Rumors and Runs in Opaque Markets: Evidence from the Panic of 1907

Caroline Fohlin
Thomas Gehrig
Marlene Haas *

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Abstract

Using a new daily dataset for all stocks traded on the New York Stock Exchange from 1905 to 1910, we provide the first in-depth, microstructure analysis of the Panic of 1907 - one of the most severe financial crises of the 20th century and quantify the critical role of asymmetric information in the generation of panic conditions. We first show that quoted equity bid-ask spreads rose six-fold, from 0.5% to 3%, during the peak weeks of the crisis. We then implement a spread decomposition procedure and pinpoint the source of the illiquidity spike in the adverse selection component, that is, the fear of informed trading. Moreover, we show that information costs rose most steeply in the mining sector - the origin of the panic rumors - and in other sectors with opaque corporate reporting standards. In addition to wider spreads and tight money markets, we find other hallmarks of information-based liquidity freezes: trading volume dropped and price impact rose. Importantly, despite short-term cash infusions into the market, and abatement of the run, we find that the market remained relatively illiquid for several months following the panic. We go on to show that rising illiquidity enters positively in the cross section of stock returns. Thus, our findings demonstrate how opaque markets can easily transmit an idiosyncratic rumor into a long-lasting, market-wide crisis. Our results also demonstrate the usefulness of illiquidity measures to alert market participants to impending market runs.

Keywords: Illiquidity, Rumors, Panic, Price Discovery

JEL classification: G00, G14, N00, N2

*Fohlin (fohlin@jhu.edu) is at Johns Hopkins and Emory Universities. Gehrig (thomas.gehrig@univie.ac.at) and Haas (marlene.haas@vgsf.ac.at) are at the University of Vienna and at the Vienna Graduate School of Finance. This material is based upon work supported by the U.S. National Science Foundation under Grant No. 0850576 to Fohlin. We are grateful to Floris Daverveldt for extensive research assistance. The paper greatly benefited from discussions with Nikolaus Hautsch, Gyöngyi Lóránth, Albert S. Kyle, Klaus Ritzberger, Walter Schachermayer, Ellis Tallman, and Joseph Zechner. We are grateful to the participants of the University of Vienna Brown Bag Seminar and the 2014 Conference of the Vienna Graduate School of Finance for comments and suggestions. Gehrig thanks the Collegio Carlo Alberto for its hospitality. All errors are our own.
1 Introduction

The Panic of 1907 marked the beginning of the end of unregulated capital markets and weak central monetary authority in the United States. Much like the recent global financial crisis, the severity and duration of the after effects set off an immediate outcry from the public and reactions from federal and state governments. While private initiatives - the concerted effort organized by John Pierpont Morgan - ultimately contributed to resolving the crisis, it provided central banking advocates the ammunition they needed to push through the Federal Reserve Act, and in the meantime the provision of emergency currency via the Aldrich-Vreeland Act (which would come into play in the summer of 1914). The episode prompted the famous Money Trust hearings in Congress that led to the Clayton Antitrust Act, as well as a state level investigation in New York that ultimately led to tighter control over access to trading at the NYSE. These regulatory steps laid the foundation for the more far-reaching interventions such as the U.S. Securities and Exchange Commission (SEC) that emerged much later. 1

We study this episode, as it provides one of the best examples of a financial crisis based on rumors and information asymmetry rather than economic fundamentals (Frydman et al. (2012) 2). Because it took place in an era of weak corporate governance law, highly variable accounting practices, and essentially no regulation of stock markets - all compounded by rudimentary information technology - traders faced a continual threat of informational contagion (e.g. Bernstein et al. (2014)) and difficulties in assessing counterparty risk. Information opaqueness allowed a rumor to seem like valid, fundamental news. In the environment of October, 1907, market participants saw a general decline in market prices combined with a failed stock market corner of Heinze’s brokerage house and plummeting United Copper prices as a consequence. This stirred rumors and anxiety. Moreover, it caused panic across the board because markets were opaque and information was difficult to verify. Accordingly, bad rumors were compounded by herding.

While many previous researchers have examined the panic at the aggregate level, we are able to offer a much more nuanced view of the unfolding crisis by exploiting a new database of daily transaction, quotation, and volume data for all stocks traded on the NYSE from 1905 to 1910.3 We uncover a range of new results. First, the stock market (the NYSE) showed signs of deteriorating liquidity - rising bid-ask spreads and price impact measures - starting in September of 1907, in advance of the most acute period of crisis. The heightened illiquidity lasted until March 1908, several months after the run

1This paper builds on an earlier study by Fohlin et al. (2008).
2See also Gorton (1988), Calomiris and Gorton (1991), and Moen and Tallman (1992) for earlier work on this.
3See Fohlin (2015) for more detail on the larger data collection project.
ended. Notably, our spread decompositions show that adverse selection risk - the result of asymmetric information - accounts for the greatest part of this illiquidity problem. As we predict, the effects are most pronounced in the most opaque market segments. The mining sector, the target of the stock manipulations that led to the Panic in the first place, also operated with some of the least transparent accounting and governance procedures. In addition, we relate stock market illiquidity with interest rates in the money market (call loans), the primary source of funding for stock transactions.

In a final set of tests, we show that it is possible to predict the cross section of stock returns based on estimated microstructure cost factors. The fact that we can predict asset prices with liquidity measures demonstrates the first order importance of microstructure cost factors for stock returns.

The remainder of the paper is organized as follows. Section 2 describes the trading environment in the years surrounding the panic, and Section 3 describes the exact timeline of events of the Panic of 1907. Section 4 outlines the hypotheses that underlie this research. Sections 5 and 6 describe the data and methodology. Section 7 presents the analysis of transaction costs and decompositions, and section 8 presents our exploratory asset pricing analysis. Section 9 concludes.

2 The New York Stock Exchange Trading Environment

In the period analyzed in our study, the NYSE was owned by its members and largely self-regulated. Among the key regulations were those that dealt with membership. Joining the exchange was a costly venture: a new member had to pay a membership fee and then buy the seat of an existing member. The exchange had fixed the number of seats at 1,100 in 1879, so that the prices of seats varied with the market. These prices ranged between $4,000 and $4,500 in 1870 (approximately $125,000 in 2013 terms) and between $64,000 and $94,000 in 1910 (roughly $1.5-2.5 million in 2013). The Governing Committee of the exchange held ultimate responsibility for exchange operations and had the power to fine or even to expel members for infractions against exchange rules. The value of a member’s seat worked as collateral in these cases or in the event of bankruptcy (Mulherin et al. (1991)). The courts upheld these powers as well as the exchanges’ right to restrict trading solely to its members and to set other rules (Mulherin et al. (1991)).

The NYSE implemented relatively stringent listing standards and requirements, including registration of all shares (to prevent stock watering), minimum shareholder numbers, and a qualitative assessment of risk. Oil stocks, for example, could not be listed in their early years because they were deemed too risky. External regulation of exchange
operations or of listed corporations was set in place much later. Corporate reporting law generally remained vague in the United States until after the Great Depression. Internal incentives and particularly the desire to access outside funds from investors encouraged a growing number of companies to disclose their balance sheets and income statements. Following this movement, the NYSE began to recommend in 1895 that listed companies should provide both a balance sheet and an income statement in annual reports to investors. Such reporting then became mandatory in 1899. Still, the adherence to and enforcement of the rule remained weak for many years, and the content of these reports varied significantly in their extent and accuracy (Archambault and Archambault (2005) and Sivakumar and Waymire (1993)). In particular, companies in sectors subject to rate regulation saw the greatest incentive to publish their accounts, but their regulation also created incentives to manipulate their earnings statements (Archambault and Archambault (2011)). New laws and exchange rules requiring audited accounts developed only after the Panic of 1907 (Sivakumar and Waymire (1993) and Sivakumar and Waymire (2003)).

