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

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Abstract

We provide empirical evidence on the effects of news about financial intermediaries' net worth on the aggregate economy based on a high-frequency identification strategy. We measure "financial shocks" as the idiosyncratic changes in market value of large U.S. intermediaries' net worth in a narrow window around their earnings announcements. We document sizable effects of financial shocks on the market value and borrowing costs of nonfinancial firms and macroeconomic outcomes. Evidence based on sign restrictions suggests that shocks primarily affecting credit supply drive these effects. In addition, the effects of financial shocks are larger 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 role do financial intermediaries play in macroeconomic fluctuations? The history of financial crises suggests that negative news about intermediaries' net worth can be rapidly followed by financial distress and economic downturns (see, for example, Bernanke, 1983; Reinhart and Rogoff, 2009a; Gertler and Gilchrist, 2018). For instance, the month following the announcement of Lehman Brothers' bankruptcy saw some of the largest declines in the U.S. stock market on record and was followed by a sharp contraction in economic activities. Motivated by these episodes, this paper proposes a high-frequency identification strategy to study the effects of news about financial intermediaries' net worth on the aggregate economy. The key idea of our strategy is to focus on the information contained in the earnings releases of large financial intermediaries. In the spirit of the high-frequency approach to studying the effects of monetary policy shocks (surveyed by Nakamura and Steinsson, 2018a), our strategy exploits the fact that these earnings announcements cause a discontinuity in the information released around these events about intermediaries' net worth.

We begin by implementing the high-frequency identification within an event-study framework, using tick-level stock price data from the New York Stock Exchange's Trade and Quote for a sample of 18 large U.S. financial intermediaries and constituents of the S&P 500 Index. For each earnings announcement, we define the "financial shock" as the stock price change of the individual intermediary releasing their earnings announcement within a narrow window (60 minutes) around the announcement.[1] We then estimate its effect on the stock price changes of nonfinancial firms in the same narrow window. The identifying assumption for interpreting these estimates as causal is that, in the narrow window around the earnings announcement, changes in the stock price of the individual intermediary releasing their earnings are driven by the information contained in the announcement. Under this assumption, we document that a financial shock equivalent in size to a 1% change in the market value of the financial intermediaries in our sample leads to a 0.25% change in the market value of nonfinancial firms. We complement these estimates with a heteroskedasticity-based

[1] We use the term "financial shock" to express the fact that our variable encodes new information revealed in the earnings announcement of a financial intermediary. We emphasize that, as our variable is not a structural object, we do not use the term "shock" in the sense of representing a structural disturbance, as often used for monetary, fiscal, or technology shocks in the empirical macroeconomics literature (see, for example, Ramey, 2016).

identification, which imposes weaker identifying assumptions than the event-study framework by allowing for common factors that affect financial and nonfinancial firms and for simultaneity between these variables. The estimated coefficients indicate that a 1% change in the market value of the financial intermediaries in our sample leads to a 0.36% change in the market value of nonfinancial firms.

Using the high-frequency financial shocks, we then examine their effects on bond markets and macroeconomic outcomes. In bond markets, financial shocks affect the spreads of high-risk bonds and the excess bond premium (Gilchrist and Zakrajšek, 2012) of nonfinancial firms. We also present within-firm-level evidence of the effects of financial shocks. Using security-level data on bond holdings by each financial institution, we show that among bonds issued by the same firm with similar characteristics, those more heavily held by financial intermediaries that are reporting earnings show a larger sensitivity to financial shocks. To investigate the impact on macroeconomic variables, we turn to monthly data and employ an external-instrument vector autoregression (Stock and Watson, 2012; Mertens and Ravn, 2013; Gertler and Karadi, 2015). We document that financial shocks have lasting effects on industrial production, unemployment, macro uncertainty, and borrowing costs.

