Information Acquisition in Antebellum U.S. Credit Markets*

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Abstract

If a lender can easily obtain more information about a borrower, under what conditions will he choose to do so? Using a hand-collected dataset from the records of the first credit reporting agency that allows me to directly observe when lenders acquired information about their borrowers, I find evidence that lenders did not always seek information even though it was inexpensive and easily available. Instead, lenders were more likely to start accessing the reports for a borrower after they heard bad news, be it aggregate or borrower-specific. These results show that lenders require relatively more information about borrowers during an economic downturn, suggesting that information constraints likely play a more important role in credit market outcomes during these times. Furthermore, lenders responded to bad news about a borrower in their loan portfolio by acquiring information about other borrowers. This result sheds light on how one default can affect the larger credit network through contagious information acquisition.

Any opinions, findings, conclusions, and recommendations expressed in this material are those of the author and do not necessarily reflect the views of the Federal Deposit Insurance Corporation.

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1 Introduction

Asymmetric information is one of the primary sources of inefficiency in credit markets. A lender may choose not to extend credit to a borrower if he cannot be certain about the borrower's quality. A natural question is: if a lender can easily obtain more information about a borrower, under what conditions will he choose to do so? Surprisingly, we know almost nothing empirically about the answer to this question. The reason for this gap in the literature is that we generally do not observe when lenders acquire information. In many modern settings, information acquisition is unobservable because lenders and investors do not pay for access to information.[1] In other cases, information producers are simply reluctant to provide researchers with proprietary data on how their business functions.

In this paper, I study the world's first credit reporting agency, The Mercantile Agency, which was founded in the United States in 1841. The records of the Agency allow me to investigate information acquisition empirically for the first time. Using a hand-collected dataset of credit report inquiries, I establish three facts about information acquisition in a credit market. First, subscribers to the Mercantile Agency accessed surprisingly few of the reports that the Agency produced, despite the low marginal cost of accessing an additional report. Second, subscribers were more likely to start accessing the reports for a borrower after they heard bad news, be it aggregate or borrower-specific. Finally, subscribers were more likely to acquire information about a borrower if one of the subscriber's other borrowers defaulted.

The Mercantile Agency, later known as R.G. Dun & Co., provided wholesale suppliers of goods with information about merchants around the country to whom the suppliers extended trade credit. I have compiled every credit report that the Agency produced about New Orleans mercantile establishments between 1850 and 1860, as well as the inquiries made by New York City subscribers

[1] For example, issuers, rather than investors, pay to have securities rated. Hence, there is no record of which rating an investor paid attention to or when.

concerning these reports. This dataset allows me to observe directly which reports each subscriber did (and did not) access, as well as approximately when the reports were viewed.

This paper examines when subscribers started accessing credit reports about a firm. I use survival analysis to estimate the relationship between adverse aggregate and firm-specific shocks and the time a subscriber waits to inquire about a firm. This empirical strategy identifies the conditions under which a subscriber was most likely to access reports. The main empirical challenge is that, due to the nature of the data, I am unable to observe the exact date of a subscriber inquiry. Instead, I only observe that an inquiry occurred between the dates of one report and the subsequent report. For example, the Mercantile Agency produced a report about the merchant P.A. Lanauze on July 20, 1857, and another on January 26, 1858. I know that three subscribers inquired after Lanauze between those two dates, but the data do not give an exact date. Hence, the true inquiry date is time-interval censored. This paper contributes to the econometric literature by extending the standard duration model to account for this interval censoring.

The data reveal that subscribers accessed little of the information that the Agency supplied. Although subscribers paid for a year-long subscription and had a low marginal cost of accessing each report, subscribers only accessed 35% of the total reports the Agency produced. This result is consistent with a rational inattention model in which a lender has limited cognitive processing capacity and, as a result, only pays attention to information likely to change his business decisions.

When did subscribers choose to pay attention to the credit reports that they did? My results show that subscribers were more likely to acquire information after they heard aggregate or borrower-specific bad news. A subscriber was 15% more likely to access a firm's credit report when there was an adverse shock to the New Orleans cotton market and 5% more likely to access a firm's credit report when there was an adverse shock to the New York City money market. I do not find evidence that lenders responded to good news about the economy. The existing literature suggests that lending generally increases during a boom period, yet these results suggest that subscribers

waited until the adverse shock before they acquired information. Hence, these results suggest that subscribers were not completely informed when they originated loans during a boom period. After the adverse shock, subscribers checked on the loans they originated during the boom and scrutinized new borrowers more closely.

Furthermore, I find that subscribers were 48% more likely to access a credit report about a firm after that firm defaulted on a loan. This result provides further evidence that subscribers often originated loans without consulting a credit report. Lenders may have had some information about borrowers went they first contracted but they did not use all information that was cheaply available. Furthermore, this result is consistent with a model of ex-post verification; lenders require information after a borrower defaults and the lender has to determine the nature of the default and the amount of value that he can recover.

Finally, I find that subscribers were 51% more likely to access a credit report about a firm if one of the subscriber's other borrowers defaulted particularly if the firm and the defaulting borrower were in the same industry or ethnic group. This result, consistent with a credit market exposed to a high degree of counter-party risk, suggests that lenders learned about broader market conditions and more specific shocks that might impact their borrowers from their own portfolios. Uncertain whether the default was caused by an aggregate or firm-specific shock, subscribers accessed credit reports about multiple firms to resolve this uncertainty.

If subscribers were more likely to acquire information about borrowers after an adverse shock to New Orleans, how did they react to a major financial disturbance in New York City? To address this question, I consider the financial panic that overtook the United States in 1857. On August 24, 1857, the Ohio Life and Trust Company, of Cincinnati, Ohio, failed. Seven weeks later, on October 13, New York City banks suspended operations and did not resume until December 11.[2] I find that subscribers were, if anything, less likely to obtain information about New Orleans firms during

[2] All of my regressions control for the financial panic to ensure that it does not drive my results.

1857. There are two possible explanations for this finding. First, fewer firms defaulted in the Southern United States than in Northern cities. During this period, lenders may have focused their information gathering on firms in cities that were relatively more affected by the panic. Second, interruptions in New York City bank operations may have mechanically reduced interest in credit reports. Subscribers often used credit reports as proof that a promissory note was sound when discounting the note at a bank. Credit report inquiries may have decreased simply because note discounting stopped when New York City banks suspended operations.

This research contributes to the fields of information economics and economic history by exploring how subscribers acquired information through the Mercantile Agency in the 19th Century. A long tradition in economics studies the structure of information (e.g., asymmetric or incomplete information). The theoretical literature on information acquisition discusses how that structure arises when agents can choose their information sets.[3] In order to generate testable predictions, most theory focuses on information acquisition in centralized market settings where information is partially revealed in prices. In a centralized market, investors take into account strategic motives when they acquire information. For example, an investor may acquire less private information if he expects prices to reveal all information. In this paper, I study a more decentralized market in which prices do not reveal information. In a decentralized setting, lenders and investors face a different decision problem when they acquire information because they cannot rely on prices for information and do not have to worry about their information being revealed in prices. We know relatively little about information acquisition in decentralized markets despite their prevalence, for example over the counter asset markets and home mortgage lending. Furthermore, the empirical literature relies on indirect measures, such as price co-movement or fund performance, to test the theoretical models.[4] For the first time, my paper measures information acquisition directly.

Recent studies in finance have shown that the design of markets and securities can affect how

[3] See, for example, Veldkamp (2011), Grossman and Stiglitz (1980), and Van Nieuwerburgh and Veldkamp (2010).
[4] See, for example, Klenow and Willis (2007) and Kacperczyk, et al. (2012).

much information investors acquire. For example, Dang, Gorton, and Holmstrom (2009) show that investors require less information to trade debt securities than they do for equity.[5] Studies have also shown that in environments where only limited information is acquired during normal times, a sudden shock can lead to more information production.[6] For example, Calomiris and Gorton (1990) argue that depositors run on banks to learn about the quality of the bank. The financial accelerator model presented by Bernanke, Gertler, and Gilchrist (1996) argues that investors flee to high quality investments when there are adverse shocks to financial markets. My work offers direct evidence consistent with these theories but in a credit market directly connected to trade.

Most of the literature on the history of the Mercantile Agency relies on contemporary reports to study the operations and broader importance of the Agency.[7] There have been few attempts to undertake the rigorous analysis of primary sources needed to determine the role of credit reporting in 19th century commerce.[8] My research contributes to our understanding of the Mercantile Agency and the role of credit reporting in the development of the US economy by studying how lenders actually used credit reports.

The rest of the paper proceeds as follows. In section 2, I provide background on the 19th-century American trade credit market and the origins of credit reporting. In section 3, I introduce a new dataset that I have compiled from the credit report records of the Mercantile Agency. In section 4, I discuss the conceptual framework that I use to analyze these data. In section 5, I describe the estimation strategy. I present results from the estimation in section 6. Section 7 concludes.

[5] See, also, Gorton and Pennachi (1990) and Townsend (1979).
[6] See Dang, et al. (2009), Farhi and Tirole (2012), and Gorton and Ordonez (2012).
[7] See Norris (1978), Foulke (1941), Olegario (2003, 2006), and Atherton (1946).
[8] Carruthers and Cohen (2010) and Flandreau and Mesevage (2014) are two notable exceptions.

2 Background

Throughout the nineteenth-century, retail and wholesale merchants from around the United States converged on New York City twice per year in order to find wholesale suppliers from whom they could buy goods.[9] The merchants would then sell these goods in their local markets. Before merchants could buy the goods though, they had to convince suppliers to trade with them and arrange for credit. If a merchant had cash, he could buy the goods outright. However, most buyers did not have enough cash or chose not to use it. Instead, they arranged a trade credit contract with the supplier: the supplier agreed to send goods to the buyer's local market and the buyer gave him a promissory note in exchange. The promissory note stated that the buyer would pay the supplier a fixed amount of money at a fixed time in the future. Promissory notes could be used in court as proof of a transaction and could be discounted at a bank to provide the supplier with liquidity. For most of the nineteenth-century, the majority of consumer goods in the U.S., e.g. boots and shoes, dry goods, produce, groceries, and furniture, were distributed from northeastern port cities, like New York City, on trade credit contracts such as those covered by a promissory note.[10] Through trade credit suppliers were lenders and buyers were borrowers.

The reliance of trade on credit exposed suppliers to the risk that the buyer would not repay the note on time or at all. Default occurred for many reasons. For example, the mercantile buyer and supplier implicitly agreed to a contract price for the goods and the local market price might have dropped by the time the merchant was able to sell. The merchant may or may not have been able cover the difference with his own assets. There was also always the chance that the merchant was a drunk or would sell the goods and run off to Mexico. Hence, suppliers faced a variety of risks, based on everything from market volatility to dishonest trading partners.