The NYSE operated a continuous auction market during this period; having converted from the call auction method in 1871, due to space and time constraints. The system functioned much like a modern continuous market, in which transactions occurred throughout the trading day at whatever terms could be agreed upon by the parties involved, with no guarantee of a single price. While the continuous auction method eliminated the problem of overcrowding and the excessive time taken in each call auction, it created a new problem: order imbalance. In general, random arrival reduces market liquidity, creating greater chance of order imbalance and price volatility compared to a call auction (Kregel (1995)). The evolution of the trading method led to the creation of two distinct types of intermediaries. The first type, brokers, traded on behalf of their customers and received set commissions as their payment. The others, jobbers, bought and sold shares in order to make markets in securities, and they received the spread between bid and ask prices as their compensation. The increasing number and sophistication of jobbers then encouraged their specialization in particular stocks.

3 The Panic of 1907

In light of the recent global financial crisis, the panic that hit the U.S. financial system in the fourth quarter of 1907 has gained renewed interest among economists (Frydman et al. (2012) and Bordo and Haubrich (2010)). The Panic of 1907 followed a time period in which the economy had experienced a downturn. This downturn displayed characteristics also observed in earlier financial crises (Moen and Tallman (1992)): interest rates increased,
stock prices decreased sharply, output in the real economy fell significantly, and financial institutions suffered from deposit withdrawals (see Gorton (1988) and Kindleberger and Aliber (2011)).

The panic began on October 16, 1907, with the failure of the brokerage firm of Otto Heinze. Heinze’s brokerage house was forced to close when he attempted to corner shares of the United Copper Company and pull a classic short squeeze. The manipulations caused wild swings in the price of United Copper, but the price ultimately plummeted and forced Otto into financial ruin. United Copper was partly owned by Otto’s brother, the notorious copper magnate, F.A. (Augustus) Heinze. The Heinze failure set off rumors that certain financial institutions had financed the failed short squeeze and therefore held unpayable debts from Otto Heinze. But Augustus was the key link in the rumor chain, as he had just a few months prior moved to Manhattan and taken an active interest in banking and finance - including Presidency of the Mercantile Bank and directorships at several other banks and trust companies. Thus, as rumors spread about counterparties to Otto’s brokerage firm, depositors ran on Mercantile National and on the trust companies with known ties to Heinze; first and foremost, the Knickerbocker Trust Company with $69 million in assets (Tallman and Moen (1990)). After the closure of Knickerbocker Trust Company on Tuesday, October 22nd, depositors rapidly began withdrawals from other trust companies. In an era in which investors learned price information by traveling to or phoning their brokers-who, in turn, relied on a stream of information printed onto ticker tape arriving via telegraph-the only way to learn news in real time was to appear in person. The now famous photograph in Harper’s Weekly following the peak of the panic, gives an impression of what that “price discovery” process looked like (see Figure 1 from Harper’s Weekly).

As this summary of events and the extensive reporting in the Commercial and Financial Chronicle of the time as well as numerous other researchers point out, this panic was purely rumor-based. Market participants could observe the runs on trusts and banks that had close ties to the Heinze brothers, but they had no way of accurately evaluating the fundamental values of either the financial institutions or the corporations whose stocks served as collateral on millions of dollars’ worth of loans. The opaque information environment allowed the rumors to spread, while the resulting runs forced liquidations at financial institutions and yielded significant negative consequences for the real sector.

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4 For extensive details, see the Smithsonian Magazine article from September 2012 and Chapter 6 of Parker and Whaples (2013).
5 See the detailed reporting in the Commercial and Financial Chronicle in the weeks during and following the panic.
6 Again, see the extensive details reported in the Commercial and Financial Chronicle.
Moen and Tallman (1992) point out that loans at trust companies contracted by 37% between August 22 and December 19, 1907. Loans at banks contracted by 19% during that same period. The biggest problem for trusts was their lack of access to the Clearing House Association of New York, a private clearing house that also acted as an emergency lender to its members in crisis times. The trusts simply were not part of this club (Tallman and Moen (2014)). Hence, as suggested by Moen and Tallman (1992) and Bruner and Carr (2008), the main mechanism through which this panic spread to the real sector was a contraction of loans.

The panic might have deepened if not for the rescue measures implemented in short order: The Treasury Department’s $25 million deposit in New York banks followed on October 24th by J. P. Morgan’s now-famous bailout plan involving large sums of his own money and that of the city’s top bankers. On October 26th, the New York Clearing House Association issued Clearing House loan certificates for its member banks (Tallman and Moen (1990) and Tallman and Moen (2012)). To further calm the markets, treasury certificates were issued on November 19th and 20th. Notably, as Rodgers and Payne (2012) find and as is described in Kindleberger and Aliber (2011), the announcement by the Bank of France that it would discount American commercial paper for gold Eagles held in the Bank’s reserves ultimately seemed to have stopped the downward spiral of equity prices. According to Rodgers and Payne (2012), the Bank of France repeated its announcement between November 22 and December 7, 1907. The authors also conclude that the Bank of France actions signaled an ongoing ability to provide liquidity, and thereby a more enduring resolution of the crisis, in contrast to Morgan’s temporary injection of funds.
Wilson and Rodgers (2011) point out that, in addition to the various policy responses, the structure of the U.S. capital markets proved to be beneficial for the economy during the Panic of 1907. For example, the payment system for bond-transactions was not necessarily tied to banks. Hence, investors could continue to receive payments even with banks in trouble. Additionally, most bond indentures stipulated that coupon and principal payments had to be made in gold, which further explains why the Bank of France announcements proved so helpful in stabilizing the market.

The severity of the Panic of 1907 brought calls for reform of the financial system, with a particular focus on curbing potentially destabilizing activities in the stock markets and the need for a lender of last resort to backstop the banking system. Consequently, on May 28, 1908, Congress passed the “Aldrich-Vreeland Act” that permitted banks to coordinate during crisis episodes and provided for emergency currency to infuse liquidity into the system when widespread insolvency threatened. Additionally, the Act introduced the National Monetary Commission and charged it with investigating the Panic of 1907 and recommending measures to regulate capital markets and the banking system (Calomiris and Gorton (1991)). Most of those reports pointed out the need for an official lender of last resort. The Commission submitted its final report in 1912 and on December 23, 1913, Congress passed the Federal Reserve Act.

4 Rumor-based Liquidity Freezes

The Panic of 1907 features a range of asymmetric information problems, including lack of transparency and informed trading by certain market participants (for example, those involved in the United Copper Company stock corner) and a highly uncertain general environment due to the dissemination of rumors about financial institutions’ insolvency. The theoretical literature offers a variety of models that capture most of these elements of financial crises that we can use to derive testable hypotheses for this particular episode.

Bernardo and Welch (2004) offer a theoretical framework which explains how rumor-based runs on financial markets may come about. In order to avoid the liquidation of shares at a bad “post-run” price, each investor may prefer selling shares today at the “in-run” price. If many investors think alike, this in itself will cause a run on financial markets. Based on this intuition and the underlying model, Bernardo and Welch (2004) conclude that liquidity runs and crises are not necessarily caused by liquidity shocks per se, but instead by the fear of future liquidity shocks. He and Manela (2014) show the same effect in a different framework. They study dynamic rumor-based runs on financial institutions with endogenous information acquisition. Agents who are unsure about banks’ liquidity worry that other agents, who might have received even worse signals, withdraw before
them. Hence, in order to front-run those agents with even worse signals, they start the run on the financial institution themselves. The fear of being too late increases the incentives to run. Thus, He and Manela (2014) and Bernardo and Welch (2004) offer an appropriate rationale for the happenings in the autumn of 1907.

The initial impetus for the Panic resulted from the failure of a short squeeze via a stock corner. However, since the participants in that stock corner were highly connected people in the business world of 1907, rumors and fears about impending liquidations of interconnected companies and financial institutions, spurred investors to sell their shares immediately in order to avoid coming in last. If this line of arguments holds true, we should observe increased adverse selection risk as well as increased trading volume right after the failure of Heinze’s stock corner. Both increased adverse selection risk and increased selling pressure should in turn drive up bid-ask spreads, making trading more expensive and traders reluctant to do so.

