Financial Intermediaries and the Macroeconomy: Evidence from a High-Frequency Identification*

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Abstract

We provide empirical evidence of the causal effects of changes in financial intermediaries' net worth in the aggregate economy. Our strategy identifies financial shocks as high-frequency changes in the market value of intermediaries' net worth in a narrow window around their earnings announcements, based on U.S. tick-by-tick data. Using these shocks, we estimate that news of a 1% decline in intermediaries' net worth leads to a 0.2%–0.4% decrease in the market value of nonfinancial firms. These effects are more pronounced for firms with high default risk and low liquidity and when the aggregate net worth of intermediaries is low.

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1. Introduction

What effect do financial intermediaries have on the macroeconomy? This question, which has been central to macroeconomics since at least the Great Depression, has received significant attention from researchers in recent decades (see, for example, Bernanke, 1983; Reinhart and Rogoff, 2009a; Gertler and Gilchrist, 2018). The main empirical challenge in measuring the aggregate effects of intermediaries is that macroeconomic conditions that originate outside the financial system affect the balance sheets of intermediaries, which makes it difficult to isolate their aggregate effects on the economy.

In this paper, we propose a high-frequency (HF) identification strategy to study the causal effects of financial shocks on the aggregate economy. Our empirical strategy focuses on changes in individual financial intermediaries' net worth in a narrow window around their earnings announcements. In the spirit of the HF event-study approach to identifying monetary-policy shocks (surveyed by Nakamura and Steinsson, 2018a), our empirical strategy exploits the fact that earnings announcements are lumpy, which causes a discontinuity in the content of financial news released around these events. Using these shocks, we document that declines in the market value of intermediaries' net worth leads to substantial effects on the market value of nonfinancial firms. These effects are more pronounced for firms with high default risk and low liquidity and when the aggregate net worth of the financial system is low.

Our paper begins by constructing an HF measure of financial shocks in the U.S. economy. Our measure of financial shocks uses tick-by-tick data on intermediaries' stock prices in 60-minute windows around their earnings releases. We exploit the fact that publicly traded financial intermediaries have considerable market size, so idiosyncratic news about these intermediaries can have an effect on total financial net worth, as in the recently proposed "granular" identification strategy (Gabaix and Koijen, 2020).

We then use HF financial shocks to study the effect of changes in intermediaries' net worth on nonfinancial firms. We provide evidence using two empirical strategies. One is an event-study approach, whose identifying assumption is that in a 60-minute window around intermediaries' earnings announcements, changes in the stock price of intermediaries that are releasing earnings are driven by information contained in these announcements. The other is a heteroskedasticity-based identification strategy (Rigobon, 2003; Rigobon and Sack, 2004; Hébert and Schreger, 2017), whose identifying assumption is that the variance of intermediaries' stock price during earnings-announcement events is larger than in nonevents, while the variance of nonfinancial firms is the same during event and nonevent periods. Using these two strategies, we document that a 1% change in intermediaries' net worth leads to a 0.2% to 0.4% percent change in the market value of nonfinancial firms in the S&P 500. These effects are larger for small firms, as measured by returns of the S&P SmallCap 600 and Russell 2000 indices; are robust to the frequency of analysis and weighting of the dependent variables; and affect firms' financing costs in both bond markets and equity markets. In bond markets, financial shocks particularly affect the yields of high-risk bonds. For these bonds, we present additional within-firm-level evidence of the effects of financial shocks: Using security-level data on holdings by each financial institution, we show that within bonds issued by the same firm and with similar characteristics, those more heavily held by financial intermediaries that are reporting earnings exhibit a larger sensitivity to financial shocks.

Our empirical analysis also provides supportive evidence on the channels through which financial shocks affect nonfinancial firms. First, we show that the effects we identify are governed by periods in which the aggregate net worth of the financial system is low, which suggests an important role for aggregate net worth channels (as stressed, for instance, by Gertler and Kiyotaki, 2010 and Brunnermeier and Sannikov, 2014). Consistent with this, we find a substantive role for intermediaries' net worth when using tools from the monetary policy literature (Cieslak and Schrimpf, 2019; Jarociński and Karadi, 2020) to decompose this channel from a borrowers' information channel—i.e., the information on nonfinacial firms' investment opportunities contained in intermediaries' earnings releases. Second, we show that firms more severely affected by financial frictions—e.g., higher credit risks and lower liquidity—are more severely affected by the financial shocks, which suggests that firms' financial positions matter in the aggregate transmission of these shocks (as highlighted, for example, in Khan and Thomas, 2013; Jermann and Quadrini, 2012; Christiano, Motto and Rostagno, 2014).

Our findings are consistent with a large body of empirical work that provides evidence that the net worth of financial intermediaries affects firms (e.g., Khwaja and Mian, 2008; Amiti and Weinstein, 2011; Chodorow-Reich, 2014; Huber, 2018) and asset prices (e.g., Coval and Stafford, 2007; Adrian, Etula and Muir, 2014; He, Kelly and Manela, 2017; Siriwardane, 2019; and He and Krishnamurthy, 2018 for a recent survey). An important element in the identification strategy developed in this body of work is the cross-sectional exposure of firms or assets to intermediaries. Our paper complements this literature by documenting intermediaries' aggregate effects. To date, empirical work on aggregate effects has used time-series methods (see, for example, Bernanke, 2018; Gertler and Gilchrist, 2018); a combination of cross-sectional and regional data (Gertler and Gilchrist, 2019); and model-based inference (see, for example, Christiano, Eichenbaum and Trabandt, 2015; Herreño, 2020). Our empirical analysis provides evidence on intermediaries in the aggregate economy—as well as on the role of aggregate intermediaries' net worth in shaping these effects—based on an HF identification strategy. We consider our method to be complementary to prior empirical work, with the advantage that HF methods require milder assumptions for the identification of aggregate effects (as discussed by Nakamura and Steinsson, 2018b, in the context of monetary policy shocks).[1]

[1] For additional work using the HF approach to study the effect of monetary policy shocks in the economy, see Cook and Hahn (1989); Kuttner (2001); Cochrane and Piazzesi (2002); Gürkaynak, Sack and Swanson (2004); Bernanke and Kuttner (2005); and Gorodnichenko and Weber (2016), among others.

2. Data

Our measure of financial shocks uses tick-by-tick data on intermediaries' stock prices in a window around their earning releases. We obtain tick-level stock prices from the New York Stock Exchange's Trade and Quote (TAQ). The TAQ database contains intraday trades timestamped to the second for all securities listed on the New York Stock Exchange, American Stock Exchange, Nasdaq, and SmallCap issues. We collect earnings announcements' precise dates and times from the Institutional Brokers' Estimate System (IBES). Our baseline sample focuses on the commercial banks, investment banks, and securities dealers included in the S&P 500 Index during the period 1998 to 2014.[2] We focus on these types of intermediaries because their direct involvement in lending activities in the economy renders them more likely to be linked to the macroeconomy, which is our main focus of analysis. Table 1 details the set of 18 financial intermediaries selected using our main criteria, together with the period in which they are included in our analysis. Table 1 also shows that financial intermediaries in our sample represent 67% of the total equity of U.S. depository institutions, measured by the Federal Reserve's Flow of Funds. Therefore, our sample is based on large financial institutions, whose individual changes in net worth are likely to represent a significant change in the net worth of the entire financial sector.[3] In our period of analysis, we obtain 870 announcements of earnings, with roughly four per institution–year. Table D.1 in the Internet Appendix provides detailed information on all earnings announcements by

[2]We access the TAQ database through the University of Michigan's subscription to Wharton Research Data Services (WRDS), for which data is available from 1993 to 2014. We start the sample in 1998, when precise time stamps in IBES becomes available. The financial intermediaries we use in the analysis correspond to NAICS 522110 and 523110, which are included in the S&P 500 consecutively for at least 10 years to focus on a balanced sample, and we exclude regional banks (GICS 40101015) to focus on granular intermediaries.

[3]Recent work on "granular" economies, pioneered by Gabaix (2011), argues that shocks to large actors in the economy can lead to substantial aggregate fluctuations (see, for example, Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi, 2012; Di Giovanni and Levchenko, 2012; Galaasen, Jamilov, Juelsrud and Rey, 2020). Gabaix and Koijen (2020) discuss how idiosyncratic shocks to large players in the economy that affect aggregates constitute powerful instruments. Appendix A discusses the importance of granularity for identifying the effects of financial shocks in an illustrative theoretical framework.

Table 1: Financial Intermediaries Included in the Sample

Financial Intermediary	**Ticker**	**Start**	**End**	**Avg Equity ($ billion)**	**Share of Sample**	**Share of Aggr Equity**
Citicorp	CCI, C	1998Q1	2014Q4	148.8	26.8%	13.2%
Bank of America	BAC	1998Q1	2014Q4	136.4	24.6%	12.1%
Wells Fargo	WFC	1998Q1	2014Q4	73.6	13.3%	6.5%
Goldman Sachs	GS	2002Q3	2014Q4	51.7	6.8%	3.9%
Morgan Stanley	MWD, MS	1998Q1	2014Q4	37.3	6.7%	3.3%
J.P. Morgan Chase	CMB, JPM	1998Q1	2014Q4	36.0	1.1%	6.3%
Wachovia	WB	1998Q1	2008Q4[a]	35.8	4.2%	4.0%
Merrill Lynch	MER	1998Q1	2008Q4[b]	25.4	3.0%	2.8%
U.S. Bankcorp	USB	1998Q1	2014Q4	22.1	4.0%	2.0%
Bank One	ONE	1998Q1	2004Q2[c]	19.8	1.3%	3.0%
Bank of New York Mellon	BK	1998Q1	2014Q4	18.7	3.4%	1.7%
Fleet Boston Financial	FBF	1998Q1	2004Q1[d]	14.9	0.9%	2.3%
Lehman Brothers	LEH	1998Q1	2008Q3	12.6	1.4%	1.4%
Ameriprise Financial	AMP	2005Q4	2014Q4	8.6	0.8%	0.6%
First Chicago	FCN	1998Q1	1998Q4[e]	8.2	0.0%	1.5%
MNBA Corp	KRB	1998Q1	2005Q4[f]	7.6	0.6%	1.0%
Bankboston	BKB	1998Q1	1999Q3[g]	4.9	0.1%	0.9%
Northern Trust	NTRS	1998Q1	2014Q4	4.6	0.8%	0.4%
Mean				37.1	5.56%	3.71%
SD				42.4	8.04%	3.68%
Min				4.6	0.04%	0.41%
Max				148.8	26.82%	13.16%
Total				667.0	100.00%	66.82%

Notes: This table lists the financial intermediaries included in the sample and their tickers in the TAQ. "Avg Equity" is the time-series average of total shareholder equity of the financial intermediary. "Share of Sample" measures a financial intermediary's equity as a share of the equity of all financial intermediaries in the sample. "Share of Aggr Equity" represents a financial intermediary's equity as a share of the aggregate equity of U.S. depository institutions. [a]Acquired by Wells Fargo. [b]Acquired by Bank of America. [c]Merged with J.P. Morgan Chase. [d]Acquired by Bank of America. [e]Merged with Banc One to form Bank One. [f]Acquired by Bank of America. [g]Merged with Fleet to form Fleet Boston.

intermediaries contained in our sample.

We study the effects on nonfinancial firms using intraday stock prices of the S&P 500 constituent securities, also obtained from the HF TAQ database. Our main analysis focuses on the movements of these nonfinancial constituents in a narrow window that matches that of financial shocks. We complement this analysis with additional daily indices data from

FRED and Bloomberg—the S&P 500 Ex-Financial, S&P SmallCap 600, and Russell 2000 indices. Appendix Table B.1 presents descriptive statistics of daily stock returns in our period of analysis, and shows that days with financial shocks exhibit descriptive statistics similar to those of the whole period of analysis.

We also study the effect of financial shocks on the corporate bond market using several data sources. First, we use daily data on U.S. corporate bond indices from the Intercontinental Exchange Bank of America (ICE BofA), obtained from FRED.[4] Our analysis covers a wide range of ratings from investment grade to high yield. Second, we study the effects on excess bond premia, developed by Gilchrist and Zakrajšek (2012) and extended to daily frequency by Gilchrist, Wei, Yue and Zakrajšek (2021), which measures risk premia as the residuals from projecting firms' bond spreads on their probabilities of default using Merton's 1974 model. Third, we study the within-firm effects of financial shocks by using individual bond-level data from the constituents of corporate bond indices. For each of these bonds, we have information on option-adjusted spreads and bond characteristics from the ICE BofA; transaction-level data in the secondary market from the Trade Reporting and Compliance Engine (TRACE); and the share of bonds (at cusip level) held by each reporting financial institution from Bloomberg. Appendix Table B.2 reports descriptive statistics for bond data.

[4]The choice of daily frequency takes into account the less liquid nature of bond markets as well as the day-end settlement time of major participants (such as mutual funds).

3. Measuring High-frequency Financial Shocks

3.1. Construction of shocks

We define HF financial shocks as changes in the stock price of the intermediaries that report earnings in a narrow window around their earnings announcements:

$$\varepsilon_t^{\mathrm{F}} = \theta_{i,q(t)}(\log P_{i,t+\Delta^+} - \log P_{i,t-\Delta^-}), \tag{1}$$

where t is the time of an announcement for financial intermediary i (expressed in minutes within a day); $P_{i,t}$ is the stock price of institution i at time t; Δ^+ and Δ^- control the size of the window around the announcement; and $\theta_{i,q(t)}$ is the market capitalization of institution i as a share of the total market capitalization of institutions in our sample in the quarter $q(t)$ before announcement. For announcements made within trading hours[5], we select $\Delta(t)^-$ to be 20 minutes before the announcement and $\Delta(t)^+$ to be 40 minutes after the announcement, following Nakamura and Steinsson (2018b) for monetary-policy shocks. For announcements that occur after trading hours, we compute the financial shock as the change between the closing and opening log prices. Given that our measure is more precise for announcements made within trading hours, we create two measures of financial shocks: a "narrow" measure that includes only this type of announcement and a "broad" one that includes both types of shocks. Appendix Figure B.1 illustrates our HF-identified shocks with four graphical examples. Panels (a) and (b) show two shocks that occur inside trading hours, with their magnitudes corresponding to median positive and negative shocks inside trading hours; Panels (c) and (d) illustrate shocks that occur outside of trading hours.

Table 2 reports descriptive statistics for the narrow measure of financial shocks. The first column shows the HF changes in log prices of reporting institutions around their earn-

[5]Intraday data from the TAQ are available for hours inside the Consolidated Tape hours of operation, which were 8:00–18:30 Eastern Time as of August 2000 and 4:00–18:30 Eastern Time as of March 2004.

Table 2: Financial Shocks

	Changes in Stock Prices		HF Financial Shocks	
	Reporting Intermediaries	All Intermediaries	Reporting Intermediaries	All Intermediaries
Mean	−0.16	−0.12	−0.03	−0.03
Median +	1.22	4.64	0.06	0.38
Median −	−1.22	−5.95	−0.08	−0.42
Std deviation	2.68	12.43	0.30	0.98
5th percentile	−4.59	−17.80	−0.56	−1.51
95th percentile	3.81	20.76	0.31	1.65
Observations	343	343	343	343

Notes: This table shows descriptive statistics for the "narrow" measure of financial shocks, with earnings releases inside of market trading hours, including pre-market and extended trading, if available. Changes in the stock prices of reporting financial intermediaries are constructed as described in the main text, and changes in the stock prices of all intermediaries are the unweighted sum of all sample intermediaries' stock price changes around reporting intermediaries' earning releases. HF financial shocks for reporting intermediaries are weighted by the market net worth of the financial intermediary as a fraction of the total market net worth of the sample in the quarter, and HF financial shocks for all intermediaries are the weighted sum based on all sample intermediaries. "Median +" and "Median −" refer to median positive and median negative shocks.

ings announcements. All statistics are displayed in percent. On average, the price changes of reporting institutions are close to zero, with a standard deviation of 2.7%. Median positive and negative shocks are close to 1%. The third column shows descriptive statistics of HF financial shocks—which, as shown in (1), weight each change in log price of reporting institutions by their market share. Weighting overall reduces the magnitude of the shocks, resulting in a standard deviation of 0.30% and median positive and negative shocks of 0.06% and −0.08%, respectively. We also report changes in the financial sector around earnings announcements. The second column reports the unweighted sum of HF changes in the log prices of all sample intermediaries included in the sample around an earnings announcement, and the fourth column reports the sum weighted by market share. Shocks based on all sample intermediaries are similarly centered around zero, and have amplified median positives and negatives and greater volatility compared with the baseline financial shocks.

3.2. Financial content of the shocks

Internet Appendix E conducts a set of exercises to examine the content of our measure of financial shocks. First, Appendix E.1 uses data on unexpected earnings in announcements to show that stock price movements from financial institutions tend to be positively associated with their surprise earnings, which suggests that financial shocks encode the information on earnings released in the announcements.

Second, Appendix E.2 conducts a set of textual analyses of news coverage of intermediaries' earnings announcements (from *Wall Street Journal* articles on intermediaries' earnings announcements). The textual sentiment of these news items is positively associated with earnings surprises and HF shocks. Topics covered in the news articles revolve around intermediaries' idiosyncratic performance, and most prominently in core business areas: loans, mortgages, and investment banking and trading. Narratives constructed in the articles attribute stock price movements to earnings performance relative to forecasts and attribute earnings results to bank-specific factors, such as business mixes and loan outcomes. All evidence from textual analysis suggests that market participants attribute the changes in market values around earnings announcements to intermediaries' idiosyncratic factors.

The third exercise shows that financial shocks are not linked systematically to information available at the moment of earnings releases. For this, Appendix E.3 uses a state-of-the-art machine-learning model and shows that HF financial shocks are not predictable based on macroeconomic or financial data available before the shocks, which suggests that financial shocks are not driven by information on the rest of the economy that was available before intermediaries' earnings were released.

Fourth, Appendix E.4 reports the volatility of the stock prices of financial intermediaries and nonfinancial firms during event windows that include intermediaries' earnings announcements and compares it with the volatility during nonevent windows. These moments show that the volatility of financial intermediaries' stock prices during their earnings announcements increases by substantially more than those of nonfinancial firms during those events, which is consistent with the fact that intermediaries' earnings announcements contain more information about financial intermediaries than about nonfinancial firms. Based on this, in our empirical analysis in the next section we conduct a heteroskedasticity-based identification. This can be conducted even if common factors affect both intermediaries and nonfinancial firms during their earnings announcements, as long as the variance of intermediaries' stock price during earnings-announcement events is larger than on nonevent dates. In contrast, those of nonfinancial firms are the same during both event dates of earnings releases of financial intermediaries and nonevent dates.

4. The Aggregate Effects of Financial Shocks

Theoretical background We now use HF financial shocks to study the aggregate effects of financial intermediaries. Our empirical analysis is guided by theories that link the balance sheets of intermediaries to macroeconomic dynamics and asset prices (e.g., Gertler and Kiyotaki, 2010; He and Krishnamurthy, 2012, 2013; Brunnermeier and Sannikov, 2014; Maggiori, 2022, and references therein). In these models, a decline in the net worth of financial intermediaries (driven, for example, by a negative realization of returns on their investments) leads to contraction in the supply of funds for nonfinancial firms and a decline in nonfinancial firms' investment and market value. The strength of this effect is governed by the degree of financial frictions faced by intermediaries (see Appendix A). Therefore, analyzing the effects of financial shocks on the market value of nonfinancial firms can be informative regarding the degree of financial frictions faced by financial intermediaries—and, ultimately, regarding their macroeconomic role.

Our empirical implementation focuses on changes in intermediaries' market values, for which high-frequency data is available. Even though changes in book values are not observable at high frequency, in Appendix A we show that there is a tight link between an intermediary's book value and market value. More importantly, a large fraction of U.S. banks' assets (e.g., trading assets and available-for-sale securities) are reported marked-to-market. Laux and Leuz (2010) estimate that these marked-to-market assets constitute 36% of large banks' assets. As a result of the accounting standards, changes in intermediaries' market values directly affect their book values.

4.1. Event-time analysis

Our main empirical strategy is an event-time study. The analysis is conducted at the constituent level for nonfinancial firms in the S&P 500. We estimate the impact of financial shocks on the market value of nonfinancial firms by estimating

$$\Delta y_{jt} = \alpha_j + \beta \varepsilon_t^{\mathrm{F}} + u_{jt}, \tag{2}$$

where the dependent variable, Δy_{jt}, is the HF log price change of nonfinancial stock j in the 60-minute window around a financial shock; $\varepsilon_t^{\mathrm{F}}$ is the narrow measure of the financial shock; α_j is a cusip fixed effect; and u_{jt} is a random error term. The fixed effect absorbs unobserved effects from time-invariant stock characteristics. The coefficient of interest, β, measures the elasticity of the market value of nonfinancial firms to financial shocks. The identifying assumption we use to interpret these effects as causal is that in the 60-minute window around intermediaries' earnings announcements, changes in the stock prices of intermediaries that release earnings are driven by information contained in these announcements and not by other factors that affect the stock prices of nonfinancial firms in an announcement-time window, contained in u_{jt}. We cluster standard errors two ways to account for correlation within stocks and within periods.

Table 3 reports the main results of estimating the aggregate effects of financial shocks.

Table 3: Effects of Financial Shocks on the Market Value of Nonfinancial Firms

	(1)	(2)	(3)	(4)
	Releasing Intermediaries		**All Intermediaries**	
Fin shock (narrow)	0.291**	0.292**	0.183***	0.189***
	(0.140)	(0.147)	(0.061)	(0.060)
Observations	104,167	104,167	103,591	103,591
R^2	0.014	0.015	0.032	0.034
Macro controls	no	yes	no	yes
Cusip FE	yes	yes	yes	yes
Double-clustered SE	yes	yes	yes	yes

Notes: This table estimates variants of the event-time regression in (2): $\Delta y_{jt} = \alpha_j + \beta\varepsilon_t^{\mathrm{F}} + u_{jt}$, where Δy_{jt} is the HF log price change of a nonfinancial S&P 500 constituent stock j; $\varepsilon_t^{\mathrm{F}}$ is the narrow measure of the HF financial shock; and α_j is a cusip fixed effect. Macro controls include output, employment, and an indicator variable for recession. Columns 3 and 4 replace $\varepsilon_t^{\mathrm{F}}$ with an HF shock constructed using the price changes of all sample intermediaries, as described in the main text, whose estimate is more comparable to heteroskedasticity-based estimates. Standard errors are two-way clustered at shock and cusip level and reported in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

The baseline result in the first column shows that a 1% change in the net worth of financial intermediaries leads to a 0.3% change in the net worth of nonfinancial firms.[6] Controlling for business-cycle variables—output, employment, and a recession indicator—affects neither the estimated elasticity nor the standard errors, as shown in the second column.