[9] Suppliers were usually wholesale merchants or jobbers. A jobber was a type of intermediate merchant that bought large quantities of goods from wholesale merchants and sold smaller packages of goods to merchants around the country. See Porter and Livesay (1989).

[10] Some suppliers also extended credit on open accounts, without an explicit promise to pay. For a more detailed description of trade see Porter and Livesay (1989). For more on promissory notes see Foulke (1941).

In the face of these risks, suppliers needed information about the expected payoff and extent of risk in order to decide whether to trade and whether to extend credit. There were several options available to a supplier. He could learn about aggregate market conditions from the commercial and financial press, as well as from his past experience and connections with other suppliers.[11] To learn about merchant-specific payoffs and risks the supplier could rely on any prior experience with the buyer, obtain a letter of recommendation from an attorney or established merchant in the buyer's local market, or inquire about a credit report at a mercantile credit reporting agency. The supplier could then evaluate all of this information and determine if the expected payoff from trade with a merchant was worth the potential risk of default.[12]

If the supplier relied on information from credit reports, he most likely subscribed to the Mercantile Agency, the leading reporting agency. Lewis Tappan founded the Agency in 1841 with the express purpose of providing suppliers with merchant-specific information about their trading partners. Later known as R.G. Dun & Co, the company remained a market leader throughout the nineteenth-century, along with its main competitor, J.M. Bradstreet & Co. In 1933, R.G. Dun and Bradstreet merged to form Dun & Bradstreet, which still provides business and credit information today.[13]

A New York City supplier could subscribe to the Mercantile Agency for an annual fee that was proportional to his sales.[14] Most firms paid around $100 per year for a subscription. But Claflin, Mellin & Co paid $1,000 for a year long subscription in 1858.[15] In 1864, H.B. Claflin & Co., the successor to Claflin, Mellin & Co., made $72 million in sales.[16] Prior to the American Civil

[11]For more on subsidized newspapers in the 19th century, see John (1995).

[12]The payoff included the profit of the trade if the merchant did not default as well as the potential benefit of establishing a new trading partner to work with in the future. There were also other ways to mitigate the risk of the trade. For example, most suppliers discounted promissory notes at banks. They were still liable in this case to repay the bank if the merchant defaulted on the promissory note but the bank shared some of the risk.

[13]For more on the histories of R.G. Dun and J.M. Bradstreet & Co. see Norris (1978), Foulke (1941), and Madison (1974).

[14]Subscribers were not only suppliers and the firms covered by reports were not only merchants. Existing scholarship agrees that these were the main parties and I will adopt this convention for this paper. In future work I will discuss the value that the credit reports may have had to other parties such as banks.

[15]Account Book, Dun & Bradstreet Collection.

[16]Chandler (1977) p. 218

War, a subscription permitted a supplier to go to the New York City headquarters and inquire after any firm contained in the credit reports, as many times as he wanted.[17] The clerk at the Agency retrieved a large ledger for the city or county where the merchant was located and found the page that contained his entry. The establishment that the merchant represented usually had several reports in the entry for his firm, about two per year since the Agency began reporting on it. The clerk read the most recent report out loud to the subscriber and may have given a summary of the previous reports. Afterwards, the clerk wrote down the subscriber's identification number at the end of the report, indicating that the subscriber had been there and heard the report.[18] Subsequent reports that the Agency received about the firm were written down after this number (and other subscriber numbers), filling up the space in the ledger allocated to the merchant.[19] Figure 1 shows an example of subscriber inquiry numbers in the credit report ledger for Savannah, Georgia.[20]

3 Data

For this paper, I have constructed a dataset of all credit reports written about New Orleans mercantile firms between January 1850 and December 1860 from the R.G. Dun Credit Report Records, Louisiana Volumes 9 through 11. I focus on New Orleans in the 1850s for several reasons. New

[17] After the War, the Agency changed their subscription terms. For example, subscribers paid for access to a fixed number of reports and could pay an additional fee for more reports.

[18] We know that the numbers after reports are subscriber ID numbers from extensive evidence contained within the reports themselves. In addition, a subscriber book from circa 1900 (Volumes 34 and 35 in the Dun & Bradstreet Records) gives ID numbers and names of subscribers that I have used to verify that the numbers occur after reports for firms in the same lines of business as subscribers.

[19] This was how a New York City subscriber inquired after credit reports. The system worked slightly different for subscribers located near one of the Agency's many branches. Branches managed the local correspondents who wrote reports and accepted inquiries from local subscribers. However, branches only kept copies of local reports, not reports for other parts of the country. Hence, if a subscriber outside of New York needed information about a concern outside of their region, his local branch had to send a request to the main office. The clerk at the main office recorded the branch ID number after the report and sent a copy of the report to local branch, where the subscriber could then access it.

[20] In general, researchers are not allowed to photograph the R.G. Dun & Co. Credit Report Volumes. I use Savannah as an example instead of New Orleans because Savannah is the sample document that the archive provides to researchers for the purpose of presentations.

Orleans was the 5th largest city in the U.S. at the time and the largest American city over 500 miles away from New York City, which makes it ideal for studying long distance information acquisition. Further, the cotton market provides clearly defined and measurable aggregate fluctuations in New Orleans during a period in time when there were limited aggregate statistics. Finally, I limit the period of study to the 1850s because subscribers to the Mercantile Agency paid a flat yearly fee to access unlimited credit reports during this period.

The dataset consists of 37,435 reports written about 4,584 firms. It contains several firm-level variables: firm name; line of business; address (if available); changes in the firm (i.e. dissolutions, additions of partners, etc.); ethnicity of partners; the dates of the first and last reports; total number of reports in records.[21] For each credit report in the time period of interest, the dataset contains the following variables: date of report; information about content (i.e. change in firm structure, death of partner, default event, etc.); and the identification numbers of subscribers or branches who inquired after the report. See table 1 for the summary statistics for the New Orleans 1850-1860 sample.

The structure of the data is best described using an example. For this purpose I will discuss the credit report history of the merchant P. Adolphe Lanauze. Lanauze was a retail hardware merchant in New Orleans who went out of business in 1870. On April 25, 1851, the correspondent "PM" wrote Lanauze's first credit report for the Mercantile Agency. It read: "Been in business sometime, has 2 stores joining. Worth about $30 thousand. Good and safe. There is no [co-partner]. Creole Frenchman." This was a standard credit report during the 1850s. During the early years of the Agency, the credit reports were mostly written by local attorneys and businessmen.[22]

[21]For 92% of firms with a report in the 1850s, I have collected the full set of reports. The firms for which I do not have full reports have subsequent reports in much later volumes that can be collected in the future. In my data, ethnicity is defined as what the Agency reported for at least one of the partners. Ethnic group sometimes means place of birth, such as Ireland or Germany, but can also mean Creole or Free Person of Color. See the online appendix for relative frequencies of different ethnicities in the credit reports. In future work, I will verify the accuracy of these Agency defined ethnicities.

[22]For example, Abraham Lincoln was a correspondent, according to the Illinois Attorney Ledger. I have only

The correspondent usually noted the firm's net worth (often in the form of real estate or slaves), the composition of the firm (in this case no co-partner), the ethnicities of the partners, and a character assessment of the partners.[23]

Agency correspondents wrote a total of 18 reports about Lanauze between 1851 and 1860 and an additional 6 reports between 1861 and 1870.[24] Most of the subsequent reports simply reiterated the details from the first report. All of the reports on New Orleans merchants followed this general format: detailed first report, repetition of original information in most subsequent reports, and detailed updates when a major event occurred. Major events included default-type events (i.e. having a note protested), legal trouble, or the death of a partner. Lanauze did not experience any legal problems and seems to have always paid his notes on time. The only event that revealed any potential trouble was in July 1857, when he lent his brother money after a business failure. The text of all of Lanauze's reports can be found in the online appendix.[25]

When Lanauze's first credit report arrived in NYC, a clerk recorded his name, line of business, and his first report in the first ledger of reports for Orleans Parish, Louisiana. The clerk then left room for subsequent reports about Lanauze before recording the name of the next merchant. In the credit report ledger, the number 695 is written after the text of Lanauze's first report. This number indicates that the subscriber with identification number 695 heard the report. In order to access the credit reports, subscribers visited on the main office and asked to hear the reports of firms. After a clerk read the report aloud to the subscriber, he recorded the subscriber's unique ID number after the text of the report. When the next report arrived from New Orleans in March 1852, the clerk simply entered the information after the numbers and the previous report, filling up the

identified two of the correspondents in New Orleans: Edward E. Dunbar, who was a partner at the Agency for a few years, and B.W. Cohen, the compiler of the early New Orleans City Directories. See LA Volume 10 page 396 for B.W. Cohen's entry.

[23]Most firms in the New Orleans 1850-1860 sample were unlimited liability partnerships. There were only a few cases of corporations.

[24]Most reporting stopped 1861 for the duration of the American Civil War and resumed in 1866. However, a few merchants did receive reports during the war.

[25]For more about the language used in the credit reports, see Olegario (2006).

space allocated in the ledger for Lanauze. The location of the number in the reports indicates the approximate timing of the inquiry. While we do not know the exact date on which subscriber 695 inquired after Lanauze, we know that he inquired sometime between April 1851 (the date of the report) and May 1852 (the date of the next report).

Figure 2 plots the months on which Lanauze's reports were written with a vertical line at the month of the report. The timing of reports for Lanauze reflects the pattern for most firms. Firms generally received about two reports per year with an occasional extra report. However, reports were not updated on a strict schedule at fixed months. Hence, there were not always exactly six months between reports.[26]

The subscriber ID numbers of the 15 NYC subscribers who inquired after Lanauze between 1850 and 1860 are listed on the y-axis of figure 2. The month of the first report that each subscriber inquired after is marked with a circle. The month of any subsequent reports that each subscriber inquired after is marked with a triangle and connected to the first inquiry with a dotted line. Lanauze received a total of 21 inquiries, 6 of which were by a subscriber inquiring for a second or third time. Despite the many inquiries he received, no one ever heard 9 out of his 18 reports, as indicated with an open circle on those report months.[27] As we will see, it was not uncommon for the Agency to produce reports that no subscriber ever heard.

Within my data, I have identified 2,128 unique NYC subscribers who inquired after at least one report in New Orleans, and a total of 21,830 inquiries by those subscribers. Ten Agency branches in other cities across the US accounted for another 6,525 inquiries.[28] Panels A and B in table 2

[26] I measure reports at a month level because, while all report dates give a month and year, not all give a day.

[27] The 50% of reports for Lanauze that did not receive NYC inquiries did not have inquiries from other branches. The report written on January 1858 also received an inquiry from a subscriber in Boston but this report was also heard by three NYC subscribers.