Hellwig and Zhang (2012) show that the role of information changes during a crisis. They demonstrate that markets tend to be more liquid at the onset of a crises than towards the end. Specifically, they argue that the strategies over information gathering may depend on the liquidity in a given market. Strategic information acquisition may change across agents due to changing assets’ liquidity and valuation uncertainty about future states of the world. A vicious cycle may evolve in reaction to an unexpected event (i.e., in this case the failure of a stock corner) that leads to increased informational risk, which in turn leads to higher spreads, which again reinforces the trader’s view that informational risk has indeed increased, and therefore spreads increase even more. The spiraling information problem freezes liquidity in the market, such that we should observe increasing illiquidity over the course of the crisis (also pointed out by Donaldson (1992)) as well as constantly increasing adverse selection risk for the cross section of companies.

These theories do not address the impact that liquidity interventions might have on the vicious cycle of increased informational risk and freezing liquidity. As described in Section 3, on October 24, 1907, J.P. Morgan - together with other wealthy individuals - pledged large sums of money in order to calm markets and restore confidence. We expect that this intervention as well as other measures put in place by the Clearing House Association and the Treasury significantly contributed to ending the liquidity freeze. This should be reflected in declining spreads, increasing trading volume, and a reduction in overall informational risk as well as valuation uncertainty.

On the timing of events, Gorton (1988) is able to classify the business cycle of 1907/8 rather precisely from May 1907 to July 1908, the Panic, however, to October 1907 only. Using a unique dataset on both the bond and stock market, Tallman and Moen (2014) provide empirical evidence for both asset markets that the serious financial distress already
started prior to the suspension of Knickerbocker Trust and hence prior to what Gorton (1988) classifies as the 1907 Panic.

Moving beyond the timing of historical crises, Calomiris and Gorton (1991) theoretically and empirically review two competing views on how bank runs can possibly emerge: random withdrawals vs. “asymmetric information” runs, where panics are caused by depositor revisions in the perceived risk of a bank when they are uninformed about the health of a bank and receive adverse news about the state of the economy. By reviewing a large set of bank crises, they find that banks’ self-regulation used to be quite effective in mitigating bank panics. They furthermore are able to show that the banking environment used to be opaque and hence informationally risky, but that this has changed with the changing business models of banks and the ability to sell loans on the open market.

Kyle and Obizhaeva (2012) turn the focus of why panics and crashes emerge to whether they are predictable. By comparing price declines in stock markets with predictions from a market microstructure invariance measure, they are able to show that early warning systems are actually feasible and that those can be easily implemented.

Due to data restrictions, none of these papers is able to empirically evaluate changes in the intensity of a crisis and its roots (fundamental changes vs. information-based panic). We help fill this gap in the literature by tracking changes in informational risk closely and thereby provide evidence of how crises in stock markets can form based on panics rather than fundamentals. To our knowledge, we are the first to do so (compare Goldstein (2010)).

To be specific, we conjecture and then later test the following hypothesis:

**Hypothesis 1:** Adverse selection risk drives illiquidity during a rumor-based panic, in particular, during the Panic of 1907.

We further expect to find the most severe adverse selection effects in stocks that have the least transparency regarding their financial performance and in which stocks are most prone to manipulations, such as naked short sales, corners and short squeezes. Mining stocks ranked among the worst in this regard, and it was the failed corner on the United Copper Company that lay at the center of the panic. The United Copper Company was incorporated in 1902 by F. Augustus Heinze, the brother of Otto Heinze and a copper magnate who had fought for years - largely against the Amalgamated Copper - to get access to lucrative copper mines in Butte, Montana. According to an article of the New York Times of April 29, 1902, Heinze also held stakes through United Copper Company in a number of other mining companies such as The Montana Ore Purchasing Company, The Nipper Consolidated Copper Company, The Minnie Healy Mining Company, The
Corra Rock-Island Mining Company, and the The Belmont Mining Company. So based on the wide-spread connections of the Heinze brothers in the mining sector we conjecture the following hypothesis:

**Hypothesis 2:** In the historical context of this panic, the effect of adverse selection is particularly strong in the mining sector.

Based on the differing extent and thoroughness with which different industries published their accounting information (Archambault and Archambault (2005)), we furthermore expect stocks in the more transparent sectors (e.g., utilities and railroad sector, which provided accounting information to the public in great detail) to suffer from lower informational risk than other sectors, such as manufacturing and mining, that published meager information on a sporadic basis. Transparency arguably mitigates potential for insider trading and adverse selection costs, assuming that insiders provide accurate information.9

That information asymmetry and adverse selection risk might not only differ across industries, but also across certain types of stocks is suggested by Hellwig and Zhang (2012). The authors show in an OTC-market setting that information acquisition may differ across liquid and illiquid markets. Chang (2012) goes a step further and demonstrates how limited market participation can arise as a result of informational frictions and how it then leads to distinct notions of illiquidity. In her theoretical framework she analyzes two types of informational frictions: sellers’ private information about the quality of their assets and their private information of what motivates them to trade (e.g., different needs for liquidity). Her model thereby is able to endogenously generate and identify the effects that adverse selection risk might have on transaction costs and volumes. In this environment, the trader who wants to sell her asset quickly is either trying to get rid of a low-quality asset, or simply has an urgent need for cash. If the other side of the transaction, the buyer, cannot differentiate between the two motives for trading, adverse selection risk will increase. This phenomenon should arise especially for illiquid stocks, as they are traded less frequently and market participants have more difficulty determining the fundamental value of the stock. Hence, we expect to find that adverse selection risk differs significantly between liquid and illiquid stocks. We expect to find that adverse selection risk increases even more during crisis times. In a highly uncertain period, those problems might be disproportionatively greater than in non-crisis times. Thus, we expect to find the following hypothesis to hold:

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8See New York Times Article from April 29, 1902 regarding United Copper Company.
9We do note that transparency may be illusory in this period, as companies rarely produced audited accounts.
**Hypothesis 3a:** *Adverse selection risk affects illiquid stocks more than liquid stocks.*

Listing on the NYSE brought with it a certification of quality, based on the exchange’s listing requirements, which involved a vetting process and disclosure of financial statements. As a way to ward off competitors, the NYSE also maintained an "unlisted department" to trade in stocks that 1. could not meet NYSE listing requirements or 2. chose not to report the information required for an application for an official listing. Hence, since the NYSE did not impose any disclosure rules on stocks trading in the unlisted department, less public information was available about these stocks, and consequently they presumably faced greater susceptibility to information shocks and rumors than stocks for which more information was available publicly. Moreover, episodes of heightened uncertainty may exacerbate such information problems. Thus, we expect that unlisted stocks are particularly vulnerable to rumors:

**Hypothesis 3b:** *Adverse selection risk affects unlisted stocks more than listed stocks.*

### 5 Data

We use newly-gathered data on daily transactions, quotations, and volumes for all stocks trading on the NYSE during 1905 through 1910. We checked the data thoroughly for possible transcription mistakes and standardized the many variations on each firm’s name. We then implemented a thorough automated search for potential errors, based on inconsistencies across variables (e.g., "high" price that is not the highest price for the day or ask prices exceed the respective bid prices). We hypothesized that it is not possible for the closing bid and ask prices to deviate from the last trading price by a large amount and therefore dropped observations for which the bid or ask deviated from the last price by more than $10. The number of observations dropped by this procedure, range from five to 70 observations depending on the respective year.

We next compute bid-ask spreads, mid-quotes, and a trade direction indicator variable.

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10 The data constitute a portion of the new NYSE database for 1900-1925 created by and discussed in greater detail in Fohlin (2014), funded by grants from the U.S. National Science Foundation. The raw data come from the NYSE listings printed each day in the New York Times, via the Proquest digital archive. The images are not machine readable, and Optical Character Recognition (OCR) methods proved infeasible, so the data were all entered by hand. An earlier paper provided some initial cleaning and analysis of the 1900 and 1910 waves of the data, and we proceed generally in line with that earlier work of Gehrig and Fohlin (2006).

