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## Credit Market Freezes

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### I. Introduction

Financial market freezes—by which we mean large declines in the volume of transactions in both the primary and the secondary markets that occur over a nontrivial period of time—are typically observed during financial crises. For example, issuance of corporate, mostly railroad, bonds collapsed during the financial crisis of 1873 and did not resume until 1879. Likewise, there was a considerable decline in bond issuances in the financial crises of 1884, 1893, and 1907. Similar patterns can be observed during the Great Depression when issuance of bonds by industrial firms fell dramatically in 1931 and did not recover until 1935.<sup>1</sup> In particular, issuance of real estate bonds, which accounted for 23% of the total corporate bond issuance in the 1920s, came to a halt in 1929 when the market for such bonds dried up. Junk bond issuances that boomed in the first half of the 1980s collapsed in 1990 with the market remaining frozen until 1993. The information technology (IT) revolution led to a boom in issuance of bonds by telecommunication companies, which were in turn purchased and securitized into collateralized bond obligations (CBO). The massive defaults by telecom companies in 2001 and 2002 led to a collapse of the bond securitization market and CBOs have since disappeared. A more recent example of a market freeze took place during the financial crisis of 2008–2009 with the collapse of the structured finance market—the largest and fastest growing financial market in the years leading to the crisis. In particular, not only did the market for mortgage-backed securities such as residential mortgage-backed securities (RMBS) and collateralized debt obligations (CDOs) collapse, but, also, other nonhousing segments of the structured finance markets—ranging

from commercial loans securitizations to asset-backed securities—came to a halt, and even the issuance of corporate bonds declined significantly.

Credit freezes and liquidity dry-ups during financial crises affect secondary markets as well. During the financial crisis of 2008–09 illiquidity in the bond market rose dramatically. For example, according to Bao, Pan, and Wang (2011), aggregate illiquidity doubled from its precrisis levels in August 2007, and tripled in March 2008 during the collapse of Bear Stearns. By September 2008, during the Lehman Brothers default and the bailout of AIG, bond illiquidity was five times its precrisis level. As we show in our analysis below, illiquidity in the bond market also rose sharply in the panic of 1873—one of the worst financial crises during the National Bank era. For example, bid-ask spreads doubled from their precrisis levels in August 1873 and remained elevated for more than a year.

This paper analyzes liquidity in bond markets during financial crises with an emphasis on the most recent crisis of 2008–2009. In doing so, we compare two main theories of liquidity in markets: (1) asymmetric information and adverse selection, and (2) heterogenous beliefs.

The classic literature explaining liquidity and frictions in trade between economic agents relies on fundamental insights developed in the information economics literature. As first shown in Akerlof (1970) and Spence (1973), private information held by economic agents generates adverse selection in which buyers demand discounts reflecting their concern about the negative information held by sellers. Dang, Gorton, and Holmström (2012, 2013) and Holmström (2015) apply these insights to develop an asymmetric information theory of liquidity in bond markets. This is the first theory we test to understand the determinants of liquidity in bond markets during financial crises.

The fundamental insight of Dang, Gorton, and Holmström is that the payoff structure of debt contracts generates two regions in which bonds will trade. When bond default risk is relatively low, bond payoffs will be comparatively insensitive to underlying firm value. The value of private information, and hence adverse selection between economic agents, will be relatively low. As a result, when default risk is low, debt is informationally insensitive and liquidity will be high. In contrast, when default risk rises, the sensitivity of bond value to underlying firm value increases as the firm is nearing its default boundary. Private information in this region is valuable, adverse selection is therefore high, and debt liquidity will decline. The main prediction of the Dang et al.

model is thus that bond illiquidity will rise as bond value declines, with the bond moving from the informationally insensitive to the informationally sensitive regions.

The second theory of bond liquidity we analyze stems from the literature on heterogeneous beliefs (see, e.g., Harrison and Kreps 1978; Varian 1989; Harris and Raviv 1993). By assuming that agents hold different fundamental opinions about underlying asset values—some agents are optimistic while others are pessimistic—the literature on heterogeneous beliefs evades the classic no-trade results in the information economics literature (e.g., Rubinstein 1975; Hakansson, Kunkel, and Ohlson 1982; Milgrom and Stokey 1982). Adverse selection is thus mitigated—indeed, dissipated—by agents' high certainty in the correctness of their own opinion of asset value: agents engage in trade for their own *perceived* mutual benefit. Differences of opinion can thus promote trade and increase liquidity. Indeed, if agent A values an asset more than agent B, and believes B's valuation to be simply wrong, then agent A does not fear adverse selection in purchasing the asset from B, nor will she require a discount in doing so. Our empirical tests are aimed, therefore, at analyzing to what extent differences of opinion are positively related to liquidity in debt markets during the financial crisis of 2008–2009.

One caveat about the theoretical prediction that differences of opinion lead to higher liquidity is that the theory relies on assumptions regarding the *joint* distribution of beliefs and endowments. To the extent that opinion dispersion rises in a manner perfectly correlated with the distribution of endowments, it need not be the case that trade and liquidity will rise with the degree of the dispersion. Consider, for example, a scenario with two agents differentiated by their beliefs about asset value—an optimist and a pessimist—where the optimist owns the asset. If, now, opinion dispersion rises in such a way as to make the optimist even more optimistic and the pessimist more pessimistic, there should be no associated increase in trade or market liquidity.<sup>2</sup> Still, if there are numerous agents, and the changes in agents' opinions are not perfectly aligned with current asset holdings, increased dispersion will facilitate trade.

Before turning to testing the ability of the models to explain liquidity of credit markets during financial crises, we begin by providing descriptive evidence on credit issuance dry-ups. We collect data on bond issuance during the period surrounding the 1873, 1929, and 2008–2009 financial crises. The results show that in all three crises there is a sub-

stantial decline in bond issuance during and after the onset of the crisis. While the evidence is consistent with liquidity dry-ups and market freezes during downturns in the spirit of Myers and Majluf (1984) and Lucas and McDonald (1990), we cannot rule out that the reduction in issuances is driven by lack of corporate demand for credit stemming from a reduction in investment opportunities. Hence, in our main analysis we focus on liquidity in secondary markets—that is, market liquidity—as opposed to liquidity in primary markets—that is, funding liquidity.<sup>3</sup>

We begin by empirically testing the main prediction of the Dang, Gorton, and Holmström model—namely that during financial crises bond illiquidity rises as bond value declines. To operationalize the empirical tests, we use standard measures of bond illiquidity for the 1873 and 2008–2009 crises. Specifically, we use bid-ask spreads as a measure for bond illiquidity during the 1873 crisis. For the 2008–2009 financial crisis we use  $\gamma$ —the negative covariance of log-price changes in two consecutive periods—that has been proposed by Roll (1984) and has been recently used by Bao et al. (2011) as a measure of bond illiquidity.<sup>4</sup>

Using our hand-collected data from the nineteenth century, as well as TRACE data for the 2007–2009 period, we provide graphical evidence that bond illiquidity rises when bond values deteriorate. For example, the correlation between bid-ask spreads and bond prices during the 1873–1876 period is  $-0.909$ . Likewise, the correlation between  $\gamma$  and bond prices during the 2007–2009 period is  $-0.858$ . Both correlations are statistically significant at the 1% level. We next test the prediction that bond illiquidity rises as bond price declines in financial crises more formally by estimating a regression model in which the dependent variable is bond illiquidity and the main explanatory variable is lagged bond price. Our results confirm the negative association between illiquidity and bond prices in both the 1873 and 2008–2009 financial crises, even after we control for bond and year-by-month fixed effects. Our evidence confirms the fundamental prediction of the asymmetric information theory of bond liquidity in Dang et al. (2012): bond illiquidity rises as bond price declines during financial crises.<sup>5</sup>

We continue by analyzing the main prediction of the heterogeneous beliefs theory—that is, differences of opinion between economic agents should promote liquidity. Measuring differences of opinion is not trivial as this requires gauging the subjective beliefs of agents engaged in trade. We employ two proxies of differences of opinions in our analysis. The first proxy for differences of opinion in debt markets is the absolute

value of the difference between the credit rating of Moody's and S&P in notches.<sup>6</sup> Our second measure of opinion heterogeneity is analyst earnings forecast dispersion. Following the literature on analyst forecast dispersion (see, e.g., Diether, Malloy, and Scherbina 2002), we calculate for each bond-month in our sample the ratio of its firm's standard deviation of analysts' current-fiscal-year annual earnings per share forecasts to the absolute value of the mean analyst forecast.

There are two important caveats to these proxies for opinion dispersion. First, even if the measures accurately capture differences of opinion regarding firm value among rating agencies and among equity analysts, these measures may not accurately reflect differences of opinion among the relevant market participants who are actually trading in the bond markets. Second, it could very well be that incentive structures, career concerns, institutional reputational concerns, and the like are influencing earnings forecasts and credit ratings, implying that the actual beliefs of the analysts and rating agencies are different from those announced to the market. We employ these measures because of their availability, and while they have been used extensively in the literature, we proceed with the analysis with these caveats in mind.

First, we show that the difference of opinion measures rise substantially during the crisis. The S&P-Moody's credit-rating difference, as well as analyst earnings forecast dispersion, spike up post-Lehman collapse—both attaining a maximum in March 2009—before declining. Taken together with the rise in illiquidity during the crisis described above, the fact that mean opinion dispersion *increased* post-Lehman serves as prima facie evidence against the main prediction of the heterogeneous beliefs literature of a positive relation between opinion dispersion and liquidity. A simple means comparison analysis confirms the time-series evidence. Sorting bonds into bins by their degree of bond-rating difference results in a positive and monotonic relation between opinion dispersion and illiquidity. Similarly, sorting bonds by deciles of analyst earnings forecast dispersion uncovers a qualitatively similar result: higher dispersion is associated with increased illiquidity, with the effect being particularly pronounced in the top two deciles of analyst forecast dispersion.