The financial shocks we measure contain information both about financial intermediaries and about nonfinancial firms' conditions (e.g., their productivity or demand). We use sign restrictions to decompose the effect of financial shocks into two broad types of channels: those that primarily affect credit supply and affect lending and borrowing costs in opposite directions (e.g., the effect of intermediaries' net worth on the supply of funds); and those that primarily affect credit demand and affect lending and borrowing costs in the same direction (e.g., information about nonfinancial firms' conditions contained in news about intermediaries' earnings). We find that shocks primarily affecting credit supply are the dominant channel through which news about financial intermediaries' net worth impacts nonfinancial firms. We complement this finding with evidence that the effects we identify are more pronounced during periods when the aggregate net worth of the financial system is low, underscoring the importance of aggregate net worth channels (as stressed, for instance, by Bernanke, Gertler and Gilchrist, 1999, Gertler and Kiyotaki, 2010 and Brunnermeier and Sannikov, 2014). We also show that firms that are more severely affected by financial frictions—e.g., those with higher credit risks and lower liquidity—are disproportionately impacted by the financial shocks, which suggests that the financial positions of firms matter in the aggregate transmission of these shocks (as highlighted, for example, by 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 nonfinancial firms (e.g., Khwaja and Mian, 2008; Amiti and Weinstein, 2011; Chodorow-Reich, 2014) 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 financial intermediaries' aggregate effects. To date, empirical work on aggregate effects has used time-series methods (see, for example, Gilchrist and Zakrajšek, 2012; Stock and Watson, 2012; Jordà, Schularick and Taylor, 2013; Krishnamurthy and Muir, 2017; Bernanke, 2018; Gertler and Gilchrist, 2018; Brunnermeier, Palia, Sastry and Sims, 2021; Baron, Verner and Xiong, 2021); regional data (Huber, 2018; Gertler and Gilchrist, 2019); and model-based inference (see, for example, Christiano, Eichenbaum and Trabandt, 2015; Herreño, 2020).

We consider our high-frequency (HF) strategy to be complementary to prior empirical work, contributing to the literature along two dimensions. First, HF methods tend to require milder assumptions for the identification of aggregate effects (as discussed, for instance, in Nakamura and Steinsson, 2018b).[2] Second, our HF financial shocks can be used directly by other researchers conducting empirical research on macroeconomics, similar to the large body of evidence developed using HF monetary policy shocks. This can be particularly useful to discipline models aimed at understanding the role of financial intermediaries in determining the aggregate transmission of shocks.

2. Data

Our empirical analysis uses tick-by-tick data on intermediaries' stock prices in a window around their earnings releases. We obtain tick-level stock prices from the New York Stock

[2] 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.

Exchange's Trade and Quote (TAQ). The TAQ database contains intraday trades time-stamped 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 2020.[3] We focus on these types of intermediaries because their direct involvement in financial 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 based on 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.[4] In our period of analysis, we obtain 870 announcements of earnings, with roughly four per institution–year.

Our analysis also uses stock- and bond-price data for nonfinancial firms. For stock prices, we use intraday data on the S&P 500 constituent securities, also obtained from the TAQ database. Our main analysis focuses on the movements of these nonfinancial constituents in the same narrow window as that of financial intermediaries. We complement this analysis with additional daily indices data from FRED and Bloomberg—the S&P 500 Ex-Financials, S&P SmallCap 600, and Russell 2000 indices. Appendix Table B.1a 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.

For bond prices, we use data from several sources. First, we use daily data on U.S. corporate bond indices from the Intercontinental Exchange Bank of America (ICE BofA), obtained from FRED.[5] Our analysis covers a wide range of ratings from investment grade

[3]We start the sample in 1998, when precise time stamps in IBES became 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.

[4]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.

[5]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).