11 In a typical year the raw data contained around 1,100 different stock names, of which some 80 percent were duplicates. For example, "Am. B. Su. Co.”; "Am. Beet S. Co.”; "Am. Beet Sug. Co.”; "Am. Beet Sugar” all refer to the company: American Beet Sugar.
The trade direction indicator indicates whether the last transaction was a buy (+1), a sell (-1), or not determinable (0). We calculated this variable by comparing the last trading price with the respective mid-price (similar to Lee and Ready (1991)). If the last transaction price exceeds the respective mid-price, the trade indicator variable takes a value of +1. If the mid-price exceeds the transaction price, the trade indicator variable takes a value of -1 and zero in all other cases.

An important variable that we use for our liquidity analyses refers to monthly U.S. call money rates. This data comes from the National Bureau of Economic Research Macromistory Database and is denoted in percent. We furthermore include monthly data for gold stock reserves in our subsequent analyses which also comes from the National Bureau of Economic Research Macromistory Database and is denoted in billions of Dollars. To investigate differences between liquid and illiquid companies, we create an indicator variable that takes the value of one if a stock was in the first quantile of the spread distribution and zero otherwise. In order to control for the size of companies, we furthermore generate a dummy variable that takes the value of one if a company was in the first quantile of the trading volume distribution and zero otherwise. Descriptive statistics can be found in Table 1.

6 Methodology

In order to estimate informational costs, inventory costs, order handling costs, and their respective contribution to the bid-ask spreads on the highest frequency possible (i.e., monthly), we apply Gehrig and Haas (2015)’s refinement of the Huang and Stoll (1997) spread decomposition. The refinement insures that the three different cost components add up to a 100% of the quoted bid-ask spreads. We review the methods briefly and refer the reader to the detailed description in Gehrig and Haas (2015).

In the model of Huang and Stoll (1997), the time frame consists of three separate and sequential events. The stock’s fundamental value, $V_t$, is unobservable. The bid and ask quotes are set right after the fundamental stock value has been determined. $M_t$ denotes the quote midpoint and is calculated from the quotes that were posted by a market maker just before a transaction happened. $P_t$ denotes the respective transaction price. As described in section 3, $Q_t$ denotes the trade direction indicator variable. It takes the value of 1 if the transaction price exceeds the midquote, and it takes the value of $-1$ if the transaction price is smaller than the midquote. It equals zero if the transaction price is equal to the midquote.

Trade flows are assumed to be serially correlated. The conditional expectation of the
trade indicator variable $Q_t$ at time $t-1$ given $Q_{t-2}$ is, therefore, shown to be:

$$E(Q_{t-1}|Q_{t-2}) = (1 - 2\pi)Q_{t-2}. \tag{1}$$

where $\pi$ denotes the probability that the current trade is of opposite sign to the previous trade.

Huang and Stoll (1997) estimate equation 1 simultaneously with equation 2 in order to estimate the different cost components of the spread. In equation 2 $S_t$ denotes the equity bid-ask spread and $\alpha$ denotes the percentage of the spread that is associated with informational cost (i.e., adverse selection cost). As can be seen $\alpha$ is assigned to the difference of what the actual trade turned out to be (i.e., $\frac{S_{t-1}}{2} Q_{t-1}$) and what the market maker expected the trade to be based on the previous trade (i.e., $\frac{S_{t-2}}{2} E[Q_{t-1}|Q_{t-2}]$). Hence, $\alpha$, or informational costs, only arise if the current trade brings about a surprise relative to the previous trade. $\beta$, the percentage of the spread that is associated with inventory cost, on the other hand is assigned to the current trade and denotes the changes in the market maker’s inventory holdings that she later might need to adjust. $\epsilon_t$ refers to a public information shock. It is assumed to be serially uncorrelated.

$$\Delta M_t = \left(\alpha + \beta\right) \frac{S_{t-1}}{2} Q_{t-1} - \alpha \frac{S_{t-2}}{2} (1 - 2\pi)Q_{t-2} + \epsilon_t. \tag{2}$$

With equation 1 and 2, we have arrived at the equations that we use for our estimation procedure. The parameters of equation 1 and 2, $\alpha$, $\beta$, and $\pi$, are estimated using the generalized method of moments (GMM) procedure outlined in Hansen and Singleton (1982) and Hansen (1982). The optimal weighting matrix is constructed using the method proposed in Wooldridge (2002).

Under this procedure, the parameter estimates have to be chosen such that they minimize:

$$Q_N(\theta) = \left[N^{-1} \sum_{i=1}^{N} g(w_i, \theta) \right]^T \hat{\Lambda}^{-1} \left[N^{-1} \sum_{i=1}^{N} g(w_i, \theta) \right]. \tag{3}$$

Following the notation of Wooldridge (2002), $\theta$ is the vector of unknown coefficients. In this analysis, this vector includes the component for adverse selection risk ($\alpha$), the component for inventory holding risk ($\beta$), and the trade direction reversal probability ($\pi$). The order processing cost component is computed by subtracting $\alpha$ and $\beta$ from one. This is because those three components represent costs, which have to add up to 100% or one. $g(w_i, \theta)$ is an ($L \times 1$) vector of moment functions (or orthogonality conditions). These functions are non-linear and given by:

1. $g_1 = (Q_{t-1} - (1 - 2\pi)Q_{t-2}) Q_{t-2}$
2. \( g_2 = (Q_{t-1} - (1 - 2\pi)Q_{t-2}) S_{t-1} \)

3. \( g_3 = (Q_{t-1} - (1 - 2\pi)Q_{t-2}) S_{t-2} \)

4. \( g_4 = \left( \Delta M_t - (\alpha + \beta)\frac{S_{t-1}}{2} Q_{t-1} + \alpha \frac{S_{t-2}}{2} (1 - 2\pi)Q_{t-2} \right) S_{t-1} \)

5. \( g_5 = \left( \Delta M_t - (\alpha + \beta)\frac{S_{t-1}}{2} Q_{t-1} + \alpha \frac{S_{t-2}}{2} (1 - 2\pi)Q_{t-2} \right) S_{t-2} \)

6. \( g_6 = \left( \Delta M_t - (\alpha + \beta)\frac{S_{t-1}}{2} Q_{t-1} + \alpha \frac{S_{t-2}}{2} (1 - 2\pi)Q_{t-2} \right) (Q_{t-1} - (1 - 2\pi)Q_{t-2}) \cdot \)

\( \hat{\Lambda} \) is the optimal weighting matrix which is determined by also following Wooldridge (2002):

\[
\hat{\Lambda} \equiv \frac{1}{N} \sum_{i=1}^{N} [g(w_i, \theta)] [g(w_i, \theta)]'.
\]

7 Results

7.1 Informational Risk and Liquidity Freezes

The spread decomposition based on the method of Section 6 demonstrates significant variation in the relative weights of adverse selection costs, inventory costs, and order processing costs as contributors to overall transaction costs (Figure 3). The informational cost appears as the dominant cost factor. During the crisis, informational cost and inventory cost components comprise the largest shares: together they make up 75% of bid-ask spreads, and they intensified during the panic. In particular, during the third and fourth quarters of 1907 and first quarter of 1908 informational costs and inventory costs increased to about 85% of the overall spread; an increase of about 10% compared to normal times.