[28] I can identify unique New York City subscribers by their ID number and I know the name of the subscriber for a small subset. However, based on the unique ID, I can measure repeat inquiries of particular firms and total inquiries by an individual subscriber. Inquiries by branch subscribers were indicated by the identification number of the branch. Hence, I know if at least one subscriber at a particular branch inquired after a firm.

present statistics on firms based on whether or not a NYC subscriber ever inquired after the firm. Overall, firms had an average of about 4 years of reports between 1850 and 1860, 8.1 years of reports between 1845 and 1894, the time over which the Agency reported on New Orleans. On average, each firm had 1.8 reports per year. As mentioned earlier, firms were not reported on at fixed intervals. Further, the report dates across firms do not coincide. See table 3 for statistics on the amount of time between each report. On average, the Agency produced reports on firms on an approximately semi-annual basis. However, the time between one report and the next ranged from 1 month to 8 years.[29]

Due to the uniqueness of the NYC subscriber ID numbers, I can track subscriber inquiries within and across firms. Panel C in table 2 gives statistics for inquiries by subscribers. On average, subscribers inquired 10 times and inquired after 6.9 different firms. Further, subscribers were quite widely distributed across how many inquiries they made. One subscriber (#7) alone heard a total of 440 reports about 157 firms. Conditional on having at least one inquiry, firms had an average of 10.6 inquiries from 7.7 subscribers. As with subscribers, there was a large amount of variation over how many inquiries firms received. On the extreme end, 175 different NYC subscribers inquired after the dry goods merchant, Charles M. Simpson, a total of 314 times between 1850 and 1860. We do not know much about how the firms interacted with each other in New Orleans. But we can say something about how two firms were related based on which subscribers heard their reports. If we say that two firms are connected by having at least one common inquiring subscriber, then firms are connected to 113 other firms, on average, and as many as 747 other firms. In future work, I will further investigate the network structure of these data.

Firms often engaged in multiple lines of business or switched lines part way through the time period of interest. Furthermore, lines of business were often described in very general terms, e.g.

[29]The number of months between reports was determined by the Agency's supply of reports. In another paper, I investigate the timing of the supply of reports to determine how inquiries and particular events changed the amount of time until the next report.

"Dealer," or very narrow terms, e.g. "Adjuster of Average." This makes it difficult to assign firms to industries. For the purpose of this paper, I have defined several large categories of industries and assigned a firm to an industry if it was ever listed as engaged in that line. As a result, a firm can be assigned to multiple industries. For example, a firm can be categorized as a commission merchant and engaged in the cotton trade. Table 4 presents statistics on several of the largest industries to give a sense of the lines of goods covered in the reports.

Default events were not overly common within the reports: only about 3% of reports mention a default event, where default events include protest, sued, failed, etc.[30] However, 16.7% of the firms experienced at least one default event. Hence, many firms were impacted by default.

Over 2,000 suppliers in New York City paid for access to the credit reports produced by the Mercantile Agency and accessed at least one report about New Orleans. Those subscribers, however, never asked about 2,524 of the New Orleans mercantile establishments that the Agency reported on, who represent 55% of the total number of firms in New Orleans. Including inquiries from branches outside of New York City, the total number of firms which no subscriber ever asked about only drops to 2,178.[31] Even for firms that subscribers inquired after, the Mercantile Agency provided more information than subscribers heard. The Agency supplied 25,520 reports on the 45% of firms after which NYC subscribers inquired. However, subscribers never heard 16,250 of these reports, 64% of inquired firm reports. Including the reports for firms that never had inquiries, the Agency supplied 27,965 reports that no NYC subscriber ever heard.[32] These numbers are also presented in table 5.

Furthermore, there was usually a substantial lag between when the Agency started reporting on

[30] See the online appendix for a breakdown

[31] The lack of inquiries for firms can't be explained by a lack of reports for firms without inquiries. Firms without inquiries had fewer reports on average than firms with inquiries but still enough reports for a subscriber to have inquired. See table 2.

[32] The rest of the reports were not necessarily inquired after by other branches. If we add in inquiries from branches, there were still 24,337 reports that no subscriber ever heard.

a firm and when a subscriber first accessed a report for the firm. Conditional on the subscriber eventually inquiring after a firm, there were at least 3.7 years, on average, between when the Agency first reported on the firm and when the subscriber first asked about the firm. Most of the time that a subscriber inquired about a firm, he never heard another report for the same firm. Of the 15,029 times that a subscriber asked about a firm for the first time, only 4,256 inquiries were followed by at least one more inquiry.[33] Conditional on a subscriber having heard multiple reports about one firm, he waited at least 15 months, on average, between each inquiry.

4 Conceptual Framework

Why would suppliers have paid for access to the Mercantile Agency credit reports but then used the service so little? After a subscriber paid his year long subscription fee, his marginal cost of hearing another report was merely the cost of visiting the Agency's office, yet he only ever accessed a few reports and often did not bother to hear other reports while he was already at the office.[34] How can we understand this? Economic theory suggests a model of rational inattention in which, for example, lenders have a finite capacity for processing information and choose to allocate their attention towards information that they expect to affect their decisions.[35] The lender only needs to hear a credit report if he expects to make a different decision when he has the additional information from the decision he would make without it.

A lender uses information to decide what actions to take. There are a few times over the life of a loan when a lender might need to take an action. First, the lender needs to decide whether or not

[33] This is an underestimate because many firms continue beyond 1860 and I do not count subsequent inquiries beyond 1860.

[34] Furthermore, conditional on visiting the office, the marginal cost of hearing an additional report was approximately zero.
The Mercantile Agency's main office in New York City was located at 314 Broadway and a sub-office at 111 Broadway.

[35] See Sims (2003). Where does the information capacity come from? Possibly in the form of hiring clerks to go to the office or from the trade off between learning more about your trading partners and finding new trading partners.

to lend in the first place.[36] Second, after the loan origination, the lender can decide to discount the promissory note at a bank. Finally, if the borrower defaults or if the lender expects a borrower to default, the lender can take different actions to resolve the loan. For example, the lender could sue the borrower or offer an extension on the loan.

For each of these lending decisions, a lender has existing information obtained passively through interactions with their borrowers or by observing the market. He can choose to acquire additional information to help decide his best course of action. If a lender acquires information prior to extending a loan, we say that a lender is screening his borrower. A lender is monitoring the loan if he acquires information about the loan or the borrower prior to the maturity date of the loan. A lender acquires information after the borrower defaults in order to verify the default ex-post.[37]

The lender only acquires additional information to make lending decisions if he expects the additional information to change his decision. The lender can chose an action based on his initial information. Prior to actually accessing a credit report, a subscriber had an expectation about what a report might tell him and how it might impact his business decisions. If the subscriber had limited processing capacity, then he would only choose to access a credit report if he expected the information that he received from the report to alter his initial decision. In this framework, when would subscribers choose to allocate attention towards credit reports?

I first ask whether the value of a credit report varied with the aggregate state of the economy. Did lenders expect the information from credit reports to influence their lending decisions in some aggregate states of the world but not in others? For example, if the economy was doing well, lenders were willing to lend to more borrowers. Historical accounts reveal that, during boom periods, wholesale suppliers aggressively sought out new customers to take advantage of the boom. Even though suppliers knew that many mercantile borrowers eventually failed, they did not consider the

[36] When do lending opportunities arise? The best we can tell, borrowers generally sought out lenders. However, there is some evidence that lenders searched for borrowers during boom periods.

[37] This situation is also called costly state verification.

risk of not getting paid worth the risk of losing a new customer.[38] In this case, a credit report was less likely to indicate to a subscriber that he should not lend to any particular firm because he wanted to lend to most firms. However, if there was an adverse aggregate shock, a subscriber might have started paying attention to credit reports in order to screen borrowers. Furthermore, lenders did not need to verify defaults when the market was doing well because fewer borrowers defaulted. I consider how two types of aggregate shocks changed the value of a credit report: shocks to the subscriber's market (NYC) and shocks to the borrower's market (New Orleans). Subscribers were borrowers as well as lenders in this setting: jobbers purchased goods on credit from other wholesalers in New York City; wholesalers and jobbers often discounted promissory notes at NYC banks in exchange for cash. A subscriber may have needed more information about the risk profile of his portfolio if he became more financially constrained.

Subscribers also knew about aggregate market conditions in New Orleans from his business contacts and the financial press. Did subscribers respond to news about the New Orleans aggregate market? I look at the price of cotton in New Orleans. Cotton was the primary staple crop of the US in the 1850s and New Orleans was the main port through which planters exported their cotton to textile manufacturers in the American Northeast and England. Cotton factors in New Orleans marketed the crop of planters around the American South and obtained the supplies for the planter that were necessary for maintaining a plantation. Hence, much of the commerce in New Orleans depended either directly or indirectly on the cotton market.[39] Subscribers may not have paid attention to credit reports when the cotton price was high but then decided to be more cautious when the price suddenly dropped.

Next, I investigate how the value of a credit report changed when the subscriber received merchant-specific news. In particular, I ask whether subscribers started accessing a firm's credit reports as a form of ex-post verification after that firm defaulted. A subscriber could learn about a firm default

[38] See Olegario (2003) p. 5

[39] For more on the New Orleans cotton market and the role of cotton factors, see Woodman (1968)

in multiple ways. First, the subscriber knew if the firm defaulted on one of the subscriber's contracts. The subscriber also might learn about a borrower default through rumors in the mercantile community. I also ask whether a subscriber heard credit reports for other firms when he learned that one of his borrowers defaulted.

Credit reports were potentially very useful for monitoring for potential default and post-default verification because of the legal framework of insolvency in the United States in the 1850s. The sooner that creditors could learn about a default, or potential default, the better off they would be. If a creditor anticipated that a debtor would default he could move quickly to put a lien on a piece of property and position himself higher in the hierarchy of creditors to ensure that he recovered some value.[40] If a creditor moved too slowly, other creditors could claim all available assets. Lenders also needed to know when one of their borrowers defaulted on a different loan. If a merchant borrowed on a promissory note and eventually defaulted, the creditor could not sue until after the maturity date of the note.[41] In the meantime, the merchant arranged a settlement with his other creditors, leaving nothing for the holder of the promissory note. In this case, the only remaining option for the holder of the promissory note was to offer an extension on the note.

After a debtor defaulted on a loan, a creditor could either liquidate or renegotiate the loan. If the lender decided to liquidate, he did so either through the court or through an agreement with the debtor and, potentially, other creditors. When he chose to go to court, the creditor had to pay high legal fees, such as court costs or lawyer costs, and often had to wait for an extended period before he recovered any value. Further, he could not be certain about how much he could recover through the court, even if he knew the borrower had seizable assets. Antebellum debtors often sold assets to their preferred creditors prior to officially defaulting and left other creditors with nothing. In Louisiana, the civil code specified privileged creditors that were automatically repaid first in the

[40] See "Law of Debtor and Creditor in Louisiana" Hunt's Merchants' Magazine (XV, pps. 70-75, 471-475), (XVI, pps. 53-57, 165-71, 281-285). Also Balleisen (2001).

