-by-firm using that firm’s leverage in October 2007 and its asset volatility in October 2008. As is clear in the figure, the percentiles of this counterfactual cross-section distribution of the Distance to Insolvency shown in the third column are quite similar to those found for the actual distribution in October 2008 (shown in the second column) and quite different from those found for the cross-section distribution in October 2007 (shown in the first column).

On the basis of this evidence, we argue that the collapse of the distribution of Distance to Insolvency in the fall of 2008 is primarily due, in an accounting sense, to an increase in asset volatility (business risk) rather than an increase in leverage. In this sense, the collapse in the cross-section distribution of the Distance to Insolvency in the fall of 2008 does not appear to be due to an increase in leverage (a drop in net equity) as would be predicted by many current models of financial frictions and business cycles.

4.3.1 Government-backed financial firms, 1997-2011

In the empirical work discussed above, we have focused on a broad definition of financial firms and even of large financial firms and we have found that the evolution of the distributions of financial soundness for these two sets of firms do not show distinctive patterns relative to other firms, even in those time periods that are called financial crises.

One might argue that our findings here are driven by our failure to identify the right set of financial firms to examine. Perhaps financial crises get started and economic shocks are amplified only when the financial soundness of an even narrower subset of “systemically important financial institutions” (SIFIs) deteriorates. Identifying the correct set of “systemically important financial institutions” is of particular importance going forward given that the thrust of much of the new regulatory framework that has been implemented in the wake of the recent crisis is aimed at identifying SIFIs and placing them in a special regulatory category. Historically, however, many different types of financial institutions have been deemed “systemically important” by regulators: large commercial banks such as Continental Illinois, universal banks such as Wachovia, Bank of America, and Citicorp, dealer banks such as Bear Sterns, Lehman Brothers, and Merrill Lynch, hedge funds such as Long Term Capital Management, and insurance companies such as AIG. Because these firms have been engaged in very different line of business within the financial sector, it is quite challenging to identify them \textit{ex-ante}. 
In an effort to examine whether the distribution of financial soundness for a group of SIFIs behaved in a distinctive manner in this most recent crisis, we examine the Distance to Insolvency of a set of institutions identified as “systemically important” ex-post: the 18 publicly traded bank holding companies that the Federal Reserve recently subjected to stress tests, together with six large financial institutions that failed during the most recent crisis (AIG, Bear Stearns, Lehman, Merrill Lynch, and Wachovia). We refer to this set of firms as government-backed large financial institutions (GBLFIs) and list their names in Table 3. We focus on the 1997-2011 time period.

In Figure 18 we show the 10th (in grey), 50th (in red), and 90th (in orange) percentiles of the distribution of Distance to Insolvency for the set of GBLFIs together with the median (in purple) of the distribution of Distance to Insolvency for all financial firms. As is clear in this figure, from 1997 to the summer of 2007, the distribution of Distance to Insolvency for the GBLFIs is centered on the median for all financial firms. In contrast, from the late summer of 2007 through 2011, the distribution of Distance to Insolvency of the GBLFIs lies well below the median for all financial firms. In fact, for most of this period, the median financial firm has a Distance to Insolvency at or above the 90th percentile for the set of GBLFIs. Thus, we find in this figure that the distribution of the Distance to Insolvency for the GBLFIs was quite similar to that for all financial firms in advance of the most recent crisis but has been substantially worse than that for all financial firms in the four years since the crisis began.

In Figure 19 we show the 10th (in grey), 50th (in red), and 90th (in orange) percentiles of the distribution of Distance to Insolvency for the set of GBLFIs together with the median (in purple) of the distribution of Distance to Insolvency for the 50 largest firms by market capitalization, both non-financial and financial. Again, as is clear in this figure, from 1997 to the summer of 2007, the distribution of Distance to Insolvency for the GBLFIs is centered on the median for all large firms. In contrast, from the late summer of 2007 through 2011, the distribution of Distance to Insolvency of the GBLFIs lies well below the median for all large firms. Again, for most of this period, the median large firm has a Distance to Insolvency at or above the 90th percentile for the set of GBLFIs. Thus, again we find in this figure that the distribution of the Distance to Insolvency for the GBLFIs was quite similar to that for all large firms in advance of the most recent crisis but has been substantially worse than that for all large firms in the four years since the crisis began.

As a final empirical exercise, we examine whether the evolution of Distance to Insolvency for the six institutions in the set of GBLFIs that failed during the most recent crisis was distinctive in advance of their failure relative to the evolution of the distribution of
Distance to Insolvency for all of the GBLFIs. In the six panels of Figures 20 and 21 we show the 10th (in grey), 50th (in red), and 90th (in orange) percentiles of the distribution of Distance to Insolvency for the set of GBLFIs together with the Distance to Insolvency (in purple) for each of AIG, Bear Stearns, Lehman, Merrill Lynch, Wachovia, and Washington Mutual.