When plotting the absolute cost components in Dollar-terms (Figures 4) it becomes apparent that adverse selection costs dominate transaction costs and thus contribute most to constraining liquidity in the market. During the panic information costs increased steeply from $0.007 to $0.02, while inventory holding costs increased from $0.003 to $0.009 and order processing costs from $0.004 to $0.01. Hence, the cost decomposition supports the view that uncertainty and information asymmetry - namely rumors - drove the 1907 crisis. This finding accords well with our hypothesis, based on theoretical models of rumor-based market runs (He and Manela (2014) and Bernardo and Welch (2004)). In a sense, we also find similar results to what Hellwig and Zhang (2012) predict, that is, that the role of information changes from the onset of a crisis to the end. In the case of the Panic of 1907, we see an increase of informational costs from the onset of the Panic on. However, the real peak of rumor-contagion is reached when the Panic is already evolving (i.e., October
1907), not at the very beginning of it. This suggests that the spreading informational risks (i.e., rumors) affected the whole stock market and worked contagiously during the crisis. Obviously, in the case of information production through fear and rumors, information production may reduce market efficiency (Dang et al. (2010)).

Alternative liquidity measures bolster our results on different risk factors. In particular, volume (measured as the daily number of shares traded), transaction costs (measured as relative bid-ask spreads), price impact (measured by the so-called invariance measure proposed by Kyle and Obizhaeva (2013) and Kyle and Obizhaeva (2012) for a trade of 1000 shares) and price sensitivity associated with one additional unit of trading volume (from Amihud (2002)) all demonstrate the liquidity freeze phenomenon (see Figures 9 to 8). The number of shares traded on an average trading day dropped from about 3000 shares per day to about 200 shares; spreads more than tripled from about 0.5% before the crisis to about 2.5% during the Panic; and the Amihud illiquidity measure also more than doubled. The invariance measure of Kyle and Obizhaeva (2012), measuring the impact on stock price of a 1000-share trade, also more than triples over the course of the Panic from about 0.3% before the Panic to about 1% during the Panic. It does, however, react earlier to the Panic than the Amihud measure and increases once the Heinzes’ stock corner scheme started to hit the markets. Notably, the daily number of shares traded increases sharply once informational costs increase (Figure 7). This pattern suggests that traders - because of the increased informational risk they were facing and the spreading fear and rumors - increased their trading activity in order to front-run other traders and to be on the “safe side”. However, once J.P. Morgan intervened on October 24th, 1907, stock markets calmed down: the number of shares traded per day decreased to pre-crisis levels, as did informational costs and order processing costs. The decline in volume affirms that Morgan’s measures helped to stop the “liquidity freeze” in the stock market. Importantly, the cash injection only had short-term effect on trading volume. About two months after the intervention of J.P. Morgan and his colleagues, the number of shares traded decreased sharply (i.e., severely below pre-crisis levels) and stayed on a depressed level for about a year (Figure 7). Thus, even though the risk factors that influence the behavior of market makers returned to their pre-crisis levels, the uncertainty that stymies traders persisted much longer. This finding demonstrates that a rumor-based liquidity crisis can severely destroy traders’ confidence in markets, thereby freezing liquidity far beyond the actual crisis period. Box plots of relative bid-ask spreads, the number of shares traded, the Invariance measure, and the Amihud illiquidity measure (Figures 10 to 14) elaborate further on the means and medians, indicating growing dispersion of each measure as well.

Stock returns show a severe depression during the Panic of 1907 (Figure 9), but clearly returns had been falling for several months prior to the crisis. All companies and sectors
experienced severe declines in returns during the panic, but the crisis hit the mining sector the hardest. That sector also took the longest to recover from the crisis. Returns of mining companies stayed on a depressed and volatile level until the beginning of 1909.

We confirm these graphical results in panel regression analyses of spreads and their components (Table 2). Here, the dependent variables (i.e., \( k \)) are 1. relative bid-ask spreads (column 2), defined as the difference between ask and bid prices divided by the average of ask and bid prices; 2. informational costs (column 3), defined as the adverse selection component times the relative bid-ask spread, 3. inventory costs (column 4), defined as the inventory holding component times the relative bid-ask spread, and 4. order processing costs (column 5), defined as the order processing component times the relative bid-ask spread. We regress each dependent variable on a crisis indicator and monthly call money rates from the National Bureau of Economic Research Macrohistory Database. The crisis indicator takes the value of one if the time period equals the third or fourth quarter of 1907 or the first quarter of 1908 and zero otherwise. We base the timing of the crisis on both past literature and our own analysis of volatility. Papers such as Frydman et al. (2012) and Bordo and Haubrich (2010) date the panic to exactly this time period. Our own statistical analysis of volatility over time falls in line with the literature, indicating that volatility rose sharply at the end of the third quarter of 1907 and then began a decline that lasted until March 1908 (Figure 2). Volatility in this case is measured as a 30-day rolling window of the standard deviation of stock returns. Call money is short-term inter-bank lending, typically secured by gold or stocks. In the period we analyze, the call money rate represents the marginal cost of financing for stock purchases. To assess the impact of call money rates on market liquidity specifically during the Panic of 1907, we furthermore include an interaction term of both the crisis indicator variable and call money rates. The exact econometric model thereby looks as follows:

\[
Y_{k,i,t} = \beta_0 + \beta_1 \text{Crisis}_t + \beta_2 \text{CallMoney}_t + \beta_3 \text{Crisis}_t \cdot \text{CallMoney}_t + \beta_2 X_{j,i,t} + F E_t + T E_t + \epsilon_{i,t}
\]  

(5)

Where:

- \( Y_{k,i,t} \): Dependent variables \( k \):
  * Relative Bid-Ask Spreads of company \( i \)
  * Adverse Selection Costs of company \( i \)
  * Inventory Holding Costs of company \( i \)
  * Order Processing Costs of company \( i \)
- \( X_{j,i,t} \): Control variables \( j \):

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* Liquidity indicator variable (highly liquid vs. illiquid stocks)
* Size indicator variable (large vs. small stocks based on number of shares traded)

– FE: Firm fixed effects
– TE: Time fixed effects

The resulting estimates show that relative spreads and most components (except for order processing costs) relate positively and significantly with call money rates. This indicates that indeed call money rates drove liquidity as well as informational costs and inventory holding costs. This result is also economically significant: an increase in call money rates by one percent leads to an increase in relative spreads by 0.2%. The effect of call money rates on market liquidity is amplified during the panic: relative spreads relate statistically very significantly to call money rates. This amplification during the crisis, however, does not hold for all cost components equally. Informational costs are not statistically significant, whereas order processing costs (including monopoly rents) are. The latter tend to increase during the panic period, when call money rates were rising as well. Fading liquidity obviously reduces transactions demand and, hence, increases market power, potentially due to the exit of dealers.

Thus, call money rates, reflecting money market liquidity, drove a substantial part of stock market liquidity during this period and did so all the more during the panic episode of late 1907 and early 1908. We therefore interpret the Panic of 1907 as a liquidity crisis. Call money rates also relate especially robustly with informational costs and inventory holding costs; highlighting the channel linking call money rates to spreads. \(^\text{12}\)

In order to confirm that the findings on call money rates are robust across different liquidity dimensions and also hold at a higher frequency, we perform a similar regression analysis but with daily data (Table 3). Specifically, we regress different measures of liquidity on daily call money rates and a crisis indicator variable. \(^\text{13}\) In order to exploit the daily call money rates, we use correspondingly high frequency liquidity measures: daily relative bid-ask spreads (column 2), defined as the difference between ask and bid prices divided by the average of ask and bid prices, daily trading volume (column 3), defined as the number of shares traded per day, the daily Amihud Ratio (column 4), defined as the ratio of the absolute return for a stock (\(|r_t|\)) to trading volume in monetary terms over a day (see Amihud (2002)), quasi-volatility (column 5), defined as the day’s highest price minus its lowest price divided by the last price of that day, and the Invariance measure (column 6) (see Kyle and Obizhaeva (2013)). The regressors include an indicator for

\(^{12}\)The crisis indicator variable is omitted in this regression due to collinearity with the interaction term.