More formally, we estimate a regression model relating bond illiquidity to differences of beliefs using our two measures of opinion dispersion. Regressions are run with year-by-month fixed effects—soaking up common time-series variation—and bond fixed effects that control for non-time-varying bond characteristics. The results show that the Moody's-S&P

bond-rating difference is positively related to bond illiquidity. Similarly, the opinion dispersion measure based on analyst forecast dispersion is also positively related to illiquidity, with the effect concentrated in high levels of forecast dispersion. In contrast to the heterogeneous beliefs theory, increased opinion dispersion does not seem, therefore, to contribute to increased liquidity.

We then run a “horse race” between the Dang, Gorton, and Holmström asymmetric information theory of bond liquidity and the heterogeneous beliefs theory. Estimating regression models relating bond liquidity to bond price, as well as the two measures of opinion dispersion, we show that while the relation between illiquidity and price during the 2008–2009 financial crisis remains negative and statistically significant, the relation between bond illiquidity and opinion dispersion is not statistically significant once bond price is added as a covariate.<sup>7</sup> We continue by estimating the portion of the aggregate increase in bond illiquidity during the financial crisis that can be explained simply by the reduction in bond prices, that is, by the main prediction of the Dang et al. asymmetric information theory of bond liquidity. Using the estimated coefficients from the regression of illiquidity on lagged bond price, and integrating over the full distribution of changes in bond price, we conclude that between a quarter and a third of the increase in bond illiquidity after the collapse of Lehman Brothers in September 2008 can be attributed solely to the concurrent reduction in bond prices.

To summarize, our empirical results are consistent with the information asymmetry theory of liquidity as in Dang et al. (2012). When bond value deteriorates, bond illiquidity increases, as would be predicted by adverse selection stemming from the bond entering a region in which its value is informationally sensitive. The negative relation between bond illiquidity and price explains a large fraction of the rise in illiquidity during the financial crisis, although a sizable fraction remains unexplained.

In contrast, using two proxies for belief dispersion—the Moody’s-S&P difference in bond rating and analyst forecast dispersion—we find little support for the hypothesis that liquidity is enhanced as differences of opinion rise. At the aggregate level, as well as using panel data analysis at the individual-bond level, opinion dispersion did not increase liquidity during the crisis period. If anything, the opposite seems to hold, with illiquidity and dispersion positively related, particularly when using the bond-rating difference measure of belief dispersion.

Our results points to a strong link between crises and the dry-ups of market liquidity. We find that asset prices play a crucial role in deter-

mining liquidity in debt markets during financial crises. It is precisely when prices decline market-wide that liquidity dries up and issuance of new liabilities becomes difficult, reducing the supply of capital for firms already pushed into distress due to the crisis. Illiquidity in credit markets can have dire consequences for households as well. Precautionary savings in the form of fixed-income securities become hard to sell and households in need of liquid funds may find liquidity difficult to obtain precisely when they need it most.

These results have implications for the efficacy of monetary interventions meant to strengthen the economy during downturns through increased lending by the financial sector. In particular, the asymmetric information theory of liquidity suggests that if these interventions occur when borrower balance sheets are weak, liquidity will not easily flow from the financial sector into the economy. Weak borrower balance sheets will imply that issued liabilities will be informationally sensitive, limiting borrowers' ability to raise debt capital. Monetary interventions meant to inject liquidity from the financial sector into the real economy can thus arrive "too late." In contrast, monetary interventions that occur at an earlier stage—when balance sheets are still sufficiently strong that liabilities issued by borrowers are relatively informationally insensitive—will have a larger effect. As a corollary, if monetary interventions are rendered ineffective because they arrive too late in the cycle, the asymmetric information theory of liquidity suggests that fiscal policy may be effective in complementing monetary policy. In particular, strengthening borrower balance sheets directly through fiscal policy shifts corporate liabilities into a less informationally sensitive region in which monetary interventions meant to increase lending become effective.<sup>8</sup>

The rest of the paper is organized as follows. Section II presents evidence on credit issuance freezes in three financial crises. Section III provides evidence on liquidity and informational sensitivity in financial crises. Section IV evaluates the explanatory power of belief dispersion for liquidity in financial crises. Section V studies the explanatory power of bond prices in explaining illiquidity during the 2008–2009 crisis. Section VI concludes.

## II. Funding Illiquidity during Financial Crises

We define credit market freezes as large declines in the volume of transactions in both primary and secondary credit markets that occur over a

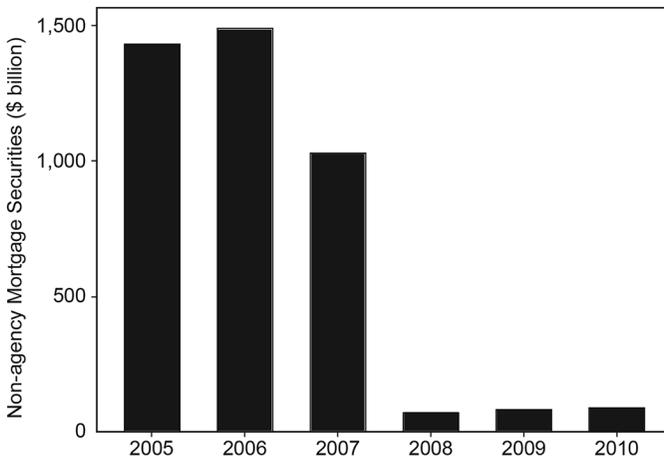


Fig. 1. Nonagency mortgage securities issuance: 2005–2010

nontrivial period of time. This section provides descriptive evidence on credit market issuance freezes during the financial crises of 1873, 1929, and 2008–2009.

#### A. Credit Issuance Freezes in Three Financial Crises

The most recent example of a credit market freeze took place during the financial crisis of 2008–2009 with the collapse of the structured finance market—the largest and fastest growing credit market in the years leading to the crisis. Issuance of structured finance securities, and especially collateralized debt obligations (CDOs), grew dramatically between 2003 and 2006. While the year 2007 was on track to surpass the record numbers of 2006, the credit crisis that began in summer 2007 brought the market for structured finance to a halt.<sup>9</sup> The collapse of the securitization market is well illustrated in figure 1, which uses issuance data to illustrate the dramatic decline in issuance of nonagency mortgage securities from 2005 to 2010.<sup>10</sup> Not only did the market for mortgage-backed securities such as RMBS and CDOs collapse, but also other, nonhousing segments of the structured finance markets ranging from commercial loans securitizations (CLO) to asset-backed securities (ABS) came to a halt, and even the issuance of corporate bonds declined significantly. Figure 2 demonstrates that issuance of nonmortgage, asset-backed securities collapsed during the crisis and stayed at a low level in the following years. The decline in the volume of bond issuance was not confined

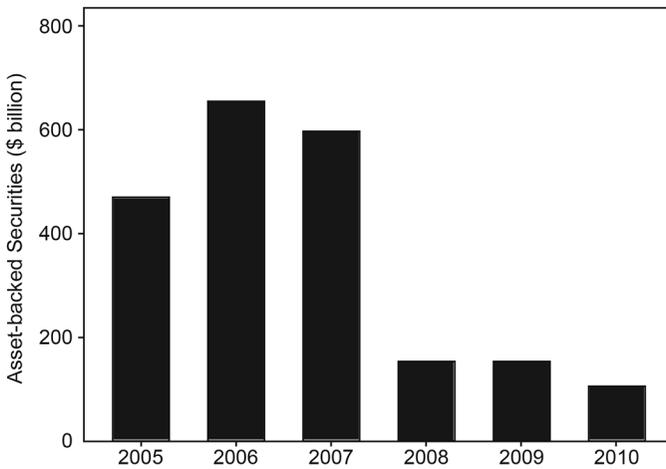


Fig. 2. Asset-backed securities issuance: 2005–2010

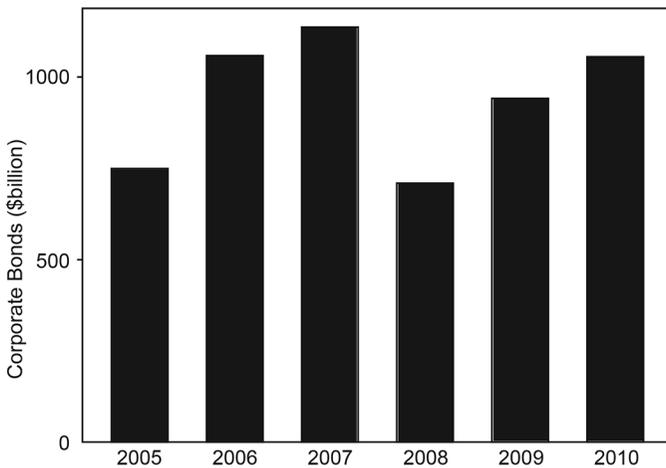


Fig. 3. Corporate bonds issuance: 2005–2010

only to securitized assets. Figure 3 shows that issuance of corporate bonds also declined considerably in 2008 and returned to its precrisis level only in 2010.<sup>11</sup>

We now turn to another credit market freeze that took place during the financial crisis of 1873. The crisis of 1873 is one of the classic international crises according to Kindleberger (1990). It is also one of Sprague's (1910) four crises of the US National Banking era that eventually led to the creation of the Federal Reserve in 1914. The 1873 crisis is