Financial news released through the earnings announcements of these granular intermediaries can potentially influence the net worth of other intermediaries that have yet to report earnings; Appendix Figure B.2 shows that shocks to the market value of an earnings-releasing intermediary leads to a 0.2% increase in the market value of other nonreleasing

[6]Re-expressing the effects in terms of earnings surprises, we estimate in Internet Appendix Table E.1 that earnings surprises that are one standard deviation below analysts' expectations lead to a 0.1% decline in the net worth of nonfinancial firms. To put these estimated coefficients into perspective, we note that during September 2008 the market value of financial intermediaries contracted by 10% (or \$.14 trillion) and that of nonfinancial firms in the S&P 500 by 7.8% (or \$.62 trillion). A back-of-the envelope calculation based on our empirical estimate would indicate that 38% of the contraction in the market value of nonfinancial firms during this period could be accounted for by the contraction of the market value in the net worth of financial intermediaries.

intermediaries. In the third and fourth columns of Table 3, we account for these effects and alternatively measure the financial shock based on the price changes of all sample intermediaries (i.e., $\varepsilon_t^{\mathrm{F}} = \sum_{i \in \mathcal{I}_q} \theta_{i,q(t)}(\log P_{i,t+\Delta^+} - \log P_{i,t-\Delta^-})$, where $\mathcal{I}_q$ denotes the set of intermediaries reporting earnings in quarter q). As with the baseline shocks, changes in financial net worth lead to changes in the net worth of nonfinancial firms. The estimated elasticity of 0.2 is slightly smaller than the baseline estimate, which reflects a smaller role of non-releasing intermediaries in the rest of the economy.

Robustness analysis In the Internet Appendix, we conduct a series of analyses to verify the robustness of the findings. First, the effects of financial shocks are robust to the weighting of the dependent variables. Appendix Table F.1 uses as the dependent variable S&P 500 nonfinancial constituents' log changes in net worth weighted by their market values at the beginning of the quarter. The estimated impact, at 0.2, is slightly smaller than the equal-weighted benchmark, which suggests that the financial shocks have a stronger effect on smaller firms. The table also reports the effect on the broad S&P 500 Index, measured through the exchange-traded fund SPDR at high frequency, similar to the baseline estimates in terms of both economic magnitude and statistical significance.

Second, these effects do not depend on the frequency of analysis or the set of nonfinancial firms. Appendix Table F.2 shows that the effects are amplified at daily frequency and are not specific to firms included in the S&P 500 Index but also influence additional indices; these include the S&P SmallCap 600 and Russell 2000. The impact of financial shocks is larger for the smaller and riskier firms included in these indices, which leads us to further study the heterogeneous transmission in Section 5.

Third, Appendix Table F.3 shows that the effects of financial shocks are robust and stronger if we instead use the broad measure of financial shocks, including announcements made outside of trading hours. A related concern is that intermediaries may strategically release worse earnings outside of trading hours. Appendix Figure F.1 plots the realized earnings results against the hours of earnings announcements, and shows no evidence of the strategic timing.

Fourth, Appendix Table F.4 accounts for the systematic comovements between financial and nonfinancial stocks. We estimate the time-varying beta between the S&P 500 Ex-Financial and S&P 500 Financial indices in the month before the financial shock. Then we remove the predicted component of the HF financial shocks attributable to a systemic component and use the residuals as the shock. The estimated elasticity of 0.5 is statistically significant and larger than our baseline estimate, which shows that the effects are not driven by the systemic comovements.

Placebo tests We also conduct two placebo exercises to provide further evidence for our interpretation of the event-time results. The first exercise, shown in Appendix Figure B.3, demonstrates that the HF shocks do not have an effect on the market value of nonfinancial firms during the days before the shock, which suggests that the effects are not driven by pretrends. This figure also shows that the HF shocks do not have an impact on the days after the shocks, which suggests that the information in financial shocks is incorporated in the value of nonfinancial firms on the day of the shock and there are no offsetting forces on consecutive days that revert the impact effects of these shocks.

The second set of exercises shows that the effects we identify for financial shocks are not found if we follow a similar procedure to identify shocks that originate in nonfinancial firms. To conduct this exercise, we follow an HF procedure similar to that developed in Section 3 for financial shocks but focus on the earnings announcements of nonfinancial firms included in the Dow Jones index. Appendix Table B.4b shows the results of estimating the event-time regression but using the shock to nonfinancial firms instead of the financial shock. Results indicate a baseline estimate that is negative, not statistically significant, and unstable across specifications (e.g., has a negative point estimate when we use the narrow version of the shocks but a positive point estimate with a broad version of the shocks). To render the shocks further comparable, Appendix Table B.4c restricts the number of Dow Jones firms used in placebo shocks to equal the number of financial intermediaries included in financial shocks, keeping the top nonfinancial firms by market value. Again, placebo shocks do not display an effect similar to that of financial shocks.[7]

Furthermore, we construct HF placebo shocks for each of the 10 nonfinancial sectors in the S&P 500. As in the procedure for financial shocks, we collect precise dates and times for nonfinancial firms' earnings releases and compute their log price changes in a narrow 60-minute window around the announcement, weighted by their market values. We estimate $\Delta \log y_t^{-s} = \alpha + \beta \varepsilon_t^s + u_{st}$ for each sector $s \in \{$energy, materials, information technology, ...$\}$, where ε_t^s is the placebo shock and y_t^{-s} is the equity index that excludes the placebo shock sector. Appendix Table B.5 reports the estimates, all of which are statistically insignificant; this suggests that the effects we identify in our empirical model are specific to financial intermediaries.

Bond markets Finally, financial shocks also have effects on bond spread. We estimate the magnitude and persistence of the effects using Jordà's 2005 local projections:

$$\Delta_h z_t = c_h + \beta_h \varepsilon_t^{\mathrm{F}} + u_t \tag{3}$$

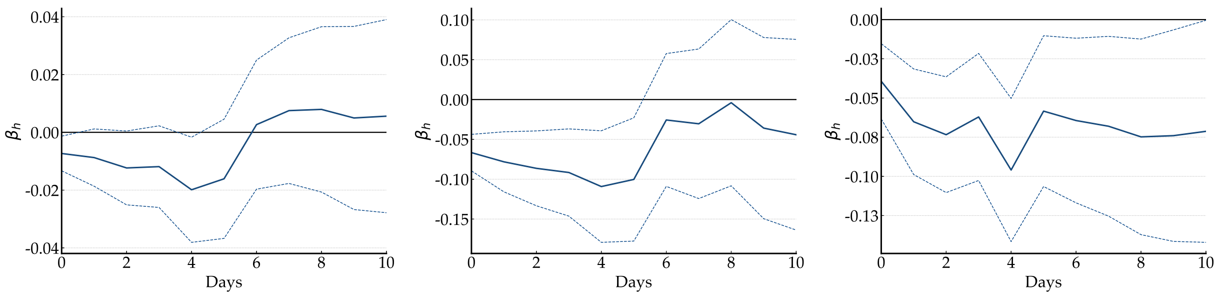
where z_t is the bond spread of interest; $\varepsilon_t^{\mathrm{F}}$ is the broad measure of financial shocks to match the daily frequency of bond indices; and β_h estimates the semielasticity of corporate bonds to financial shocks for horizon h.

Panels (a) and (b) in Figure 1 show that declines in the market value of intermediaries

[7] The disconnect between placebo shocks and the rest of the economy can arise from either a lack of transmission from earnings results to stock prices or a disconnect between nonfinancial firms' net worth and the rest of the economy. Internet Appendix Table E.1 shows that the earnings surprises of placebo Dow Jones firms transmit similarly to their stock prices as do the earnings surprises of financial intermediaries, both with an elasticity of 0.2; this indicates that the differential impacts of financial shocks and placebo shocks arise from their different roles in the economy.

Figure 1: Effects of Financial Shocks on Corporate Bonds

(a) Investment-grade spreads **(b)** High-yield spreads **(c)** Excess bond premium



Notes: The figures show the estimated cumulative responses, β_h, for horizon h from estimating local projections $\Delta_h z_t = c_h + \beta_h \varepsilon_t^{\mathrm{F}} + u_t$. The dependent variable, z_t, is the option-adjusted spreads for the investment-grade U.S. corporate bond index, the option-adjusted spreads for the high-yield U.S. corporate bond index, and the excess bond premium. ε^{F} denotes the broad measure of financial shocks. Dotted lines represent 90% confidence intervals.

lead to higher spreads for firms.[8] Although the benchmark spreads for both investment-grade and high-yield bonds are affected, high-yield bond spreads rise more substantially in response to a negative financial shock: 1% decline in the market value of intermediaries results in 6–10-basis-point higher spreads for high-yield bonds. Panel 1c shows that financial shocks also have an effect on the excess bond premium (Gilchrist and Zakrajšek, 2012), which removes the expected default risk from the bond spread and effectively measures the risk-bearing capacity of the financial sector. The effect is persistent, with 1% decline in the market value of intermediaries resulting in a 4–10-basis-point higher excess bond premium.

We further unpack the effect for different credit ratings in Appendix Figure B.4, which shows that the impact of financial shocks is increasing with a bond's credit risk: The semielasticity of bonds rated CCC or lower is one magnitude larger than that of bonds rated AAA. In addition, the effects are persistent for high-yield bonds.

[8] We measure spreads as the option-adjusted spread (used, for example, by Anderson and Cesa-Bianchi, 2020), defined as the amount by which the government spot curve is shifted to match the present value of discounted cash flows to the corporate bond's price, which incorporates both a maturity adjustment (Gilchrist, Yankov and Zakrajšek, 2009), by computing the spread relative to a risk-free security of matching maturity, and an option adjustment (Duffee, 1998), by removing the price of the embedded option.

Table 4: Effects of Financial Shocks Identified through Heteroskedasticity

	(1)	(2)	(3)	(4)
	Heteroskedasticity-based		**Event-time (All Intermediaries)**	
Baseline	0.360***	0.361***	0.183***	0.189***
SE	(0.028)	(0.028)	(0.061)	(0.060)
95% CI	[0.296, 0.412]	[0.295, 0.412]		
Observations	1,281	1,281	103,591	103,591
Macro controls	no	yes	no	yes

Notes: This table reports the heteroskedasticity-based estimator for β from the bivariate model (4) implemented with an instrumental variable framework. First-stage F-statistics are 423 and 421 for columns 5 and 6, respectively. Standard errors and confidence intervals are computed with stratefied bootstrap, as described in the text. For comparison, event-time estimates in Columns (3) and (4) in Table 3 are repeated. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

4.2. Alternative identification strategies

Heteroskedasticity-based identification A potential concern about the event-time approach is that factors unrelated to the release of earnings of intermediaries may ultimately be related to the stock prices of nonfinancial firms, even within a narrow window around earnings announcements. We allow for this possibility by conducting an alternative estimation using a heteroskedasticity-based identification strategy (Rigobon, 2003; Rigobon and Sack, 2004). This strategy can be conducted even in the presence of common factors that affect the market values of both intermediaries and nonfinancial firms, as long as the variance of intermediaries' stock prices during earnings-announcement event times is larger than in nonevent times, while those of nonfinancial firms are the same during both earning releases of financial intermediaries and nonevent times.

To conduct the estimation based on heteroskedasticity for the same 60-minute event window that matches the frequency from the event-time analysis, we consider the bivariate model

$$\begin{aligned}\Delta\nu_t^{\mathrm{F}} &= \alpha\Delta y_t + \Phi' Z_t + e_t \\ \Delta y_t &= \beta\Delta\nu_t^{\mathrm{F}} + \Gamma' Z_t + u_t,\end{aligned} \tag{4}$$

where $\Delta\nu_t^{\mathrm{F}}$ is the log change in a value-weighted index of intermediaries' stock prices in the 60-minute window around an earnings result announced at time t; Δy_t is the log change in a value-weighted index of nonfinancial firms' stock prices in the same window; and Z_t is a vector of control variables. The coefficient of interest, β, estimates the impact of changes in financial net worth on nonfinancial net worth.

Unlike the event-time analysis used to estimate (2), the heteroskedasticity-based approach uses data from both times in which intermediaries release their announcements and times in which they do not. We define events as the times in which the financial intermediaries in our sample report earnings and compare with nonevents, defined as the times in which nonfinancial firms in the S&P 500 releases earnings. To isolate the effects of financial intermediaries, we exclude from the set of nonevents nonfinancial firms' earnings that are within 2 days of a financial earnings event.

We estimate the coefficient of interest, β, following the instrumental variable implementation developed by Rigobon and Sack (2004). Standard errors and confidence intervals use the bootstrap procedure developed by Hébert and Schreger (2017) to correct for small-sample bias.[9]

Table 4 shows the results from estimating the effects of financial shocks on nonfinancial firms using a heteroskedasticity-based approach. The elasticity is estimated to be 0.4 and statistically significant. To compare estimates from the event-time and heteroskedasticity-based approaches, we include in the third and fourth columns the event-time regressions

[9]We use 1,000 repetitions of a stratified bootstrap, resampling with replacement from events and nonevents.

with financial shocks based on the price changes of all sample intermediaries and not just the reporting intermediary. A full comparison of the two identification strategies, for different weightings and frequency, is reported in Appendix Table B.6. Although weaker assumptions are imposed, the effects of financial shocks identified through heteroskedasticity are stronger than the event-study estimates, which suggests that our baseline results based on event-time analysis provide a lower bound on the impact of financial shocks.

Granular instrumental variable The effects we document of large financial intermediaries on the rest of economy motivate a natural implementation of the granular-instrumental-variable strategy developed in Gabaix and Koijen (2020). Therefore, we conduct an alternative identification based on a granular instrumental variable (GIV). Two assumptions are necessary for the GIV to be a valid instrument. Exogeneity requires that even though all financial earnings may contain information about the macroeconomy, large intermediaries experience idiosyncratic shocks to their net worth that are uncorrelated macro factors. Relevance requires that idiosyncratic shocks to large intermediaries affect the net worth of all financial firms, as we verify in Figure B.2.

We consider the model

$$\Delta y_t = \beta \Delta \nu_t + u_t \tag{5}$$

where y_t denotes nonfinancial firms' net worth and $\nu_t = \sum_i \nu_{it}$ denotes the financial sector's net worth. The coefficient of interest is β, which measures the effects of financial net worth on nonfinancial net worth. An intermediary's net worth ν_{it} consists of an aggregate factor, η_t, and an idiosyncratic factor, ε_{it}:

$$\Delta \nu_{it} = \eta_t + \varepsilon_{it}. \tag{6}$$

Unlike the baseline HF shocks that include only large financial intermediaries, in constructing the GIV we include all intermediaries in the S&P 500 regardless of size. Following the notation of Gabaix and Koijen (2020), we use "S" to denote size-weighted and "E" to denote equal-weighted. The GIV is defined as

$$z_t \equiv \sum_i s_{it}\Delta\nu_{it} - \sum_i \frac{1}{N}\Delta\nu_{it} = \sum_i s_{it}\Delta\varepsilon_{it} - \sum_i \frac{1}{N_t}\Delta\varepsilon_{it} \equiv \Delta\varepsilon_{St} - \Delta\varepsilon_{Et}, \tag{7}$$

where s_{it} is the size weight, measured as the net worth of intermediary i as a fraction of the total net worth of S&P 500 intermediaries, and $1/N_t$ is the equal weight, with N_t denoting the number of financial intermediaries in the S&P 500 Index. The GIV is the time-varying difference between size-weighted and equal-weighted changes in intermediaries' market values, and can be interpreted as idiosyncratic shocks to large intermediaries.[10]

Table B.7 reports the estimated impact of financial firms on nonfinancial firms. We measure financial and nonfinancial net worth using the S&P 500 Financials Index and S&P 500 Ex-Financials Index, respectively. In Column (4) we focus on days on which granular financial intermediaries included in the baseline HF shocks report earnings to ensure the exogeneity assumption of the GIV. Using the GIV as an instrument,[11] we estimate that a 1% decline in the market value of financial firms leads to a 0.3% decline in the market value of nonfinancial firms. Both the magnitude and the statistical significance of the estimates under the GIV strategy are in line with those from our baseline event-study regressions.

[10] An important requirement for the GIV is that there indeed exist large intermediaries in our sample. To verify this, we plot the market capitalization of financial firms in the S&P 500. Figure B.5 shows a distribution that is visibly right-skewed. We then perform a formal test for the fat tail by fitting a Pareto Type I distribution and estimating the Pareto rate to be 0.2, which is indeed below the threshold Pareto rate of 2 for a fat-tailed distribution.

[11] We estimate β through a two-stage procedure. The first stage regresses changes in the financial sector's net worth ($\Delta\nu_t$) on the GIV (z_t). The predicted value of $\Delta\hat{\nu}_t$ captures changes that are driven by granular intermediaries. Then, the second stage estimates the coefficient of interest β from $\Delta y_t = \beta\Delta\hat{\nu}_t + u_t$.

5. Inspecting the Transmission Mechanism

How do financial shocks transmit to the rest of the economy? This section provides supportive evidence that the transmission of financial shocks is linked to intermediaries' net worth and to nonfinancial firms' financial positions.

5.1. The role of intermediaries' net worth

We provide three pieces of evidence to support the role of intermediaries' net worth in the transmission of financial shocks: One studies how the effect of financial shocks depends on aggregate net worth; another conducts a decomposition of the effects of financial shocks; and a third exploits within-firm variation of bond spreads.

5.1.1. Aggregate state dependency

Empirical evidence on the role of financial intermediaries in the macroeconomy often comes from analyzing episodes of financial crises (Reinhart and Rogoff, 2009b; Chodorow-Reich, 2014; Huber, 2018). Motivated by this evidence, we begin by investigating the importance of aggregate conditions in the transmission of financial shocks. We decompose the effects of financial shocks on nonfinancial firms by estimating

$$\Delta y_{jt} = \alpha_j + \beta_w \cdot \varepsilon_t^{\mathrm{F}} \mathbb{1}(N_t > \bar{N}_t) + \beta_u \cdot \varepsilon_t^{\mathrm{F}} \mathbb{1}(N_t < \bar{N}_t) + \Gamma' Z_t + u_{jt}, \tag{8}$$

where $\varepsilon_t^{\mathrm{F}} \mathbb{1}(N_t < \bar{N}_t)$ denotes financial shocks on dates on which the financial system is undercapitalized (i.e., when the market value of intermediaries' net worth is below its HP trend $\bar{\varepsilon}_t$) and Z_t is a vector of macro controls and their interaction with financial shocks. The coefficients of interest, β_w and β_u, estimate the effect of financial shocks on the rest of the economy when the financial system is well and undercapitalized, respectively.

Table 5 displays the results, which show that the impact of financial shocks is driven

Table 5: Aggregate State Dependency

	(1)	(2)	(3)
	S&P500 constituents		
Fin shock	0.292**		
	(0.139)		
Well capitalized		0.142	0.102
		(0.183)	(0.233)
Undercapitalized		0.331**	0.295**
		(0.161)	(0.142)
Adjusted R^2	0.009	0.010	0.015
Observations	103,792	103,792	103,792
Macro controls	no	no	yes
Cusip FE	yes	yes	yes
Double-clustred SE	yes	yes	yes

Notes: This table estimates $\Delta y_{jt} = \alpha_j + \beta_w \varepsilon_t^{\mathrm{F}} \mathbb{1}(N_t > \bar{N}_t) + \beta_u \varepsilon_t^{\mathrm{F}} \mathbb{1}(N_t^{\mathrm{F}} < \bar{N}_t) + \Gamma' Z_t + u_{jt}$, where $\varepsilon_t^{\mathrm{F}}$ is the narrow HF shock; $\mathbb{1}(N_t^N < \bar{\varepsilon}_t)$ is an indicator variable for dates on which the market value of intermediaries' net worth is below its HP trend; and Z_t is a vector of macro controls that include output, payrolls, a recession indicator, and their interaction terms with the financial shocks. Standard errors are two-way clustered at shock and firm level and reported in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

by their effects on dates on which the financial system is undercapitalized. When the financial system is well capitalized, the effects of financial shocks on nonfinancial firms are economically small and statistically insignificant. This state dependency indicates that a key component driving the aggregate effects of intermediaries in the economy is the overall condition of the financial system (as stressed, for instance, by Gertler and Kiyotaki, 2010; Brunnermeier and Sannikov, 2014).

5.1.2. A decomposition of shocks

Financial earnings may convey information that is not confined to the financial sector. Similar to the Fed's "information effect" that Romer and Romer (2000) and Nakamura and Steinsson (2018b) document in the context of monetary-policy shocks, the performance of financial intermediaries may reveal information about the general health of the economy, which has a direct impact on investment opportunities for nonfinancial firms. Motivated by this, we now decompose the information contained in the HF shocks into information about intermediaries' net worth and information about nonfinancial firms' investment opportunities.

Our strategy in disentangling these two channels exploits the comovements of interest rates and stock prices around earnings announcements, in the spirit of the approaches developed by Cieslak and Schrimpf (2019) and Jarociński and Karadi (2020) to decompose monetary shocks into a monetary-policy shock and a central-bank-information shock. The key idea of our identification strategy is that information about intermediaries' net worth and information about nonfinancial firms' investment opportunities should have different effects on nonfinancial firms' excess bond premia (EBP, in Gilchrist and Zakrajšek, 2012): On the one hand, positive news about intermediaries' net worth is associated with an increase in lenders' supply of funds, and should lead to a decline of the EBP. On the other hand, positive news about nonfinancial firms' investment opportunities should be associated with an increase in borrowers' demand for funds, and lead to an increase in the EBP. We formalize this idea in Appendix Section A.5. Using this model, in Figure A.3 we illustrate the opposite directions in which borrowing rates react following shocks in these two channels.