\(^{13}\)The daily data of U.S. call money rates was kindly provided to us by Ellis Tallman, who also uses this proprietary dataset in his recent paper (see Tallman and Moen (2014)).
the crisis period of October 16, 1907 (the day of the stock corner failure) to January 21, 1908 to daily call loan rates. Call Money Rates × Crisis denotes an interaction term of both the crisis indicator variable and call money rates. We also include lagged dependent variables in each regression specification to account for autocorrelation in the dependent variables. The daily call loan rate data covers September 30, 1907, to February 19, 1908, which therefore sets the period of our regressions.

In line with our monthly results, all three of our daily liquidity measures relate positively and statistically significantly with the call loan rates, confirming that money markets played a key role in transaction costs (see Table 3). Moreover, rising call money rates during the crisis led to significant deterioration of liquidity (higher spreads and price impact, and lower volume) compared to normal times.

To confirm that these findings are robust and attributable specifically to call money rates, we assess the underlying factors moving call money rates and whether those factors simultaneously drive market liquidity. In particular, we regress call money rates on the level of U.S. gold stock reserves, our crisis indicator variable, and an interaction term of the crisis indicator variable and the level of gold stock reserves. The monthly data for gold stock reserves comes from the National Bureau of Economic Research Macrohistory Database and is denoted in billions of Dollars. Call money rates show a strong inverse correlation with the level of gold stock reserves (Table 4). Call rates also rose significantly during the Panic of 1907, however, this effect was partly offset by gold imports during the crisis: the interaction term between the crisis indicator variable and the level of gold stock reserves is negative and statistically significant, suggesting that as the level of gold stock rose towards 1908 (as described by Rodgers and Payne (2012)), call money rates decreased and helped relieve the tight liquidity conditions of the crisis period. Interestingly, rising gold stocks do not directly ameliorate illiquidity in the stock market; including that variable in the models of Table 2 yields insignificant results. Rather, call money rates capture the impact of gold flows completely. Hence, we confirm Rodgers and Payne (2012)’s finding that the rising level of gold stock helped to end the crisis. But it did so via call money rates and did not directly improve stock market liquidity.

7.2 The Mining Sector at the Heart of the Crisis

In order to analyze our second hypothesis, that adverse selection risk hit worst in the most opaque and rumor-ridden sector (mining companies), we compare relative bid-ask spreads and the different cost factors by industry. Indeed, the panic hurt mining stocks’ liquidity the most. Besides the fact that the mining sector experienced the greatest decline in stock returns during the Panic of 1907, when compared to all other sectors (see Figure 9), spreads of mining companies rose from about 2% before the crisis to about 5% during
the Panic of 1907 (Figures 15 to 17). This sharp rise in illiquidity results entirely from adverse selection risk (Figures 18 to 20): adverse selection costs (in dollar-terms) triple from $0.01 to $0.03, the steepest increase across all industries. Most importantly, adverse selection costs remain high, even after rescue measures took place. This finding indicates that the rumor-based crisis infected mining stocks severely enough to endure over the longer term. The other two cost types show less significant increases during the Panic of 1907.

The other sectors do experience higher adverse selection costs as well, which supports our hypothesis that informational risk was an important driver of this overall liquidity freeze. But all other industries react after the mining sector which suggests that the mining sector - due to the connections of the Heinze brothers, and the overall opacity of the sector and its activities - was really at the heart of this Panic.

We also confirm our related hypothesis that stocks in the sectors that published accounting information on a relatively frequent basis (such as the railroad and utilities sectors), do indeed experience lower adverse selection costs compared to other industries, such as manufacturing. Relative transparency, therefore, turns out to be beneficial in terms of lower adverse selection risk and increased stock market liquidity.

7.3 The Informational Advantage

Our third hypotheses conjectured that illiquid (e.g. low volume, high price impact, or unlisted) stocks were affected disproportionally more by informational risk than liquid stocks. To test our hypothesis, we divide the cross section of companies into two subsamples: a “liquid” one and an “illiquid” one. We define liquid stocks as those falling into the lowest quartile of relative spreads and illiquid stocks as those falling in the highest quartile of that distribution. As we predict, the most illiquid stocks experience significantly greater increases in informational costs, inventory costs, and order processing costs than liquidity ones (Figure 5). All three spread components are more than three times as large for illiquid stocks than for liquid stocks. Furthermore, informational costs increased during the Panic of 1907 for illiquid stocks, whereas the other two cost types even declined slightly during the crisis. This suggests that illiquid stocks are particularly subject to adverse selection risk during a liquidity freeze.

We find similar results in comparing listed and unlisted companies: the latter get hit by higher informational costs than do the former (Figures 6). As we expect that unlisted stocks generally suffer more from higher informational costs due to the lack of certification and absence of disclosure rules, the adverse selection problems should intensify during a financial crisis. Information costs were especially elevated when rumors were most active in the last quarter of 1907. It also took longer for adverse selection risk to decrease
in unlisted stocks compared to listed stocks. This implies that investments in listed companies that had to publish accounting information, indeed served as a hedge against adverse selection risk and especially so in times of heightened uncertainty. This lends robustness both to our sector analyses, in which we showed that companies from sectors that published on average more than other sectors were subject to less adverse selection risk, and to our illiquidity results from Hypothesis 3a.

8 Asset Pricing Implications

As demonstrated previously, asymmetric information and other market frictions significantly affect liquidity and hence bid ask spreads and their measurable components. In this section we check whether these drivers of liquidity risk are also priced in the market. Due to data constraints, we offer this analysis as a preliminary exploration and a robustness test, rather than a fully-fledged asset pricing analysis. In particular, we are missing a proper short-term, risk-free rate as well as firm dividends at this stage. Accordingly, for now, we are limited to working with gross stock returns. Hence, company specific returns are computed as follows, where \( P_{i,t} \) is the last trading price of month \( t \) and \( P_{i,t-1} \) is the last trading price of month \( t-1 \):

\[
R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \quad (6)
\]

Market (gross) returns are then computed by equally-weighting individual stock returns:

\[
R_{m,t} = \frac{1}{N} \sum_{i=1}^{N} \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \quad (7)
\]

The fact that liquidity risk is priced in stock returns has already been shown for modern markets by Pástor and Stambaugh (2003) and Acharya and Pedersen (2005). Following this strand of the literature, we first test for the liquidity risk premium in our data, before assessing the impact of the three components of liquidity risk (i.e., adverse selection, inventory holding, and operating costs). In order to do so we follow Fama and MacBeth (1973) and set up a two stage estimation procedure. The first stage time series regressions estimate firm characteristics, such as betas and factor loadings, for a number of return generating factors. In the second stage, we regress the cross-section of returns on

\footnote{We tried a long-term rate as provided by Shiller (2000) with little success, and we have so far not identified a short-term rate at a high enough frequency. We are proceeding with collecting and integrating dividends into the database, however, the work requires extensive hands-on work and will take some time to complete.}
firm characteristics. These marginal contributions are generally interpreted as the market implied price of the associated factor risk.

In order to test whether the results of Pástor and Stambaugh (2003) and Acharya and Pedersen (2005) also hold “out-of-sample” (i.e., in our period), we set up the following first stage regression estimation using four different liquidity measures, along the lines of the past work: 1. the company-specific Amihud measure, 2. company-specific relative bid-ask spreads, 3. market-wide average Amihud measure, and 4. market-wide average spreads.

\[ R_{i,t} = \beta_1 R_{m,t} + \beta_2 \text{LiquidityMeasure}_{j,i,t} + \epsilon_{i,t} \quad (8) \]

In the second stage, the cross-section of stock returns are regressed on the estimated factor loadings of the first stage:

\[ \mathbb{E}(R_i) = \lambda_1 \hat{\beta}_1 + \lambda_2 \hat{\beta}_2 + \eta_{i,t} \quad (9) \]

To correct for potential heteroskedasticity and autocorrelation in the errors, we estimate robust standard errors in this specification as well as in all of the following ones.

The results for all first-stage time-series regressions (which are available upon request from the authors) show that on average \( \beta_1 \)-coefficients are statistically significant and positive with an average of about one.

We clearly confirm the expected liquidity results for our much earlier time period (Table 5). In the second-stage models, all four liquidity measures enter with positive and statistically significant signs. The \( R^2 \)s lie between 0.58 and 0.74.