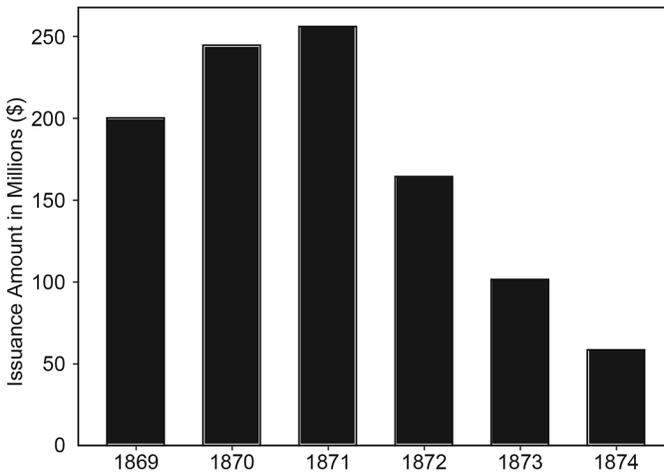


Fig. 4. Corporate bonds issuance: 1869–1874

traditionally viewed as a classic banking panic triggered by the failure of commercial banks linked to the railroad industry. In turn, the crisis heralded a six-year recession according to the NBER business-cycle reference dates. We collect information on issuance of bonds, mostly by railroad companies, for the years 1869–1874 from the *Commercial and Financial Chronicle* (CFC)—a weekly business publication that was first published in 1865 and reported detailed business news, as well as detailed prices of bonds and stocks. Figure 4 displays the volume of corporate bonds issuance from 1869 to 1874. As figure 4 demonstrates, bond issuances declined dramatically in 1873 and 1874 compared to their level in 1870 and 1871. While we do not have detailed information on bond issuance after 1874, contemporary observers of the 1873 financial crisis have argued that bond issuance collapsed during the financial crisis of 1873 and did not resume until 1879.

We provide additional evidence on credit issuance freezes from the financial crisis of 1929. The crisis began on October 1929 with a crash of the stock market that marked the beginning of the Great Depression. According to Mishkin (1991):

The outcome of the panic period starting October 23 and culminating in the crash on October 29 was a negative return for the month of October of close to 20%. This was the largest monthly negative return in the stock market up to that time.<sup>12</sup>

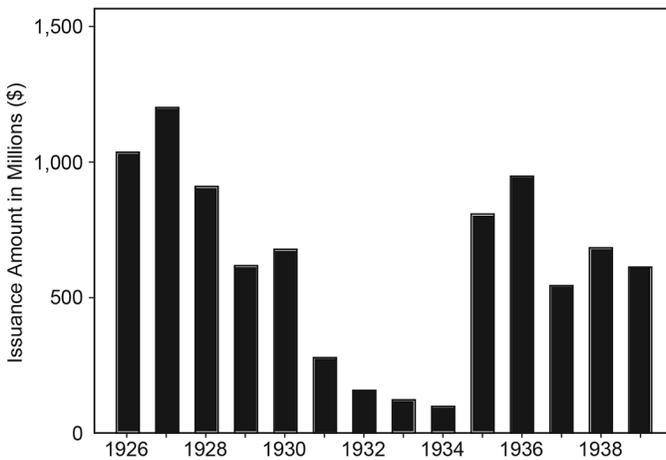


Fig. 5. Industrial bonds issuance: 1926–1939

Figure 5 plots the volume of corporate bond issuance of all industrial firms from 1920 to 1940 in millions of current dollars.<sup>13</sup> As figure 5 demonstrates, issuance of bonds by industrial firms declined in 1929 and then fell dramatically in 1931. The corporate bond market remained frozen until 1935. Benmelech, Frydman, and Papanikolaou (2017) use the collapse of the corporate bond market to identify the effects of funding shortage on firms' employment. They show that bonds were the primary source of debt financing for large firms in the 1920s and that the collapse of the bond market during the Great Depression led firms to layoff many of their employees. Figure 6 provides additional information on credit market freezes during the Great Depression. The figure presents data on issuance of real estate bonds from 1925 to 1934 in millions of current dollars.<sup>14</sup> According to Goetzmann and Newman (2010), total issuance of real estate bonds grew from \$57.7 million in 1919 to \$695.8 million in 1925. By 1928 new issues of real estate bonds surpassed railroad bond issuance and accounted for 23% of the total corporate bond issuance. As figure 6 illustrates, and consistent with evidence in figure 1 for the 2008–2009 financial crisis, real estate bond issuance collapsed during the crisis with the market for these bonds all but disappearing.

Our results show that in all three crises there is a substantial decline in bond issuance during and after the onset of the crisis. The evidence is consistent with liquidity dry-ups and market freezes during downturns in the spirit of Myers and Majluf (1984) and Lucas and McDonald

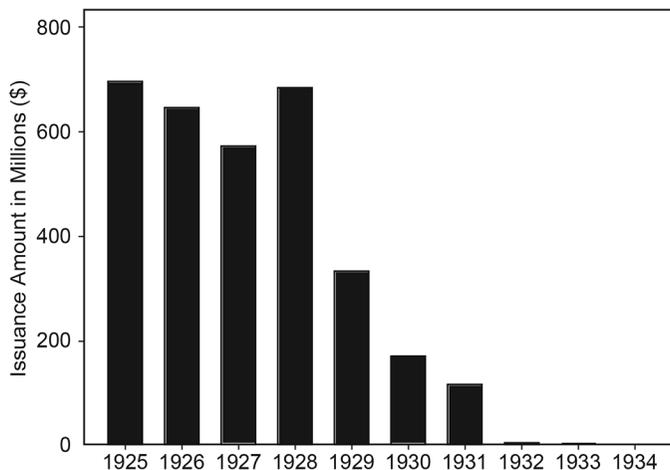


Fig. 6. Real estate bonds issuance: 1925–1939

(1990). Still, we cannot rule out that the reduction in issuances is driven by a lack of corporate demand for credit stemming from a reduction in investment opportunities.

We next turn to provide suggestive evidence on credit market freezes in secondary markets in which market liquidity dries up. Providing such evidence requires information on prices of bonds in secondary markets, which we have collected for two notable financial crises: the 1873 financial crisis and the more recent 2008–2009 crisis.

### III. Market Liquidity and Informational Sensitivity

Market liquidity is a notoriously ambiguous concept. By liquidity in secondary markets, we are referring to what is commonly known as “market liquidity”—that is, the ease with which assets are traded (see, e.g., Brunnermeier and Pedersen 2009). In our analysis we employ two measures of market liquidity common in the literature— $\gamma$  and bid-ask spreads that we define below. In particular, we do not focus on volume of trade as a measure of liquidity, since exogenous variation in the demand for funds is likely to play an important role in determining agents’ need to sell their asset holdings—particularly during financial crises—irrespective of the ease with which assets are traded. Put differently, trading volume may be high not because markets are liquid, but because investors require funding.

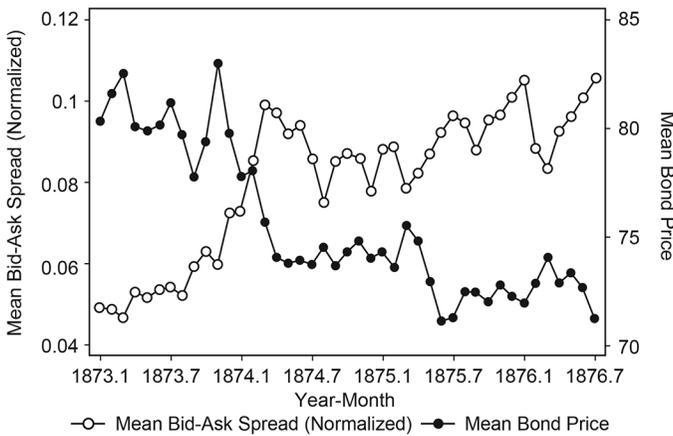


Fig. 7. Bid-ask spreads and bond prices: 1873–1876

#### A. The Financial Crisis of 1873

We collect weekly information from the CFC on prices of corporate—mostly railroad—bonds from January 1873 up to the end of June 1876. The data include the name of the security, the issuing firm, and the bid and ask prices that prevailed for each security during the week. There are 69,444 bond-week observations in our data set. The CFC reports bid or ask prices for 56,717 bond-week observations, and 12,727 bond-week observations do not have pricing information, suggesting that these bonds were not traded during the week in which the information is not reported. We begin our analysis by calculating an index of bid-ask spreads for bonds that have information on both bid and ask prices. We define the relative bid-ask spread for bond  $i$  in week  $w$  as:

$$Spread_{i,w} = \frac{Ask_{i,w} - Bid_{i,w}}{Mid\ price_{i,w}}, \quad (1)$$

where  $Mid\ price_{i,w}$  is defined as  $(Ask_{i,w} + Bid_{i,w}) / 2$ . Next, we calculate  $Spread_t$  as an equal-weighted time-series average of  $Spread_{i,w}$  across bonds and within a month  $t$ .

Figure 7 presents the monthly evolution of bid-ask spreads from January 1873 to June 1876. As the figure shows clearly, bid-ask spreads increased from 0.052 in August 1873 to 0.060 in September 1873 when the crisis started and 0.063 in October 1873. As the financial crisis intensified with more failures of banks and railroad companies, the mean bid-ask

spread reached 0.099—almost twice as high as its level before the crisis. Figure 7 also displays the evolution of the mean bond midprice using the data we have collected from the CFC. As figure 7 shows, the decline in bond prices is associated with higher bid-ask spreads—indicating that the bond market became less liquid as bonds' prices declined. The correlation between the mean bid-ask spread and mean bond price is  $-0.909$ , and is statistically significant at the 1% level.