Based on these, we decompose the financial shocks based on their correlation with the EBP, as

$$\boldsymbol{\varepsilon}^{\mathrm{F}} = \boldsymbol{\varepsilon}_{\text{lender}} + \boldsymbol{\varepsilon}_{\text{borrower}}, \tag{9}$$

where bold letters denote vectors of length T. We impose sign restrictions whereby $\varepsilon_{\text{lender}}$ is negatively correlated with changes in interest rates, Δy, and $\varepsilon_{\text{borrower}}$ is positively correlated with interest rates. That is, the decomposition satisfies

$$\begin{bmatrix} \boldsymbol{\varepsilon}^{\mathrm{F}} & \Delta \boldsymbol{y} \end{bmatrix} = \begin{bmatrix} \boldsymbol{\varepsilon}_{\mathrm{lender}} & \boldsymbol{\varepsilon}_{\mathrm{borrower}} \end{bmatrix} \begin{bmatrix} 1 & - \\ 1 & + \end{bmatrix} \tag{10}$$

$$\boldsymbol{\varepsilon}_{\mathrm{lender}}^{'} \boldsymbol{\varepsilon}_{\mathrm{borrower}} = 0 \tag{11}$$

$$\mathrm{var}(\varepsilon_{\mathrm{lender}}) + \mathrm{var}(\varepsilon_{\mathrm{borrower}}) = \mathrm{var}(\varepsilon^{\mathrm{F}}). \tag{12}$$

Two assumptions are embedded in the decomposition. First, in the narrow window around a financial intermediary's earnings announcement, its stock price is driven by two shocks—one that conveys information about lenders' net worth and one that conveys information about borrowers—and by no other shocks. Second, sign restrictions on the comovements between financial shock price movements and interest rates are satisfied.[12] We implement this method using EBP daily data from Gilchrist *et al.* (2021) (described in more detail Section 2). To match the daily frequency of the EBP, we use the broad measure of HF financial shocks in the decomposition. We then estimate an event-time regression with the decomposed shocks to examine the importance of each channel:

$$\Delta y_t = \alpha + \beta_{\mathrm{lender}} \varepsilon_{\mathrm{lender}} + \beta_{\mathrm{borrower}} \varepsilon_{\mathrm{borrower}} + u_t, \tag{13}$$

where the dependent variable is the daily changes in the S&P 500 Ex-Financials Index.

Table 6 reports the decomposed effects of the lenders' and borrowers' information channels, along with the total effects of financial shocks. Under the decomposition, the lender

[12] We perform the decomposition using Givens rotation. See Kilian and Lütkepohl (2017) and Jarocinski (2020) for details on estimating structural VAR under sign restrictions with Givens rotation matrix. The decomposition in (10) is set identified. Following Jarocinski (2020), we select the unique rotation such that the share of variance explained by the lenders' financing shock is equivalent to the variance share from the "poor man's sign restrictions" approach—that is, $\mathrm{var}(\varepsilon_{\mathrm{lender}})/\mathrm{var}(\varepsilon^{\mathrm{F}}) = 0.38$. Under the alternative approach, a shock is classified as either a lenders' shock or a borrowers' information shock. It is classified as a lenders' shock if it is negatively correlated with the excess bond premium and a borrowers' information shock otherwise.

channel has an effect on nonfinancial firms similar to or larger than that of baseline financial shocks. This demonstrates that intermediaries' net worth is an important channel through which financial shocks affect the rest of the economy. Columns (1) and (2) show that the borrowers' information channel is also positive, albeit not statistically significant in the baseline model, which suggests that information about nonfinancial firms' investment opportunities potentially contained in intermediaries' earning releases do not drive the effects of financial shocks estimated in the baseline empirical model. Columns (3) to (6) show that borrowers' information channel is stronger for small firms, as measured by returns of the S&P SmallCap 600 and Russell 2000 indices, suggesting that intermediaries' earnings might contain more information on the investment opportunities of these firms.

Table 6: Decomposed Effects of Financial Shocks

	(1)	(2)	(3)	(4)	(5)	(6)
	SP500 Ex-Fin		**SmallCap**		**Russell**	
Fin shock	0.910***		1.287***		1.385***	
	(0.228)		(0.282)		(0.293)	
Lenders' channel		1.306***		1.562***		1.659***
		(0.341)		(0.412)		(0.420)
Borrowers' channel		0.382		0.919*		1.020*
		(0.431)		(0.541)		(0.565)
R^2	0.062	0.078	0.073	0.077	0.077	0.081
Observations	344	344	344	344	344	344
Robust SE	yes	yes	yes	yes	yes	yes

Notes: This table reports estimates from $\Delta y_t = \alpha + \beta_{\text{lender}}\varepsilon_{\text{lender}} + \beta_{\text{borrower}}\varepsilon_{\text{borrower}} + u_t$, where $\varepsilon_{\text{lender}}$ and $\varepsilon_{\text{borrower}}$ are decomposed as described in the main text using sign resitrctions. Heteroskedasticity-robust standard errors are reported in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

5.1.3. Within-firm variation

Finally, we provide supportive evidence on intermediaries' net worth channel by exploiting the variation in individual bond prices within a firm around financial shocks. The idea of this exercise is to compare the prices of bonds issued by the same firm and with similar characteristics but held by different financial intermediaries.

To do so, we collect additional bond-level data, focusing on the constituents of ICE BofA's CCC and Lower Corporate Index, in which the impact effect of financial shocks is the strongest. For each of these bonds, we have information on bond option-adjusted spread, together with various characteristics—index weightings, ratings, residual maturities, average trailing 30-day spreads, and month-to-date changes in spreads. The index consists of 3,937 bonds. Table B.2 presents descriptive statistics for the individual bond spread together with those for days with and without the earning releases of financial intermediaries, which exhibit similar descriptive statistics. To further control for a bond's liquidity, we construct a proxy for bid-ask spread following Gilchrist, Wei, Yue and Zakrajšek (2020) and using transaction-level data from TRACE.[13]

We also gathered data from Bloomberg on the share of bonds (at cusip level) held by each reporting financial institution.[14] This information is available at quarterly frequency, so we collect data for each financial shock and for each outstanding bond in the quarter before the shock. To study the within-firm heterogeneous impacts of financial shocks, we restrict the sample of bonds to those issued by firms with at least 10 bonds outstanding. Table B.3 reports descriptive statistics for bond holdings. On average, the financial intermediaries in our sample represent 6% of the total outstanding amount. These holdings exhibit heterogeneity, with a standard deviation of 12%, which can be used to study the differential effects of bonds that are more or less strongly held by institutions releasing earnings reports.

[13] We first remove reporting errors in TRACE data using the Dick-Nielsen (2014) filter. For a given day, we define, as in Gilchrist *et al.* (2020), a bond's bid price as the average price of the bond sold by a dealer to a customer; a bond's ask price as the average price of the bond bought from a dealer by a customer; and a bond's mid-price as the average inter-dealer price. Then we measure the bid-ask spread as the difference between a bond's bid and ask prices, divided by the mid-price.

[14] Bloomberg's information on shareholder and debtholder ownership combines a number of sources including issuers, fund companies, custodians, stock exchanges, public share registries, 13Fs, and individual stakeholder filings. Its data fact sheet reports coverage of 527,000 fixed income securities: 70,000 unique fund portfolios, 93,000 institutional investors, and 444,000 insiders from 179 countries.

With the additional bond-level data, we study within-firm variation by estimating the local projection

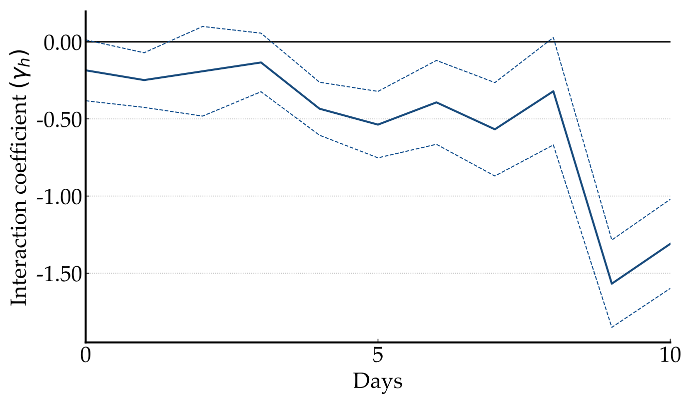
$$\Delta_h z_{k(j)it} = \alpha_{jt} + \gamma_h \theta_{k(j)it} \varepsilon_t^{\mathrm{F}} + \Gamma' Z_{jt} + u_{jith}, \tag{14}$$

where $\Delta z_{k(j)it}$ is cumulative changes in bond k's option-adjusted spreads over h days; $\varepsilon_t^{\mathrm{F}}$ is the narrow HF financial shock around intermediary i's earnings announcement; $\theta_{k(j)it}$ is the share of bond k issued by firm j held by intermediary i in the quarter proceeding its earnings announcement in period t; α_{jt} is a firm-by-shock fixed effect; and Z_{jt} is a vector of bond controls that includes bond holdings $\theta_{k(j)it}$, a categorical variable for bond ratings, remaining maturity, trailing average, and month-to-date changes in spreads. We estimate (14) by focusing on the subset of firms with more than 10 bonds outstanding—which allows us to exploit the within-firm variation in bonds' exposure to intermediaries—and on bonds rated CCC or worse—which, as shown above, are most exposed to financial shocks; this yields a sample of 172 bonds issued by 21 firms. Standard errors are double-clustered by shock and firm.

The firm-by-shock fixed effect absorbs the average response of a firm's bonds to a given shock. Therefore, the coefficient of interest in (14) is γ_h, which measures how the semielasticity of a bond's spreads to a financial shock depends on the holdings of intermediaries who release earnings reports during the shock. Under the hypothesis that the effects of financial shocks on nonfinancial firms are driven by an information channel, the coefficient γ_h for each horizon h should not be different from zero, because bonds issued by the same firm and with similar characteristics should be similarly affected by the information.

Figure 2 reports that the estimated coefficient for γ_h is negative and statistically significant, which indicates that within a firm, bonds that have more substantial holdings by an intermediary releasing an earnings report have a larger sensitivity in absolute value to fi-

Figure 2: Within-firm Variation



Notes: This figure reports estimates of γ_h from $\Delta_h z_{k(j)it} = \alpha_{jt} + \gamma_h \theta_{k(j)it} \varepsilon_t^{\mathrm{F}} + \Gamma' Z_{jt} + u_{jith}$, where $\Delta_h z_{k(j)it}$ is cumulative changes in bond option-adjusted spreads; $\varepsilon_t^{\mathrm{F}}$ is the narrow HF shock; $\theta_{k(j)it}$ is the holdings of bond k by intermediary i; α_{jt} is a firm-by-shock fixed effect; and Z_{jt} is a vector of bond controls that includes bond holdings $\theta_{k(j)it}$, a categorical variable for bond ratings, remaining maturity, average spreads in the previous 30 days, and month-to-date changes in spreads. Standard errors are two-way clustered at shock and firm level. Dotted lines represent 90% confidence intervals.

nancial shocks. Appendix Figure F.2 additionally controls for bond liquidity, and also shows a significant marginal effect driven by connection to the earnings-reporting intermediary.[15] These results are consistent with financial shocks' having an effect on the security prices of nonfinancial firms through financial intermediaries' net worth, which under short-term trading frictions can translate into different prices for bonds with similar risk (see Morelli, Ottonello and Perez, 2021).

5.2. The role of firms' financial positions

We also provide evidence that nonfinancial firms' financial positions play an important role in our results, as argued in the literature on models of firms' financial frictions and financial shocks (see, for, example, Khan and Thomas, 2013; Jermann and Quadrini, 2012; Christiano *et al.*, 2014). We do so by documenting how nonfinancial firms' financial positions (leverage,

[15]The transaction-level TRACE data used to construct the bid-ask spread is only available from July 2002, which substantially restricts the sample. Therefore, we keep the liquidity control as a robustness test rather than including it in the baseline.

credit risk, and liquidity) affect their responses to financial shocks.[16] In particular, we estimate the model

$$\Delta y_{jt} = \alpha_j + \alpha_{sq} + \beta\varepsilon_t^{\mathrm{F}} + \gamma\varepsilon_t^{\mathrm{F}} x_{jt} + \Gamma' Z_{jt} + u_{jt}, \tag{15}$$

where the dependent variable, Δy_{jt}—as in previous sections—is the log changes in nonfinancial firms' stock prices in the 60-minute window around a financial shock; $\varepsilon_t^{\mathrm{F}}$ is the narrow HF financial shock; x_{jt} is an indicator variable for firms with high leverage, investment-grade credit rating, or high liquidity; α_j is a firm fixed effect; α_{sq} is a sector-by-quarter fixed effect; and Z_{jt} is a vector of firm controls: the firm characteristic x_{jt}, lagged sales growth, lagged size, lagged current assets as a share of total assets, and an indicator for fiscal quarter. The coefficient of interest, γ, measures how the effect of financial shocks depends on a firm's financial position. For this analysis, we expand the sample from S&P 500 nonfinancial constituents to all publicly traded nonfinancial firms in the U.S., which is matched with Compustat firm characteristics. Standard errors are two-way clustered by firm and shock.

Table 7 reports the results from estimating (15), which show that firms' financial positions tend to affect their responses to financial shocks. Credit risk and liquidity are important sources of heterogeneity for the transmission of financial shocks: Firms with lower credit ratings and lower liquidity are those most affected by financial shocks. We interpret this evidence as suggesting that firms' financial positions (and, potentially, financial heterogeneity) matter in the transmission of financial shocks.[17]

[16] A similar strategy has been used in the literature that analyzes the heterogeneous effects of monetary policy shocks on nonfinancial firms (Ottonello and Winberry, 2020; Anderson and Cesa-Bianchi, 2020; Jeenas, 2019).

[17] It is worth highlighting the fact that firms' heterogeneity in the response to financial shocks differs from financial heterogeneity in response to the monetary-policy shocks documented in previous literature. To facilitate this comparison, Appendix Table C.1 reports the heterogeneous responses of firms in our sample for high-frequency monetary policy shocks, based on changes in fed funds futures in a 60-minute window around an FOMC announcement, as in Gorodnichenko and Weber (2016). Consistent with previous studies (e.g., Ottonello and Winberry, 2020), firms with higher credit ratings are more responsive to monetary policy; this is in contrast to firms with lower credit ratings' being the most responsive to financial shocks.

Table 7: Heterogeneous Responses by Firms

	(1) **Average**	(2) **Leverage** (High)	(3) **Credit Ratings** (Invt Grade)	(4) **Liquidity** (Liquid)
Fin shock	0.264**	0.252**	0.330**	0.283**
	(0.109)	(0.108)	(0.142)	(0.109)
Fin shock × Characteristic		0.024	-0.075*	-0.038**
		(0.018)	(0.043)	(0.015)
Adjusted R^2	0.023	0.023	0.039	0.023
Observations	598,572	598,572	162,267	598,530
Firm controls	no	yes	yes	yes
Quarter-sector FE	yes	yes	yes	yes
Double-clustered SE	yes	yes	yes	yes

Notes: This table estimates $\Delta y_{jt} = \alpha_j + \alpha_{sq} + \beta \varepsilon_t^{\mathrm{F}} + \gamma \mathbb{1}_{x_{jt}} \varepsilon_t^{\mathrm{F}} + \Gamma' Z_{jt} + u_{jt}$, where $\varepsilon_t^{\mathrm{F}}$ is the narrow HF shock, $\mathbb{1}_{x_{jt}}$ is an indicator variable for firms with high leverage, investment-grade credit rating, or high liquidity; α_j is a firm fixed effect; α_{st} is a sector-by-quarter fixed effect; and Z_{jt} is a vector of firm controls: the firm characteristic $\mathbb{1}_{x_{jt}}$, lagged sales growth, lagged size, lagged current assets as a share of total assets, and an indicator for fiscal quarter. Standard errors are two-way clustered at shock and firm level and reported in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

6. Concluding Remarks

In this paper, we propose a new measure of financial shocks based on HF changes in the market value around intermediaries' earnings announcements. We then exploit the "granularity" of financial shocks, stemming from the fact that U.S. publicly traded financial intermediaries have considerable size, to study the effects of financial shocks on the aggregate economy. We document intermediaries' substantial effects on the market value and borrowing costs of nonfinancial firms. The effects are stronger for firms with high default risk and low liquidity levels and when the financial system is undercapitalized.

The HF financial shocks developed in the paper can be used directly by researchers conducting empirical research on macroeconomics, similar to the large body of evidence developed using HF monetary-policy shocks. Our empirical findings on the effect of intermediaries on the aggregate economy can also be useful when combined with macrofinance models aimed at understanding the role of financial frictions in determining the aggregate transmission of shocks. We leave the combination of models with these empirical estimates for future research.

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Appendices

A. An Illustrative Theoretical Framework

In this section, we consider the model that motivates our empirical analysis. We use the model to show how our empirical analysis can inform the degree of financial frictions faced by intermediaries, which ultimately govern their role in the macroeconomy. We also use the model to further discuss the identifying assumptions in our empirical analysis.

A.1. Environment

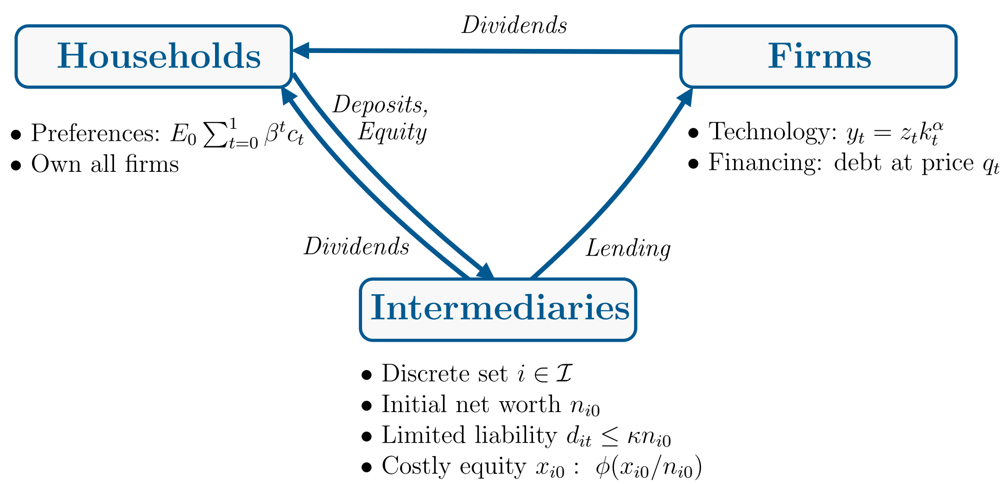
There are two periods, $t = 0, 1$, and two goods: final and capital goods. The economy is populated by a unit mass of identical households and nonfinancial firms and a discrete set of intermediaries indexed by $i \in \mathcal{I}$. Figure A.1 summarizes the model economy.

Households have preferences over consumption given by $c_0 + \beta \mathbb{E}_0 c_1$, where c_t is the consumption of final goods in period t and $\beta \in (0, 1)$ is a subjective discount factor. Households start with an initial endowment of final goods of y_0.

Nonfinancial firms have access to a technology to produce final goods in period 1 using capital input: $y_t = z_t k_t^{\alpha}$, where z_t is an aggregate productivity shock with a bounded support, and to a linear technology to accumulate capital goods out of the final good. Capital fully depreciates after production. Firms cannot raise equity and can only finance their investment by borrowing from financial intermediaries, in the amount b_1 and at the price q_0.

Financial intermediaries are firms owned by households, with an initial endowment of final goods or net worth n_{i0}. They specialize in lending to nonfinancial firms. To finance these loans, intermediaries can also raise external finance from households in the form of deposits, d_{i1}, and equity, x_{i0}, both of which are subject to frictions, modeled following the literature of frictional financial intermediaries (e.g., Gertler and Kiyotaki, 2010; Morelli *et al.*, 2021). On the deposit side, intermediaries face limited liability constraints, which link their deposits to their net worth: $d_{i1} \leq \kappa n_{i0}$, with $\kappa \geq 0$. On the equity side, intermediaries face a cost to raise equity $\phi\left(\frac{x_{i0}}{n_{i0}}\right)$. As in the quantitative corporate finance literature (e.g., Gomes, 2001; Hennessy and Whited, 2007), these costs are designed to capture flotation costs, adverse-selection premia, and other costs associated with raising external finance. The parameter $\phi \geq 0$ governs the degree of intermediaries' frictions to raise external finance and is a key object in our analysis. The case of $\phi = 0$ corresponds to a frictionless case that is isomorphic to an economy in which households directly finance firms.

Figure A.1: Model Economy



A.2. Optimization

Households In period 0, after perceiving their initial endowment and the net transfers from their initial ownership of nonfinancial firms and intermediaries, households choose their investments in financial securities: deposits on financial intermediaries, d_1, and shares of nonfinancial firms and intermediaries, a_{f1} and a_{i1}. Households' problem is then given by

$$\begin{aligned}
\max_{d_{i1},a_{f1},a_{i1}} \; & c_0 + \beta \mathbb{E}_0 c_1 && (16)\\
\text{s.t. } & c_0 + p_{f0}a_1 + \sum_{i\in\mathcal{I}} p_{i0}a_{i1} + d_1 = \; y_0 + \pi_{f0} + p_{f0} + \sum_{i\in\mathcal{I}}(\pi_{i0} + p_{i0})\\
& c_1 = \; \pi_{f1}a_1 + \sum_{i\in\mathcal{I}} a_{i1}\pi_{i1} + R_d d_1,
\end{aligned}$$

where households' initial shares of nonfinancial firms and financial intermediaries have been normalized to one; π_{ft} and π_{it} denote the net transfers from nonfinancial firms and intermediary i to households in period t; p_{f0} and p_{i0} denote the price of shares of nonfinancial firms and financial intermediary i in period 0; and R_d denotes the gross interest rate on deposits. Households' optimal choice of financial securities implies that

$$R_d = \frac{1}{\beta}, \qquad p_{f0} = \beta\mathbb{E}_0\pi_{f1}, \qquad p_{i0} = \beta\mathbb{E}_0\pi_{i1}, \tag{17}$$

which determine the equilibrium deposit rate and share prices.