[41] Also for other types of debt instruments. See Balleisen (2001) p 87

case of debtor insolvency.[42]

If a borrower defaulted, the lender had to decide whether or not to bring the borrower to court. Debtors and creditors often opted for legal assignment instead of resolving failure through courts. Under legal assignment, debtors transferred their assets to a third party who distributed the proceeds of the sale of assets to the creditors as per an agreement between the debtor and creditors.[43] Legal assignment allowed parties to credibly commit to resolve failures quickly.

Creditors also frequently chose to renegotiate the terms of a loan rather than liquidate the debt entirely. For example, lenders allowed borrowers to extend the length of the loan if they thought there was a chance the borrower might be able to pay in full in the future. A creditor's best course of action after default depended on the nature of the default and the current status of the borrower. For example, if the borrower had low or negative net worth, the lender would be better off renegotiating the terms of the original loan than bringing the case to court.

Credit reports frequently provided information about whether a default occurred, why the default occurred, and the financial position of the merchant. Hence, subscribers likely used credit reports to determine the best course of action after a borrower defaulted on a loan. If the subscriber was uncertain about whether a default had occured or might occur, he could hear a credit report to learn the status of the borrower. If a borrower failed to repay a loan on time, the subscriber could hear a report to determine whether he should (a) sue the borrower in court; (b) settle the default out of court in an agreement with the debtor and other creditors; or (c) provide relief on the debt by offering an extension.

[42]Privileged creditors included wives, lessors, and commission merchants or factors. The latter class was particularly important in Antebellum Louisiana. Factors had privilege upon "the property of the principal in their hands, for the payment of their expenses, commissions, and advances, and for the general balance due them." See page 56 of Hunt's Merchant Magazine Volume XVI.

[43]Ibid.

5 Empirical Strategy

To answer the questions laid out in the previous section, I investigate when subscribers first decided to access a credit report for a firm and how that timing depended on aggregate and firm specific shocks. To do this, I use survival analysis to estimate the number of months between when the Agency started reporting on a firm and the month that a subscriber first heard a credit report. My empirical strategy allows me to exploit the fact that I observe when subscribers did and did not acquire information, an empirical setting that is unavailable during modern times. To do this I use maximum likelihood estimation (MLE) to test a duration model with time varying covariates.The exact dates of a subscriber inquiries are time-interval censored, which poses a challenge for my estimation strategy. I adapt the standard duration model to correct for interval censoring of the inquiry date.

We know that an inquiry of a particular report occurred between the date that a report was written and the date that the next report was written, not the exact date of the inquiry. For an example, see figure 3. Suppose that the Mercantile Agency supplied reports on a firm in months x, y, and z. Next, suppose that a subscriber inquired after the firm at date t^* and heard the report written on date y. In the data, we observe that the report written on date y had an inquiry. From the point of view of the econometrician, we only know that the true inquiry occurred at some point between y and z.

Interval censoring causes a problem because standard statistical techniques for understanding how variables affect the timing of events require knowledge of the exact dates of the events. Further, the high degree of variation in interval lengths prevents me from standardizing observations by measuring inquiries at a lower frequency (for example, bucketing inquiries into 6 month intervals instead of month intervals).

In the standard formulation of a duration model, we can write the likelihood of the data in terms

of the hazard function. Let p index the subscriber-firm pair ij. Let t index the duration time in months since the Agency started producing reports about firm $i(p)$ of pair p. Let $\theta(t;X)$ be the hazard function, the probability that a subscriber $j(p)$ of pair p inquired after the firm $i(p)$ at time t conditional on not having inquired yet and time-invariant covariates X. If we observed exact inquiry dates $\{t_p\}$, then the likelihood function for a discrete time duration model would be:

$$\mathscr{L} = \prod_{p=1}^{P} \left[\theta(t_p;X) \prod_{s=0}^{t_p-1} [1-\theta(s;X)] \right]$$

If we include time-varying covariates (TVC), we can adjust the likelihood function accordingly: [44]

$$\mathscr{L} = \prod_{p=1}^{P} \left[\theta(t_p;X(t_p)) \prod_{s=0}^{t_p-1} [1-\theta(s;X(s))] \right]$$

However, since we do not know the exact date of the inquiry we cannot estimate the basic hazard model with TVC. To solve this problem, I assume that the inquiry was equally likely to have occurred at any point in the interval.[45] Let $\tau_p = [\tau_p^1, \tau_p^{K_p}]$ be the report interval for the first inquiry for pair p, where the inquiry could have occurred on any date in the interval. Assume that there was an equal probability, $\frac{1}{K_p}$, that the inquiry occurred at any month τ_p^k in the inquiry interval. Then we can write the likelihood function:

$$\mathscr{L} = \prod_{p=1}^{P} \frac{1}{K_p} \left[\prod_{k=1}^{K_p} \theta(\tau_p^k;X(\tau_p^k)) \prod_{s=0}^{\tau_p^k-1} [1-\theta(s;X(s))] \right]$$

The key to correcting for interval censoring in a duration model with TVC is that if there is positive probability that the inquiry occurred on the second month in the report window then the likelihood

[44] See Lancaster (1990) for assumptions on time-varying covariates.

[45] To use this method you have to assume some probability distribution over the interval. The uniform assumption is rather ad hoc. However, there is no particular reason to believe that an inquiry was more likely to occur at towards the beginning or the end of the report interval. In the online appendix I show parameter estimates under various other distributional assumptions.

also must put positive probability that the inquiry did not occur on the first month. This complication is only a problem if there are time varying covariates.

There are many potential specifications for the underlying hazard function, $\theta(t;X(t))$. In this paper I adopt a parametric approach and assume that the baseline hazard follows a Weibull distribution. Under the Weibull assumption, the hazard function takes the form

$$\begin{aligned}\theta(t;X) &= \frac{1}{\sigma}\lambda(X)\left[t\lambda(X)\right]^{\frac{1}{\sigma}-1} \\ \lambda(X) &= \exp\{X\beta\}\end{aligned}$$

The parameter σ is called the scale parameter of the hazard function. The scale of the baseline hazard function tells us the average behavior for when subscribers typically obtain information about firms for the first time. When σ is greater than one, then the hazard function decreases with time. If the scale parameter is between 0.5 and 1 then the hazard function increases with time at a decreasing rate. If the scale parameter is between 0 and 1 then the hazard function increases at an increasing rate. Finally, when $\sigma = 1$ the baseline hazard is constant and the inquiry time follows an exponential distribution.

In my main specification I estimate σ and $\{\beta_n\}$ using maximum likelihood estimation, under the following parameterization:

$$\begin{aligned}\ln(\lambda) &= \alpha + \beta_1^* FirmDefault_{i(p)t} + \beta_2^* PortfolioDefault_{pt} + \\ &\quad \beta_3^* Pos\Delta IR_t + \beta_4^* |Neg\Delta IR|_t + \beta_5^* Pos\Delta CotPrice_t + \\ &\quad \beta_6^* |Neg\Delta CotPrice|_t + Z_t'\delta + C_{i(p)}'\gamma \qquad (1)\end{aligned}$$

Where Z_t is a matrix of time varying controls. I include seasonal fixed effects (quarter dummy variables) and annual US cotton production to control for the short and long run cyclicality of

demand for trade credit. I include dummy variables for months in 1857 to ensure that my main results are not driven by the financial panic in 1857. I report the coefficients on these panic dummy variables in there results section. $C_{i(p)}$ is a matrix of firm specific controls including ethnicity fixed effects and industry fixed effects.[46]

I use a report of a default as a proxy for news of a potential default. $FirmDefault_{i(p)t}$ is equal to one between the dates $t^1_{i(p)}$ to $t^k_{i(p)}$ when a firm $i(p)$'s report at date $t^1_{i(p)}$ mentioned default. If the default was reported at date t^1_i then the default must have occurred before that date. Default in the credit reports means a default type event and includes such events as having a note protested, being sued, being "embarrassed", and being sold out by the sheriff.[47]

$PortfolioDefault_{pt}$ is a proxy for a the subscriber $j(p)$ receiving news of a default for some borrower, not $i(p)$, in his portfolio. I use prior inquiries of a subscriber to proxy for lending because I do not observe the subscriber's actual portfolio. If subscriber $j(p)$ inquired after some firms $\{d\}$ prior to date t and the report for for at least one firm, d_k, mentions default at date t then $PortfolioDefault_{pt} = 1$, otherwise it is equal to 0.[48]

I use the change in the price of cotton in New Orleans from the last month as a proxy for an aggregate shock to the New Orleans market. I separate the change in price into the increase in price over the last month, $Pos\Delta CotPrice$ and the absolute value of the decrease in price over the last month, $|Neg\Delta CotPrice|$ to distinguish between the effects of "good" and "bad" news about the cotton market on the probability of a subscriber inquiry. The New Orleans cotton price series is from the New Orleans newspaper *Commercial Bulletin, Price Current and Shipping List.* I use the change in the monthly average interest rate in New York City on prime commercial notes with

[46]Firm ethnicity is defined as the ethnicity of the firm's partners that the Mercantile Agency mentions in the credit reports. See the online appendix for summary statistics on firm ethnicity.
The annual US cotton production series is from the NBER's Macroeconomic Time Series ICPSR 7644. All other control variables come from the Credit Report data.

[47]See the online appendix for a detailed breakdown of the default variable and summary statistics.

[48]For a firm to be included in the set $\{d\}$ at time t, the subscriber had to have inquired prior to date t with probability one. Hence, firms are not included in the set until after the end of the the first inquiry interval.

a 4 to 6 month maturity as a proxy for an aggregate shock to the NYC money market. As with the cotton price variables, I separate changes in the interest rate into an increase, $Pos\Delta IR$, and the absolute value of the decrease, $|Neg\Delta IR|$. The New York City interest rate series is collected from the NYC publications the *Journal of Commerce* and *Shipping & Commercial List, and New-York Price Current.* See table 6 for summary statistics for the price of cotton and the interest rate between 1850 and 1860.

6 Results

6.1 First Inquiries 1850-1860

Table 7 presents the exponentiated estimated coefficients, or hazard ratios, from equation (1), where $HR = exp(\beta/\sigma)$. All specifications include dummy variables for quarter, dummy variables for months in 1857, and annual cotton production. The first column includes only changes in the price of cotton in New Orleans over the previous month. Column 2 contains only changes in interest rate on commercial bills over the past month. The third column includes only variables relating to the default of the firm $i(p)$. Column 4 contains only a dummy variable for a portfolio default by some firm $-i(p)$ that subscriber $j(p)$ had inquired after in the past. The final column of the table presents the fully specified model.