Table 1: Financial Intermediaries Included in the Sample

Financial Intermediary	Ticker	Start	End	Avg Equity ($ billion)	Share of Sample	Share of Aggr Equity
Bank of America	BAC	1998Q1	2020Q4	170.0	21.7%	12.6%
Citicorp	CCI, C	1998Q1	2020Q4	164.7	21.1%	12.2%
J.P. Morgan Chase	CMB, JPM	1998Q1	2020Q4	151.5	19.4%	11.2%
Wells Fargo	WFC	1998Q1	2020Q4	105.5	13.5%	7.8%
Goldman Sachs	GS	2002Q3	2020Q4	51.7	3.6%	3.9%
Morgan Stanley	MWD, MS	1998Q1	2020Q4	48.5	6.2%	3.6%
Wachovia	WB	1998Q1	2008Q4[a]	35.8	2.2%	4.0%
U.S. Bankcorp	USB	1998Q1	2020Q4	29.2	3.7%	2.2%
Merrill Lynch	MER	1998Q1	2008Q4[b]	25.4	1.6%	2.8%
Bank of New York Mellon	BK	1998Q1	2020Q4	24.4	3.1%	1.8%
Bank One	ONE	1998Q1	2004Q2[c]	19.8	0.7%	3.0%
FleetBoston	FBF	1998Q1	2004Q1[d]	14.9	0.5%	2.3%
Lehman Brothers	LEH	1998Q1	2008Q3	12.6	0.8%	1.4%
Jefferies	JEF	2018Q3	2020Q4	8.9	0.1%	0.4%
First Chicago	FCN	1998Q1	1998Q4[e]	8.2	0.0%	1.5%
Ameriprise	AMP	2005Q4	2020Q4	7.7	0.7%	0.5%
MBNA Corp	KRB	1998Q1	2005Q4[f]	7.6	0.3%	1.0%
Northern Trust	NTRS	1998Q1	2020Q4	6.0	0.8%	0.4%
BankBoston	BKB	1998Q1	1999Q3[g]	4.9	0.0%	0.9%
Mean				47.2	5.26%	3.87%
SD				56.4	7.58%	4.02%
Min				4.9	0.02%	0.42%
Max				170.0	21.75%	12.59%
Total				897.2	100.00%	73.62%

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 FleetBoston.

to high yield. Second, we use data on the "excess bond premium," 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, to study the within-firm variation of bond prices, we use 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 Tables B.1b and B.2 report descriptive statistics for bond data.

3. Empirical Strategy

We propose a high-frequency approach to study the effect of news about financial intermediaries' net worth on nonfinancial firms, which exploits price changes in a narrow window around intermediaries' earning announcements. We consider two strategies within this approach: an event-study framework and a heteroskedasticity-based identification, each of which we describe next.

3.1. Event-study framework

Our first empirical strategy is an event-study framework, which consists of estimating the following model:

$$\Delta y_{jt} = \alpha_j + \beta \cdot \theta_{i,q(t)} \Delta p_{\mathrm{F},i,t} + \varepsilon_{jt}, \tag{1}$$

where Δy_{jt} denotes the change in an outcome variable of interest for nonfinancial firm j in a window around an intermediary's earnings announcement at time t (e.g., the log stock prices of nonfinancial firms and their bond spreads); $\Delta p_{\mathrm{F},i,t}$ denotes the change in log stock prices of financial intermediary i announcing earnings at time t, within the same window around this announcement; $\theta_{i,q(t)}$ represents the market capitalization of institution i as a share of the total market capitalization of all institutions in our sample, measured in the quarter $q(t)$ before announcement (used as a scaling, as explained below); α_j is a nonfinancial firm fixed effect, and ε_{jt} is a random error term. Our baseline analysis considers announcements made within trading hours and measures stock price changes within 20 minutes before the announcement and 40 minutes after the announcement, following Nakamura and Steinsson (2018b) for monetary policy shocks.[6] We cluster standard errors two ways to account for potential correlation within outcomes of nonfinancial firms and within periods.