We argue that the evidence from the 1873 financial crisis is consistent with the Dang et al. model of the effect of the information-sensitivity of debt on liquidity and liquidity dry-ups in debt markets. The main prediction of the model is that when underlying values deteriorate, debt shifts from being informationally insensitive and becomes informational sensitive, adverse-selection problems rise, and liquidity drops. We now turn to conduct a similar analysis of the relation between bond prices and market liquidity during the financial crisis of 2008–2009.

### *B. The Financial Crisis of 2008–2009*

We use bond-pricing data from FINRA's TRACE (Transaction Reporting and Compliance Engine). Our initial sample is similar to the one we use in Benmelech and Bergman (2017) and includes all corporate bonds traded in TRACE. We keep bonds with a time to maturity of at least six months and standard coupon intervals (including zero-coupon bonds). Our sample is composed of "plain vanilla" corporate bonds—we do not include securitized assets in the sample and exclude bonds that are issued by financial firms, as well as convertible, puttable, and fixed-price callable bonds.

As a measure of illiquidity we use  $\gamma$ , which is defined as the negative covariance of log-price changes in two consecutive periods:<sup>15</sup>

$$\gamma = -Cov(\Delta p_t, \Delta p_{t-1}). \quad (2)$$

Figure 8 presents the evolution of the  $\gamma$  measure of illiquidity over time from January 2006 to December 2010, as well as an index of bond prices that is constructed based on actual bond transactions from TRACE. As the figure demonstrates, and consistent with our findings for the financial crisis of 1873, bond prices and bond illiquidity are negatively correlated. Figure 8 illustrates very clearly the spike in bond illiquidity that coincides exactly with the dramatic decline in corporate bond prices:  $\gamma$  increases from 0.680 in January 2007 to 3.434 in September 2008, the month in which Lehman Brothers filed for bankruptcy,

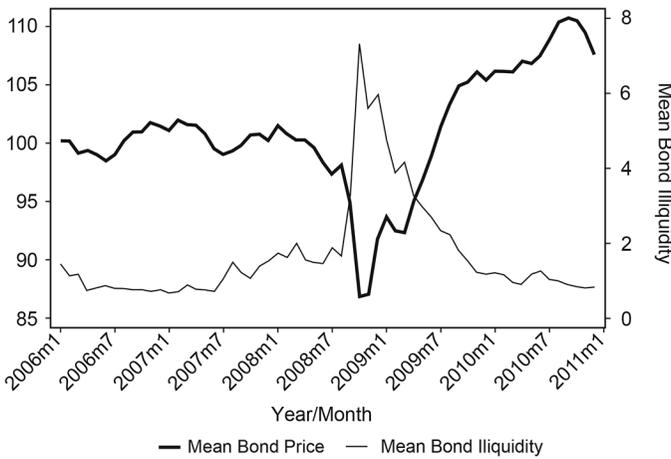


Fig. 8. Illiquidity and bond price: 2007–2009

and to 7.312 in October 2008. The correlation between  $\gamma$  and bond prices during the 2007–2009 period is  $-0.858$  and is statistically significant at the 1% level. Consistent with our findings for the 1873 crisis, we find support for Dang et al. (2013) that when underlying values deteriorate liquidity drops.

Figure 9 refines the analysis in figure 8 by stratifying the time-series evolution of the  $\gamma$  by credit rating. For the ease of graphical representation, we classify bonds into four categories of bond credit ratings where rating category 1 includes the highest quality bonds and category 4 includes the lowest credit-quality bonds. As figure 9 clearly demonstrates, and consistent with Dang et al. (2012), lower credit-rating bonds exhibit higher levels of illiquidity.<sup>16</sup> Moreover, lower quality bonds—especially those in categories 3 and 4—become particularly illiquid during the height of the financial crisis of 2008–2009.

### C. Regression Analysis of Bond Prices and Liquidity during Financial Crises

Our graphical evidence for the financial crises of 1873 and 2008–2009 suggests that bond prices and bond liquidity are negatively correlated during financial crises. We next test the prediction that bond illiquidity rises as bond price declines in financial crises more formally by estimating the following baseline specification:

$$Illiquidity_{i,t} = \beta_0 + \beta_1 \times Price_{i,t-1} + b_t\theta + c_t\delta + \varepsilon_{i,t}, \quad (3)$$

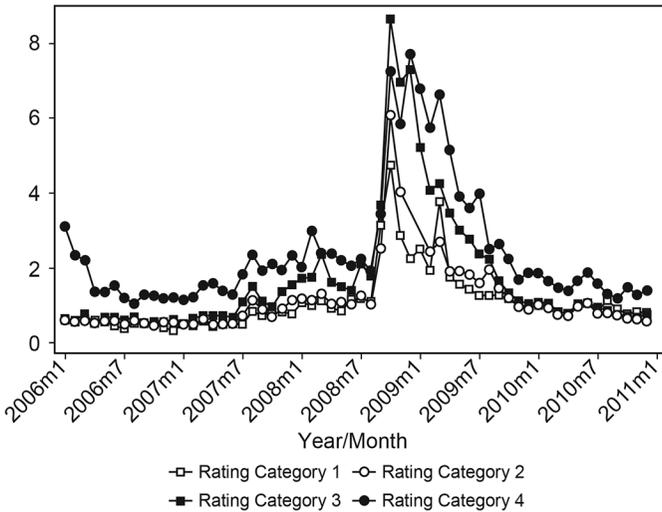


Fig. 9. Average illiquidity by credit rating: 2007–2009

where *Illiquidity* is either  $\gamma$  for the 2007–2009 period or the normalized bid-ask spread  $Spread_{i,t}$  for the 1873–1876 period, subscripts indicate bond ( $i$ ) and either month (for 2007–2009) or week (for 1873–1876) ( $t$ ),  $Price_{i,t-1}$  is bond price,  $\delta_t$  is a vector of either year or year  $\times$  month fixed effects,  $\theta_i$  is a vector of bond fixed effects—and  $\varepsilon_{i,t}$  is the regression residual. We report the results from estimating variants of regression 3 in table 1. Tables throughout this paper report regression coefficients and standard errors clustered at the bond level (in parentheses). The main explanatory variable in the table is lagged bond price. Columns (1)–(2) report results for the 2007–2009 period, while columns (3)–(4) report results for the 1873–1876 period.

The results reported in column (1) are based on regression 3, which is estimated with year and bond fixed effects. There is a negative association between illiquidity and bond prices, suggesting that bonds with lower prices are more illiquid (high  $\gamma$ ). We obtain very similar results when we include year  $\times$  month—instead of just year—and bond fixed effects (column [2]). The association between  $\gamma$  and bond price remains negative and significant at the 1% level when we control for bond fixed effects. Likewise, column (3) shows that bid-ask spreads are negatively correlated with bond prices during the 1873–1876 period after controlling for bond and year fixed effects. Column (4) repeats the analysis presented in column (3) and adds year  $\times$  month fixed effects. The re-

**Table 1**  
Bond Illiquidity and Lagged Prices

	Gamma (1)	Gamma (2)	Bid-Ask Spread (3)	Bid-Ask Spread (4)	<b>AQ: For tables 1, 4–8, do the asterisks in the table bodies indicate signifi- cance levels? Notes OK as set?</b>
Price <sub>t-1</sub>	-0.204*** (0.005)	-0.169*** (0.006)	-0.0033*** (0.0005)	-0.0032*** (0.0006)	
Constant	21.592*** (0.523)	17.768*** (0.611)	0.299*** (0.037)	0.296*** (0.037)	
Bond FE	Yes	Yes	Yes	Yes	
Year FE	Yes	No	Yes	No	
Year * month FE	No	Yes	No	Yes	
Period	2007–2009	2007–2009	1873–1876	1873–1876	
Observations	41,672	41,672	27,170	27,170	
Adj - R <sup>2</sup>	0.417	0.458	0.745	0.747	

\*\*\*Significant at the 1 percent level.

\*\*Significant at the 5 percent level.

\*Significant at the 10 percent level.

sults are statistically significant at the 1% level, suggesting that bonds that experienced lower prices during the 1873 financial crisis also became less liquid. An important concern regarding the negative relation between bond illiquidity and bond price is one of reverse causality. Rather than declines in bond values causing illiquidity to rise, it could be that bond prices are declining due to an expected (future) reduction in bond liquidity. In Benmelech and Bergman (2017) we conduct detailed analysis to address this endogeneity concern, using instrumental variables and nonlinearities around the default boundary.

#### IV. Liquidity and Belief Dispersion during the Financial Crisis

A large literature discusses how heterogeneous beliefs can promote trade and liquidity in financial markets (see, e.g., Harrison and Kreps 1978; Varian 1989; Harris and Raviv 1993). This literature provides an alternative theory to trade than that provided by classic asymmetric information and adverse selection theories (Akerlof 1970; Spence 1973). By assuming that agents hold different fundamental opinions about underlying asset values—some agents are optimistic while others are pessimistic—the literature on heterogeneous beliefs evades the classic no-trade results in the information economics literature (e.g., Rubinstein 1975; Hakansson et al. 1982; Milgrom and Stokey 1982). Agents engage in trade for their own perceived mutual benefit. In this section

we analyze the relation between differences of opinion and liquidity in the bond market.

Measuring heterogeneous beliefs among market participants is clearly challenging. To test the heterogeneous beliefs theory we use two imperfect measures to proxy for differences of opinion in market participants' assessment of the future value of bonds during the financial crisis. The first measure is the difference between the S&P and Moody's bond credit rating, and is defined as:

$$\text{Rating difference}_{i,t} = |S \& P_{i,t} - \text{Moody}'s_{i,t}|.$$

Since there is a direct correspondence between the Moody's and S&P rating systems, we simply calculate for each bond and month the (absolute value) notch difference between the Moody's credit rating and the S&P credit rating. Credit-rating data are taken from Mergent FISD.