For a hazard model with time varying covariates, the key to interpreting hazard ratios is to consider two subscriber-firm pairs, p_1 and p_2, with identical histories up to some date t. If, all else equal, pair p_1 experienced the value X^1_{tk} for covariate k and pair p_2 experienced the value X^2_{tk} then, at date t, the subscriber in pair p_1 is $\exp\{\frac{\beta_k}{\sigma}(X^1_{tk} - X^2_{tk})\}$ times more likely to inquire after his firm than the subscriber in pair p_2 is to inquire after his firm. For example, suppose that at time t a subscriber was considering whether to inquire after two different firms that had the exact same histories up

to time t and that the subscriber had not inquired yet. If one of the firms had recently defaulted at t while the other had not, then, according to the estimated coefficient, we would expect that the subscriber was about 48% more likely to inquire after the firm that defaulted than the firm that did not. I plot the estimated baseline survival function and the estimated survival function after a firm default in figure 4.

Columns (1) and (5) show that when a subscriber heard about a sudden drop price of cotton in New Orleans, he was about 15% more likely to access a credit report about a New Orleans firm. However, he was slightly less likely to access a report after a positive shock to the cotton market. Controlling for defaults and the interest rate in New York, the effect of a positive shock is statistically insignificant. These results suggest that the lender's valuation of a credit report increased when there was an adverse aggregate shock to the borrower's market. Even though the subscriber could have accessed a report earlier, he primarily needed information from the report when he heard bad news about New Orleans. However, it is unclear whether subscribers acquired more information for the purpose of checking on existing borrowers or to screen potential borrowers prior to lending. We only know that the subscriber was more likely to access a report for the first time after a bad shock. A cotton shock probably increased the value of a credit report for both screening and monitoring purposes. During a boom, the subscriber wanted to lend to everyone because he expected that even low quality merchants would repay during a boom. At the sign of a downturn, however, he could no longer rely on the boom to make everyone profitable. Hence, after a drop in the price of cotton the subscriber paid attention to credit reports when he encountered new potential borrowers because there were more "bad" borrowers that he wanted to avoid. During a boom, fewer borrowers defaulted and lenders did not expect many borrowers to default. As a result, subscribers acquired less information about borrowers for the purpose of monitoring or ex-post verification.

I find that subscribers were 5.7% more likely to inquire after a firm after a one percentage point

increase in the interest rate on commercial paper from the previous month. This is consistent with a financial accelerator style model in which lenders seek higher quality lenders when they experience a liquidity shock.[49] If the interest rate on commercial notes increased, subscribers had to pay more to obtain liquidity in the form of discounting their commercial bills at the bank. As a result, they scrutinized their existing and potential borrowers more closely. I also find that a decrease in the interest rate increased the probability of an inquiry, although the effect is statistically insignificant when controlling for default and cotton price fluctuations. This could imply that subscribers obtained more information about their borrowers in response to volatility in the interest rate. However, it is likely that the results related to NYC interest rates are confounded by the role of banks in discounting bills and the banks' preferences for credit report inquiries. The interest rate on commercial bills was determined by the demand for liquidity from wholesalers in NYC and the supply from banks willing to discount notes. A decrease in the interest rate implied that subscribers were able to discount their bills at the bank at a lower rate. However, we have evidence that banks often required proof that the notes under discount were of high quality and discounters used credit reports as evidence.[50] If a lower rate meant that subscribers discounted more notes at the bank and the bank had a higher demand for evidence in the form of credit reports then we might expect that a decrease in the interest rate might also increase the probability of a subscriber inquiring after a report.[51]

Subscribers were 48% more likely to first hear a credit report for firm $i(p)$ if the firm recently defaulted. This result has several implications. First, if we assume that a subscriber would not have been interested in a defaulting firm unless he was already contracting with that firm, then this result implies that some subscribers contracted with firms without hearing a credit report first. Second, subscribers had other sources of information for firm-specific shocks that compelled them to

[49] See Bernanke, Gertler, and Gilchrist (1996).

[50] See Gibbons (1859).

[51] Banks also subscribed to the Mercantile Agency and could have been directly inquiring after borrowers when suppliers discounted notes. I cannot identify enough individual banks in the subscriber list to test this hypothesis.

hear a report. For example, subscribers probably acquired information from rumors in New York, newspapers, as well as contacts in New Orleans. The default mentioned in the credit reports may even have been a default against the subscriber himself. Whatever the source of the information, a subscriber was more likely to start accessing credit reports for a firm after he had heard news that the firm had defaulted.

Subscribers were 51% more likely to hear the credit report for a firm if one of the subscriber's other borrowers defaulted. This result could have two possible explanations, both related to the nature of an aggregate shock in this setting. An aggregate shock could take two forms: (1) a shock hit multiple firms simultaneously and affected all firms' ability to repay; or (2) one firm defaulted for a (possibly) idiosyncratic reason and, as a result, the firm's counter-parties in New Orleans were more likely to default.[52] From the perspective of the lender, these types of aggregate shocks may have been indistinguishable. One explanation for positive effect of a portfolio default is that subscribers were reacting to some aggregate shock to New Orleans of the first type that I have not controlled for. Alternatively, the subscriber could have actively learned about the New Orleans market when he observed that one of his borrowers defaulted. The subscriber may have checked on other firms to determine if the default was an aggregate event or an isolated incident. The subscriber may have also inquired after other firms that he knew (or expected) were counter-parties of the firm that defaulted. In section 6.3, I further investigate what subscribers may have learned from a portfolio default.

6.2 First vs. Subsequent Inquiries

As mentioned earlier, it is unclear if a firm was already a debtor when a subscriber first accessed a credit report. It could have been that the subscriber contracted with the firm without hearing a

[52] We know from the text of the credit reports that firms were often "implicated" the failures of other New Orleans firms.

credit report first or they contracted prior to the Agency writing reports about the firm. We can be fairly confident, however, that the subscriber and firm had an existing relationship if the subscriber heard a subsequent report about the firm.

In table 8, I compare the estimates for the time to first inquiry hazard model to estimates for a time to subsequent inquiry hazard model. For the subsequent inquiry model, the analysis time is measured as the number of months from the first report date after the last inquiry to the month of the subsequent inquiry. I include all subscriber-firm pairs in the analysis, even those for which the subscriber never inquired a second time. Hence, unlike the first inquiry model, pairs can be censored if the subscriber did not inquire for a subsequent time by the end of 1860.

Results are similar for both models except that bad news seems to have had a slightly larger effect on the probability of a subsequent inquiry. Also, the interest rate on commercial notes seem to have little effect on the probability of a subsequent inquiry. While first inquiries might have been a subscriber inquiring after a potential or an existing borrower, subsequent inquires were more likely a subscriber inquiring after an existing borrower. Hence, the subsequent inquiry model estimates imply that subscribers monitored their borrowers when they received bad news. The similarity between these two models supports the notion that some of the first inquiries were actually subscribers hearing credit reports for existing borrowers.

6.3 Portfolio Defaults

Why did subscribers access credit reports for different firms when one of their borrowers defaulted? Did they learn about industry specific shocks? Did they learn about trouble in a particular social network? Were they more cautious about their portfolios after the first time one of their borrowers defaulted? In table 10, I further investigate the impact of a portfolio default on the probability that a subscriber inquired after a credit report. I estimate the Weibull hazard of first inquiry model

under the following parameterization

$$\begin{aligned}\ln(\lambda) &= \alpha + \beta_1^* FirmDefault_{i(p)t} + \beta_2^* PortfolioDefault_{pt} + \beta_3^* Exposed_{pt} + \\ &\quad \beta_4^* PortfolioDefault_{pt} \times SameIndustry_{pt} + \beta_5^* PortfolioDefault_{pt} \times SameEthnicity_{pt} + \\ &\quad \beta_6^* PortfolioDefault_{pt} \times SameIndustry_{pt} \times Heard_{pt} + \\ &\quad \beta_7^* PortfolioDefault_{pt} \times SameEthnicity_{pt} \times Heard_{pt} + \delta_t \qquad (2)\end{aligned}$$

where $PortfolioDefault_{pt}$ is defined as before; $Exposed_{pt}$ is a dummy variable equal to one if at least one firm that the subscriber $j(p)$ had inquired after prior to t had defaulted; $SameIndustry_{pt}$ is a dummy variable equal to one if $PortfolioDefault_{pt} = 1$ and the firm that defaulted was in the same industry as the firm $i(p)$; $SameEthnicity_{pt}$ is a dummy variable equal to one if $PortfolioDefault_{pt} = 1$ and a partner in the firm that defaulted was of the same ethnicity as the firm $i(p)$; $Heard_{pt}$ is a dummy variable equal to one if the subscriber actually heard the credit report that mentioned the portfolio default.[53] In this specification I drop all control variables and include only month-year dummy variables.

I find that after a subscriber was exposed to a default of one of his borrowers, he was ever after more cautious about his portfolio in the sense that he was 15% more likely to hear a report for a firm.[54] However, subscribers still responded to individual portfolio defaults after being exposed. This result provides some evidence of the salience of default on lender behavior.

Subscribers were 51% more likely to inquire after a firm if a previously inquired firm in the same industry defaulted and 59% more likely to inquire after a portfolio default for a firm within the

[53] $Exposed_{pt}$ is different than $PortfolioDefault_{pt}$. If $PortfolioDefault_{pt} = 1$ for the first time at time s then $Exposed_{pt} = 1$ for all $t > s$ and zero for all $t \leq s$.

[54] Under the Weibull assumption we can interpret the estimated coefficients in terms of a proportional hazard model or in terms of an accelerated failure time model. Hence, we can also say that subscribers waited less time before accessing a firm's credit report after one of his borrowers had defaulted.

same ethnicity.[55] These results suggest that subscribers did learn about specific industries or social networks through these portfolio shocks. However, subscribers were still 27% more likely to hear a credit report for a firm even when if the portfolio default was in a different industry and ethnic group.

Finally, a subscriber did not actually have to access the credit report that mentioned a portfolio default for the default to impact how much information he acquired about other firms. This is further evidence that subscribers reacted to information that they obtained outside of the reports. Subscribers learned of the borrower default from one source and checked credit reports in response.