Clearly, in all of these figures we see that Distance to Insolvency for these six failing firms fell to a very low level (below 1) in advance of failure. In this sense, our findings are consistent with the more general pattern of Distance to Insolvency in advance of bankruptcy shown in Figure 6. More striking, however, is the clear evidence that the cross-section variation in Distance to Insolvency for these GBLFIs in any given month is quite small relative to the movement in the distribution of Distance to Insolvency over time: during this time period the risk that any one GBLFI is unsound relative to the others is small relative to the risk that the whole group of GBLFIs becomes unsound together. This pattern is particularly apparent in the fall of 2011: these figures indicate that the whole group of GBLFIs was nearly as unsound at that time as they were in early 2008 or mid 2009.

5 Conclusion

This paper is intended as a contribution to measurement: we propose a simple and transparent method for measuring the financial soundness of firms that can be broadly applied to all publicly traded firms in the economy. Many of our findings echo those that others have found (particularly Moody’s Capital Markets Research) using fully developed structural credit risk models, spreads on credit default swaps, and spreads on corporate bonds as alternative market-based indicators of the financial soundness of firms. Clearly much more work needs to be done to examine the theoretical and empirical relationship between these alternative indicators of financial soundness.

We identify three recessions in which a macroeconomic downturn coincides or follows shortly after a substantial deterioration in the distribution of financial soundness across all firms: 1932-33, 1937, and 2008. We find that the other recessions in this time period are not associated with significant deteriorations in the distribution of financial soundness across all firms. Of course, since our findings uncover only a correlation (or lack thereof) between financial soundness and recession, they do not establish causation. We do, however, see our findings as consistent with the hypothesis that financial frictions may have played a significant role in the recessions of 1932-33, 1937, and 2008, and that financial frictions (as envisioned by current theories) did not play a significant role in
other recessions during this time period. We hope that our research will provoke more
detailed studies of the differences between these three recessions and other recessions to
see if a stronger empirical and theoretical basis for causal links between financial frictions
and the evolution of the macroeconomy can be developed.

We also find little or no evidence that the evolution of financial soundness across
financial firms differs meaningfully from that for all firms, even during the three crisis
episodes. In the recessions of 1932-33, 1937, and 2008, the timing and magnitude of
the collapse in financial soundness that occurred for all firms was the same as that for
financial firms, both large and small. We find only weak evidence that the distribution
of financial soundness for a set of “systemically important financial institutions” deteri-
orated in a distinctive manner in advance of the most recent financial crisis. While we
recognize that this evidence does not rule out the hypothesis that there is a set of “sys-
temically important financial institutions” that merit special regulatory attention because
of the outsized impact they have on the macroeconomy, we do interpret this finding as
raising some questions as to how it is that the financial soundness of these financial firms
plays a particularly important role in crises and recessions. Clearly further empirical and
theoretical work in this area is needed.

Finally, we interpret our findings regarding the financial soundness of government-
backed large financial institutions in the four years since the most recent financial crisis
began as somewhat distressing in light of the heightened regulatory scrutiny that these
financial institutions have received over that period. Why it is that these firms continue
to look financially weak relative to their peers is an open question that we cannot answer.
A Leland (1994) structural model

Under the true “physical” measure, the value of the firm’s assets, \( V_A \), follows a Geometric Brownian motion with drift \( \mu_A \) and volatility \( \sigma_A \). The firm pays a dividend \( \delta V_A \) per period. Under the risk-neutral measure, the value of the firm’s assets follows

\[
dV_A = (r - \delta)V_A \, dt + \sigma_A V_A dB^Q_t.
\]

The intuition for the risk neutral drift of \( r - \delta \) is simply that, under the risk neutral measure, the expected return from buying the assets at \( V_A \), selling at \( V_{A+dt} \) and receiving the dividend flow \( \delta V_A \, dt \), should be equal to \( r dt \). Assume that the equity holders have to pay \( c \) (per unit of time) to the debt holders until either (i) equity holders choose to default or, (ii) creditor exercise their right to force equity holders to default, when the value of asset reaches a protective covenant threshold \( V_{A0} \). Let \( \tau_P \) be the first time asset value falls below the protective covenant threshold, \( V_{A0} \). Equityholders’ problem is to choose a stopping time \( \tau \) in order to solve

\[
w(V_A) = \sup_\tau \mathbb{E}^Q \left[ \int_0^{\tau \wedge \tau_P} (\delta V_A - c) e^{-rt} \, dt \right].
\]