The second measure of differences of opinion employed in our analysis is analyst earnings forecast dispersion. To calculate this dispersion, we match each bond issue to the relevant firm's equity using the six-digit CUSIP. For each month, following Diether et al. (2002), we then calculate the ratio of the standard deviation of analysts' current-fiscal-year annual earnings per share forecasts to the absolute value of the mean forecast.<sup>17</sup> This analyst earnings forecast dispersion measure proxies for differences of opinion regarding firm equity, and so is expected to be a better measure of differences of opinion for bond values with lower credit quality.<sup>18</sup>

$$\text{Forecast dispersion}_{i,t} = \frac{\sigma(\text{EPS forecast}_{i,j,t})}{|\text{Mean}(\text{EPS forecast}_{i,j,t})|}$$

where  $i$  indicates stock,  $j$  indicates analyst, and  $t$  indicates month. EPS forecast is the analysts' forecast at each month for current fiscal year annual earning per share.

#### A. Liquidity and Belief Dispersion: Descriptive Evidence

Table 2 provides summary statistics of the distribution of the Moody's-S&P bond-rating difference over the sample period 2007–2010. As can be seen, just over 50% of observations exhibit no rating difference. Over a third of bonds exhibit a rating difference of one notch, approximately 9% of bond-months exhibit a rating difference of two notches, and 2% of the sample exhibits a difference of three notches or more. Table 3 provides the distribution of analyst earnings forecast dispersion. As can

**Table 2**  
Bond-Rating Differences: Summary Statistics

Rating Diff.	Frequency	Percent
0	57,117	52.62
1	39,815	36.68
2	9,465	8.72
3	1,298	1.2
4	532	0.49
5	114	0.11
6	163	0.15
7	30	0.03
8	2	0
9	1	0
10	8	0.01
11	1	0
12	1	0
13	2	0
Total	114,572	100

**Table 3**  
Analysts' Forecast Dispersion: Summary Statistics

Mean	0.134
Median	0.030
Std.	0.642
p25	0.013
p75	0.084
Min.	0
Max.	33.3
Observations	46,635

be seen, the median ratio of earnings forecast dispersion—that is, the ratio of standard deviation to mean analyst forecasts—is 0.03, with a 75th percentile of 0.084.

Figures 10 and 11 portray the evolution of dispersion of opinion over the crisis using the two differences of opinion variables. As can be seen in figure 10, analyst earnings forecast dispersion increased greatly following the collapse of Lehman Brothers, with median forecast dispersion more than doubling from 0.024 in September 2008 to its peak of 0.077 in March 2009. The figure clearly shows that earnings forecast dispersion is seasonal, with a yearly frequency. This seasonality arises due to the fact that dispersion is calculated each month with respect to the (fiscal) year-end earnings forecasts. This dispersion will naturally

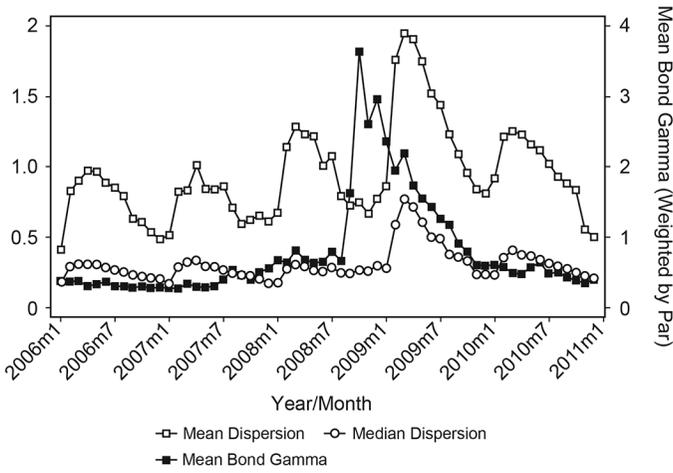


Fig. 10. Mean and median analyst forecast dispersion and bond illiquidity: 2007–2009

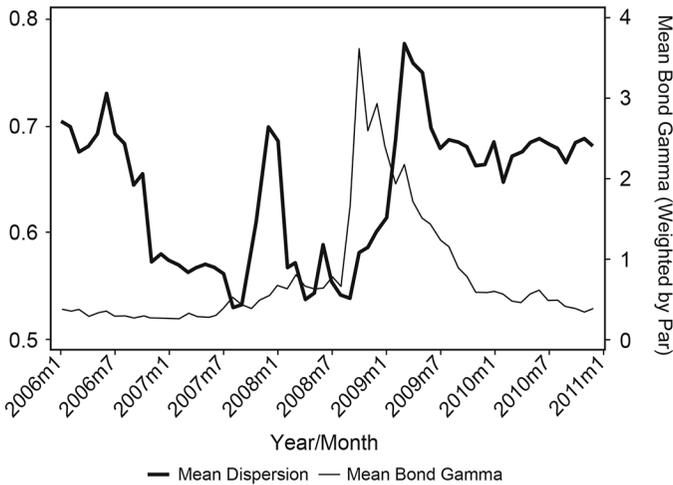


Fig. 11. Mean rating dispersion and bond illiquidity: 2007–2009

decline toward the latter part of the year, as the time until the earnings report shortens. The fact that the dispersion measure is calculated with respect to the end-of-year forecast also explains why the large rise in the measure does not occur immediately after Lehman’s collapse in September 2008, but rather early in 2009.

Figure 11 depicts the evolution of the Moody’s-S&P bond-rating difference over the crisis. Here we see a spike in the bond-rating difference

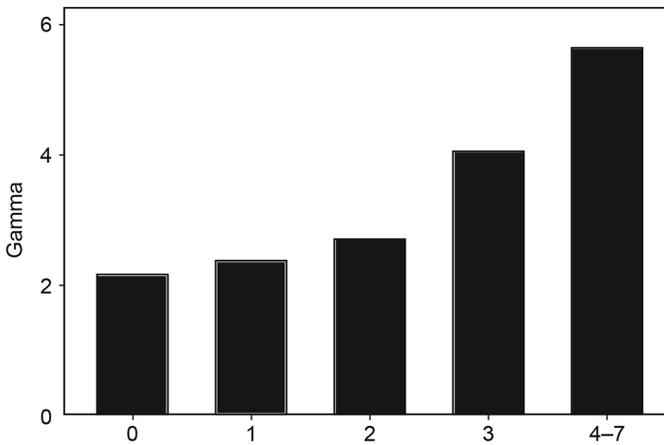


Fig. 12. Average illiquidity by lagged bond-rating difference: 2007–2009

at the end of 2007, and another larger spike post-Lehman (with a lag as bond ratings take time to adjust). The Moody's-S&P rating difference rises from a mean value of 0.54 in September 2008 to a peak of 0.78 in March 2009.<sup>19</sup> Bond-rating differences decline by August 2009 and remain relatively constant thereafter, but at a level higher than that of early 2007. Indeed, in January 2010, the mean credit-rating difference is 0.67.

Figures 10 and 11 also present the evolution of monthly (par-value-weighted) mean bond illiquidity, as proxied by the  $\gamma$  illiquidity measure. As discussed above, illiquidity sharply rose during the crisis. We note that the concurrent rise of illiquidity and rise of our proxies for differences of opinions during the crisis provides prima facie evidence against the hypothesis that heterogeneous beliefs promote liquidity.

#### B. *An Empirical Analysis of the Relation between Liquidity and Belief Dispersion*

Figure 12 displays average illiquidity calculated over different levels of Moody's-S&P credit-rating difference, while figure 13 depicts average bond illiquidity over the 10 deciles of (lagged) analyst forecast dispersion.<sup>20</sup> Illiquidity in both figures, and throughout the analysis below, is measured by  $\gamma$ . Consistent with the comovement of illiquidity and opinion dispersion depicted in figures 10 and 11, figure 12 shows that illiquidity rises with credit-rating dispersion and particularly so

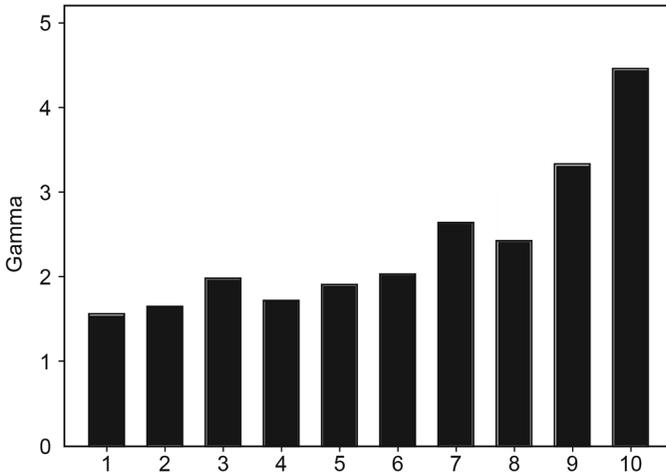


Fig. 13. Average illiquidity by lagged dispersion of analysts forecast: 2007–2009

for bond-rating differences of three notches or more. Similarly, figure 13 shows that illiquidity rises with higher analyst forecast dispersion. Similar to figure 12, the increase in illiquidity is most pronounced for the top two deciles of forecast dispersion.

Moving to regression analysis, table 4 regresses  $\gamma$  on indicator variables defined over the Moody's-S&P bond-rating differences.<sup>21</sup> Importantly, the regression is run with bond and year-by-month fixed effects to absorb non-time-varying bond determinants of illiquidity, as well as market-wide variation in illiquidity during the crisis. Identification is thus obtained by comparing the illiquidity of two bonds with different measures of the Moody's-S&P spread in the same month and year (as compared to each bond's mean illiquidity).