6.4 Panic of 1857

We've seen that subscribers accessed credit reports for borrowers after a bad aggregate shock to New Orleans or NYC. But how did subscribers react to an adverse financial shock to most of the country? To answer this question I turn to the financial panic that occurred in 1857. Most scholars date the start of the panic period as the end of August 1857 when the Ohio Life and Trust Company suspended in Cincinnati. Throughout September and October, banks in several major cities in the Northern United States suspended payments.[56]

In all regression specifications, I included monthly dummy variables for months in 1857 to ensure that my results are not purely driven by the panic or the conditions that led to the panic in early 1857. Table 9 reports the hazard ratios for the panic dummy variables that correspond to columns (1) and (2) in table 8 (first vs. subsequent inquiries). Surprisingly, the estimated panic hazard ratios imply that subscribers were, if anything, less likely to inquire after firms during the financial panic. This result is contrary to what we might expect during a financial panic, which is that financial

[55] The overall effect of a same industry portfolio default is $1.273 \times 1.188 = 1.51$.

[56] For more about the Panic of 1857 see Calomiris and Schweikart (1991).

market participants acquire too much information.[57] For example, in a bank run, depositors might withdraw their money from a bank to learn whether the bank is stable enough to sustain a run. However, depositors might produce "too much" information if too many people withdraw funds and cause an illiquid, but not insolvent, bank to fail.

There are several possible explanations for the result that subscribers were less likely to obtain information about firms during the panic. First, if subscribers often used credit reports to provide evidence of quality on a promissory note for a bank to discount, then we might expect inquiries to decrease when banks suspended in New York. If banks stopped discounting notes (as we know they did) then it would have been unnecessary for a subscriber to hear a credit report in order to convey the information to a bank. Second, it is possible that subscribers did not think they needed to inquire after particular firms because they assumed that every firm was in trouble. Finally, they may have merely been less likely to inquire about New Orleans firms because they were more concerned about firms in other locations. The online appendix reports the relative firm default rates during the Panic for various American cities. We know, ex post, that New Orleans faired far better than most cities in terms of business failures and subscribers may have known this as well. Also, New Orleans banks did not suspend (except for two banks for a couple of days), which may have been a signal to NYC lenders that business conditions in New Orleans were relatively stable compared with other cities. Further research into the experiences of other cities and the role of credit reports in bank note discounting will shed light on this finding.

6.5 Robustness Checks

All regressions included all industries. I check to make sure none of the large industries drove the results by running the main regression excluding the main industries one at a time. The only case

[57] One way to think about a bank run is that depositors run on their bank to produce information about the quality of their bank. See Calomiris and Gorton (1991).

in which the results are sensitive to dropping an industry are with Dry Goods, when the coefficient on firm default increases. When I run the regression on only Dry Goods firms, I find that subscriber were less likely to inquire after a dry goods firm after the firm defaulted. This explains why the coefficient for all industries is small relative to the portfolio default variable. This suggests that dry goods suppliers may have been more likely to use credit reports to screen potential borrowers, which is consistent with the number of inquiries there were for dry goods firms. See table 11.

I run the main regression assuming various different specifications of the baseline hazard distribution: allow the Weibull scale to vary by industry; assume a log-logisitic baseline hazard, a standard accelerated failure time distribution that allows for a hump shape in the hazard function; Cox proportional hazard model which allows for a fully non-parametric baseline hazard. All of the qualitative results go through although, as expected, the magnitudes change slightly. See table 12.

I also try various assumptions on the interval censoring corrections. Two extreme assumptions: all subscribers inquired on the date the report was written; and all subscribers inquired in the last month before the next report. Next, I assume that the probability of an inquiry over the report interval follows a beta distribution and use various assumptions for the parameters of the distribution. For all specifications that I've tried, the default and portfolio default results go through. The cotton and interest rate results are sensitive to different assumptions on the timing of the inquiry. However, there is no particular reason to assume that subscribers would be more likely to inquire on one of the interval than the other. In future work I will simultaneously estimate the hazard model and predict the likely inquiry date within the interval.

7 Conclusion

The goal of this paper has been to provide empirical evidence on how lenders acquire information about their borrowers through accessing credit reports. To do this, I have introduced a novel

dataset compiled from the credit report records of the first mercantile credit reporting agency that allows me to observe approximately when New York City subscribers accessed credit reports about borrowers in New Orleans between 1850 and 1860. Using these data I have demonstrated three main facts about the way lenders acquire information. First, subscribers only acquired a fraction of the reports that the Agency supplied, even though the information was inexpensive and easily available to subscribers. Second, when they did access credit reports, subscribers were more likely to do so after an adverse shock to the aggregate economy or the individual borrower. Finally, subscribers were more likely to acquire information about a borrower if one of the subscriber's other borrowers defaulted.

The results of this paper have a broader implication on how information constraints affect credit market outcomes. In a credit market in which lenders can only obtain information about their borrowers at a high cost, such as the mercantile trade credit market pre-1841 or the credit market in a developing country, my results suggest that costly information acquisition primarily causes the market to be inefficient when the economy is in a downturn. The information cost is less likely to bind when the aggregate economy is stable, or when it has collapsed, as in the case of a financial panics.

The results also point to the role that the Mercantile Agency played in the development of the 19th century US economy. Prior to the introduction of credit reporting, lenders obtained information about their borrowers through recommendation letters and word of mouth. These sources were sufficient to sustain lending during good times. In fact, lenders continued to use these sources after credit reports were introduced. However, my results suggest that these sources of information were insufficient when there were adverse shocks to the economy or to individual borrowers. Hence, credit reports primarily facilitated lending when the economy was less stable.

My findings also have broader implications for who has access to credit. Subscribers did not always check credit reports before they contracted, which suggests that lenders did not need all

available information in order to lend. During goods times, suppliers extended credit freely with relatively little information. During bad times, they needed more information to lend. If a lender was uninformed when he contracted, he was necessarily less selective about to whom he extended credit. Hence, in boom periods, lenders provided broader access to credit. This could have been beneficial to the broader economy because it meant that young firms with limited ability to signal quality were more likely to obtain credit during a boom, they did not have to prove they were good. This was particularly important for a developing commercial community like the mid 19th century US. Many of the mercantile establishments in the US at the time were young. If firms were required to provide proof of quality when they borrowed from suppliers, many firms would have been left out of trade.

On the other hand, this mechanism also likely increased access to credit for low quality borrowers. If lenders screened potential lenders closely they would not lend to some subset of firms, but during a boom the lender did not screen and ended up lending to some of the bad borrowers. If the bad borrower eventually defaulted then the subscriber was hurt in the long run. Further, I have shown that when one borrower defaults, the subscriber acquired more information about his other borrowers, which could lead to a systemic event. Introducing one bad borrower to a system that is so interconnected could increase the fragility of the system.

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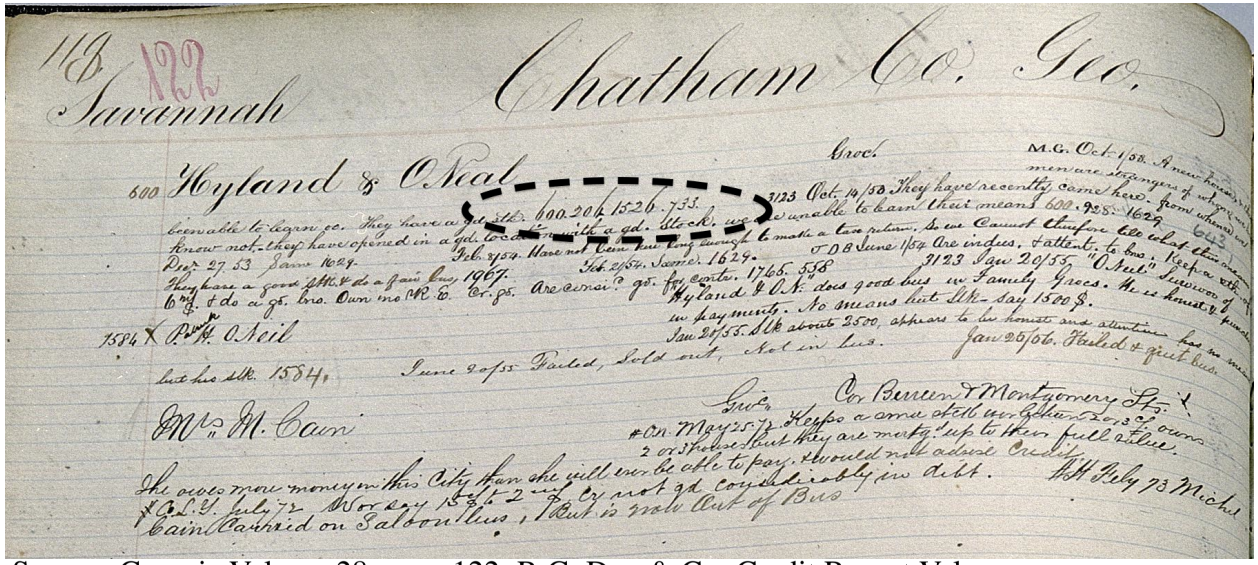
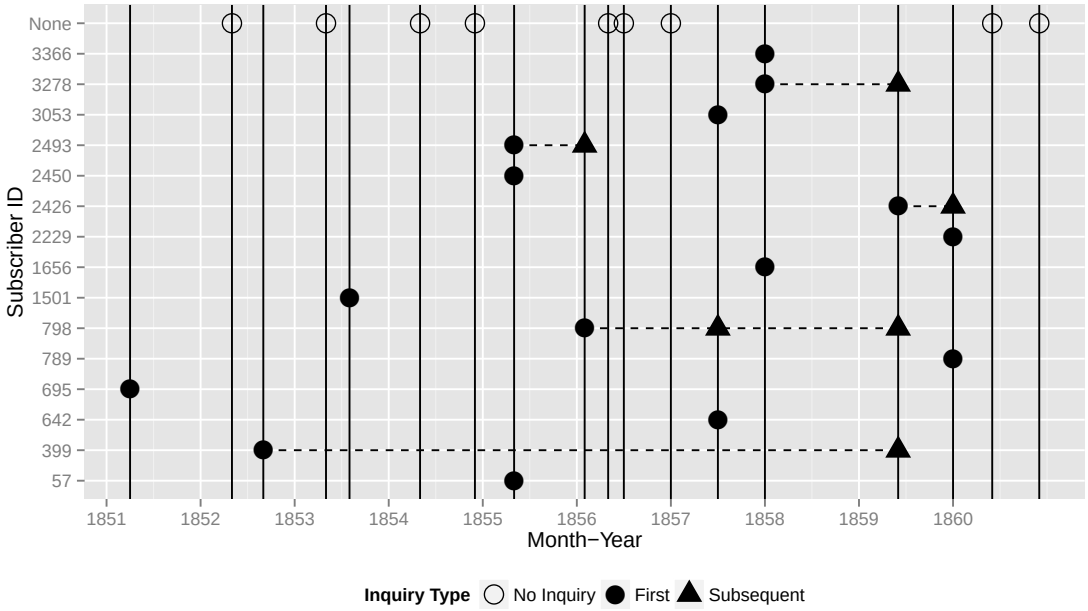
Figure 1: Savannah Credit Report Ledger with Subscriber Inquiries



Source: Georgia Volume 28, page 122. R.G. Dun & Co. Credit Report Volumes.