Our decomposition allows us to assess the impact of the three components of liquidity risk and to determine whether these factors are priced individually in the market. Hence we proceed by replacing the composite illiquidity measures with the vector of spread components:

\[ R_{i,t} = \beta_1 R_{m,t} + \beta_2 \text{ASCost}_{i,t} + \beta_3 \text{HCost}_{i,t} + \beta_4 \text{OPCost}_{i,t} + \epsilon_{i,t} \quad (10) \]

The 70 company-specific time-series regressions produce statistically significant, positive \( \beta_1 \)-coefficients with an average of about one (Figure 21). The \( R^2 \)s lie between about 0.40 and 0.97.

In the second stage, the cross-section of stock returns are again regressed on the estimated factor loadings of the first stage:

\[ \mathbb{E}(R_i) = \lambda_1 \hat{\beta}_1 + \lambda_2 \hat{\beta}_2 + \lambda_3 \hat{\beta}_3 + \lambda_4 \hat{\beta}_4 + \eta_{i,t} \quad (11) \]

Once again, we find that the market risk premium is both statistically significant and
positive (Table 6). Moreover, the premia on each of the components of bid-ask spreads is significant and positive, suggesting that the market rewarded exposure to each of the underlying components of liquidity risk. In other words, information risk, inventory risk, and order processing costs are each priced separately in the market.

Overall, we find strong evidence of predictability of asset returns based on liquidity risk and its underlying components over and above market returns (i.e., systematic risk). Thus, insofar as transaction costs can be predicted, liquidity factors, and, hence, asset prices can be predicted. These results highlight the first order importance of transaction cost factors for asset pricing in rapidly developing U.S. markets over 100 years ago, similar to modern emerging markets (see Bekaert et al. (2007)). We are optimistic that a more refined asset pricing analysis incorporating excess returns and dividend yields will confirm and extend the insights from this exploratory analysis.

9 Conclusion

Our analysis offers several new insights into the role of information in financial markets, and in particular, how critical a role information transparency plays in mitigating adverse selection problems that destabilize markets. The period of our study, surrounding one of the worst financial crises in over 100 years, provides a unique window on the performance of self-regulated asset markets operating under constrained information in the face of uncertainty shocks from unverifiable rumors.

By decomposing equity bid-ask spreads into their underlying cost components, we find that the Huang and Stoll decomposition procedure provides a powerful tool to analyze price formation over the course of a crisis. Specifically, we find that adverse selection costs play a dominant role in increasing transaction costs and thus contribute most to freezing liquidity. We find that all of our measures of liquidity show severe deterioration of market quality along with an increase in informational risk. Importantly, short-term cash infusions did not have a lasting effect on trading volume, even though the different risk factors recovered.

Our results demonstrate that an ostensibly short-run, rumor-based liquidity freeze can severely harm confidence in financial markets over extended periods, constraining liquidity far beyond the most acute phase of the panic. We show further that asymmetric information problems play out - as the theory suggests - in predictable cross-sectional variation in illiquidity. In particular, the liquidity crisis hit the mining sector most severely, because it lay at the heart of the crisis both in terms of illiquidity and heightened informational risk. The mining sector also ranked among the least transparent sectors of the economy and, along with many manufacturing enterprises, provided sparse information to investors. We
find that these types of stocks suffered most from adverse selection costs, while the regulated and more transparent utilities and railroads suffered the least. Moreover, both extremely illiquid stocks as well as stocks traded in the NYSE’s more opaque “unlisted” department also suffered significantly more during the Panic than well-certified (listed) and liquid stocks.

Finally, our analysis also generates insights for asset pricing. In particular, we show that it is possible to predict asset prices based on estimated components of bid-ask spreads. Informational costs, inventory holding costs, and order handling costs all incur risk premia above and beyond the standard market beta. Hence, the predictability of transaction costs and liquidity also implies predictability of asset prices. In this sense, asset prices are informationally efficient in, at most, a weak sense. Our findings demonstrate the first order relevance of liquidity components for asset pricing. An obvious next step in the analyses of rumors in opaque markets is to proceed with collecting and integrating dividends and a risk-free interest rate into our current database in order to confirm the results of gross returns for excess returns. Moreover, we are currently investigating other information shocks and liquidity freezes (such as the San Francisco earthquake, on April 18, 1906) in order to add to the richness and robustness of our results.
References


10 Figures and Tables

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<th>Variables</th>
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Table 1: Descriptive Statistics: 1905-1910

Figure 2: Median Volatility: 1905-1910
Figure 3: Average Cost Components (as Percentage of Bid-Ask Spreads): 1905-1910
Figure 4: Informational Costs, Inventory Costs, and Order Processing Costs: 1905-1910

Figure 5: Informational Costs, Inventory Costs, and Order Processing Costs: Liquid vs. Illiquid Stocks
Figure 6: Infomational Costs, Inventory Costs, and Order Processing Costs: Listed vs. Unlisted Stocks
Figure 7: Median of Relative Spreads & Trading Volume: 1905-1910

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Figure 10: Box Plots of Transaction Prices: The Panic of 1907
Figure 11: Box Plots of Relative Bid-Ask Spreads: The Panic of 1907

Figure 12: Box Plots of Trading Volume: The Panic of 1907
Figure 13: Box Plots of Invariance Measure: The Panic of 1907

Figure 14: Box Plots of Amihud Illiquidity Measure: The Panic of 1907
Figure 15: Box Plots of Relative Bid-Ask Spreads per Industry

Figure 16: Box Plots of Trading Volume Per Industry
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Figure 18: Informational Costs across Industries: 1905-1910
Figure 19: Inventory Costs across Industries: 1905-1910

Figure 20: Order Processing Costs across Industries: 1905-1910
Table 2: Regression Analyses for the Panic of 1907

This table reports the results from panel regression estimations. The dependent variables are relative bid-ask spreads (column 2), defined as the difference between ask and bid prices divided by the average of ask and bid prices, informational costs (column 3), defined as the adverse selection component times the relative bid-ask spread, inventory costs (column 4), defined as the inventory holding component times the relative bid-ask spread, and processing costs (column 5), defined as the order processing component times the relative bid-ask spread. The regressors include a dummy variable that indicates crisis times and which takes the value of one if the the time period equals the third or fourth quarter of 1907 or the first quarter of 1908 and zero otherwise. A second regressor refers to monthly U.S. call money rates. This data comes from the National Bureau of Economic Research Macrohistory Database and is denoted in percent. Call Money Rates × Crisis denotes an interaction term of both the crisis indicator variable and call money rates. Controls include the following variables: trading volume; a dummy variable that indicates whether a stock was rather liquid and, hence, takes the value of one if a stock was in the first quantile of the liquidity distribution and zero otherwise; an interaction term between the crisis dummy and the liquidity dummy; a dummy variable that takes the value of one if a company was in the first quantile of the size distribution of companies and zero otherwise; an interaction term between the crisis dummy and the size dummy. The dataset consists of U.S. companies listed at the New York Stock Exchange for the period from 1905 to 1910. The t-statistics are based on standard errors adjusted for heteroskedasticity and within-firm/year clustering (see Petersen (2009)), and are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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* t-statistics in parentheses based on HAC standard errors
Table 3: Regression Analyses for the Panic of 1907: Daily Rates