Nonfinancial firms In period 0, nonfinancial firms choose the capital to produce in the following period, k_1. Their problem is given by

$$\begin{aligned}
\max_{k_1\geq 0, b_1, \pi_{f0}\geq 0} \; & \pi_{f0} + \beta\mathbb{E}_0\pi_{f1} && (18)\\
\text{s.t. } \pi_{f0} = \; & q_0 b_1 - k_1\\
\pi_{f1} = \; & z_1 k_1^{\alpha} - b_1,
\end{aligned}$$

where b_1 denotes nonfinancial firms' borrowing from financial intermediaries at the price q_0. Nonfinancial firms' choice of capital is characterized by the Euler equation

$$\frac{1}{q_0} = \mathbb{E}_0 z_1 \alpha k_1^{\alpha-1}, \tag{19}$$

which equates the marginal cost of capital—given by the interest rate on borrowing $\frac{1}{q_0}$, because borrowing is the marginal source of financing—to its expected marginal benefit (because of the assumed properties for the production technology, the nonnegative dividend constraint is always binding).

Financial intermediaries Given its initial net worth n_{i0}, the problem of financial intermediary i is given by

$$\begin{aligned} \max_{x_{i0}, b_{i1}} \ & \pi_{i0} + \beta \pi_{i1} \\ \text{s.t. } \ \pi_{i0} =& \ -x_{i0} \left(1 + \mathbb{1}_{\{x_{i0}>0\}} \phi \left(\frac{x_{i0}}{n_{i0}}\right)\right), \\ \pi_{i1} =& \ b_{i1} - R_d d_{i1}, \\ q_0 b_{i1} =& \ n_{i0} + x_{i0} + d_{i1}, \\ d_{i1} \leq& \ \kappa n_{i0}, \end{aligned} \tag{20}$$

where b_{i1} is the lending by intermediary i to nonfinancial firms. Intermediaries' problem has no uncertainty because, for simplicity, debt is assumed to be risk free. In an interior solution with $x_{i0} > 0$, intermediaries' optimal allocation is characterized by

$$1 + 2\phi \left(\frac{x_{i0}}{n_{i0}}\right) = \beta R_d + \mu_i \tag{21}$$

$$\beta R_d + \mu_i = \beta \frac{1}{q_0}, \tag{22}$$

with complementary slackness condition

$$(d_{i1} - \kappa n_{i0})\mu_i = 0, \tag{23}$$

where μ_i denotes the Lagrange multiplier associated with the limited liability constraint of intermediary i. Equation (21) implies that intermediaries equate the marginal costs of the two sources of financing: the marginal cost of raising equity with the shadow marginal cost of deposits. In addition, Equation (22) implies that intermediaries equate the marginal cost of external finance with the return on lending. Note that (21) and (22) imply that when the rate on lending exceeds the deposit rate ($\frac{1}{q_0} > R_d$), limited liability constraints bind ($\mu_i > 0$ for all i) and all intermediaries raise the same external finance relative to their net worth $\chi_0 \equiv \frac{x_{i0}}{n_{i0}}$.

A.3. Equilibrium

To define the equilibrium, we normalize the total mass of shares of nonfinancial firms and each financial intermediary to one. The equilibrium in this economy is then defined as follows:

***Definition* 1.** *Given intermediaries' initial net worth* $(n_{i0})_{i\in\mathcal{I}}$ *and nonfinancial firms' productivity process* $\{z_0, z_1\}$*, an equilibrium is a set of state-contingent households' allocations* $\{c_0, c_1, d_1, a_{f1}, (a_{i1})_{i\in\mathcal{I}}\}$*; nonfinancial firms' allocations* $\{\pi_{f0}, \pi_{f1}, b_1, k_1\}$*; financial intermediaries' allocations* $(\pi_{i0}, \pi_{i1}, d_{i0}, x_{i0}, b_{i1})_{i\in\mathcal{I}}$*; and prices* $\{q_0, p_{f0}, p_{i0}\}$ *such that*

i. Given prices, households' allocations solve (16)*; nonfinancial firms' allocations solve* (18)*; and financial intermediaries' allocations solve* (20)*.*

ii. Asset markets clear—i.e., $b_1 = \sum_{i\in\mathcal{I}} b_{i1}$*,* $d_1 = \sum_{i\in\mathcal{I}} d_{i1}$*,* $a_{f1} = 1$*, and* $a_{i1} = 1$ *for all* i*.*

We represent the equilibrium of the model using a demand-supply-of-funds scheme (similar to that developed by Morelli *et al.*, 2021). On the side of intermediaries, focusing on the equilibrium in which their limited liability constraints bind, by integrating intermediaries' flow-of-funds constraints and imposing market clearing for the debt market, we obtain a relationship between capital k_1 and interest rates $\frac{1}{q_0}$ that we label the *aggregate supply of funds*:

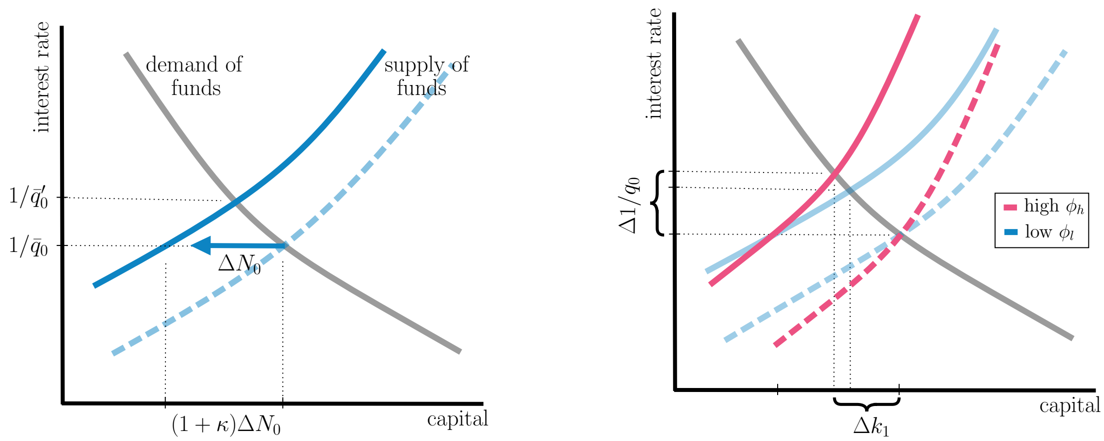
$$\mathcal{K}^s(q_0, N_0, \phi) = N_0(1 + \kappa + \mathcal{X}(q_0, \phi)), \tag{24}$$

where $\mathcal{K}^s(q_0, N_0, \phi) = q_0 \sum_{i \in \mathcal{I}} b_{i0}$; $N_0 = \sum_{i \in \mathcal{I}} n_{i0}$ denotes aggregate net worth; and $\mathcal{X}(q_0, \phi) = \frac{1}{2\phi}\left(\beta \frac{1}{q_0} - 1\right)$. The relationship between the supply of funds and interest rates is upward sloping for $\phi > 0$ (i.e., $\frac{\partial \mathcal{K}^s(q_0, N_0, \phi)}{\partial(1/q_0)} > 0$) because, in this case, intermediaries face an upward-sloping cost to raise external finance (governed by ϕ), which implies that to supply more funds, the returns on lending must be larger. On the side of firms, the Euler equation for capital (19) implies a relationship between capital and interest rates, which we label the *aggregate demand of funds*: $\mathcal{K}^d(q_0) = (q_0 \mathbb{E}_0 z_1 \alpha)^{\frac{1}{1-\alpha}}$. This relationship between the demand of funds and interest rates is downward sloping (i.e., $\frac{\partial \mathcal{K}^d(q_0)}{\partial(1/q_0)} < 0$), which reflects the fact that lower borrowing costs decrease the marginal cost of capital and are associated with higher investment by firms. Figure A.2a represents the equilibrium capital and interest rates as the intersection between the aggregate supply and demand of funds.

A.4. The real effects of financial shocks: Model and empirical analysis

Effects in the model Consider now a "financial shock": an unexpected change in the initial idiosyncratic net worth of some intermediary $\iota \in \mathcal{I}$. Since each intermediary has a mass of net worth, the change in some intermediary's net worth leads to a change in the initial aggregate net worth (i.e., $\frac{\partial N_0}{\partial n_{\iota 0}} > 0$); this is the assumption we refer to in the empirical analysis as "granularity." Given that the model features aggregation across intermediaries, we can analyze the effect of this idiosyncratic shock by analyzing the effect of a change in the aggregate net worth N_0.

Figure A.2: The Aggregate Effects of Financial Shocks and the Degree of Intermediaries' Financial Frictions



(a) The Aggregate Effects of Financial Shocks **(b)** The Role of Intermediaries' Frictions

Panel (a) of Figure A.2 represents the effect of a contraction in the initial aggregate net worth N_0 in the equilibrium investment and interest rates. This shock implies that financial intermediaries have fewer internal resources to lend, which reduces the aggregate supply of funds for a given level of interest rates and increases equilibrium interest rates. In the empirical analysis of Section 5.1 we refer to this as the *intermediaries' net worth channel* in the transmission of financial shocks. Panel (b) shows that the aggregate effects of the shock on investment and interest rates depend on intermediaries' degree of financial frictions, measured by the marginal cost of external finance ϕ. Economies in which intermediaries have a higher marginal cost of external finance ϕ have a steeper aggregate supply of funds curve because intermediaries require a larger increase in interest rates in order to issue external finance to finance lending to nonfinancial firms. Changes in the initial aggregate net worth have a larger impact on investment because financial intermediaries require higher increases in interest rates to be willing to recapitalize by raising external finance. In economies with a smaller ϕ, intermediaries face a flatter marginal cost curve of external finance; changes in the initial net worth of intermediaries have a smaller impact on investment because intermediaries can more easily recapitalize, and they require a smaller increase in interest rates to be willing to recapitalize and increase lending. In the extreme case in which intermediaries face no cost of external finance, the aggregate supply of funds becomes perfectly elastic, and changes in the initial net worth of intermediaries have no effects on investment or interest rates. The following proposition formalizes this result.

***Proposition* 1.** *If $\phi = 0$, then $\frac{\partial k_1}{\partial N_0} = 0$. If $\phi > 0$ and for large enough z_1 such that intermediaries' limited liability constraints bind (i.e., $\mu_i > 0$ for all i), then $\frac{\partial k_1}{\partial N_0} > 0$ with $\partial \frac{\partial k_1}{\partial N_0} / \partial \phi > 0$ for $\phi \to 0$.*

Proof. See Section A.6. □

This discussion suggests that analyzing the macroeconomic effects of idiosyncratic financial shocks—as we do in our empirical analysis—is highly informative on the degree of financial frictions faced by intermediaries. We next discuss the link between the model experiment and the empirical analysis in more detail.

Link to empirical analysis Our high-frequency identification strategy aims to isolate idiosyncratic changes in the net worth of intermediaries, as in the model experiment above. Due to data availability, the empirical analysis focuses on changes in the market value of net worth, while the shock in the model is to the book value n_{i0}. However, in the model there is a tight link between these two objects: Combining (17) with intermediaries' flow of funds constraints under binding limited liability constraints, the price of the shares of intermediaries is given by $p_{i0} = \beta n_{i0} \left(\frac{1+\chi_0+\kappa}{q_0} - \frac{1}{\beta}\kappa \right)$. The empirical analysis also focuses on the market value of nonfinancial firms, which in the model has a tight link with nonfinancial firms' capital: Using (17) and nonfinancial firms' flow-of-funds constraint, we can express the share price of nonfinancial firms as $p_{f0} = \beta(\mathbb{E}_0 z_1 k_1^\alpha - b_1) = \beta(1-\alpha)\mathbb{E}_0 z_1 k_1^\alpha$. It follows that the same characterization of responses in the previous section for k_1 also applies to p_{f0}.

In addition, the empirical analysis uses excess bond premium data, which can be linked in the model to the spread between nonfinancial firms' borrowing rate $\frac{1}{q_0}$ and the rate $\frac{1}{\beta}$.

The model experiment can be used to further discuss the identifying assumptions used in our empirical analysis to estimate the effects of financial shocks on the real economy. First, in the model, changes in individual intermediaries' net worth affect the aggregate net worth (i.e., $\frac{\partial N_0}{\partial n_{\iota 0}} > 0$). For this reason, our empirical analysis focuses on large intermediaries, which are likely to satisfy this condition. Second, the model experiment considers changes in intermediaries' idiosyncratic net worth while keeping fixed nonfinancial firms' productivity z_0; in the absence of this assumption, changes in productivity could lead to changes in the demand for funds that are unrelated to those of intermediaries' net worth. For this reason, our empirical analysis focuses on changes in intermediaries' market value in a narrow window around their earnings announcement, which is likely to satisfy this condition.

A.5. Extending the model for a borrowers' information channel

So far, our model has focused on the intermediaries' net worth channel in the transmission of financial shocks. This section extends our model to include a borrowers' information channel, as we consider in our empirical analysis of Section 5.1.2. For this, we assume that news that affects intermediaries' net worth can potentially contain information about nonfinancial firms' expected productivity, i.e., $\frac{\partial \mathbb{E}_0 z_1}{\partial n_{\iota 0}} = \varphi \geq 0$.

Panel (a) of Figure A.3 represents the effect of the borrowers' information channel on the equilibrium investment and interest rates. A contraction in the initial aggregate net worth N_0 is associated with a lower expected productivity for nonfinancial firms, which shifts the demand-of-funds curve, $\mathcal{K}^d(q_0) = (q_0 \mathbb{E}_0 z_1 \alpha)^{\frac{1}{1-\alpha}}$, to the southwest. This channel implies that nonfinancial firms' production scale is lower, which reduces the aggregate demand of funds for a given interest rate and decreases equilibrium interest rates. Panel (b) of Figure A.3 represents the total effect of a financial shock, incorporating the intermediaries' net worth channel from the previous section, which shifts the supply curve. For a contraction in intermediaries' initial aggregate net worth N_0, both channels contribute to a contraction of nonfinancial firms' investment and market value. The overall effects on interest rates are indeterminate, depending on the relative strength of each channel, governed by the degree of intermediaries' financial frictions ϕ and the information content of financial shocks φ. Panel (b) represents the case in which the effect of intermediaries' balance sheet effect dominates and, consistent with our empirical analysis, interest rates increase in response to a negative financial shock.

Figures A.2 and A.3 show that the intermediaries' balance sheet channel and the borrowers' information channel of financial shocks have effects of the same sign on nonfinancial firms' market value but opposite effects on interest rates, which exhibit a negative comovement with nonfinancial firms' value for the intermediaries' balance sheet channel and positive comovement with nonfinancial firms' value for the borrower's information channel. This provides a theoretical identification for our empirical strategy to decompose the channels through which financial shocks affect the economy in Section 5.1.2. Given that our model decomposition is for risk-free debt, we conduct the decomposition in the empirical analysis using data on the excess bond premium (from Gilchrist and Zakrajšek, 2012; Gilchrist *et al.*, 2021), which extracts the component of nonfinancial firms' yields that is not related to their probability of default.

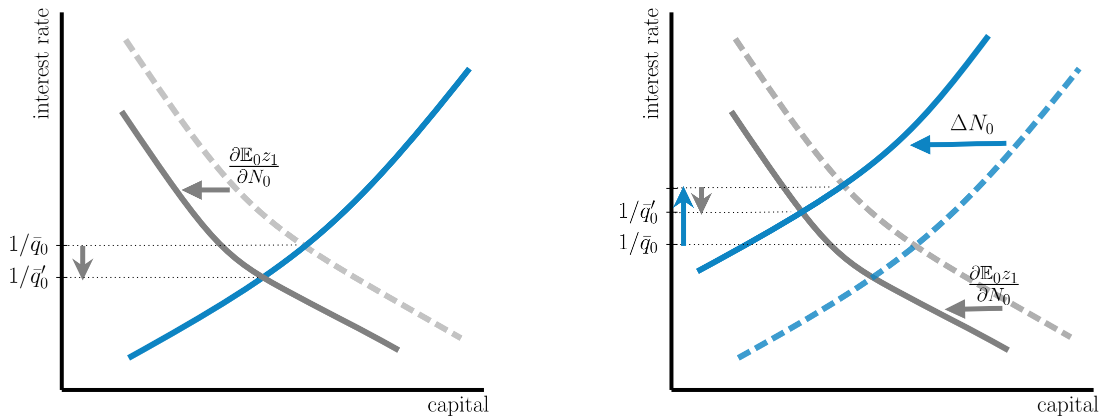
A.6. Proofs

Proof of Proposition 1.

Proof. First, if $\phi = 0$, then intermediaries' optimality conditions (21) and (22) imply that $q_0 = \beta$. Nonfinancial firms' optimality condition (19) implies that $1 = \beta \mathbb{E}_0 z_1 \alpha k_1^{\alpha-1}$, meaning that $\frac{\partial k_1}{\partial N_0} = 0$.

For $\phi > 0$, conjecture that for large enough $\mathbb{E}_0 z_1$, intermediaries' limited liability con-

Figure A.3: Asset price comovements for the intermediaries' net worth channel and borrowers' information channel



(a) Borrowers' Infomation Channel

(b) Intermediaries' Net Worth Channel and Borrowers' Information Channel

straints bind ($\mu_i > 0$ for all i). From (21), in such equilibria, all intermediaries raise the same external finance relative to their net worth $\chi_0 \equiv \frac{x_{i0}}{n_{i0}}$. Combining (19) and (24), we obtain an implicit function that determines equilibrium capital as a function of aggregate net worth $\mathcal{K}(k_1, N_0, \phi) = 0$, with

$$\mathcal{K}(k_1, N_0, \phi) = k_1 - N_0(1 + \kappa + \frac{1}{2\phi}\left(\beta \mathbb{E}_0 z_1 \alpha k_1^{\alpha-1} - 1\right)). \tag{25}$$

Note that $\frac{\partial \mathcal{K}(k_1,N_0,\phi)}{\partial k_1} = 1 - N_0 \frac{1}{2\phi} \beta \mathbb{E}_0 z_1 (\alpha - 1) k_1^{\alpha-2} > 0$; and that $\frac{\partial \mathcal{K}(k_1,N_0,\phi)}{\partial N_0} = -(1 + \kappa + \frac{1}{2\phi}\left(\beta \mathbb{E}_0 z_1 \alpha k_1^{\alpha-1} - 1\right))$, which, for an equilibrium around which financial intermediaries raise equity, is negative. By the implicit function theorem, it follows that $\frac{\partial k_1}{\partial N_0} > 0$, as stated in the proposition. Using these expressions, it follows that $sign(\partial \frac{\partial k_1}{\partial N_0} / \partial \phi) = N_0 \frac{1}{2} \beta \mathbb{E}_0 z_1 (1 - \alpha) k_1^{\alpha-2} - \phi \chi_0$, which is positive for $\phi \to 0$.

Finally, we verify the conjecture that for large enough $\mathbb{E}_0 z_1$, intermediaries' limited liability constraints bind. We do so by contradiction. Assume that, contrary to our conjecture, intermediaries' limited liability constraints do not bind for any $\mathbb{E}_0 z_1$. In such equilibrium, by

(21), intermediaries do not raise external finance (i.e., $x_{i0} = 0$ for all i); and by (22), $q_0 = \beta$. Given N_0, let $k_1^* = N_0(1+\kappa)$ be the maximum level of capital that satisfies the limited liability constraint without external equity. Let z_1^* denote the level of expected productivity that satisfies nonfinancial firms' Euler equation (19) $\frac{1}{\beta} = z_1^* \alpha (k_1^*)^{\alpha-1}$. Consider now some level of expected productivity $\hat{z}_1 > z_1^*$. Let $\hat{k}_1$ denote the level of capital that satisfies nonfinancial firms' Euler equation (19) $\frac{1}{\beta} = \hat{z}_1 \alpha (\hat{k}_1)^{\alpha-1}$. Since $\hat{k}_1 > k_1^*$, it follows that $\hat{k}_1 > N_0(1+\kappa)$, which contradicts the assumption that the limited liability constraint does not bind.

$\square$

B. Additional Tables and Figures

Table B.1: Daily Returns of Equity Indices

	Release	**Nonrelease**	**All Days**
SP500 Ex-Financials			
Mean	-0.03	0.03	0.02
	(0.06)	(0.02)	(0.02)
Std Deviation	1.32	1.12	1.14
	(0.04)	(0.01)	(0.01)
Observations	486	5,048	5,534
SmallCap 600			
Mean	0.03	0.03	0.03
	(0.07)	(0.02)	(0.02)
Std Deviation	1.58	1.39	1.41
	(0.05)	(0.01)	(0.01)
Observations	486	4,603	5,089
Russell 2000			
Mean	0.02	0.02	0.02
	(0.08)	(0.02)	(0.02)
Std Deviation	1.70	1.46	1.48
	(0.05)	(0.01)	(0.01)
Observations	486	4,603	5,089

Notes: This table shows descriptive statistics (in percent) of daily returns of equity indices (S&P 500 Ex-Financials, S&P Small Cap 600, and Russell 2000). Returns are computed as daily log differences. “Release Days” refer to days with earnings releases by financial intermediaries in the sample; “Nonrelease Days” refer to days without earnings releases; “All Days” include both release days and nonrelease days. Standard errors are in parentheses.

Table B.2: Daily Changes in Bond Spreads

	Release	**Non-Release**	**All Days**
Excess bond premium			
Mean	-0.46	0.02	-0.02
	(0.51)	(0.12)	(0.12)
Std Deviation	9.43	7.91	8.04
	(0.36)	(0.09)	(0.08)
Observations	344	4,215	4,559
Investment grade			
Mean	-0.10	0.02	0.01
	(0.12)	(0.03)	(0.03)
Std Deviation	2.65	2.63	2.64
	(0.09)	(0.02)	(0.02)
Observations	487	6,139	6,626
High yield			
Mean	-0.57	0.07	0.03
	(0.47)	(0.13)	(0.12)
Std Deviation	10.33	10.13	10.15
	(0.33)	(0.09)	(0.09)
Observations	487	6,139	6,626
CCC constituents			
Mean	1.20	1.80	1.74
	(0.29)	(0.10)	(0.09)
Std Deviation	110.09	106.81	107.17
	(0.20)	(0.07)	(0.06)
Observations	146,670	1,238,294	1,384,964
N Bonds	3,308		

Notes: This table shows descriptive statistics (in basis points) of daily changes in the excess bond premium, option-adjusted spreads of ICE BofA's investment-grade and high-yield indices of U.S. corporate bonds, and option-adjusted spreads for nonfinancial constituent bonds in ICE BofA's CCC & Lower index. "Release Days" refer to days with earning releases by financial intermediaries in the sample; "Nonrelease Days" to days without earnings releases; "All Days" include both release days and nonrelease days. Standard errors are in parentheses.