As can be seen in table 4, increased credit-rating differences between Moody's and S&P are associated with higher bond illiquidity. Difference of opinion, as captured by bond-rating divergence, does not seem to promote liquidity, as would be predicted by the heterogeneous beliefs literature. The economic effect is substantial: controlling for year and month-by-bond fixed effects, as compared to bonds with no disagreement between Moody's and S&P rating, bonds where the respective ratings differ by three notches exhibit a  $\gamma$  illiquidity measure that is higher by 1.26 units, representing approximately 70% of the mean during the crisis. Bonds with a four-notch divergence in ratings exhibit a  $\gamma$  illiquidity measure that is higher by 3.03 units, or 165% of mean  $\gamma$ .

**Table 4**  
Bond Illiquidity and Bond-Rating Differences

	Gamma (1)	Gamma (2)
Rating diff. 1	0.024 (0.104)	0.014 (0.092)
Rating diff. 2	0.977*** (0.215)	0.658*** (0.202)
Rating diff. 3	1.615** (0.705)	1.263** (0.636)
Rating diff. 4	3.562*** (0.932)	3.030*** (0.868)
Constant	0.696*** (0.080)	0.336*** (0.095)
Bond FE	Yes	Yes
Year FE	Yes	No
Year * month FE	No	Yes
Observations	41,148	41,148
<i>Adj</i> - <i>R</i> <sup>2</sup>	0.274	0.393

\*\*\*Significant at the 1 percent level.

\*\*Significant at the 5 percent level.

\*Significant at the 10 percent level.

Table 5 runs the analogous regression using indicator variables defined over the quintiles of analyst forecast dispersion. As can be seen, the relation between analyst forecast dispersion and bond illiquidity is generally weak, but the highest quintile of forecast dispersion exhibits substantially larger illiquidity than the lowest quintile of earnings forecast dispersion: with bond and year-by-month fixed effects, the difference between the two quintiles is 0.318, or approximately 250% of the mean level of illiquidity.

Although the positive relation between analyst forecast dispersion and bond illiquidity is not supportive of the heterogeneous beliefs theory, we cannot rule out that endogeneity, and in particular omitted variables, are biasing our results. Indeed, one potential explanation for the positive relation between belief dispersion and illiquidity is that dispersion in beliefs increase when underlying bond values deteriorate. Such a negative relation between belief dispersion and bond price would occur if, for example, heterogeneous beliefs are more likely to arise when bonds become riskier.<sup>22</sup> The positive relation between bond illiquidity and higher bond opinion dispersion in tables 4 and 5 may then simply be reflecting the negative relation between bond price and

**Table 5**  
Bond Illiquidity and Analysts' Forecast Dispersion

	Gamma (1)	Gamma (2)
Forecast dispersion 2	-0.010 (0.082)	0.099 (0.078)
Forecast dispersion 3	-0.146* (0.089)	0.030 (0.092)
Forecast dispersion 4	0.132 (0.122)	0.066 (0.125)
Forecast dispersion 5	0.382** (0.174)	0.318* (0.174)
Constant	0.650*** (0.105)	0.174 (0.125)
Bond FE	Yes	Yes
Year FE	Yes	No
Year * month FE	No	Yes
Observations	22,571	22,571
<i>Adj</i> - <i>R</i> <sup>2</sup>	0.277	0.402

\*\*\*Significant at the 1 percent level.

\*\*Significant at the 5 percent level.

\*Significant at the 10 percent level.

illiquidity combined with the negative relation between bond price and rating dispersion.

Figures 14 and 15 provide initial evidence on the relation between bond risk and opinion dispersion, showing the evolution of the two measures of opinion dispersion during the crisis calculated over four categories of bond credit ratings.<sup>23</sup> Figure 15, which depicts the evolution of average bond-rating differences by bond credit-rating groups, sorts the bonds based on the higher between the Moody's and S&P credit rating. The figures depict the monthly par-value weighted average opinion dispersion measure. As can be seen, lower-rated bonds (rating category 4) exhibit the sharpest rise in opinion dispersion during the crisis. In addition, figure 15 shows a substantial increase in the rating dispersion for the highest credit rating. This is a result of Moody's, but not S&P, downgrading AAA-rated bonds.

To further understand the relation between bond prices and opinion dispersion, table 6 regresses the change in opinion dispersion—either Moody's-S&P credit-rating difference or analyst forecast dispersion—on the change in bond price. As can be seen, difference of opinion, as proxied by bond-rating differences, rise when bond price declines, al-

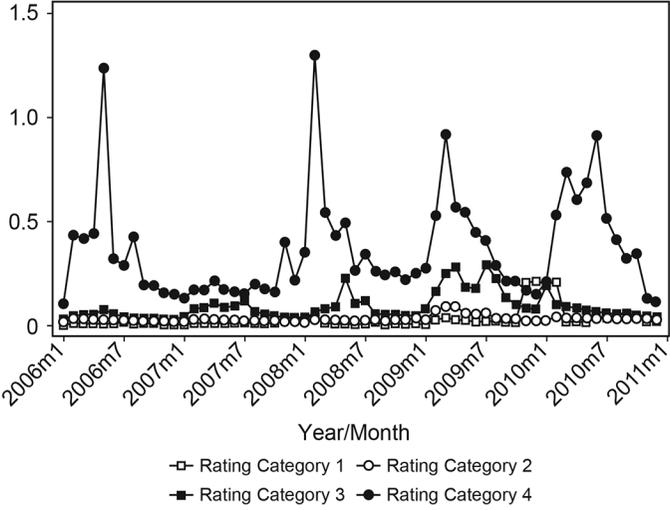


Fig. 14. Analysts forecast dispersion by Moody's credit rating: 2007–2009

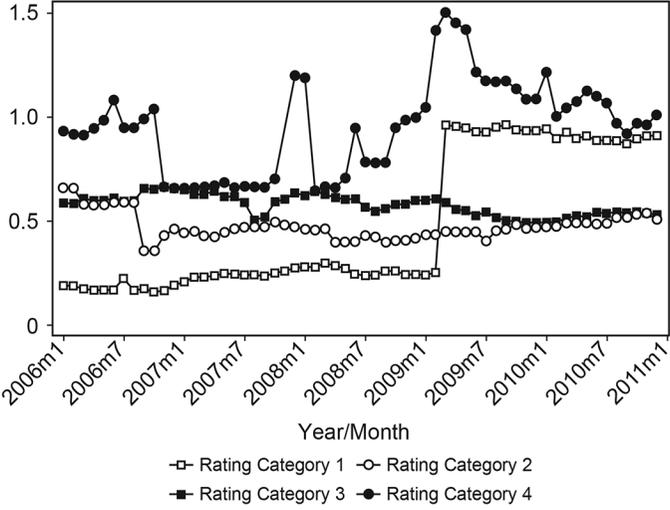


Fig. 15. Mean bond-rating difference by credit rating: 2007–2009

though the effect is not economically large: a one standard deviation decline in bond price increases bond-rating dispersion by approximately 2.5% of the mean rating dispersion (column [1]). However, calculating the effect over bond-month observations where the  $\gamma$  illiquidity measure is not missing—that is, the sample over which the relation between

**Table 6**  
Changes in Rating Differences and Analyst Dispersion and Price Changes

	$\Delta$ Rating Difference	$\Delta$ Rating Difference	$\Delta$ Analysts Dispersion	$\Delta$ Analysts Dispersion
$\Delta$ Price	-0.001*** (0.000)	-0.003*** (0.001)	-0.000 (0.001)	0.004 (0.002)
Constant	0.004*** (0.001)	0.005*** (0.001)	0.002*** (0.000)	0.000 (0.002)
Year * month FE	Yes	Yes	Yes	Yes
Gamma not missing	No	Yes	No	Yes
Observations	108,518	41,267	46,363	22,475
$Adj - R^2$	0.00595	0.00593	0.00642	0.00869

\*\*\*Significant at the 1 percent level.

\*\*Significant at the 5 percent level.

\*Significant at the 10 percent level.

illiquidity, bond price, and opinion dispersion is analyzed—triples this economic magnitude, to approximately 7.5% of the mean rating difference. The last two columns of table 6 analyze the relation between analyst forecast dispersion and bond price, showing that it is not statistically significant.

### C. *Asymmetric Informational and Belief Dispersion: A Horse Race*

Table 7 conducts a “horse race” between the two theories of bond illiquidity: the asymmetric information theory, which predicts that illiquidity should decline with bond price, and the heterogeneous beliefs theory, which predicts that differences of opinion promote liquidity. Specifically, the specifications in the table relate the  $\gamma$  measure of bond illiquidity to price as well as to indicator variables defined over the different levels of bond-rating difference. As usual, all regressions are run with bond and year-by-month fixed effects. As can be seen in table 7, illiquidity as measured by  $\gamma$  is still negatively related to bond price—consistent with the asymmetric information theory of liquidity of debt (as in Dang et al. 2012) and the results above. However, as the second column of the table shows, bond-rating dispersion is no longer related to illiquidity in a statistically significant manner once bond price and bond-by-year fixed effects are included.

In a similar manner, table 8 regresses the  $\gamma$  illiquidity measure on both bond price and analyst forecast dispersion. As in table 7, bond price is

**Table 7**  
The Effects of Bond-Rating Differences and Bond Price  
on Bond Illiquidity

	Gamma (1)	Gamma (2)
Rating diff. 1	-0.079 (0.083)	-0.062 (0.079)
Rating diff. 2	-0.009 (0.146)	0.034 (0.146)
Rating diff. 3	-0.902** (0.442)	-0.694 (0.438)
Rating diff. 4	-0.940* (0.504)	-0.450 (0.483)
Price <sub>t-1</sub>	-0.210*** (0.005)	-0.174*** (0.006)
Constant	22.159*** (0.523)	18.314*** (0.611)
Bond FE	Yes	Yes
Year FE	Yes	No
Year * month FE	No	Yes
Observations	41,148	41,148
Adj - R <sup>2</sup>	0.421	0.461

\*\*\*Significant at the 1 percent level.