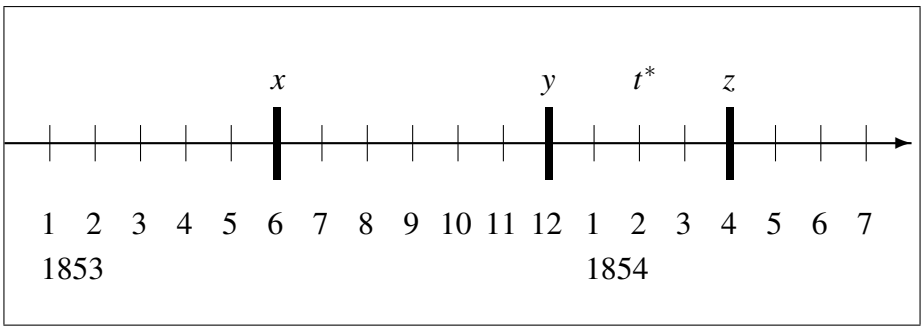
Notes: Subscriber identification numbers indicating inquiries circled with dotted line. The circled numbers indicated that NYC subscribers 206, 1520, and 733 and the Baltimore branch (#600) inquired after Hyland & O'Neal between October 1, 1853 and October 14, 1853.

Figure 2: Report Dates and Inquiries for P. Adolphe Lanauze



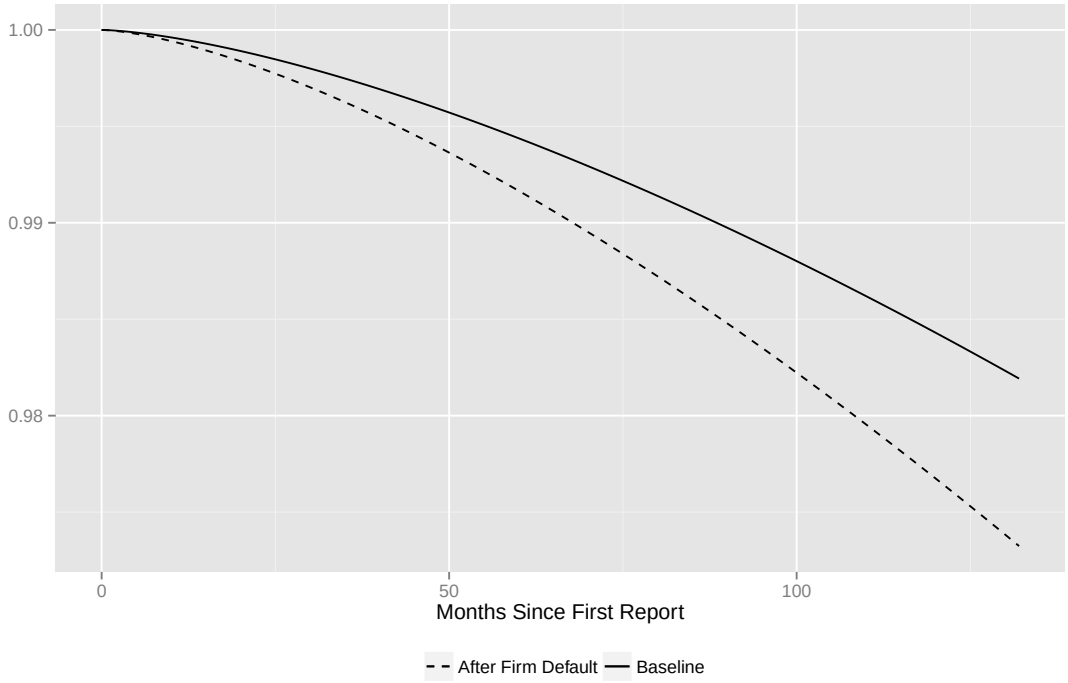
Source: Louisiana, Vol. 9, p. 358, R.G. Dun & Co. Credit Report Volumes.
Notes: Vertical lines indicate months on which the Mercantile Agency supplied reports for P. Adolphe Lanauze. Subscribers that inquired after Lanauze listed on y-axis. First credit report that each subscriber heard for Lanauze is marked with a circle at the month on which the report was written. Subsequent report inquiries marked with a triangle. The 9 reports for Lanauze that no subscriber heard are marked with an open circle.

Figure 3: Example of Time-Interval Censoring of Inquiry Date



Notes: Suppose Agency supplied reports for a firm at dates x, y, and z. If a subscriber inquired about the firm at date t^* and heard the report from date y then we would observe that he had inquired some time between y and z. We would not observe t^*.

Figure 4: Estimated Survival Function of Waiting Time to First Inquiry



Notes: Estimated Weibull survival function based on parameter estimates found in table 7.

Table 1: Credit Reports and Inquiries of New Orleans Firms 1850-1860

	Number
Firms	4,584
Reports	37,435
NYC Subscribers	2,128
NYC Inquiries	21,830
NYC Inquired Reports	9,270

Source: Louisiana, Vol. 9-12, R.G. Dun & Co. Credit Report Volumes. (New Orleans 1850-1860 Sample)
Notes: Firm included in sample if it had at least one report between January 1850 and December 1860. Sample includes all reports written about New Orleans firms between January 1850 and December 1860. Sample of subscribers includes all NYC subscribers that inquired after a New Orleans firm in the sample period. NYC inquiries are the total number of subscriber ID numbers that appeared after New Orleans credit reports. A report is an inquired report if at least one subscriber inquired after it.

Table 2: Summary Statistics for New Orleans Firms and New York City Subscribers

A. Firms Inquired After by NYC Subscriber					
	N	Median	Mean	Max	SD
Reports	2,060	11.0	12.4	50	8.7
Years in Reports (between 1845 and 1890)	2,060	9.9	11.2	47	8.1
Years in Sample (between 1850 and 1860)	2,060	5.0	5.5	11	3.7
Inquiries	2,060	3.0	10.6	314	20.2
Reports with Inquiries	2,060	3.0	4.5	32	4.9
Maximum Inquiries for One Report	2,060	2.0	2.9	35	3.4
Subscribers Inquiring	2,060	3	7.7	175	12.6
Other Firms with Common Subscriber Inquiring	2,060	74	113	747	121.5
B. Firms Not Inquired After by NYC Subscriber					
	N	Median	Mean	Max	SD
Reports	2,524	3	4.7	28	4.9
Years in Reports (between 1845 and 1890)	2,524	3.75	5.6	38	6.4
Years in Sample (between 1850 and 1860)	2,524	2.16	2.7	11	2.9
C. NYC Subscribers					
	N	Median	Mean	Max	SD
Inquiries	2,128	4	10.3	440	23.2
Firms Inquired	2,128	3	7.0	157	11.6

Source: New Orleans 1850-1860 Sample. See table 1.
Note: Only NYC inquired firms and reports. Reports and inquiries measured between January 1850 and December 1860. Years in reports measured between 1845 and 1894. Firms subscribers inquiring is the number of subscribers that inquired after the firm in the sample period. For each firm, unique network connections is the total number of other firms that share at least one inquiring subscriber.

Table 3: Months Between New Orleans Reports: 1850-1860

A. Months Until Next Report by Report for All Firms					
Report Type	N	Median	Mean	Max	SD
All Reports	32,778	5	5.6	100	5.13
Inquired Reports	8,592	5.00	5.8	80	4.83
B. Months Until Next Report by Report for Firms with NYC Inquiries					
Report Type	N	Median	Mean	Max	SD
All Reports	23,416	5.00	5.2	97	4.67
Inquired Reports	8,592	5.00	5.8	80	4.83
Not Inquired Reports	14,824	4.00	4.9	97	4.53
C. Months Until Next Report by Report for Firms without NYC Inquiries					
Report Type	N	Median	Mean	Max	SD
Not Inquired Reports	9,362	6	6.7	100	6.03

Source: New Orleans 1850-1860 Sample. See table 1.
Note: Statistics exclude last report for each firm prior to 1861.

Table 4: Industry Statistics

Industry	Firms	Reports	Subscribers	Inquiries
Boots & Shoes	192	1,568	300	755
Banking	95	787	67	94
Clothing	325	2,355	418	1,641
Comm. Merch.	867	8,832	667	1,998
Cotton	295	3,578	334	895
Drugs	247	2,087	236	1,272
Dry Goods	308	2,827	888	5,655
Furniture	243	1,235	174	588
Grocer	522	3,706	427	2,043
Jewelry	159	1,380	263	945
Liquor	173	1,551	180	412
Produce	230	1,890	148	236

Source: Louisiana, Vol. 9-12, R.G. Dun & Co. Credit Report Volumes.
Note: Industries defined by author, based on reported industry in credit reports. Table does not include all industries. Firms could be in multiple industries at one time and could switch industries. Hence, the sum of firms over the industries is not equal to the total number of firms. Reports are total reports, not inquired reports. Only report NYC inquiries.

Table 5: Firms and Reports with Inquiries

	(1) N	(2) Total Reports	(3) Inquired Reports	(4) % Reports Inquired
All Firms	4,584	37,435	13,098[a]	35%
Inquired Firms (by Any)	2,406	28,793	13,098[a]	45%
Inquired Firms (by NYC)	2,060	25,520	9,270[b]	36%
Not Inquired Firms (by Any)	2,178	8,642	0	0%
Not Inquired Firms (by NYC)	2,524	11,915	0	0%

Source: New Orleans 1850-1860 Sample. See table 1.

[a] Reports inquired after by any subscriber, including branch subscribers.

[b] Reports inquired after by only NYC subscribers.

Notes: A firm is inquired (by Any) if a subscriber in NYC or at one of the Agency branches inquired after at least one report for that firm. A firm is inquired (by NYC) if a subscriber in NYC inquired after at least one report for that firm. The first column gives the number of firms in each category. The second column gives the total number of reports for firms in each category. Column (3) gives the number of reports inquired after for each category. Column (4) gives the percent of reports inquired after = Column (3)/Column(2).