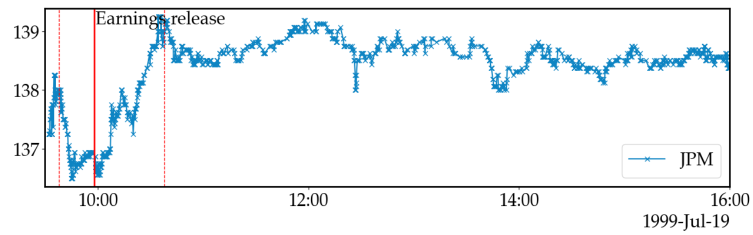
Table B.3: Bond Holdings by Intermediary

Financial Intermediary	**Mean**	**SD**	**Min**	**Max**
J.P. Morgan Chase	2.6	8.7	0	100
Goldman Sachs	0.9	3.1	0	62
Ameriprise Financial	0.8	3.4	0	100
Morgan Stanley	0.5	4.6	0	100
Citicorp	0.4	3.1	0	93
Northern Trust	0.3	1.8	0	93
Wells Fargo	0.3	2.3	0	100
Bank of New York Mellon	0.3	2.6	0	100
Merrill Lynch	0.1	1.7	0	82
U.S. Bancorp	0.003	0.03	0	1
Bank of America	0.001	0.04	0	1
All	6.0	12.0	0	100

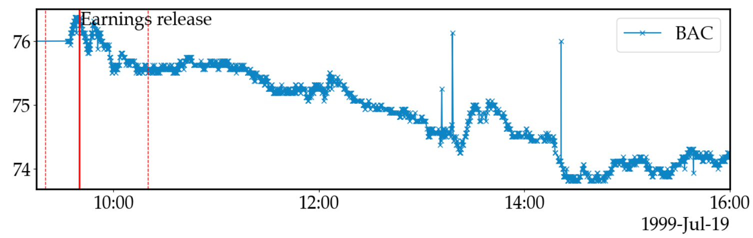
Notes: This table shows descriptive statistics for the shares of bonds held by financial intermediaries, displayed in percent. The set of bonds includes bonds rated CCC or lower in ICE issued by firms with at least 10 bonds outstanding.

Figure B.1: Construction of Financial Shocks

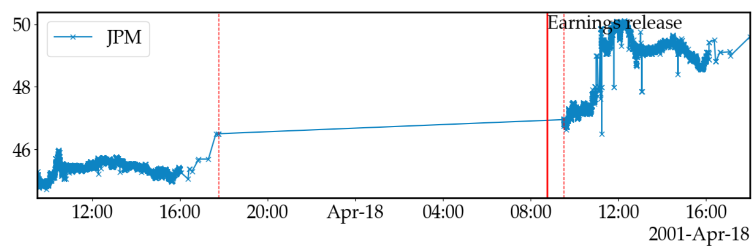
(a) Median Positive Shock (Inside Regular Trading Hours)



(b) Median Negative Shock (Inside Regular Trading Hours)



(c) Median Positive Shock (Outside Regular Trading Hours)



(d) Median Negative Shock (Outside Regular Trading Hours)

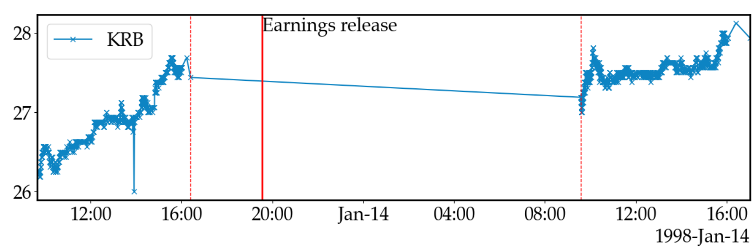
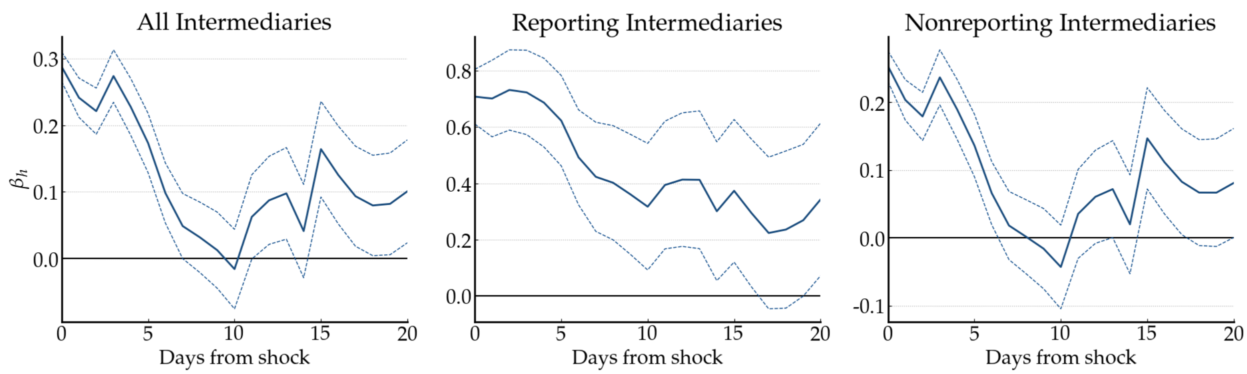
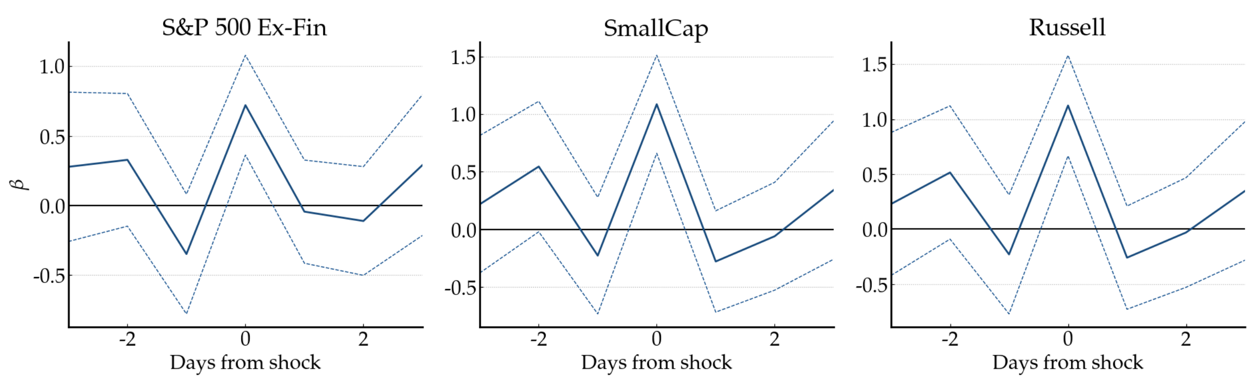


Figure B.2: The Effect of Financial Shocks on the Financial Sector's Net Worth



Notes: The figures show the cumulative responses of financial intermediaries' market capitalization to individual unweighted financial shocks. The left panel shows market capitalization responses from all financial intermediaries in our sample in response to a financial shock. The middle panel shows the market capitalization response from the intermediary that reports the earnings underlying the financial shock. The right panel shows the market capitalization response from all remaining nonreporting intermediaries.

Figure B.3: Placebo Tests: Financial Shocks on Nonevent Days



Notes: The figures show placebo tests with nonevent days. Specifications take the form $\Delta \log y_{t+j} = c + \beta\varepsilon_t + u_t$. Changes in dependent equity indices are constructed using alternative dates $j = -3, \cdots, 3$ around the event date, with $j = 0$ corresponding to the event date of earnings releases.

Table B.4: Financial Shocks vs. Placebo Dow Jones Shocks

(a) Financial Shocks

	SP500 Ex-Fin	**SmallCap**	**Russell**	**Obs**
Narrow	0.924***	1.348***	1.453***	272
	(0.241)	(0.296)	(0.313)	
Macro controls	0.908***	1.276***	1.381***	272
	(0.243)	(0.299)	(0.316)	
Broad	0.720***	1.085***	1.124***	486
	(0.179)	(0.213)	(0.229)	

(b) Placebo Dow Jones Nonfinancial Shocks

	SP500	**SmallCap**	**Russell**	**Obs**
Narrow	-0.205	-0.557*	-0.513	546
	(0.272)	(0.330)	(0.346)	
Macro controls	-0.158	-0.506	-0.462	546
	(0.272)	(0.329)	(0.345)	
Broad	0.334	0.064	0.135	877
	(0.220)	(0.256)	(0.268)	

(c) Placebo Dow Jones Nonfinancial Shocks
(Equal Number of Placebo Firms per Quarter as Financial Intermediaries)

	SP500	**SmallCap**	**Russell**	**Obs**
Narrow	-0.161	-0.432	-0.392	378
	(0.239)	(0.294)	(0.307)	
Macro controls	-0.096	-0.356	-0.314	378
	(0.239)	(0.291)	(0.305)	
Broad	0.282	0.071	0.134	649
	-0.204	-0.237	-0.247	

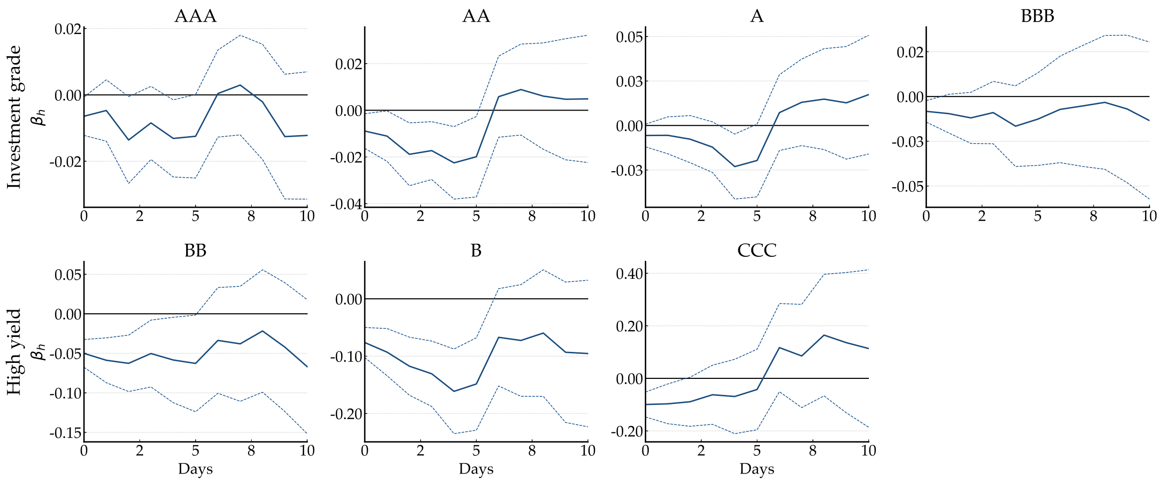
Notes: This table shows results from estimating $\Delta \log y_t = \alpha + \beta \varepsilon_t + u_t$, where $\Delta \log y_t$ is the daily log change in one of the following indices: S&P 500 Ex-Financials, S&P SamllCap 600, or Russell 2000. Panel (a) shows the estimates for β using HF financial shocks, described in the main text. Panel (b) shows placebo tests with HF shocks generated by nonfinancial firms in Dow Jones. Shock construction and regression specifications follow those for financial shocks. Firms are 3M, Alco, Philip Morris, Apple, AT&T, Bethlehem Steel, Boeing, Caterpillar, Chevron, Cisco, Coca-Cola, Dow, Dupont, Eastman Kodak, Exxon, FW Woolworth, General Electric, General Motors, Goodyear, Hewlett-Packard, Home Depot, Intel, IBM, International Paper, Johnson & Johnson, Kraft, McDonald's, Merck, Microsoft, Nike, Pfizer, Procter & Gamble, Sears, Texaco, Union Carbide, United Technologies, UnitedHealth, Verizon, Visa, Walgreens, Walmart, Walt Disney, and Westinghouse. Panel (c) shows placebo tests with HF shocks generated with the biggest Dow Jones nonfinancial firms by market value, so that the number of Dow Jones firms included in the placebo shocks equals the number of financial intermediaries included in the financial shocks. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table B.5: Effects of HF Placebo Shocks with S&P 500 Nonfinancial Firms

Dependent Variables	**Placebo Sectors**	**Effects of Placebo Shocks**
SP500 Ex-Energy Index	Energy	-0.729
		(0.617)
SP500 Ex-Materials Index	Materials	-1.261
		(0.975)
SP500 Ex-Industrials Index	Industrials	0.526
		(1.164)
SP500 Ex-Consumer Discretionary Index	Consumer Discretionary	0.410
		(0.672)
SP500 Ex-Consumer Staples Index	Consumer Staples	0.186
		(0.530)
SP500 Ex-Healthcare Index	Healthcare	1.180
		(0.871)
SP500 Ex-Information Technology Index	Information Technology	0.371
		(0.994)
SP500 Ex-Communication Services Index	Communication Services	0.212
		(1.391)
SP500 Ex-Utilities Index	Utilities	-1.536
		(1.289)
SP500 Ex-Real Estate Index	Real Estate	1.995
		(1.620)

Notes: This table reports the effects of placebo HF shocks. For each nonfinancial sector s of the S&P 500, the placebo HF shock ε_t^s is constructed following the procedure for the narrow measure of HF financial shocks described in Section 3. The specification estimated is $\Delta \log y_t^{-s} = \alpha + \beta\varepsilon_t^s + u_{st}$ for each sector $s \in$ {energy, materials, information technology, ...}, where ε_t^s is the placebo HF shock and y_t^{-s} is the equity index that excludes the placebo shock sector. Standard errors are reported in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Figure B.4: Heterogeneous effects by bond credit risks



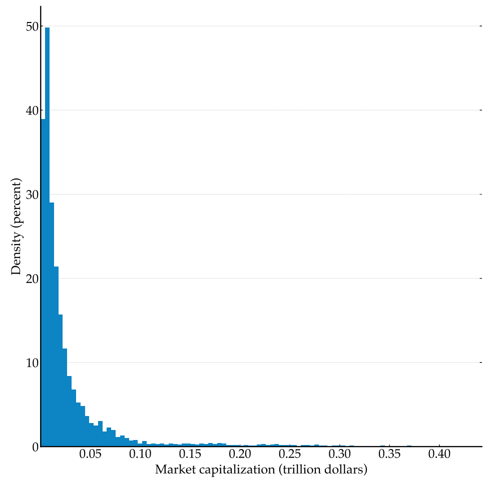
Notes: The figures show the estimated cumulative responses, β_{hr}, of the bond spreads of rating r to HF shocks at horizon h from estimating local projections $\Delta_h z_{rt} = a_{hr} + \beta_{hr}\varepsilon_t^{\mathrm{F}} + u_{rt}$, where z_{rt} is the option-adjusted spread of bond index of rating r in period t of an earnings announcement, and ε^{F} is the broad measure of financial shocks. Dotted lines represent 90% confidence intervals.

Table B.6: Comparison of Event-time and Heteroskedasticity-based Identification

Fin Shock	Freq	Dependent Variable	Freq	OLS	Heteroske-dasticity
Reporting intermediaries	60-min	SP500 nonfin constituents (equal weighted)	60-min	0.291**	-
				(0.140)	-
All intermediaries	60-min	SP500 nonfin constituents (equal weighted)	60-min	0.183***	0.408***
				(0.061)	(0.027)
All intermediaries	60-min	SP500 nonfin constituents (value weighted)	60-min	0.150***	0.360***
				(0.051)	(0.028)
All intermediaries	60-min	SP500 index ETF	60-min	0.134***	0.370***
				(0.028)	(0.027)
All intermediaries	60-min	SP500 nonfin index	daily	0.538***	-
				(0.090)	-
All intermediaries	daily	SP500 nonfin index	daily	-	0.400***
				-	(0.024)

Notes: This table compares estimators for the effects of financial shocks from event-time and heteroskedasticity-based identification for various combinations of frequency, definitions of financial shocks, and weighting of the dependent variables. A specification that is infeasible for an identification strategy is omitted. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Figure B.5: Distribution of Financial Firms in the S&P 500



Notes: This figure shows the histogram of the market capitalization of financial firms (NAICS 52) included in the S&P 500 index from 1998 to 2020. The Pareto rate of the fitted Pareto Type I distribution is 0.2.

Table B.7: Effects of Financial Firms on Nonfinancial Firms

	(1) **OLS**	(2) **GIV**	(3) **OLS**	(4) **GIV**
Financials	0.494***	0.309***	0.410***	0.268***
	(0.013)	(0.053)	(0.035)	(0.061)
R^2	0.626	0.539	0.553	0.487
Observations	5,783	5,783	489	489
Days included	all	all	earnings	earnings
Robust SE	yes	yes	yes	yes

Notes: This table shows estimates for β from fitting (6) under various specifications. The dependent variable is the S&P 500 Ex-Financials Daily Index, and the explanatory variable is the S&P 500 Financials Daily Index. The sample period is from 1998 to 2020. Column (1) shows OLS results estimated using all daily data in the sample. Column (2) shows the estimate instrumented with the GIV using all daily data in the sample. Column (3) shows OLS results estimated using earnings days of intermediaries included in the baseline HF shocks. Column (4) shows the estimate instrumented with GIV using earnings days of intermediaries included in the baseline HF shocks. Heteroskedasiticy-robust standard errors are reported in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

C. Additional Data and Results for the Heterogeneous Transmission

This appendix describes the data sources and construction for Section 5 and presents additional results on the impact of financial shocks by firm exposure and the comparison of HF financial and monetary shocks.

C.1. Data

In Section 5.2, we study heterogeneous firm responses to financial shocks with quarterly data on firm balance sheet and credit ratings from Compustat. To facilitate comparison with the monetary transmission literature, our sample construction follows that of Ottonello and Winberry (2020). We exclude financial, energy, and utility firms and firm-quarter observations that have negative capital or assets, acquisition larger than 5% of assets, investment rate in the top or bottom 0.5% of the distribution, investment spell shorter than 40 quarters, net current assets as a share of total assets higher than 10 or below -10, leverage higher than 10 or negative, quarterly real sales growth above 1 or below -1, and negative sales or liquidity.

Leverage is defined as the ratio of total debt to total assets. Liquidity is defined as the ratio of cash and short-term investment to total assets. Leverage and liquidity are demeaned and standardized at firm level so that the units are standard deviations. Credit ratings are measured as S&P's long-term issue rating of the firm. We use S&P's definition of investment grade as BBB or better and speculative grade as BB or worse, though our empirical results are robust to other cutoffs.

We include as firm controls sales growth, measured as log differences in sales deflated by the BLS implicit price deflator; size, measured as log total real assets deflated using the BLS implicit price deflator; current assets as a share of total assets; and an indicator variable for fiscal quarter. Sales growth, size, and current-to-total assets are standardized.

We also compare the effect of a financial shock with that of a monetary shock in high frequencies. The monetary shock, as constructed by Gorodnichenko and Weber (2016), is based on changes in fed funds futures in a 60-minute window around an FOMC announcement

$$\varepsilon_t^{\mathrm{M}} = \frac{D}{D-\tau}(ff^0_{t+\Delta t^+} - ff^0_{t+\Delta t^-}),$$

where t is the time of the FOMC announouncement; $ff^0_{t+\Delta t^+}$ and $ff^0_{t+\Delta t^-}$ are the Fed funds futures rate 15 minutes before and 45 minutes after the announcement; D is the number of days in the month of the announcement; and τ is the date of the announcement. For each FOMC announcement, we compute the log changes in firms' stock prices in the corresponding 60-minute window around the announcement (15 minutes before and 45 minutes after) to use as the dependent variable. We use the sample before the global financial crisis to focus on comparison with the transmission of conventional monetary policy.

C.2. Comparison of financial and monetary shocks

We now compare the effects of HF financial and monetary shocks. Both financial and monetary shocks are constructed based on a 60-minute window around the event announcement. The dependent variable is the log changes in nonfinancial Compustat firm stock prices, computed in the 60-minute window around the events to match the frequency of the shocks.

For financial shocks, we estimate (15)

$$\Delta y_{jt} = \alpha_j + \alpha_{sq} + \beta_F \varepsilon_t^{\mathrm{F}} + \gamma_F \varepsilon_t^{\mathrm{F}} \mathbb{1}_{x_{jt}} + \Gamma' Z_{jt} + u_{jt},$$

where Δy_{jt} is the log changes in stock prices in the 60-minute window around a financial shock; $\varepsilon_t^{\mathrm{F}}$ is the narrow HF financial shock; $\mathbb{1}_{x_{jt}}$ is an indicator variable for firms with high leverage, investment-grade credit rating, or high liquidity; α_j is a firm fixed effect; α_{sq} is a sector-by-quarter fixed effect; and Z_{jt} is a vector of firm controls—the firm characteristic $\mathbb{1}_{x_{jt}}$, previous-quarter sales growth, previous-quarter size, previous-quarter current assets as a share of total assets, and an indicator for fiscal quarter. Standard errors are two-way clustered at firm and shock level.

For monetary shocks, we replace the sector-by-quarter fixed effect with a sector-by-quarter seasonal fixed effect to estimate the average effect of monetary shocks, since there is typically no more than one shock per quarter:

$$\Delta y_{jt} = \alpha_j + a_{sq} + \beta_M \varepsilon_t^{\mathrm{M}} + \gamma_M \varepsilon_t^{\mathrm{F}} \mathbb{1}_{x_{jt}} + \Gamma' Z_{jt} + u_{jt},$$

where $\varepsilon_t^{\mathrm{M}}$ is the HF monetary shock and the remaining variables are as defined in (15).