\*\*Significant at the 5 percent level.

\*Significant at the 10 percent level.

still negatively related to bond illiquidity, but differences of opinion, as proxied by analyst forecast dispersion, is not related to  $\gamma$  in a statistically significant manner.

In sum, our results are consistent with the information asymmetry theory of liquidity as in Dang et al. (2012). In contrast, using two proxies for belief dispersion—the Moody's-S&P difference in bond rating and analyst forecast dispersion—we find little support for the hypothesis that liquidity is enhanced as differences of opinion rise. At the aggregate level, as well as using panel data analysis at the individual-bond level, opinion dispersion did not increase liquidity during the crisis period. If anything, the opposite seems to hold, with illiquidity and dispersion positively related, particularly when using the bond-rating difference measure of belief dispersion. However, once we control for bond price movements, belief dispersion is not related in a statistically significant manner to the  $\gamma$  measure of bond-market illiquidity.

**Table 8**  
The Effects of Analyst Dispersion and Bond Price on Bond Illiquidity

	Gamma (1)	Gamma (2)
Forecast dispersion 2	-0.041 (0.070)	0.073 (0.070)
Forecast dispersion 3	-0.090 (0.077)	0.141* (0.080)
Forecast dispersion 4	-0.114 (0.106)	0.176 (0.110)
Forecast dispersion 5	-0.370** (0.149)	0.186 (0.155)
Price <sub>t-1</sub>	-0.207*** (0.007)	-0.174*** (0.007)
Constant	21.817*** (0.642)	17.967*** (0.737)
Bond FE	Yes	Yes
Year FE	Yes	No
Year * month FE	No	Yes
Observations	22,571	22,571
Adj - R <sup>2</sup>	0.436	0.479

\*\*\*Significant at the 1 percent level.

\*\*Significant at the 5 percent level.

\*Significant at the 10 percent level.

## V. To What Extent Can Bond Price Variation Explain the Rise in Illiquidity during the 2008–2009 Crisis?

We have shown that deteriorations in bond value are associated with rises in bond illiquidity, consistent with the main prediction of the asymmetric information theory of liquidity in debt markets. To what extent can this relation, combined with the market-wide deterioration in bond prices post-Lehman collapse, explain the rise in bond-market illiquidity during the crisis?

To fix ideas, figures 16 and 17 depict the cumulative distribution function and probability density function of bond prices for August and October 2008, as well as January 2009. The figures show the large changes in the distribution of bond prices—with a sharp leftward movement of mass in the distribution of bond prices in October 2008, that is, post-Lehman—which is partially reversed by January 2009.

To understand the role of bond-price deterioration in explaining the behavior of bond-market liquidity during the crisis, we first regress bond

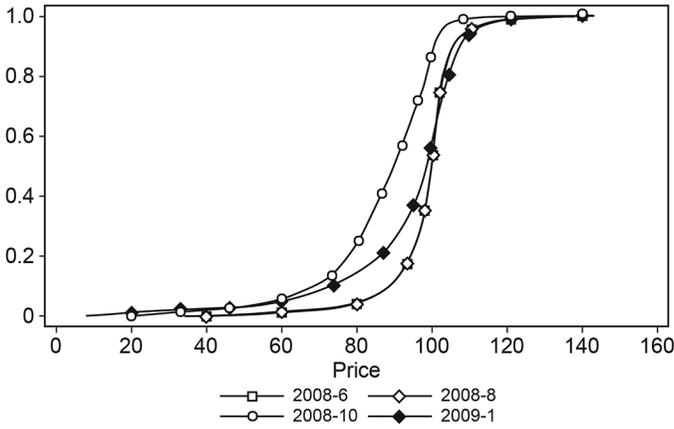


Fig. 16. Bond price cumulative distribution function: 2007–2009

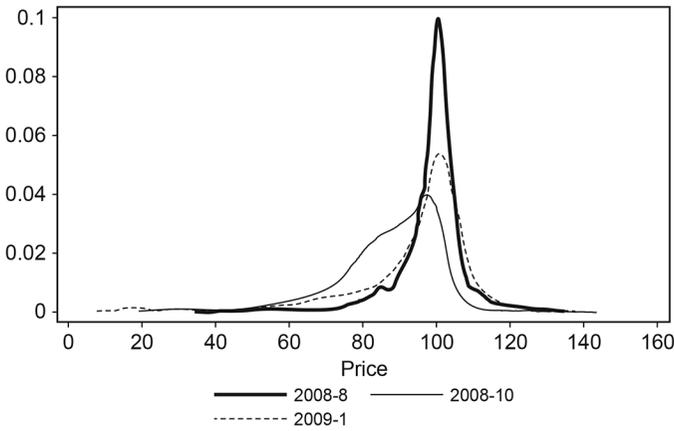


Fig. 17. Bond price probability density function: 2007–2009

illiquidity (proxied by  $\gamma$ ) on 20 indicator variables defined over 20 equal-sized bins of lagged bond price, running the following specification:

$$Illiquidity_{i,t} = \beta_0 + \sum_{k=1}^{20} \beta_k \times PriceBin_{i,t-1}^k + b_i \gamma + c_t \delta + \varepsilon_{i,t} \quad (4)$$

where *Illiquidity* is  $\gamma$ , for bond *i* in month *t*. *PriceBin* is a set of 20 indicator variables based on (within-year) 20 equal-sized bins of bond price—*PriceBin*<sub>*i,t-1*</sub><sup>*k*</sup> equals one if bond *i* is in price bin *k* at month *t* - 1;<sup>24</sup> *b*<sub>*i*</sub> is a vector of bond fixed effects, and *c*<sub>*t*</sub> is a vector of either year or year × month fixed effects.<sup>25</sup> Standard errors are clustered at the bond level.

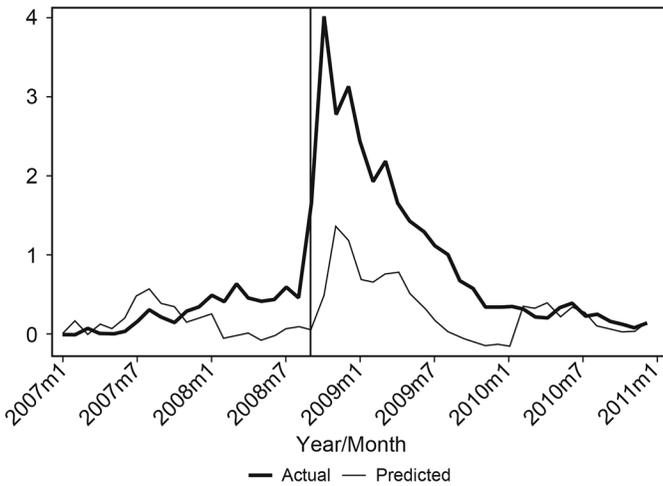


Fig. 18. Predicted illiquidity: 2007–2009 (without bond fixed effects)

Using the regression coefficients, we calculate for each bond in each month in our sample the predicted illiquidity of that bond based on the bond's price. We calculate the market-level predicted illiquidity by calculating the par-value weighted average across all bonds. Figure 18 presents for each month  $t$  the change in predicted (weighted-average) bond-market illiquidity from January 2007 to month  $t$ , together with the actual change in the weighted average bond-market illiquidity. The figure uses a regression specification that does not include bond fixed effects. Figure 19 displays the analogous predicted change in bond-market illiquidity, but uses the regression specification that includes bond fixed effects.

As can be seen, predicted and actual changes in illiquidity track each other closely up to late 2007 (i.e., precrisis) and from the first quarter of 2010 and on. In the interim period, the increase in actual illiquidity is higher than the predicted increase stemming solely from the decline in bond prices. Still, the leftward shift in the distribution of bond prices, in and of itself, can explain between a quarter and a third of the increase of the rise in actual bond-market illiquidity during the crisis.

## VI. Conclusion

This paper analyzes illiquidity in bond markets during financial crises and compares two main theories of liquidity in markets: (1) asymmetric information and adverse selection, and (2) heterogeneous beliefs. We find that when bond value deteriorates, bond illiquidity increases, con-

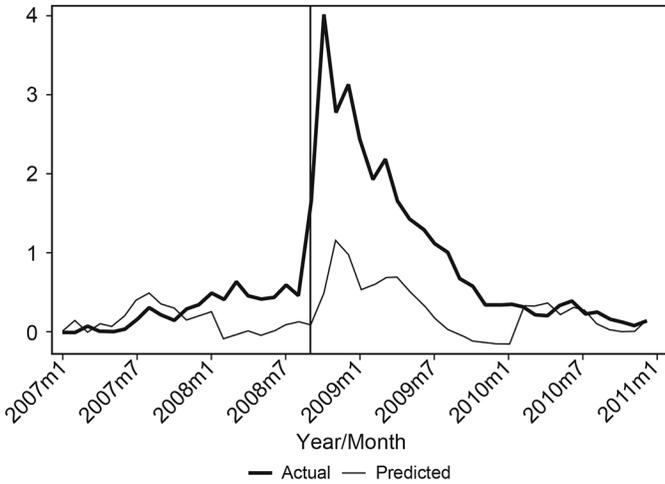


Fig. 19. Predicted illiquidity: 2007–2009 (with bond fixed effects)

sistent with an adverse-selection model of the information sensitivity of debt contracts as in Dang et al. (2012, 2013) and Holmström (2015). In contrast, we find little support for the hypothesis that opinion dispersion explains illiquidity in financial crises. Our results point to a strong link between crises and the dry-ups of market liquidity and have implications for the efficacy of monetary interventions that are designed to boost lending by the financial sector.