Table 6: Summary Statistics: Aggregate Variables

	Time Periods	Median	Mean	Min	Max	SD
New Orleans Cotton Price[a]	131	10.25	10.2	7.0	15	1.7
ΔNew Orleans Cotton Price[b]	131	0.0	0.0	-4.8	3.8	0.8
NYC Interest Rate[a]	131	7.2	7.8	3.8	27	2.9
Δ NYC Interest Rate[b]	131	0.0	-0.0	-11.0	9.15	1.9

Source: Cotton price from New Orleans Newspaper *Commercial bulletin, price current and shipping list.* From Sept. 1849 to Aug. 1855 the price is the cents per pound of Fair to Middling (quality) cotton on the first of the month. From Sept. 1855 to Aug. 1860 the price is the cents per pound on Middling (quality) cotton on the first of the month. NYC Interest Rate is the interest rate on prime endorsed business paper with 4 to 6 month maturity. The series from 1850 to August 1851 is from the *Journal of Commerce*. The series from September 1851 to Feb. 1857 is from the *Journal of Commerce, Junior*. The series from March 1857 to December 1860 is from the *Shipping & commercial list, and New-York price current.* The original interest rate series was at a (mostly) weekly frequency. The monthly rate is the mean rate over the month.

[a] Monthly frequency.

[b] One month differences.

Table 7: Maximum Likelihood Estimate of Weibull Hazard Model
Waiting Time to First Inquiry

Dependent Variable: Time to First Inquiry					
	[1]	[2]	[3]	[4]	[5]
$Pos\Delta CotPrice$	0.934*				0.951
	(-2.378)				(-1.74)
$\lvert Neg\Delta CotPrice\rvert$	1.146***				1.152***
	(4.799)				(4.928)
$Pos\Delta IR$		1.064***			1.057***
		(4.244)			(3.713)
$\lvert Neg\Delta IR\rvert$		1.039*			1.029
		(2.457)			(1.802)
Firm Default			1.488***		1.487***
			(6.813)		(6.798)
Portfolio Default				1.527***	1.517***
				(13.139)	(12.862)
Weibull Scale	0.671	0.672	0.673	0.671	0.656
	(56.07)	(55.85)	(55.63)	(59.19)	(59.46)
Controls, Season FE	Y	Y	Y	Y	Y
Log likelihood	-116,523	-117,050	-117,118	-117,105	-116,418
N	730,374	730,374	730,374	730,374	730,374

*** p <0.001; ** p <0.01; * p<0.05

Notes: Table reports maximum likelihood estimates of time to first inquiry hazard model adjusted for interval censoring given by equation (1) in the text. Baseline hazard assumed Weibull. Hazard ratios are reported: one unit increase in variable implies first inquiry for subscriber-firm *HR* times more likely. t-statistics given in parentheses. All columns include controls: industry FE, ethnicity FE, annual cotton production, quarter dummy variables, and panic month indicators for months in 1857. See table 6 for definitions of NYC interest rate (*IR*) and New Orleans Cotton Price (*CotPrice*). Firm Default is 1 if latest report at date mentioned default. Portfolio default is 1 if report written at date for a previously inquired other firm mentioned default. See the online appendix for definitions of default.

Table 8: MLE of Weibull Hazard Model
Waiting Time to First Inquiry vs. Waiting Time to Subsequent Inquiry

Dependent Variable: Time to Inquiry		
	[1]	[2]
	First Inquiry	Subsequent Inquiry
$Pos\Delta CotPrice$	0.951	0.985
	(-1.74)	(-0.373)
$\lvert Neg\Delta CotPrice \rvert$	1.152***	1.462***
	(4.928)	(7.099)
$Pos\Delta IR$	1.057***	0.986
	(3.713)	(-0.571)
$\lvert Neg\Delta IR \rvert$	1.029	0.943*
	(1.802)	(-1.963)
Firm Default	1.487***	2.007***
	(6.798)	(14.483)
Portfolio Default	1.517***	1.665***
	(12.862)	(14.278)
Weibull Scale	0.656	0.505
	(59.46)	(61.49)
Controls, Season FE	Y	Y
Log likelihood	-116,418	-59,187
N	730,374	629,919

*** p <0.001; ** p <0.01; * p<0.05

Notes: Column (1) is the same specification as column (5) in table 7. Column (2) is contains the same variables as column (1) but is the estimated hazard model for time to subsequent inquiry. A subscriber-firm pair is at risk for a subsequent inquiry starting at the first month after the previous inquiry. Pairs without realized subsequent inquiries are included in the estimation.

Table 9: MLE of First Inquiry vs. Subsequent Inquiry
Panic of 1857 Indicator Variables

Dependent Variable: Time to Inquiry		
	[1]	[2]
	First Inquiry	Subsequent Inquiry
February 1857	0.933	0.539***
	(-0.744)	(-4.269)
March 1857	0.915	0.528***
	(-0.929)	(-4.324)
April 1857	0.884	0.670**
	(-1.302)	(-2.939)
May 1857	0.801*	0.611***
	(-2.256)	(-3.313)
June 1857	1.029	0.623***
	(0.339)	(-3.787)
July 1857	0.868	0.570***
	(-1.768)	(-4.564)
August 1857	0.911	0.620***
	(-1.113)	(-3.874)
September 1857	0.487***	0.788
	(-4.683)	(-0.977)
October 1857	0.450***	0.567*
	(-5.248)	(-2.34)
November 1857	0.309***	0.221***
	(-5.169)	(-3.748)
December 1857	0.613***	0.91
	(-3.39)	(-0.41)
January 1858	0.537***	0.475***
	(-6.013)	(-4.678)

*** p <0.001; ** p <0.01; * p<0.05

Notes: This table presents the estimated coefficients on the panic dummy variables from columns (1) and (2) in table 8.

Table 10: MLE of Weibull Hazard Waiting Time to First Inquiry
Portfolio Defaults

Dependent Variable: Time to Inquiry			
	[1]	[2]	[3]
Firm Default	1.779***	1.772***	1.774***
	(9.907)	(9.832)	(9.855)
Portfolio Default	1.524***	1.273***	1.278***
	(12.369)	(4.318)	(4.101)
Exposed to Default	1.157***	1.158***	1.159***
	(7.114)	(7.139)	(7.174)
Portfolio Default x Same Industry		1.188**	1.148
		(2.650)	(1.939)
Portfolio Default x Same Ethnicity		1.249***	1.220***
		(3.557)	(2.910)
Portfolio Default x Heard			0.974
			(-0.174)
Portfolio Default x Same Industry x Heard			1.215
			(1.167)
Portfolio Default x Same Ethnicity x Heard			1.127
			(0.717)
Weibull Scale	0.628	0.628	0.628
	(62.61)	(62.64)	(62.64)
Month-Year FE	Y	Y	Y
Log likelihood	-118,022	-118,013	-118,012
N	781,444	781,444	781,444

*** p <0.001; ** p <0.01; * p<0.05

Notes: Table reports maximum likelihood estimates of time to first inquiry hazard model adjusted for interval censoring given by equation (2) in the text. Baseline hazard assumed Weibull. Includes month-year fixed effects. Firm default and portfolio default are as defined in the appendix. A subscriber-firm pair is defined as "Exposed to Default" if at least one of the subscriber's previously inquired firms has defaulted (after "Portfolio Default" is equal to one month, "Exposed" is equal to one for the rest of the sample period). For firm *i*, "Same Industry" is a dummy variable equal to one if the portfolio default occurred in the same industry as firm *i*. "Same Ethnicity" is dummy variable equal to one if the portfolio default occurred for a firm with a partner with the same ethnicity as firm *i*. "Heard" is a dummy variable equal to one if the subscriber heard the report that mentioned the portfolio default.

Table 11: Robustness Check: Industries

Dependent Variable: Time to Inquiry					
	[1]	[2]	[3]	[4]	[5]
	All	No DG	No Cotton	No Grocer	No Comm
$Pos\Delta CotPrice$	0.951	0.941	0.951	0.948	0.948
	(-1.74)	(-1.834)	(-1.718)	(-1.768)	(-1.764)
$\lvert Neg\Delta CotPrice\rvert$	1.152***	1.093**	1.143***	1.164***	1.146***
	(4.928)	(2.651)	(4.535)	(5.052)	(4.514)
$Pos\Delta IR$	1.057***	1.064***	1.059***	1.049**	1.055***
	(3.713)	(3.582)	(3.762)	(3.071)	(3.437)
$\lvert Neg\Delta IR\rvert$	1.029	1.030	1.030	1.025	1.028
	(1.802)	(1.630)	(1.854)	(1.487)	(1.657)
Firm Default	1.487	2.193***	1.420***	1.392***	1.357***
	(6.798)	(12.644)	(5.719)	(5.438)	(4.747)
Portfolio Default	1.517***	1.555***	1.508***	1.481***	1.503***
	(12.862)	(11.490)	(12.260)	(11.525)	(11.872)
Weibull Scale	0.656	0.674	0.659	0.649	0.657
Controls, Season FE	Y	Y	Y	Y	Y
Log likelihood	-116,418	-87,611	-111,030	-105,372	-104,860
N	730,374	548,942	696,806	661,422	656,428

*** p <0.001; ** p <0.01; * p<0.05

Notes: Column [1] is the main specification, same as column [5] in table 7, and includes firms for all industries. Column [2] is the same specification but without Dry Goods firms; column [3] excludes cotton firms; column [4] excludes grocers. column [5] excludes commission merchants.

Table 12: Robustness Check: Baseline Hazard Assumption

Dependent Variable: Time to Inquiry				
	[1]	[2]	[3]	[4]
$Pos\Delta CotPrice$	-0.033	-0.032	-0.033	0.995
	(-1.740)	(-1.753)	(-1.746)	(-0.175)
$\lvert Neg\Delta CotPrice\rvert$	0.093***	0.094***	0.097***	1.214***
	(4.928)	(5.173)	(5.101)	(6.718)
$Pos\Delta IR$	0.036***	0.034***	0.036***	1.032*
	(3.713)	(3.622)	(3.633)	(2.086)
$\lvert Neg\Delta IR\rvert$	0.019	0.018	0.017	1.011
	(1.802)	(1.792)	(1.626)	(0.698)
Firm Default	0.260***	0.250***	0.259***	1.509***
	(6.798)	(6.727)	(6.597)	(7.063)
Portfolio Default	0.273***	0.256***	0.278***	1.514***
	(12.862)	(12.454)	(12.767)	(12.886)
Weibull Scale	0.656	Varies	-	-
Log-Logistic Scale	-	-	0.651	-
CoxPH	N	N	N	Y
Controls, Season FE	Y	Y	Y	Y
AIC	232,972	232,597	233,175	334,356
N	730,374	730374	730374	730374

*** p <0.001; ** p <0.01; * p<0.05

Notes: Column (1) is the same as regression specification column (5) in table 7 but I report the standard coefficients (not hazard ratios). Column (2) is the same regression but allows the Weibull scale parameter to vary by industry. Column (3) gives results from the main specification assuming that the baseline hazard follows a log-logistic distribution. All coefficients are presented so that a positive coefficient means that an increase in the variable increase the probability of a first inquiry. Column (4) gives the hazard ratios from a Cox Proportional Hazard model.