Results are reported in Appendix Table C.1. Panel (a) reports the average effect and heterogeneous transmission of monetary shocks that are consistent with previous studies. The semielasticity to monetary shocks at a high frequency, of 2.2, is roughly half the size of the estimate based on daily frequency (for example, 5.31 in Gorodnichenko and Weber, 2016). Comparison of Panels (a) and (b) shows that different sources of firm heterogeneity matter for the transmission of monetary and financial shocks: Whereas firms with lower leverage and higher credit ratings are more responsive to monetary policy, firms with lower credit ratings and lower liquidity are those most affected by financial shocks.

Table C.1: Heterogeneous Firm Responses to Financial and Monetary Shocks

(a) Monetary Shocks

	(1) **Average**	(2) **Leverage** (High)	(3) **Credit Ratings** (Invt Grade)	(4) **Liquidity** (Liquid)
Monetary shock	2.205***	2.544***	2.919***	2.125***
	(0.670)	(0.711)	(1.051)	(0.635)
Characteristic		0.002	-0.053	-0.010
		(0.011)	(0.066)	(0.011)
Characteristic × Shock		-0.699***	1.379**	0.160
		(0.225)	(0.530)	(0.138)
Adjusted R^2	0.028	0.028	0.070	0.028
Observations	159,723	159,723	38,425	159,703
Firm controls	no	yes	yes	yes
Quarter-sector FE	no	no	no	no
Double-clustered SE	yes	yes	yes	yes

(b) Financial Shocks

	(1) **Average**	(2) **Leverage** (High)	(3) **Credit Ratings** (Invt Grade)	(4) **Liquidity** (Liquid)
Financial shock	0.264**	0.252**	0.330**	0.283**
	(0.109)	(0.108)	(0.142)	(0.109)
Characteristic		0.005	-0.019	-0.014*
		(0.008)	(0.018)	(0.007)
Characteristic × Shock		0.024	-0.075*	-0.038**
		(0.018)	(0.043)	(0.015)
Adjusted R^2	0.023	0.023	0.039	0.023
Observations	598,572	598,572	162,267	598,530
Firm controls	no	yes	yes	yes
Quarter-sector FE	yes	yes	yes	yes
Double-clustered SE	yes	yes	yes	yes

Notes: This table reports results from estimating

$$\Delta y_{jt} = \alpha_j + a_{sq} + \beta_M \varepsilon_t^{\mathrm{M}} + \gamma_M(\mathbb{1}_{x_{jt}} \varepsilon_t^{\mathrm{M}}) + \Gamma' Z_{jt} + u_{jt} \qquad \text{(monetary)}$$
$$\Delta y_{jt} = \alpha_j + \alpha_{sq} + \beta_F \varepsilon_t^{\mathrm{F}} + \gamma_F(\mathbb{1}_{x_{jt}} \varepsilon_t^{\mathrm{F}}) + \Gamma' Z_{jt} + u_{jt} \qquad \text{(financial)}$$

where $\varepsilon_t^{\mathrm{M}}$ and $\varepsilon_t^{\mathrm{F}}$ denote narrow HF financial and monetary shocks, respectively; $\mathbb{1}_{x_{jt}}$ is an indicator variable for high leverage, investment-grade credit ratings, or high liquidity; and Z_{jt} is a vector of firm controls—the firm characteristic $\mathbb{1}_{x_{jt}}$, lagged sales growth, lagged size, lagged current assets as a share of total assets, and an indicator for fiscal quarter. We normalize the sign of the monetary shock so that a positive shock corresponds to a decrease in the interest rate. The sample period for monetary shocks stops in 2007 to focus on conventional monetary policy. Standard errors are two-way clustered at shock and firm level and reported in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Internet Appendix

D. Earning Releases of Financial Intermediaries

Table D.1: Earning Releases of the Financial Intermediaries Used in Our Sample

1998Q1	1998Q2	1998Q3	1998Q4	1999Q1	1999Q2
07jan1998 19:20:00 LEH	13apr1998 18:36:00 FCN	13jul1998 18:59:00 FCN	07oct1998 11:34:00 KRB	07jan1999 09:06:00 LEH	13apr1999 09:59:00 MER
07jan1998 19:20:07 MWD	13apr1998 18:36:00 MER	14jul1998 18:48:00 KRB	13oct1998 09:11:00 MER	07jan1999 09:08:00 MWD	13apr1999 12:55:00 KRB
13jan1998 19:33:00 KRB	14apr1998 19:38:00 KRB	14jul1998 18:48:00 MER	14oct1998 12:09:00 WB	14jan1999 08:45:00 WB	14apr1999 09:15:00 JPM
15jan1998 20:13:00 USB	14apr1998 19:38:00 JPM	14jul1998 18:48:00 JPM	15oct1998 10:23:00 KEY	19jan1999 08:49:00 ONE	14apr1999 09:24:00 WB
15jan1998 20:13:00 BKB	15apr1998 20:27:00 BAC	15jul1998 19:19:00 BAC	15oct1998 11:16:00 BKB	19jan1999 09:03:00 MER	14apr1999 10:53:00 USB
20jan1998 21:02:00 CMB	15apr1998 20:28:00 USB	15jul1998 19:20:00 USB	19oct1998 08:46:00 NTRS	19jan1999 09:18:00 BAC	15apr1999 09:39:00 BKB
20jan1998 21:06:00 NTRS	16apr1998 19:43:00 BKB	15jul1998 19:21:00 WB	19oct1998 08:50:00 JPM	19jan1999 09:19:00 KEY	15apr1999 09:56:00 KEY
25mar1998 18:44:00 LEH	16apr1998 19:46:00 KEY	16jul1998 19:19:00 BKB	20oct1998 08:18:00 WFC	19jan1999 09:30:00 WFC	19apr1999 09:02:00 C
26mar1998 19:43:00 MWD	20apr1998 19:07:00 NTRS	16jul1998 19:21:00 KEY	20oct1998 08:51:00 CMB	19jan1999 09:36:00 NTRS	19apr1999 09:10:00 BAC
	21apr1998 20:01:00 CMB	20jul1998 19:27:00 NTRS	21oct1998 08:38:00 CCI	19jan1999 09:40:00 JPM	19apr1999 09:12:00 NTRS
	21apr1998 20:01:00 CCI	21jul1998 19:40:00 CCI	22oct1998 09:35:00 USB	19jan1999 09:43:00 CMB	20apr1999 09:07:00 ONE
	21apr1998 20:06:00 WFC	21jul1998 19:40:00 CMB		20jan1999 08:53:00 USB	20apr1999 09:19:00 WFC
	21apr1998 20:06:00 WB	21jul1998 19:46:00 WFC		21jan1999 09:57:00 BKB	20apr1999 09:31:00 CMB
	18jun1998 17:53:00 LEH	23sep1998 09:32:00 LEH		25jan1999 09:06:00 C	22jun1999 09:46:00 LEH
	18jun1998 17:53:00 MWD	24sep1998 08:58:00 MWD		19mar1999 09:11:00 LEH	24jun1999 09:02:00 MWD
				25mar1999 08:57:00 MWD	

1999Q3	1999Q4	2000Q1	2000Q2	2000Q3	2000Q4
13jul1999 08:22:00 MER	07oct1999 13:49:00 KRB	06jan2000 09:36:00 LEH	12apr2000 08:43:00 JPM	12jul2000 11:36:00 KRB	11oct2000 09:02:00 KRB
13jul1999 13:49:00 KRB	12oct1999 08:37:00 MER	10jan2000 13:47:00 KRB	12apr2000 14:24:00 KRB	13jul2000 09:30:00 JPM	16oct2000 09:17:00 NTRS
14jul1999 09:25:00 USB	13oct1999 08:52:00 WB	18jan2000 09:30:00 C	14apr2000 09:37:00 FBF	17jul2000 08:47:00 FBF	16oct2000 10:45:00 BAC
14jul1999 09:27:00 WB	14oct1999 09:30:00 USB	18jan2000 09:42:00 ONE	17apr2000 09:04:00 C	17jul2000 08:50:00 BAC	17oct2000 07:14:00 C
15jul1999 08:18:00 KEY	18oct1999 09:04:00 JPM	18jan2000 09:47:00 BAC	17apr2000 09:13:00 BAC	17jul2000 09:24:00 NTRS	17oct2000 07:52:00 KEY
15jul1999 08:19:00 BKB	18oct1999 09:07:00 C	18jan2000 09:50:00 WFC	17apr2000 09:14:00 MER	18jul2000 08:01:00 WFC	17oct2000 07:53:00 MER
19jul1999 09:30:00 C	18oct1999 09:10:00 BAC	18jan2000 09:56:00 JPM	17apr2000 10:18:00 NTRS	18jul2000 08:22:00 KEY	17oct2000 08:10:00 ONE
19jul1999 09:40:00 BAC	18oct1999 09:27:00 NTRS	18jan2000 10:03:00 USB	17apr2000 10:26:00 USB	18jul2000 08:25:00 MER	17oct2000 08:16:00 WFC
19jul1999 09:45:00 WFC	19oct1999 09:04:00 ONE	18jan2000 10:56:00 NTRS	18apr2000 09:16:00 ONE	19jul2000 08:27:00 C	17oct2000 08:42:00 FBF
19jul1999 09:58:00 JPM	19oct1999 09:22:00 WFC	19jan2000 09:10:00 KEY	18apr2000 09:28:00 WFC	19jul2000 08:32:00 CMB	18oct2000 09:03:00 JPM
19jul1999 09:58:00 NTRS	20oct1999 09:15:00 CMB	19jan2000 09:16:00 CMB	19apr2000 08:27:00 CMB	19jul2000 08:54:00 ONE	18oct2000 09:05:00 CMB
20jul1999 08:39:00 ONE	21oct1999 09:54:00 KEY	19jan2000 09:26:00 WB	19apr2000 08:47:00 WB	19jul2000 09:14:00 WB	18oct2000 09:33:00 WB
21jul1999 07:46:00 CMB	20dec1999 12:17:00 MWD	19jan2000 09:42:00 FBF	20apr2000 09:19:00 KEY	20jul2000 10:00:00 USB	19oct2000 09:07:00 USB
21sep1999 09:48:00 GS	21dec1999 09:33:00 GS	25jan2000 09:34:00 MER	16jun2000 09:20:00 LEH	19sep2000 09:13:00 GS	19dec2000 08:54:00 MWD
22sep1999 09:20:00 MWD		20mar2000 09:20:00 LEH	20jun2000 08:44:00 GS	20sep2000 16:56:00 LEH	19dec2000 19:15:00 GS
23sep1999 09:09:00 LEH		21mar2000 09:03:00 GS	22jun2000 08:57:00 MWD	21sep2000 08:49:00 MWD	
		23mar2000 09:12:00 MWD			

2001Q1	2001Q2	2001Q3	2001Q4	2002Q1	2002Q2
10jan2001 11:46:00 KRB	11apr2001 09:09:00 KRB	11jul2001 08:23:00 WB	04oct2001 10:49:00 MER	10jan2002 11:40:00 KRB	11apr2002 13:02:00 KRB
16jan2001 08:43:00 C	16apr2001 08:18:00 C	12jul2001 08:50:00 KRB	11oct2001 14:40:00 KRB	14jan2002 11:00:00 NTRS	15apr2002 06:55:00 C
16jan2001 08:53:00 KEY	16apr2001 09:30:00 BAC	16jul2001 08:24:00 BAC	15oct2001 07:36:00 BAC	15jan2002 10:04:00 WFC	15apr2002 07:17:00 BAC
16jan2001 09:00:00 BAC	16apr2001 09:42:00 NTRS	16jul2001 08:48:00 C	15oct2001 08:35:00 NTRS	15jan2002 17:35:00 USB	15apr2002 08:43:00 NTRS
16jan2001 09:07:00 WFC	16apr2001 10:02:00 WB	16jul2001 08:53:00 NTRS	16oct2001 08:28:00 ONE	16jan2002 06:58:00 KEY	16apr2002 06:37:00 FBF
16jan2001 09:17:00 NTRS	17apr2001 07:53:00 FBF	17jul2001 08:08:00 MER	16oct2001 08:48:00 WFC	16jan2002 18:54:00 JPM	16apr2002 08:30:00 ONE
17jan2001 09:30:00 FBF	17apr2001 08:42:00 ONE	17jul2001 08:28:00 ONE	16oct2001 11:06:00 USB	16jan2002 18:55:00 ONE	16apr2002 08:47:00 WFC
17jan2001 09:43:00 WB	17apr2001 08:56:00 WFC	17jul2001 08:55:00 KEY	17oct2001 06:17:00 C	17jan2002 08:54:00 C	16apr2002 12:18:00 USB
17jan2001 17:17:00 ONE	17apr2001 13:12:00 USB	17jul2001 15:18:00 USB	17oct2001 07:20:00 FBF	22jan2002 07:50:00 BAC	17apr2002 07:28:00 JPM
18jan2001 10:13:00 USB	18apr2001 08:45:00 JPM	17jul2001 18:28:00 WFC	17oct2001 07:34:00 JPM	23jan2002 07:26:00 WB	17apr2002 07:57:00 MER
23jan2001 09:07:00 MER	18apr2001 09:07:00 KEY	18jul2001 06:45:00 FBF	17oct2001 08:01:00 KEY	23jan2002 08:14:00 MER	17apr2002 08:12:00 KEY
20mar2001 08:54:00 GS	18apr2001 09:25:00 MER	18jul2001 08:52:00 JPM	19dec2001 08:24:00 MWD	29jan2002 06:59:00 FBF	18apr2002 07:52:00 WB
21mar2001 09:11:00 LEH	19jun2001 08:31:00 GS	21sep2001 08:32:00 MWD	20dec2001 08:21:00 GS	19mar2002 08:23:00 GS	18jun2002 07:27:00 LEH
21mar2001 09:17:00 MWD	19jun2001 12:12:00 LEH	25sep2001 08:23:00 LEH	20dec2001 09:29:00 LEH	20mar2002 08:19:00 LEH	19jun2002 08:29:00 MWD
	21jun2001 08:29:00 MWD	26sep2001 08:45:00 GS		26mar2002 08:35:00 MWD	20jun2002 08:56:00 GS

Continued on next page

Table D.1: Earning Releases of the Financial Intermediaries Used in Our Sample (Cont.)

2002Q3	2002Q4	2003Q1	2003Q2	2003Q3	2003Q4
11jul2002 13:47:00 KRB	15oct2002 07:54:00 BAC	15jan2003 07:13:00 KEY	14apr2003 06:12:00 C	14jul2003 06:52:00 BAC	14oct2003 07:30:00 MER
15jul2002 07:39:00 BAC	15oct2002 08:23:00 ONE	15jan2003 07:38:00 BAC	14apr2003 07:19:00 FBF	14jul2003 07:38:00 C	14oct2003 07:56:00 BAC
15jul2002 09:29:00 NTRS	15oct2002 08:28:00 WFC	16jan2003 07:26:00 FBF	14apr2003 07:30:00 BAC	15jul2003 05:50:00 WFC	15oct2003 07:01:00 WB
16jul2002 07:15:00 KEY	15oct2002 12:39:00 USB	16jan2003 07:42:00 WB	15apr2003 07:55:00 ONE	15jul2003 07:54:00 FBF	15oct2003 07:26:00 FBF
16jul2002 08:03:00 MER	15oct2002 15:55:00 C	16jan2003 08:38:00 ONE	15apr2003 08:37:00 WFC	15jul2003 09:20:00 MER	15oct2003 08:32:00 NTRS
16jul2002 08:31:00 WFC	16oct2002 07:39:00 WB	21jan2003 06:27:00 C	15apr2003 09:05:00 NTRS	15jul2003 12:00:00 USB	16oct2003 06:42:00 KEY
16jul2002 08:49:00 ONE	16oct2002 12:35:00 FBF	21jan2003 08:26:00 WFC	15apr2003 11:54:00 USB	16jul2003 07:57:00 ONE	16oct2003 08:40:00 KRB
16jul2002 12:46:00 USB	16oct2002 12:45:00 JPM	21jan2003 13:11:00 USB	16apr2003 07:40:00 WB	16jul2003 08:12:00 NTRS	20oct2003 07:33:00 C
17jul2002 08:47:00 JPM	16oct2002 14:23:00 MER	22jan2003 07:00:00 JPM	16apr2003 07:43:00 JPM	16jul2003 15:48:00 JPM	21oct2003 07:02:00 USB
17jul2002 10:02:00 C	16oct2002 14:35:00 NTRS	22jan2003 08:11:00 MER	16apr2003 07:47:00 MER	17jul2003 07:01:00 WB	21oct2003 08:00:00 WFC
18jul2002 15:16:00 WB	17oct2002 07:20:00 KEY	22jan2003 08:36:00 NTRS	17apr2003 07:53:00 KEY	18jul2003 06:54:00 KEY	21oct2003 10:17:00 ONE
19sep2002 12:15:00 MWD	17oct2002 12:06:00 KRB	23jan2003 10:09:00 KRB	23apr2003 08:57:00 KRB	24jul2003 09:11:00 KRB	22oct2003 07:33:00 JPM
24sep2002 08:23:00 LEH	19dec2002 09:43:00 MWD	20mar2003 08:24:00 LEH	18jun2003 14:28:00 MWD	23sep2003 08:26:00 GS	17dec2003 08:01:00 LEH
24sep2002 08:50:00 GS	19dec2002 09:54:00 LEH	20mar2003 08:33:00 MWD	19jun2003 08:50:00 LEH	23sep2003 09:00:00 LEH	18dec2003 08:05:00 GS
	19dec2002 10:21:00 GS	20mar2003 08:53:00 GS	25jun2003 08:28:00 GS	23sep2003 09:43:00 MWD	18dec2003 08:06:00 MWD

2004Q1	2004Q2	2004Q3	2004Q4	2005Q1	2005Q2
15jan2004 05:59:00 BAC	13apr2004 07:30:00 MER	13jul2004 07:35:00 MER	12oct2004 07:33:00 MER	18jan2005 06:50:00 BAC	15apr2005 06:00:00 C
15jan2004 06:02:00 WB	14apr2004 07:00:00 BAC	14jul2004 07:00:00 BAC	14oct2004 06:00:00 C	18jan2005 08:02:00 WFC	15apr2005 06:30:00 WB
15jan2004 06:45:00 FBF	15apr2004 06:32:00 KEY	15jul2004 06:20:00 C	14oct2004 06:31:00 BAC	18jan2005 08:56:00 USB	15apr2005 06:36:00 KEY
16jan2004 06:40:00 KEY	15apr2004 06:34:00 C	15jul2004 07:01:00 WB	14oct2004 06:55:00 KEY	19jan2005 06:01:00 WB	18apr2005 06:40:00 BAC
20jan2004 07:50:00 C	19apr2004 07:06:00 WB	16jul2004 06:23:00 KEY	15oct2004 15:26:00 WB	19jan2005 06:51:00 JPM	19apr2005 07:29:00 MER
20jan2004 07:58:00 ONE	20apr2004 08:13:00 NTRS	20jul2004 08:01:00 WFC	19oct2004 08:01:00 WFC	19jan2005 08:10:00 NTRS	19apr2005 08:01:00 WFC
20jan2004 08:06:00 WFC	20apr2004 08:45:00 WFC	20jul2004 08:31:00 USB	19oct2004 10:13:00 USB	20jan2005 06:00:00 C	19apr2005 08:12:00 NTRS
20jan2004 13:27:00 USB	20apr2004 11:05:00 USB	21jul2004 08:04:00 JPM	20oct2004 07:00:00 JPM	20jan2005 07:55:00 KRB	19apr2005 08:45:00 USB
21jan2004 07:07:00 JPM	20apr2004 14:57:00 ONE	21jul2004 08:08:00 NTRS	20oct2004 08:36:00 NTRS	21jan2005 09:40:00 KEY	20apr2005 06:59:00 JPM
21jan2004 07:31:00 MER	21apr2004 07:02:00 JPM	22jul2004 08:35:00 KRB	21oct2004 08:37:00 KRB	25jan2005 07:34:00 MER	21apr2005 17:11:00 KRB
21jan2004 09:27:00 NTRS	22apr2004 08:33:00 KRB	21sep2004 08:06:00 LEH	15dec2004 08:02:00 LEH	15mar2005 10:17:00 LEH	14jun2005 08:12:00 LEH
22jan2004 16:31:00 KRB	15jun2004 08:05:00 LEH	21sep2004 08:27:00 GS	16dec2004 08:27:00 GS	17mar2005 08:15:00 MWD	16jun2005 08:24:00 GS
16mar2004 09:00:00 LEH	22jun2004 08:04:00 MWD	22sep2004 08:10:00 MWD	21dec2004 08:08:00 MWD	17mar2005 08:22:00 GS	22jun2005 08:03:00 MWD
18mar2004 07:59:00 MWD	22jun2004 08:22:00 GS				
23mar2004 08:21:00 GS					

2005Q3	2005Q4	2006Q1	2006Q2	2006Q3	2006Q4
18jul2005 06:52:00 KRB	17oct2005 06:00:00 C	17jan2006 07:45:00 USB	17apr2006 07:03:00 WB	17jul2006 06:00:00 C	16oct2006 07:00:00 WB
18jul2005 07:40:00 BAC	17oct2005 07:26:00 WB	17jan2006 08:00:00 WFC	17apr2006 07:03:00 C	18jul2006 07:07:00 KEY	17oct2006 06:58:00 KEY
18jul2005 23:10:00 C	18oct2005 06:44:00 USB	18jan2006 07:07:00 JPM	18apr2006 06:41:00 KEY	18jul2006 07:30:00 MER	17oct2006 07:32:00 MER
19jul2005 06:25:00 KEY	18oct2005 07:32:00 KEY	18jan2006 08:04:00 NTRS	18apr2006 07:17:00 USB	18jul2006 07:45:00 USB	17oct2006 07:44:00 USB
19jul2005 06:30:00 USB	18oct2005 08:00:00 WFC	19jan2006 07:01:00 WB	18apr2006 07:33:00 MER	18jul2006 08:36:00 WFC	17oct2006 08:00:00 WFC
19jul2005 07:03:00 WB	18oct2005 08:13:00 MER	19jan2006 07:30:00 MER	18apr2006 08:00:00 WFC	19jul2006 06:59:00 JPM	18oct2006 06:59:00 JPM
19jul2005 07:30:00 MER	19oct2005 06:40:00 BAC	20jan2006 06:00:00 C	18apr2006 08:10:00 NTRS	19jul2006 07:00:00 BAC	18oct2006 08:12:00 NTRS
19jul2005 08:00:00 WFC	19oct2005 06:47:00 KRB	20jan2006 06:38:00 KEY	19apr2006 07:10:00 JPM	19jul2006 08:13:00 NTRS	19oct2006 06:01:00 C
20jul2005 07:04:00 JPM	19oct2005 06:59:00 JPM	23jan2006 06:40:00 BAC	20apr2006 07:17:00 BAC	20jul2006 07:19:00 WB	19oct2006 06:40:00 BAC
20jul2005 08:27:00 NTRS	19oct2005 08:30:00 NTRS	26jan2006 17:29:00 AMP	25apr2006 16:07:00 AMP	25jul2006 16:21:00 AMP	24oct2006 16:02:00 AMP
14sep2005 08:14:00 LEH	24oct2005 06:00:00 AMP	14mar2006 08:11:00 GS	12jun2006 08:07:00 LEH	12sep2006 08:22:00 GS	12dec2006 09:22:00 GS
20sep2005 08:28:00 GS	13dec2005 08:01:00 LEH	15mar2006 08:14:00 LEH	13jun2006 08:24:00 GS	13sep2006 08:15:00 LEH	14dec2006 07:35:00 LEH
21sep2005 08:00:00 MWD	15dec2005 08:27:00 GS	22mar2006 08:00:00 MS	21jun2006 08:00:00 MS	20sep2006 08:00:00 MS	19dec2006 07:45:00 MS
	20dec2005 08:02:00 MWD				