## Endnotes

We thank Bengt Holmström for numerous conversations. We also thank Marty Eichenbaum, Ravi Jaganathan, Dimitris Papanikolaou, Jonathan Parker, Sergio Rebelo, Steve Strongin, our NBER Macro Annual discussants V. V. Chari and Raghuraj Rajan, and seminar participants at the Goldman Sachs Global Markets Institute Academic Fellowship Conference and the NBER's 32nd Annual Conference on Macroeconomics for many comments that have improved the paper. We are grateful to Jack Bao and Kewei Hou for sharing their bond liquidity data. Shoham Benmelech, Zach Mikaya, Khizar Qureshi, Jeremy Trubnick, and Yupeng Wang provided excellent research assistance. Author contacts: e-benmelech@kellogg.northwestern.edu; nbergman@mit.edu. For acknowledgments, sources of research support, and disclosure of the authors' material financial relationships, if any, please see <http://www.nber.org/chapters/c13923.ack>.

1. See Benmelech, Frydman, and Papanikolaou (2017).
2. In fact, the opposite may hold, as if forced to trade, the optimist will have to sell to the pessimistic agent.
3. For a discussion of the relation between funding liquidity and market liquidity, see Brunnermeier and Pedersen (2009).
4. Our results also hold with alternative measures of illiquidity such as the one proposed in Amihud (2002).
5. In related work, Pérignon, Thesmar, and Vuillemy (forthcoming) empirically examine the market for certificates of deposit in Europe showing that banks experiencing

funding dry-ups subsequently exhibit decreasing performance, consistent with asymmetric information models such as Gorton and Pennacchi (1990), Calomiris and Kahn (1991), and Dang et al. (2012).

6. A one-to-one correspondence exists in the rating system of the two credit-rating agencies, and so this measure is well defined.

7. The fact that the bond-rating difference is no longer positively related to illiquidity once bond price is added as a covariate in the regression analysis likely stems from the fact that price and rating difference are negatively related: decreases in bond price are associated with increases in the Moody's-S&P rating difference. Thus, the positive relation between illiquidity and rating difference may simply be reflecting the negative relation between bond price and illiquidity combined with the negative relation between bond price and rating dispersion.

8. For a model along these lines that relies on an endogenous collateral constraint—rather than on frictions driven by asymmetric information—see Benmelech and Bergman (2012).

9. See Benmelech and Dlugosz (2010).

10. The data used to construct figures 1–3 were obtained from the Securities Industry and Financial Markets Association (SIFMA).

11. Chari, Shourideh, and Zetlin-Jones (2014) provide a dynamic adverse-selection model of secondary loan markets in which reputational considerations give rise to a multiplicity of equilibria. Small reductions in collateral values are shown to bring about collapses in the volume of new issuances.

12. Mishkin (1991, 93).

13. The data is based on table 52 in Hickman (1960).

14. The data is based on Johnson (1936a, 1936b).

15. See Bao et al. (2011) and Benmelech and Bergman (2017) for details about the intuition and the construction of the  $\gamma$  measure.

16. Benmelech and Bergman (2017) provide in-depth analysis of the relation between credit rating and bond liquidity.

17. Data on earnings forecasts are taken from I/B/E/S.

18. For example, consider a firm that has issued a very safe bond trading with a low spread to the maturity-matched Treasury. Even if there exist large differences of opinion regarding firm earnings, these should not be expected to translate into differences of opinion regarding the firm's bond value, which all market participants may agree is very safe, regardless of their position on the firm's equity value.

19. It is interesting to note that the two measures of opinion dispersion, calculated from two different markets (equity and debt) and two differing sets of market participants (rating agencies and equity analysts), attain their maximum value during the crisis in the same month—March 2009. The time-series correlation between the mean forecast dispersion and the mean rating difference is 0.47.

20. Recall that only approximately 1% of the sample has a bond rating of 4 or more.

21. The omitted variable in the regression is a Moody's-S&P credit-rating difference of zero.

22. Thus, one might expect lower belief dispersion regarding the default probability of a AAA-rated bond than for a BB-rated corporate bond.

23. Rating category 1 includes the highest-quality bonds.

24. The first price bin represents bonds with the lowest price.

25. Note that with the inclusion of bond fixed effects, the regression is identified off of changes over time in the level of illiquidity and bond price for each bond.

## References

Akerlof, George A. 1970. "The Market for 'Lemons': Quality Uncertainty and the Market Mechanism." *Quarterly Journal of Economics* 84 (3): 488–500.

- Amihud, Yakov. 2002. "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects." *Journal of Financial Markets* 5:31–56.
- Bao, Jack, Jun Pan, and Jian Wang. 2011. "Liquidity of Corporate Bonds." *Journal of Finance* 66:911–46.
- Benmelech, Efraim, and Nittai Bergman. 2012. "Credit Traps." *American Economic Review* 106:3004–32.
- . 2017. "Debt, Information, and Illiquidity." Working paper.
- Benmelech, Efraim, and Jennifer Dlugosz. 2010. "The Credit Rating Crisis." *NBER Macroeconomics Annual* 2009:161–207.
- Benmelech, Efraim, Carola Frydman, and Dimitris Papanikolaou. 2017. "Financial Frictions and Employment during the Great Depression." NBER Working Paper no. 23216, Cambridge, MA.
- Brunnermeier, Markus K., and Lasse H. Pedersen. "Market Liquidity and Funding Liquidity." *Review of Financial Studies* 22:2201–38.
- Calomiris, Charles W., and Charles M. Kahn. 1991. "The Role of Demandable Debt in Structuring Optimal Banking Arrangements." *American Economic Review* 81:497–513.
- Chari, V. V., Ali Shourideh, and Ariel Zetlin-Jones. 2014. "Reputation and Persistence of Adverse Selection in Secondary Loan Markets." *American Economic Review* 104:4027–70.
- Dang Tri Vi, Gary Gorton, and Bengt Holmström. 2012. "Ignorance, Debt and Financial Crises." Working Paper, Columbia University.
- . 2013. "The Information Sensitivity of a Security." Working Paper, Columbia University.
- Diether, Karl, Christopher J. Malloy, and Anna Scherbina. 2002. "Differences of Opinions and the Cross Section of Stock Returns." *Journal of Finance* 57:2113–41.
- Goetzmann, William N., and Frank Newman. 2010. "Securitization in the 1920s." NBER Working Paper no. 15650, Cambridge, MA.
- Gorton, Gary B., and George Pennacchi. 1990. "Financial Intermediaries and Liquidity Creation." *Journal of Finance* 45:49–72.
- Hakansson, N., J. Kunkel, and J. Ohlson. 1982. "Sufficient and Necessary Conditions for Information to Have Social Value in Pure Exchange." *Journal of Finance* 37:1169–81.
- Harris, Milton, and Artur Raviv. 1993. "Differences of Opinions Make a Horse Race." *Review of Financial Studies* 6:473–506.
- Harrison, Michael, and David Kreps. 1978. "Speculative Investor Behavior in a Stock Market with Heterogeneous Expectations." *Quarterly Journal of Economics* 92:323–36.
- Hickman, W. Braddock. 1960. *Statistical Measures of Corporate Bond Financing Since 1900*. Princeton, NJ: Princeton University Press.
- Holmström, Bengt. 2015. "Understanding the Role of Debt in the Financial System." BIS Working Paper no. 479, Bank for International Settlements.
- Johnson, Ernest A. 1936a. "The Record of Long-Term Real Estate Securities." *Journal of Land and Real Estate Economics* 12:44–48.
- . 1936b. "The Record of Long-Term Real Estate Securities: By Cities of Issue." *Journal of Land and Real Estate Economics* 12:195–97.
- Kindleberger, Charles. 1990. *Manias, Panics and Crashes*, 4th ed. New York: Basic Books.
- Lucas, Deborah, and Robert L. McDonald. 1990. "Equity Issues and Stock Price Dynamic." *Journal of Finance* 45:1019–43.

- Milgrom, Paul, and Nancy Stokey. 1982. "Information, Trade and Common Knowledge." *Journal of Economic Theory* 26:17–27.
- Mishkin, Frederic S. 1991. "Asymmetric Information and Financial Crises: A Historical Perspective." In *Financial Markets and Financial Crises*, ed. Glenn R. Hubbard, 69–108. Chicago: University of Chicago Press.
- Myers, Stewart C., and Nicholas S. Majluf. 1984. "Corporate Financing and Investment Decisions when Firms Have Information That Investors Do Not Have." *Journal of Financial Economics* 13:187–221.
- Pérignon, Christophe, David Thesmar, and Guillaume Vuillemeys. Forthcoming. "Wholesale Funding Dry-Ups." *Journal of Finance*.
- Roll, Richard. 1984. "A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market." *Journal of Finance* 39 (4): 1127–39.
- Rubinstein, M. 1975. "Security Market Efficiency in an Arrow-Debreu Economy." *American Economic Review* 65:812–24.
- Spence, Michael. 1973. "Job Market Signaling." *Quarterly Journal of Economics* 87 (3): 355–74.
- Sprague, Oliver M. W. 1910. *History of Crises under the National Banking System*. Washington, DC: National Monetary Commission, Government Printing Office.
- Varian, H. R. 1989. "Differences of Opinion in Financial Markets." In *Financial Risk: Theory, Evidence and Implications*, ed. Courtenay C. Stone, 3–37. Boston: Kluwer.

AQ: The journal name, volume,  
and page no. information for Roll  
1984 and the same for Spence 1973  
seem to have been switched. I have  
changed per an online check. Edit  
okay?