Consider equity holders starting with two different initial levels of assets, \( V_{A0} < V_{A0}' \). Clearly, the equity holders starting with \( V_{A0}' \) can always mimic the policy of equity holders and creditors starting at \( V_{A0} \) and would earn a higher payoff, implying that \( w(V_A) \) is non-decreasing. This also shows that an optimal policy is of the threshold form: there is a \( V_A^* \) such that when \( V_A \leq V_A^* \), equity holders default, or are forced into default by creditors, and continue operating the firm otherwise. Thus, the Bellman equation for the value of equity is:

\[
V_A \leq V_A^* : w(V_A) = 0
\]

\[
V_A \geq V_A^* : rw(V_A) = -c + \delta V_A + w'(V_A)(r - \delta)V_A + w''(V_A)\frac{\sigma_A^2 V_A^2}{2}.
\]

A particular solution to the second-order ODE is \( V_A - V_B \), where \( V_B = c/r \). The general solution of the corresponding homogeneous ODE is of the form \( K_1 V_A^\theta + K_2 V_A^{-\theta} \), where \( K_1 \)
and $K_2$ are constant, while $\phi$ and $\theta$ are the positive roots of:

$$\frac{\phi^2\sigma_A^2}{2} + \phi \left( r - \delta - \frac{\sigma_A^2}{2} \right) - r = 0$$

$$\frac{\theta^2\sigma_A^2}{2} - \theta \left( r - \delta - \frac{\sigma_A^2}{2} \right) - r = 0.$$  

When $V_A \to \infty$, the value of equity has to asymptote to $V_A - V_B$, implying that $K_1 = 0$. The constant $K_2$ is found by value matching $w(V_A^*) = 0$, which delivers:

$$K_2 = f(V_A^*) \text{ where } f(x) \equiv -(x - V_B) x^\theta.$$  

The optimal threshold maximizes $f(x)$ subject to $x \geq V_A^P$. Differentiating $f(x)$ with respect to $x$ reveals that it is hump shaped and reaches a unique maximum at $\frac{\theta}{1+\theta} V_B$. Therefore, the optimal threshold is:

$$V_A^* = \max \left\{ V_A^P, \frac{\theta}{1+\theta} V_B \right\} \text{ and } w(V_A) = V_A - V_B - (V_A^* - V_B) \left( \frac{V_A}{V_A^*} \right)^{-\theta}.$$  

Convexity follows because $V_A^* \leq V_B$ by our assumption that $V_A^P \leq V_B$. Simple calculation show that $w'(V_A^*) \geq 0$ and that $w'(\infty) = 1$, implying that $w(V_A)$ is non-decreasing and has a slope less than one.
Figure 1: The value of equity as a function of the value of assets.

\[
\left( \frac{V_{At} - V_{Bt}}{V_{At}} \right) \frac{1}{\sigma_{At}}
\]
\[
\left( \frac{V_A - V_B}{V_A} \right) \frac{1}{\sigma_A} \leq \frac{1}{\sigma_E} = \left( \frac{V_A - X}{V_A} \right) \frac{1}{\sigma_A} \leq \left( \frac{V_A - V_{A^*}}{V_A} \right) \frac{1}{\sigma_A}
\]

**Result 3: How tight is the bound?**

- When equity has an option to default
  - Distance to Default an upper bound on inverse of equity volatility
  - Default point \( V_A^* < V_B \)
- \( V_E \) convex in \( V_A \) implies
  \[
  \frac{1}{\sigma_A} \leq \frac{1}{\sigma_E} = \frac{1}{\sigma_A} \leq \frac{1}{\sigma_A}
  \]

- Inverse of equity volatility is close to distance to insolvency if creditors force insolvent firm into bankruptcy
- Implies \( \frac{1}{\sigma_E} \) is the distance to insolvency if creditors force an insolvent firm into bankruptcy as soon as it is insolvent.

**Figure 2:** The value of equity as a function of the value of assets.
Figure 3: The empirical relationship between credit rating and Distance to Insolvency.
Figure 4: The empirical relationship between credit rating and Distance to Insolvency for Financial Firms and All Firms.
Figure 5: The distribution of Distance to Insolvency conditional on credit rating.
Figure 6: The distribution of Distance to Insolvency for firms that declare bankruptcy in the 60 months prior to bankruptcy or delisting.
Figure 7: The distribution of Distance to Insolvency, 1926-1940.
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Figure 21: Distance to Insolvency for government-backed large financial institutions (GBLFIs) that failed during the crisis (ct’d).
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**Table 1:** Top financial companies by market capitalization, in March 1962, 1972, 1982
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Table 2: Top financial companies by market capitalization, in March 1992, 2002, 2012
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**Table 3:** Government-Backed Large Financial Institutions
References

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