2007Q1	2007Q2	2007Q3	2007Q4	2008Q1	2008Q2
16jan2007 08:00:00 WFC	16apr2007 07:00:00 C	17jul2007 06:35:00 KEY	15oct2007 06:30:00 C	15jan2008 06:30:00 C	14apr2008 09:39:00 WB
16jan2007 08:30:00 USB	16apr2007 07:02:00 WB	17jul2007 07:30:00 MER	16oct2007 06:30:00 KEY	15jan2008 08:00:00 USB	15apr2008 08:00:00 NTRS
17jan2007 07:12:00 JPM	17apr2007 06:31:00 KEY	17jul2007 08:00:00 USB	16oct2007 07:30:00 USB	16jan2008 06:59:00 JPM	15apr2008 08:15:00 USB
17jan2007 08:34:00 NTRS	17apr2007 08:21:00 NTRS	17jul2007 08:00:00 WFC	16oct2007 08:00:00 WFC	16jan2008 08:00:00 WFC	16apr2008 06:59:00 JPM
18jan2007 07:30:00 MER	17apr2007 08:26:00 WFC	18jul2007 06:59:00 JPM	17oct2007 07:08:00 JPM	16jan2008 08:34:00 NTRS	16apr2008 08:00:00 WFC
19jan2007 07:09:00 C	17apr2007 10:47:00 USB	18jul2007 08:21:00 NTRS	17oct2007 08:23:00 NTRS	17jan2008 07:07:00 BK	17apr2008 06:30:00 MER
19jan2007 07:18:00 KEY	18apr2007 06:59:00 JPM	19jul2007 07:05:00 BAC	18oct2007 06:28:00 BK	17jan2008 07:11:00 MER	17apr2008 06:30:00 BK
23jan2007 06:04:00 WB	19apr2007 07:00:00 BAC	20jul2007 07:00:00 C	18oct2007 07:01:00 BAC	22jan2008 06:35:00 KEY	17apr2008 06:50:00 KEY
23jan2007 06:45:00 BAC	19apr2007 07:30:00 MER	20jul2007 07:01:00 WB	19oct2007 07:01:00 WB	22jan2008 07:01:00 WB	18apr2008 06:30:00 C
25jan2007 16:02:00 AMP	24apr2007 16:01:00 AMP	25jul2007 16:11:00 AMP	24oct2007 07:30:00 MER	22jan2008 07:02:00 BAC	21apr2008 07:00:00 BAC
13mar2007 08:23:00 GS	12jun2007 08:10:00 LEH	18sep2007 08:04:00 LEH	24oct2007 16:01:00 AMP	24jan2008 16:29:00 AMP	22apr2008 16:01:00 AMP
14mar2007 08:08:00 LEH	14jun2007 08:24:00 GS	19sep2007 07:30:00 MS	13dec2007 08:08:00 LEH	18mar2008 08:00:00 GS	16jun2008 08:17:00 LEH
21mar2007 07:30:00 MS	20jun2007 07:30:00 MS	20sep2007 08:00:00 GS	18dec2007 08:17:00 GS	18mar2008 08:13:00 LEH	17jun2008 08:25:00 GS
			19dec2007 07:30:00 MS	19mar2008 17:00:00 MS	18jun2008 08:00:00 MS

Continued on next page

Table D.1: Earning Releases of the Financial Intermediaries Used in Our Sample (Cont.)

2008Q3	2008Q4	2009Q1	2009Q2	2009Q3
15jul2008 08:00:00 USB	06oct2008 16:10:00 BAC	15jan2009 06:30:00 JPM	13apr2009 14:10:00 GS	14jul2009 08:36:00 GS
16jul2008 08:00:00 WFC	15oct2008 06:59:00 JPM	16jan2009 06:00:00 C	16apr2009 06:29:00 JPM	16jul2009 06:29:00 JPM
16jul2008 08:07:00 NTRS	15oct2008 08:00:00 WFC	16jan2009 07:00:00 BAC	17apr2009 06:30:00 C	17jul2009 07:00:00 BAC
17jul2008 06:29:00 JPM	16oct2008 06:30:00 MER	20jan2009 16:35:00 BK	20apr2009 07:00:00 BAC	17jul2009 08:00:00 C
17jul2008 07:00:00 BK	16oct2008 06:30:00 BK	21jan2009 08:00:00 USB	21apr2009 06:23:00 BK	22jul2009 06:19:00 WFC
17jul2008 16:10:00 MER	16oct2008 07:00:00 C	21jan2009 08:14:00 NTRS	21apr2009 06:26:00 KEY	22jul2009 06:30:00 KEY
18jul2008 06:30:00 C	21oct2008 06:31:00 KEY	22jan2009 06:34:00 KEY	21apr2009 07:00:00 USB	22jul2009 06:30:00 BK
21jul2008 07:00:00 BAC	21oct2008 06:45:00 USB	28jan2009 08:00:00 WFC	21apr2009 07:42:00 NTRS	22jul2009 07:30:00 USB
22jul2008 06:47:00 KEY	22oct2008 07:00:00 WB	28jan2009 16:17:00 AMP	21apr2009 16:01:00 AMP	22jul2009 08:03:00 MS
22jul2008 07:00:00 WB	22oct2008 08:04:00 NTRS		22apr2009 07:48:00 MS	22jul2009 08:12:00 NTRS
23jul2008 16:01:00 AMP	29oct2008 16:01:00 AMP		22apr2009 08:00:00 WFC	23jul2009 16:01:00 AMP
16sep2008 08:15:00 GS	16dec2008 08:15:00 GS			
16sep2008 16:00:00 MS	17dec2008 08:00:00 MS			

2009Q4	2010Q1	2010Q2	2010Q3	2010Q4
14oct2009 06:59:00 JPM	15jan2010 06:59:00 JPM	14apr2010 06:59:00 JPM	15jul2010 06:29:00 JPM	13oct2010 06:58:00 JPM
15oct2009 07:15:00 GS	19jan2010 08:00:00 C	16apr2010 07:00:00 BAC	16jul2010 07:00:00 BAC	18oct2010 08:00:00 C
15oct2009 08:00:00 C	20jan2010 06:30:00 BK	19apr2010 08:00:00 C	16jul2010 08:00:00 C	19oct2010 06:29:00 BK
16oct2009 07:00:00 BAC	20jan2010 07:00:00 USB	20apr2010 06:30:00 BK	20jul2010 06:30:00 BK	19oct2010 06:43:00 BAC
20oct2009 06:30:00 BK	20jan2010 07:01:00 BAC	20apr2010 07:01:00 GS	20jul2010 08:05:00 GS	19oct2010 08:01:00 GS
21oct2009 06:30:00 KEY	20jan2010 08:00:00 WFC	20apr2010 07:30:00 USB	21jul2010 07:00:00 USB	20oct2010 06:45:00 USB
21oct2009 06:58:00 USB	20jan2010 08:02:00 MS	20apr2010 07:33:00 NTRS	21jul2010 08:00:00 WFC	20oct2010 07:30:00 MS
21oct2009 08:00:00 WFC	20jan2010 08:11:00 NTRS	21apr2010 06:19:00 KEY	21jul2010 08:00:00 MS	20oct2010 07:47:00 WFC
21oct2009 08:01:00 MS	21jan2010 07:54:00 KEY	21apr2010 07:47:00 WFC	21jul2010 08:13:00 NTRS	21oct2010 08:01:00 NTRS
21oct2009 08:07:00 NTRS	21jan2010 08:00:00 GS	21apr2010 08:01:00 MS	22jul2010 06:18:00 KEY	22oct2010 06:30:00 KEY
21oct2009 16:05:00 AMP	03feb2010 16:05:00 AMP	26apr2010 16:37:00 AMP	28jul2010 16:26:00 AMP	27oct2010 16:05:00 AMP

2011Q1	2011Q2	2011Q3	2011Q4	2012Q1
14jan2011 06:59:00 JPM	13apr2011 06:59:00 JPM	14jul2011 07:00:00 JPM	13oct2011 06:58:00 JPM	13jan2012 06:59:00 JPM
18jan2011 08:00:00 C	15apr2011 07:00:00 BAC	15jul2011 08:00:00 C	17oct2011 07:59:00 C	17jan2012 07:59:00 C
19jan2011 06:27:00 BK	18apr2011 06:30:00 KEY	19jul2011 06:20:00 KEY	17oct2011 08:00:00 WFC	17jan2012 08:02:00 WFC
19jan2011 07:15:00 USB	18apr2011 08:00:00 C	19jul2011 06:23:00 BK	18oct2011 07:00:00 BAC	18jan2012 06:30:00 BK
19jan2011 07:36:00 NTRS	19apr2011 06:26:00 BK	19jul2011 07:00:00 BAC	18oct2011 07:35:00 GS	18jan2012 07:00:00 USB
19jan2011 08:00:00 WFC	19apr2011 06:45:00 USB	19jul2011 08:00:00 GS	19oct2011 06:30:00 BK	18jan2012 07:14:00 NTRS
19jan2011 08:02:00 GS	19apr2011 07:30:00 NTRS	19jul2011 08:00:00 WFC	19oct2011 07:00:00 USB	18jan2012 07:40:00 GS
20jan2011 07:30:00 MS	19apr2011 08:02:00 GS	20jul2011 06:59:00 USB	19oct2011 07:15:00 MS	19jan2012 07:00:00 BAC
21jan2011 07:03:00 BAC	20apr2011 08:00:00 WFC	20jul2011 08:06:00 NTRS	19oct2011 07:37:00 NTRS	19jan2012 07:15:00 MS
25jan2011 06:33:00 KEY	21apr2011 07:15:00 MS	21jul2011 07:16:00 MS	20oct2011 06:19:00 KEY	24jan2012 08:07:00 KEY
02feb2011 16:01:00 AMP	25apr2011 16:05:00 AMP	27jul2011 16:05:00 AMP	26oct2011 16:15:00 AMP	01feb2012 16:05:00 AMP

2012Q2	2012Q3	2012Q4	2013Q1	2013Q2
13apr2012 06:58:00 JPM	13jul2012 06:59:00 JPM	12oct2012 07:02:00 JPM	11jan2013 08:00:00 WFC	12apr2013 06:59:00 JPM
13apr2012 08:03:00 WFC	13jul2012 08:02:00 WFC	12oct2012 08:00:00 WFC	16jan2013 06:30:00 BK	12apr2013 08:08:00 WFC
16apr2012 07:59:00 C	16jul2012 07:59:00 C	15oct2012 08:05:00 C	16jan2013 06:45:00 USB	15apr2013 07:59:00 C
17apr2012 07:02:00 USB	17jul2012 07:35:00 GS	16oct2012 07:35:00 GS	16jan2013 07:01:00 JPM	16apr2013 07:00:00 USB
17apr2012 07:32:00 NTRS	18jul2012 06:48:00 BK	17oct2012 07:00:00 USB	16jan2013 07:35:00 NTRS	16apr2013 07:30:00 NTRS
17apr2012 07:36:00 GS	18jul2012 07:00:00 BAC	17oct2012 07:01:00 BAC	16jan2013 07:42:00 GS	16apr2013 07:35:00 GS
18apr2012 06:38:00 BK	18jul2012 07:20:00 USB	17oct2012 07:30:00 NTRS	17jan2013 07:03:00 BAC	17apr2013 06:30:00 BK
19apr2012 06:31:00 KEY	18jul2012 07:41:00 NTRS	17oct2012 08:29:00 BK	17jan2013 08:00:00 C	17apr2013 07:00:00 BAC
19apr2012 07:00:00 BAC	19jul2012 06:30:00 KEY	18oct2012 06:31:00 KEY	18jan2013 07:16:00 MS	18apr2013 06:30:00 KEY
19apr2012 07:15:00 MS	19jul2012 07:15:00 MS	18oct2012 07:25:00 MS	24jan2013 06:15:00 KEY	18apr2013 07:15:00 MS
23apr2012 16:10:00 AMP	25jul2012 16:05:00 AMP	24oct2012 16:05:00 AMP	30jan2013 16:05:00 AMP	22apr2013 16:05:00 AMP

2013Q3	2013Q4	2014Q1	2014Q2	2014Q3
12jul2013 06:56:00 JPM	11oct2013 06:58:00 JPM	14jan2014 06:59:00 JPM	11apr2014 06:59:00 JPM	11jul2014 08:00:00 WFC
12jul2013 08:00:00 WFC	11oct2013 08:00:00 WFC	14jan2014 08:00:00 WFC	11apr2014 08:00:00 WFC	14jul2014 07:59:00 C
15jul2013 07:59:00 C	15oct2013 07:48:00 C	15jan2014 07:00:00 BAC	14apr2014 07:59:00 C	15jul2014 06:59:00 JPM
16jul2013 07:47:00 GS	16oct2013 06:30:00 BK	16jan2014 07:35:00 GS	15apr2014 07:56:00 NTRS	15jul2014 07:35:00 GS
17jul2013 06:30:00 BK	16oct2013 06:30:00 KEY	16jan2014 07:59:00 C	16apr2014 07:00:00 BAC	16jul2014 07:00:00 BAC
17jul2013 07:00:00 BAC	16oct2013 07:00:00 BAC	17jan2014 06:30:00 BK	16apr2014 07:15:00 USB	16jul2014 07:15:00 USB
17jul2013 07:00:00 USB	16oct2013 07:00:00 USB	17jan2014 07:15:00 MS	17apr2014 06:30:00 KEY	16jul2014 08:05:00 NTRS
17jul2013 07:34:00 NTRS	16oct2013 07:30:00 NTRS	22jan2014 07:35:00 NTRS	17apr2014 06:45:00 MS	17jul2014 06:30:00 KEY
18jul2013 06:14:00 KEY	17oct2013 07:35:00 GS	22jan2014 07:38:00 USB	17apr2014 07:42:00 GS	17jul2014 07:15:00 MS
18jul2013 07:15:00 MS	18oct2013 07:15:00 MS	23jan2014 06:45:00 KEY	22apr2014 06:30:00 BK	18jul2014 06:30:00 BK
24jul2013 16:05:00 AMP	29oct2013 16:05:00 AMP	04feb2014 16:05:00 AMP	28apr2014 16:05:00 AMP	29jul2014 16:07:00 AMP

E. Content of HF Financial Shocks

In this section, we provide supportive evidence on the financial content of HF shocks.

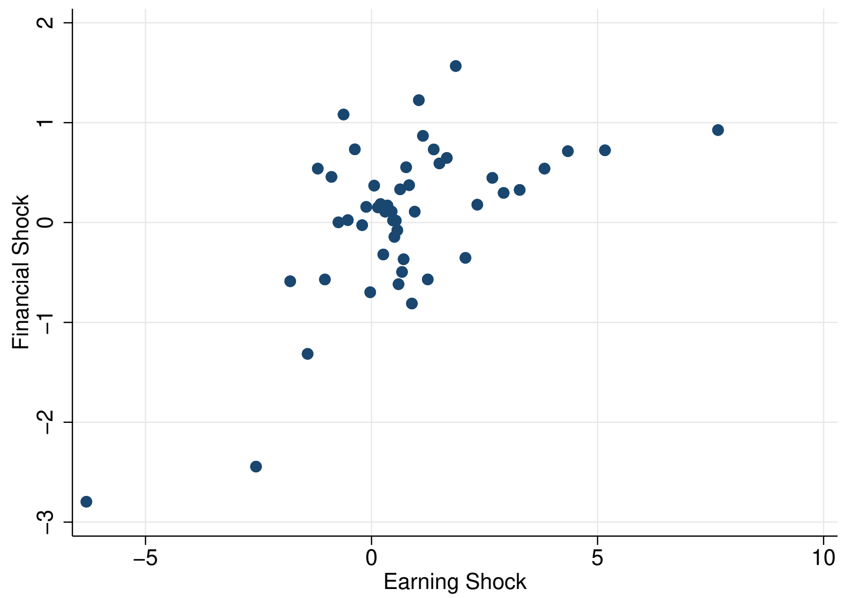
E.1. Unexpected earnings and financial shocks

Figure E.1 studies the relationship between surprise earnings and financial shocks. We measure surprise earnings using the standardized unexpected earnings following the post-earnings-announcement-drift literature (see, for example, Chordia and Shivakumar, 2006), defined as the difference between the reported earnings per share and the consensus forecast, normalized by the standard error of analysts' forecast errors. We obtain data on reported earnings and analysts' forecasts from IBES.

For each earnings announcement, we compare the unexpected earnings of financial institutions with their HF stock price movements used to construct the HF shocks. Figure E.1 shows that stock price movements from financial institutions tend to be positively associated with their surprise earnings, which suggests that financial shocks encode the information on earnings released in the announcements.

Table E.1 estimates the relationship displayed in Figure E.1 with a regression, showing that one standard deviation lower than expected earnings from financial intermediaries leads to 0.2% decline in their market values. It also shows that earnings surprises of placebo nonfinancial firms in Dow Jones display a transmission similar to their market values.

Figure E.1: Earnings Surprises and Financial Shocks



Notes: This figure shows a binned scatter plot between financial shocks and earnings surprises with 50 bins. Financial shocks are unweighted and constructed as described in the main text. Earnings surprises are measured as standardized unexpected earnings, defined in the text.

Table E.1: Transmission from earnings surprises to financial shocks

	Financial Shocks	**Placebo Shocks**
Earnings surprises	0.185***	0.221***
	(0.037)	(0.081)
R^2	0.029	0.008
Obs.	861	895

Notes: This table reports the estimates from regressing unweighted changes in the stock prices of financial intermediaries and placebo nonfinancial firms in Dow Jones. Earnings surprises are measured with standardized unexpected earnings, defined in the text. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

E.2. Textual analysis

We conduct three textual analyses to provide evidence that market participants interpret the earnings as driven by idiosyncratic factors related to intermediaries and not macroeconomic factors. Our textual sample is based on the *Wall Street Journal*'s (WSJ) coverage of intermediaries' earnings announcements. We search Factiva, a news database, and the WSJ's online archive for articles corresponding to the financial earnings announcements included in our sample and collect a textual sample of 807 articles. We remove metadata, such as dates of articles, names of reporters, and alt text of pictures, to form the corpus for analysis.

E.2.1. Sentiment analysis

The first exercise asks whether HF shocks capture the market sentiment of an intermediary's earnings outcome. To answer this question, we measure textual sentiment in the news covering an intermediary's earnings result and analyze the relationship between textual sentiment and the earnings result and stock price movements.

The sentiment of the WSJ's reporting on an earnings release is measured using the Loughran and McDonald (2011) dictionary updated in 2018, which categorizes words into four sentiments (positive, negative, uncertain, or of no particular sentiment). Compared with other dictionaries, such as the Harvard IV-4 dictionary and Lasswell value dictionary, Loughran and McDonald (2011) categorize sentiment specific to an economic context and is widely adopted in macro and financial applications (see, for example, Hassan, Schwedeler, Schreger and Tahoun, 2021). We measure positive (negative) sentiment as the percentage of positive (negative) words out of total unique words in a news piece. For robustness, we construct an additional measure of positive sentiment as the percentage of positive minus negative words out of total unique words.

Table E.2a reports the relationship between the surprise component of earnings and the news sentiment of the underlying earnings releases. It shows that better-than-expected earnings are associated with more positive coverage, which suggests that market sentiment as measured through WSJ coverage focuses primarily on the earnings outcome. Table E.2b reports the relationship between unweighted HF financial shocks and news sentiment. It shows that HF shocks capture the market sentiment, as measured through WSJ coverage. More positive news coverage is associated with more positive movements in the intermediary's stock prices within a narrow window, and more negative news coverage is associated with more negative movements in the stock prices.

E.2.2. Topic modeling

The second exercise asks whether market participants attribute earnings outcomes to intermediaries' idiosyncratic performance or to macroeconomic factors. To answer this question, we use a latent Dirichlet allocation (LDA) model (Blei, Ng and Jordan, 2003) to detect topics discussed in the WSJ's coverage of the earnings release.

LDA is a Bayesian factor model aimed at reducing high-dimensional text into a few "topics" or factors. Documents are represented as random mixtures of latent topics. Given D documents that constitute a corpus of text with V unique vocabulary and K topics, each topic k is represented by a distribution over the vocabulary $\beta_k \in \Delta^{V-1}$, and each document d is represented by a distribution over the topics θ_d^k. LDA assumes a generative process for each document and places Dirichlet priors on β_k and θ_d. The limited inputs imposed by researchers and the high interpretability of its output make it a valuable tool for detecting themes in economic text (Hansen, McMahon and Prat, 2018; Larsen and Thorsrud, 2019; Bybee, Kelly, Manela and Xiu, 2021).