This table reports the results from panel regression estimations. The dependent variables are daily relative bid-ask spreads (column 2), defined as the difference between ask and bid prices divided by the average of ask and bid prices, daily trading volume (column 3), defined as the number of shares traded per day, the daily Amihud Ratio (column 4), defined as the ratio of the absolute return for a stock (\(|r_t|\)) to trading volume in monetary terms over a day (see Amihud (2002)), and quasi-volatility (column 5), defined as the daily high prices minus daily low prices divided by the last price of that day. The regressors include a dummy variable that indicates crisis times and which takes the value of one if the time period equals October 16, 1907 (the day of the stock corner failure) to January 21, 1908, and zero otherwise. A second regressor refers to monthly U.S. call money rates. This data comes from the National Bureau of Economic Research Macroeconometrics Database and is denoted in percent. Call Money Rates × Crisis denotes an interaction term of both the crisis indicator variable and call money rates. The time period that this daily sample covers is September 30, 1907, to February 19, 1908. The t-statistics are based on standard errors adjusted for heteroskedasticity, and are reported in parentheses below the coefficient estimates. The symbols \(**, ** \) and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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<th>Amihud Ratio</th>
<th>Quasi-Volatility</th>
<th>Invariance Measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crisis</td>
<td>−0.002</td>
<td>−364.44***</td>
<td>0.00001</td>
<td>−0.002***</td>
<td>0.0132</td>
</tr>
<tr>
<td></td>
<td>(−1.04)</td>
<td>(−3.48)</td>
<td>(−0.91)</td>
<td>(−3.73)</td>
<td>(0.33)</td>
</tr>
<tr>
<td>Call Money Rates</td>
<td>0.001***</td>
<td>8.82*</td>
<td>−0.00000001</td>
<td>−0.0001***</td>
<td>0.000004</td>
</tr>
<tr>
<td></td>
<td>(5.99)</td>
<td>(2.49)</td>
<td>(−0.02)</td>
<td>(4.49)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>Call Money Rates × Crisis</td>
<td>0.001*</td>
<td>52.29***</td>
<td>−0.000004</td>
<td>0.0002*</td>
<td>−0.0004</td>
</tr>
<tr>
<td></td>
<td>(2.00)</td>
<td>(3.22)</td>
<td>(−0.01)</td>
<td>(2.48)</td>
<td>(−0.03)</td>
</tr>
<tr>
<td>Lagged Spreads</td>
<td>0.41**</td>
<td>.</td>
<td>.</td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td></td>
<td>(54.30)</td>
<td>.</td>
<td>.</td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td>Lagged Trading Volume</td>
<td>.</td>
<td>0.89***</td>
<td>.</td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td></td>
<td>.</td>
<td>(20.16)</td>
<td>.</td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td>Lagged Amihud Ratio</td>
<td>.</td>
<td>.</td>
<td>0.99***</td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td></td>
<td>.</td>
<td>.</td>
<td>(64.86)</td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td>Lagged Quasi-Volatility</td>
<td>.</td>
<td>.</td>
<td>0.98***</td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td></td>
<td>.</td>
<td>.</td>
<td>(282.97)</td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td>Lagged Invariance Measure</td>
<td>.</td>
<td>.</td>
<td>.</td>
<td>0.57**</td>
<td>.</td>
</tr>
<tr>
<td></td>
<td>.</td>
<td>.</td>
<td>.</td>
<td>(3.49)</td>
<td>.</td>
</tr>
</tbody>
</table>

Fixed effects | Yes | Yes | Yes | Yes | Yes |
Time effects | No | No | No | No | No |
Controls | No | No | No | No | No |
Within R² | 0.48 | 0.80 | 0.15 | 0.87 | 0.17 |
Observations | 3654 | 3654 | 3654 | 3654 | 3654 |

t-statistics in parentheses based on robust standard errors
Table 4: Regression Analyses for the Determinants of Call Money Rates

This table reports the results from a panel regression estimation. The dependent variable are monthly call money rates (column 2). This data comes from the National Bureau of Economic Research Macrohistory Database, is denoted in percent, and covers the period of 1905 to 1910. Call Money Rates are regressed on the level of U.S. gold stock, a crisis indicator variable, and an interaction term of both a crisis indicator variable and the level of gold stock. The crisis indicator variable takes the value of one if the the time period equals the third or fourth quarter of 1907 or the first quarter of 1908 and zero otherwise. The monthly data for gold stock comes from the National Bureau of Economic Research Macrohistory Database and is denoted in billions of Dollars. The t-statistics are based on standard errors adjusted for heteroskedasticity and within-firm/year clustering (see Petersen (2009)), and are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Call Money Rates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gold Stock</td>
<td>$-6.04^{***}$</td>
</tr>
<tr>
<td></td>
<td>($-28.81$)</td>
</tr>
<tr>
<td>Crisis</td>
<td>$12.59^{***}$</td>
</tr>
<tr>
<td></td>
<td>(18.58)</td>
</tr>
<tr>
<td>Gold Stock × Crisis</td>
<td>$-7.16^{***}$</td>
</tr>
<tr>
<td></td>
<td>($-16.44$)</td>
</tr>
</tbody>
</table>

Fixed effects: Yes
Time effects: Yes
Controls: No
Within $R^2$: 0.41
Observations: 2891

T-statistics in parentheses based on HAC standard errors
Table 5: Regression Analyses for Asset Pricing Implications I

This table reports the results from the second stage regression estimation of the two-stage estimation procedure described in Section 8. The dependent variable is the monthly average return over time of each stock. The explanatory variables include a market return beta, and the betas of four different types of liquidity measures, all of which were estimated in the first stage of the estimation procedure. The liquidity measures used in the first stage of the regressions include a company-specific Amihud measure as well as a systemic (i.e., market) Amihud measure, and company-specific relative spreads as well as systemic relative spreads. The underlying time period covers the years of 1905 to 1910. The t-statistics are based on standard errors adjusted for heteroskedasticity and autocorrelation, and are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Ind. Amihud</th>
<th>Ind. Spreads</th>
<th>Systemic Amihud</th>
<th>Systemic Spreads</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market Return Beta</td>
<td>0.0231***</td>
<td>0.0210***</td>
<td>0.0273***</td>
<td>0.0273***</td>
</tr>
<tr>
<td></td>
<td>(6.99)</td>
<td>(8.68)</td>
<td>(8.72)</td>
<td>(6.61)</td>
</tr>
<tr>
<td>Liquidity Risk Beta</td>
<td>0.0001*</td>
<td>0.0019*</td>
<td>0.0001*</td>
<td>0.0074*</td>
</tr>
<tr>
<td></td>
<td>(2.17)</td>
<td>(2.37)</td>
<td>(2.26)</td>
<td>(2.20)</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Time effects</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Controls</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Within R²</td>
<td>0.60</td>
<td>0.58</td>
<td>0.74</td>
<td>0.72</td>
</tr>
<tr>
<td>Observations</td>
<td>70</td>
<td>70</td>
<td>70</td>
<td>70</td>
</tr>
</tbody>
</table>

t-statistics in parentheses based on HAC standard errors
Table 6: Regression Analyses for Asset Pricing Implications II

This table reports the results from the second stage regression estimation of the two-stage estimation procedure described in Section 8. The dependent variable is the monthly average return over time of each stock. The explanatory variables include a market return beta, an adverse selection risk beta, an inventory holding risk beta, and an order processing risk beta, all of which were estimated in the first stage of the estimation procedure. The underlying time period covers the years of 1905 to 1910. The t-statistics are based on standard errors adjusted for heteroskedasticity and autocorrelation, and are reported in parentheses below the coefficient estimates. The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>E($R_i$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market Return Beta</td>
<td>0.0196***</td>
</tr>
<tr>
<td></td>
<td>(7.38)</td>
</tr>
<tr>
<td>AS Cost Beta</td>
<td>0.0016*</td>
</tr>
<tr>
<td></td>
<td>(2.48)</td>
</tr>
<tr>
<td>IH Cost Beta</td>
<td>0.0005***</td>
</tr>
<tr>
<td></td>
<td>(3.84)</td>
</tr>
<tr>
<td>OP Cost Beta</td>
<td>0.0011**</td>
</tr>
<tr>
<td></td>
<td>(2.68)</td>
</tr>
</tbody>
</table>

Fixed effects  No
Time effects   No
Controls       No
Within $R^2$   0.64
Observations   70

* t-statistics in parentheses
  based on HAC standard errors
Figure 21: Output First Stage with Liquidity Driving Factors