We preprocess the text to reduce the vocabulary to a set of terms that are most likely to answer the question: Do market participants attribute earnings outcomes to intermediary-specific factors or macroeconomic factors? To that end, we first transform individual bank names into a single token (for example, `JP Morgan Chase` and `Goldman` are both converted to the token `bankname`). Next, we remove numeric values, stop words (such as `a` and `the`), capitalization, and tokens with fewer than 3 characters, appearing less than 5 times, or in more than 80% of the documents, and lemmatize the tokens (for example, `increases` and `increase` are both lemmatized to `increase`). The advantage of lemmatization over stemming is that it produces more human-friendly output. Finally, we add to the vocabulary phrases (bigrams) whose frequency is higher than 10.

We estimate the LDA model using the online variational Bayes algorithm developed by Hoffman, Bach and Blei (2010) and assign symmetric Dirichlet priors. An important parameter of the model is the number of topics K. We choose K to maximize the topic coherence score (Röder, Both and Hinneburg, 2015), so that the topics produced by the model are most likely to be interpretable. Figure E.2b shows that $K = 3$ is the optimal choice of topic numbers under this criterion.

Figure E.2a reports the topics detected by the LDA model. All three topics center around an intermediary's idiosyncratic performance. The first two topics focus on loans and mortgages, the core business areas of commercial banks, and the last topic focuses on investment banking and trading. None of the topics, however, relate to the macroeconomy, which indicates that the WSJ attributes earnings outcomes to factors specific to intermediaries rather than macroeconomic fluctuations.

E.2.3. Narratives

The last textual analysis provides further context for the narratives around earnings. We focus on the coverage of individual banks and study what market participants perceive as the causes and consequences of the earnings. We focus on three banks with the most WSJ coverage (J.P. Morgan, Goldman Sachs, and Wells Fargo) and analyze the causal stories constructed in the coverage of each bank with the algorithm based on `relatio` developed by Ash, Gauthier and Widmer (2021).

The unit of analysis is a sentence. The first step in the analysis is to reduce the dimensionality by grouping terms that tend to convey the same meaning. As part of the dimensionality reduction, we perform text preprocessing by converting variants of an intermediary's name to its stock ticker (for example, `Goldman`, `Goldman Sachs` and `Goldman Sachs Group` are all converted into the token `GS`). We also convert dollar amounts (such as $200 million) and percentages (such as 2.5%) into single tokens of `dollaramount` and `percentamount`, respectively. After the preprocessing, we tag named identities (such as person names and organizations) and use the K-means algorithm to cluster terms with the same sentence embeddings. The goal of this step is to transform terms with similar meanings, such as `earnings` and `earnings outcome`, into a single token. In the estimation, we specify the number of named entities and cluster to both be 50.

The second and central step of the analysis is the semantic role labeling of a sentence, which labels the *who* is doing *what* to *whom* in a sentence. It labels the agent ("who"), the verb ("what"), and the object ("whom"). With this step, we can study the causes market participants attribute intermediaries' earnings results to.

Figure E.3 plots the top 30 narratives for each intermediary. On close inspection of the coverage of the three intermediaries, narratives around their earnings announcement fall into three categories. The first summarizes the earnings result (e.g., "bank report result," "bank highlight strong"). The second relates earnings to market expectations (e.g., "result surpass expectation," "thomson poll analyst"). The last analyzes the drivers of earnings (e.g., "attractive business risk capability hold revenue," "bank report organic growth," "bank cut loan," "bank drop credit loss provision"). Of the narratives in the last category which analyze the causes of earnings, none revolves around macroeconomic factors and all discuss intermediary-specific factors.

Table E.2: News Sentiment, Earnings Surprises, and Financial Shocks

(a) News Sentiment and Earnings

	(1)	(2)	(3)
	Earnings Surprises		
% Positive	0.862***		
	(0.148)		
% Negative		-0.484***	
		(0.065)	
% (Positive − Negative)			0.471***
			(0.051)
Observations	529	529	529
R^2	0.094	0.079	0.128

(b) News Sentiment and Stock Prices

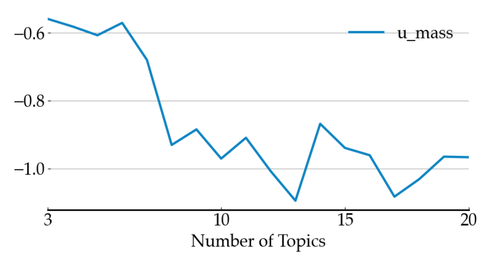
	(1)	(2)	(3)
	Stock Price Changes		
% Positive	0.377***		
	(0.125)		
% Negative		-0.133	
		(0.090)	
% (Positive − Negative)			0.160**
			(0.064)
Observations	529	529	529
R^2	0.015	0.005	0.012

Notes: Panel (a) reports the relationship between standardized surprise earnings and WSJ textual sentiment. Panel (b) reports the relationship between high-frequency changes in stock prices and WSJ sentiment. Three measures of textual sentiment in WSJ coverage are reported: percentage of unique positive/negative/positive minus negative tokens out of total unique words in an article, respectively. Robust standard errors are in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Figure E.2: LDA Topics in Earnings Coverage

(a) LDA Topics

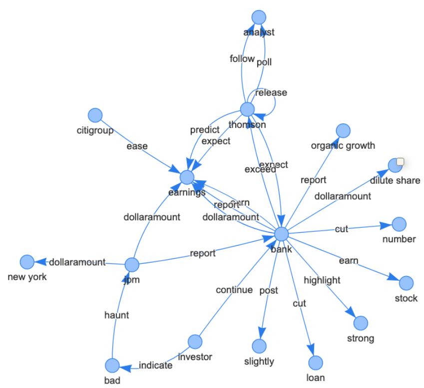
(b) Topic Coherence



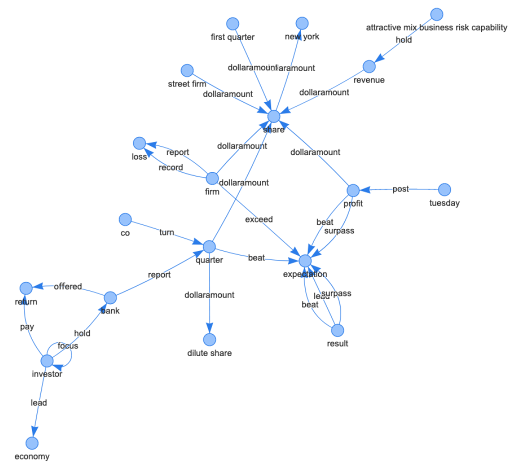
Notes: Panel (a) reports all three topics detected by the LDA model in WSJ articles. A larger font size represents a higher probability of a word or bigram appearing in an article. Panel (b) plots topic coherence measured against the number of topics K. Topic coherence is measured by $u_{\text{mass}} = \frac{2}{V(V-1)} \sum_{i=2}^{V} \sum_{j=1}^{i=1} \log \frac{P(w_i, w_j)+\varepsilon}{P(w_j)}$, where (w_i, w_j) represent a pair of vocabulary.

Figure E.3: Narratives in Earnings Coverage

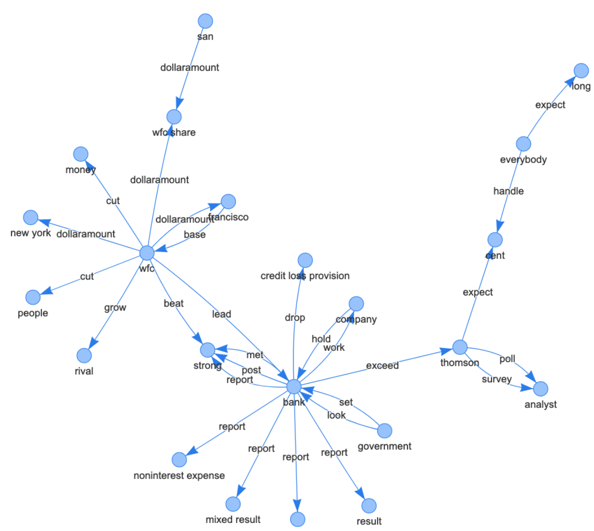
(a) J.P. Morgan



(b) Goldman Sachs



(c) Wells Fargo



E.3. Predictability of financial shocks

In this section, we use a state-of-the-art machine-learning model to provide evidence suggesting that HF financial shocks are not predictable using the macroeconomic and financial variables available prior to the shock. We use two sets of predictors. The first macro panel contains a large panel of 126 monthly macroeconomic series constructed by McCracken and Ng (2016) and available through FRED-MD. The second financial panel is of higher daily frequency and includes stock prices of the financial intermediaries in our sample, as well as the S&P 500 and VIX.

Our main forecasting model is random forests (Breiman, 2001), which produce an averaged prediction from a large collection of regression trees. Random forests incorporate nonlinearity and multi-way interactions between predictors, which renders the method useful for macroeconomic and financial forecasting (Gentzkow, Kelly and Taddy, 2019). The random-forest predictor is defined as

$$\hat{f}_{\text{rf}}^{B} = \frac{1}{B}\sum_{b=1}^{B} T(x;\Theta_b),$$

which averages the forecasts of B regression trees $T(x;\Theta_b)$, where x is the set of predictors and Θ_b characterizes the parameters in the bth tree.[18]

As Gentzkow *et al.* (2019) argue, the benefits of regression trees from nonlinearity and high-order interactions lessens with high-dimensional predictors, so we first perform variable selection with elastic net (Zou and Hastie, 2005), which is an implementation of soft thresholding regularization that drops uninformative predictors using penalized regressions. The

[18]See Hastie, Tibshirani and Friedman (2009) for a comprehensive exposition of trees and random forests.

elastic net estimator is defined by

$$\hat{\beta}_{\text{EN}} = \arg\min_{\beta} \left\{ \frac{1}{2} \sum_{i=1}^{N} (y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j)^2 + \lambda \left(\frac{1}{2}(1-\alpha)\|\beta\|_{l_2}^2 + \alpha\|\beta\|_{l_1} \right) \right\},$$

which minimizes the sum or regression residuals and a penalty term, which is a weighted average of LASSO and ridge. Following Borup and Schütte (2020), we set $\alpha = 0.5$ for an equal weight between LASSO and ridge regressions and tune the penalty parameter λ so that the elastic net selects the 20 best predictors.

We then use random forests to form predictions using 48-month rolling windows for macro predictors and quarter rolling windows for financial predictors. To assess forecastability, we compare the predictions from random forests against those from a random walk, formed with stock returns 1 day before the financial shock, converted to match the size of the 60-minute shock window. The metric for evaluating forecastability is the out-of-sample R^2 (Campbell and Thompson, 2008), defined as

$$R_{\text{oos}}^2 = 1 - \frac{\Sigma_t (y_t - \hat{y}_{m,t})^2}{\Sigma_t (y_t - \bar{y}_t)^2},$$

where $\bar{y}_t$ is the rolling-mean forecast computed on a window matching the model-estimation window and $\hat{y}_{m,t}$ is the forecast from the model. R_{oos}^2 lies in the range $(-\infty, 1]$, with negative numbers indicating that the model underperforms the historical mean of the series.

Assessments of the forecastability of financial shocks by macroeconomic and financial predictors are shown in Table E.3. Random-forest forecasts with both macro and financial predictors have negative R_{oos}^2, which suggests worse performance than historical rolling-mean forecasts. The results also suggest that incorporating panels of macro and financial variables does not help in forecasting HF financial shocks compared with a random walk.

Table E.3: Out-of-sample R^2 of Predictions of Financial Shocks

	Macro	**Financial**
Random forest	−15.1%	−16.8%
Random walk benchmark		−5.2%

Notes: This table reports the out-of-sample R^2 of random-forest forecasts based on a large panel of macroeconomic and financial variables compared with the out-of-sample R^2 of random-walk forecasts based on the stock returns one day before the shock. The out-of-sample R^2 is defined as $R^2_{\text{oos}} = 1 - \frac{\Sigma_t (y_t - \hat{y}_{m,t})^2}{\Sigma_t (y_t - \bar{y}_t)^2}$, where $\bar{y}_t$ is the rolling-mean forecast computed on a window matching the model-estimation window, and $\hat{y}_{m,t}$ is the forecast from the model. Negative numbers indicate that the forecast underperforms the rolling historical mean of the series.

E.4. Stock-price volatility for financial intermediaries and nonfinancial firms: Event vs. nonevent days

Table E.4 reports descriptive statistics for the stock price of financial intermediaries and nonfinancial firms in the S&P 500 during event windows in which intermediaries release earnings and nonevent windows. It show that the volatility of financial intermediaries' stock prices during their earnings announcements increases by substantially more than those of nonfinancial firms during these events, which is consistent with the fact that intermediaries' earnings announcements contain more information about financial intermediaries than about nonfinancial firms.

Table E.4: Summary Statistics for Event and Nonevent Windows

	Financial Intermediaries		Nonfinancial Firms	
	Release	Nonrelease	Release	Nonrelease
Mean of weighted ΔP	0.12	0.05	0.02	0.03
	(0.03)	(0.00)	(0.02)	(0.00)
SD of weighted ΔP	0.82	0.74	0.49	0.45
	(0.02)	(0.00)	(0.01)	(0.00)
Observations	862	15,171	862	15,171

Notes: This table shows summary statistics for weighted HF stock-price changes for event windows and nonevent windows. Financial intermediaries are the institutions listed in Table 1. Nonfinancial firms are constituents of the S&P 500 excluding financial firms (naics 52). Standard errors are in parentheses.

F. Robustness Analysis

In this section, we conduct additional robustness tests for the event-time analysis in Section 4.1 and within-firm variation in Section 5.1.3.

F.1. Additional robustness analysis for Section 4.1

Table F.1: Effects of Financial Shocks (Alternative Weighting of S&P 500 Firms)

	(1)	(2)	(3)	(4)	(5)
	Equal-weighted		**Value-weighted**		**HF Index**
Independent variables:					
Fin shock (narrow)	0.291**	0.292**	0.215**	0.223**	0.235**
	(0.140)	(0.147)	(0.099)	(0.104)	(0.094)
R^2	0.014	0.015	0.006	0.007	0.026
Observations	104,167	104,167	102,058	102,058	341
Macro controls	no	yes	no	yes	yes
Cusip FE	yes	yes	yes	yes	no
Double-clustered SE	yes	yes	yes	yes	no

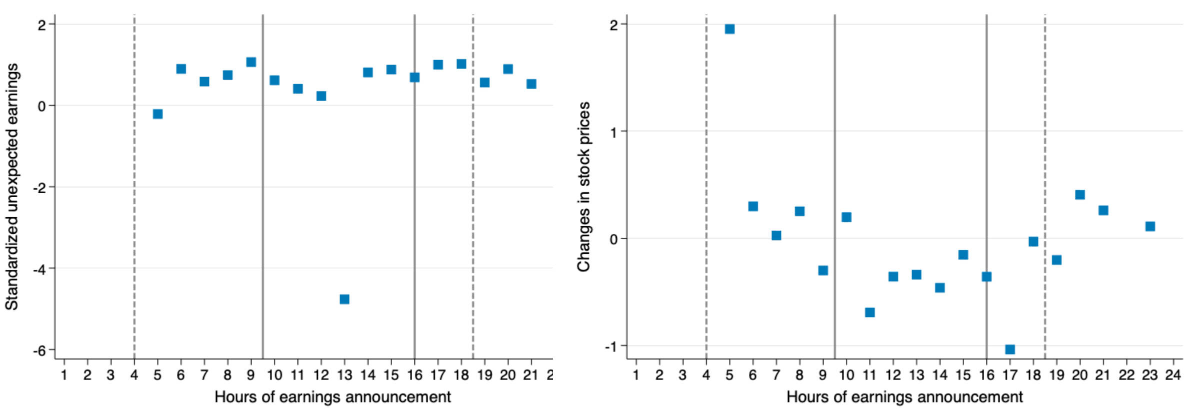
Notes: This table reports estimates from the event-time regression $\Delta y_{jt} = \alpha_j + \beta \varepsilon_t^{\mathrm{F}} + u_{jt}$ using different weighting for the dependent variable Δy_{jt}. α_j is a cusip fixed effect and $\varepsilon_t^{\mathrm{F}}$ is the narrow HF shock. Baseline Columns 1 and 2 (same as in Table 3) estimate the effect of narrow HF financial shocks on equal-weighted log price changes in S&P 500 nonfinancial constituents' stocks. Columns 3 and 4 estimate the effect of narrow HF financial shocks on the log price changes in S&P 500 nonfinancial constituents' stocks weighted by their market values at the beginning of the quarter. Standard errors in columns 1 through 4 are two-way clustered at shock and cusip level. Column 5 replaces the cusip fixed effect with a constant to estimate the effect of financial shocks on the broad S&P 500 index at high frequency, measured through the exchange-traded fund SPDR. Macro controls include output, employment, and an indicator variable for recession. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table F.2: Effects of Financial Shocks (Daily Frequency)

	SP500 Ex-Fin	SmallCap	Russell	Obs
Narrow	0.924***	1.348***	1.453***	272
	(0.241)	(0.296)	(0.313)	
Macro controls	0.908***	1.276***	1.381***	272
	(0.243)	(0.299)	(0.316)	
Broad	0.720***	1.085***	1.124***	486
	(0.179)	(0.213)	(0.229)	

Notes: This table shows results from estimating $\Delta \log y_t = \alpha + \beta\varepsilon_t^{\mathrm{F}} + u_t$, where $\Delta \log y_t$ is the daily log change in one of the following indices: S&P 500 Ex-Financial, S&P SamllCap 600, or Russell 2000; and $\varepsilon_t^{\mathrm{F}}$ is the HF financial shock, described in the main text. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Figure F.1: Earnings results and timing of announcements



(a) Surprise earnings

(b) Shock price changes

Notes: Panel (a) shows the average standardized unexpected earnings by the hour of earnings announcement. Panel (b) shows the average changes in intermediaries' stock prices by the hour of earnings announcement. Solid vertical lines represent core trading hours (9:30–16:00), and dashed vertical lines represent the hours of consolidated tape (4:00-18:30) for which the intraday data used to construct the narrow measure of financial shocks are available from TAQ.

Table F.3: Effects of Financial Shocks (Broad Measure)

	(1)	(2)	(3)	(4)	(5)
	Equal-weighted		**Value-weighted**		**HF Index**
Independent variables:					
Fin shock (broad)	0.498***	0.514***	0.479***	0.501***	0.535***
	(0.116)	(0.125)	(0.109)	(0.117)	(0.080)
R^2	0.016	0.021	0.004	0.005	0.059
Observations	256,717	256,717	252,285	252,285	849
Macro controls	no	yes	no	yes	yes
Cusip FE	yes	yes	yes	yes	no
Double-clustered SE	yes	yes	yes	yes	no

Notes: This table reports estimates from the event-time regression $\Delta y_{jt} = \alpha_j + \beta\varepsilon_t^{\mathrm{F}} + u_{jt}$ using the broad measure of financial shocks, $\varepsilon_t^{\mathrm{F}}$, which includes earnings announced outside of trading hours, described in Section 3. Columns 1 and 2 estimate the effect of broad HF financial shocks on equal-weighted log price changes of S&P 500 nonfinancial constituents stocks. Columns 3 and 4 estimate the effect of broad HF financial shocks on the log price changes in S&P 500 nonfinancial constituents' stocks weighted by their market values at the beginning of the quarter. Standard errors in columns 1 through 4 are two-way clustered at shock and cusip level. Column 5 replaces the cusip fixed effect with a constant to estimate the effect of financial shocks on the broad S&P 500 index at high frequency, measured through the exchange-traded fund SPDR. Macro controls include output, employment, and an indicator variable for recession. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

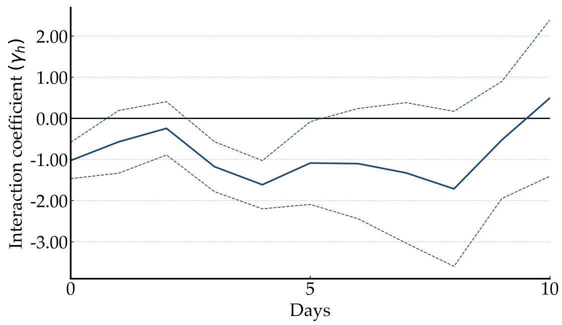
Table F.4: Controlling for the Systemic Component between Financials and Nonfinancials

	(1)	(2)	(3)	(4)
	Releasing Intermediaries		**All Intermediaries**	
Fin shock (residual)	0.518**	0.523**	0.514**	0.519**
	(0.232)	(0.247)	(0.233)	(0.248)
R^2	0.015	0.016	0.015	0.016
Observations	103,792	103,792	103,591	103,591
Macro controls	no	yes	no	yes
Cusip FE	yes	yes	yes	yes
Double-clustered SE	yes	yes	yes	yes

Notes: This table reports the results from estimating the baseline event-time regression in (2) with the explanatory variable $\varepsilon_t^{\text{resid}} \equiv \varepsilon^{\text{F}} - \hat{\beta}_t \varepsilon_t^{\text{F}}$. The time-varying $\hat{\beta}_t$ is estimated by regressing the daily changes in the S&P 500 Ex-Financials index, Δy_t, on daily changes in the S&P 500 Financials Index, $\Delta \nu_t$, in a 1-month window before the date of the earnings announcement, i.e., $\Delta y_t = \alpha + \beta \Delta \nu_t + \varepsilon_t$. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

F.2. Additional robustness analysis for Section 5.1.3

Figure F.2: Within-Firm Variation (Controlling for Liquidity)



Notes: This figure reports estimates of γ_h from $\Delta_h z_{k(j)it} = \alpha_{jt} + \gamma_h \theta_{k(j)it} \varepsilon_t^{\mathrm{F}} + \Gamma' Z_{jt} + u_{jith}$, where $\Delta_h z_{k(j)it}$ is cumulative changes in bond option-adjusted spreads; $\varepsilon_t^{\mathrm{F}}$ is the narrow HF shock; $\theta_{k(j)it}$ is the holdings of bond k by intermediary i; α_{jt} is a firm-by-shock fixed effect; and Z_{jt} is a vector of bond controls including bond holdings $\theta_{k(j)it}$, a categorical variable for bond ratings, remaining maturity, average spreads in the previous 30 days, month-to-date changes in spreads, and bid-ask spread. Standard errors are two-way clustered at shock and firm level. Dotted lines represent 90% confidence intervals.