We henceforth refer to $v_{\mathrm{F},t} \equiv \theta_{i,q(t)} \Delta p_{\mathrm{F},i,t}$ as the "HF financial shock." In a narrow

[6] Intraday data from the TAQ are available for hours inside the Consolidated Tape System 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. In robustness analysis we also consider the sample of intermediaries' earning announcements made after trading hours. In this case, we consider stock price changes between closing and opening log prices.

window around a financial intermediary's earnings announcement, $v_{\mathrm{F},t}$ measures the high-frequency change in its stock prices, scaled by its relative market share among the financial intermediaries in our sample.[7] Table 2 reports a set of descriptive statistics about financial shocks.[8] The first column shows that on average, the price changes of reporting institutions are close to zero, with a standard deviation of 2.5%. Median positive and negative shocks are close to 1%. The second column shows descriptive statistics of the financial shocks $v_{\mathrm{F},t}$, which weigh each change in the log price of reporting institutions by their market share. Weighting overall reduces the magnitude of the shocks, which results in a standard deviation of 0.30% and median positive and negative shocks of 0.06% and -0.08%, respectively. Table 2 also reports changes in the financial sector around earnings announcements. The third column reports the unweighted sum of changes in the log prices of all sample intermediaries 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.

The identifying assumption to interpret the estimates from (1) as causal is that, in the narrow window around the earnings announcement, changes in the stock price of the individual intermediary releasing their earnings are driven by the information contained in the announcement and not by other factors that affect the outcome of interest of nonfinancial firms, which are contained in ε_{jt}. Under this assumption, the coefficient of interest, β, measures the effect of the earnings announcement on nonfinancial firms' outcomes Δy_{jt} relative to its effects on the (scaled) releasing intermediaries' stock price, $v_{\mathrm{F},t}$.

It is worth highlighting the fact that the estimated coefficient β captures various mechanisms through which news about the net worth of earnings-releasing intermediaries affects nonfinancial firms' outcomes. To illustrate this, we present a simple theoretical framework in Appendix A, which describes three potential channels. First, given that intermediaries in our sample are relatively large, changes in the net worth of the intermediary releasing earn-

[7] This scaling renders the estimates more comparable with empirical models based on overall changes in the net worth of the financial intermediaries in our sample, such as those presented in Section 3.2

[8] Appendix Figure B.1 illustrates the financial 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: HF Financial Shocks: Descriptive Statistics

	Releasing Intermediaries Stock Price Changes		**All Intermediaries** Stock Price Changes	
	Unweighted	Weighted (v_{F})	Unweighted	Weighted (Δp_{F})
Mean	−0.10	−0.03	−0.20	−0.04
Median +	1.22	0.07	3.85	0.33
Median −	−1.13	−0.09	−4.94	−0.41
Std Deviation	2.48	0.28	10.57	0.85
5th Percentile	−3.92	−0.50	−14.19	−1.30
95th Percentile	3.67	0.31	13.95	1.35
Observations	523	523	523	523

Notes: This table reports descriptive statistics for stock price changes around financial intermediaries' earnings announcements. Unweighted changes of a reporting financial intermediary are based on its stock price 20 minutes before and 40 minutes after its earnings announcement. Weighted stock price changes of a reporting financial intermediary, which are referred to as the financial shock (v_{F}) in the main text, 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. Stock price changes of all intermediaries are the unweighted sum of all sample intermediaries' stock price changes around reporting intermediaries' earnings releases. Weighted stock price changes of all intermediaries, which are denoted as Δp_{F} in the main text, are the weighted sum based on all sample intermediaries. "Median +" and "Median −" refer to median positive and median negative stock price changes.

ings (driven, for example, by realizations of returns on their investments) can lead to direct effects in the supply of funds to nonfinancial firms, which in turn affects nonfinancial firms' investment decisions and market values (as highlighted in financial frictions models, such as Gertler and Kiyotaki, 2010; He and Krishnamurthy, 2012, 2013; Brunnermeier and Sannikov, 2014, among others). Second, news about the net worth of the releasing intermediary can contain information about the conditions of other financial intermediaries (e.g., their costs of raising external finance), or affect the willingness to lend of other investors (e.g., affecting their risk aversion), leading to additional effects in the supply of funds to nonfinancial firms.[9] Third, news about financial intermediaries' net worth can contain information about productivity or demand faced by nonfinancial firms. Section 5 presents additional analysis to unpack these potential mechanisms.

The content of financial shocks Appendix C conducts a set of exercises to examine the content of financial shocks, which are motivated by the identifying assumption of the event-

[9] Consistent with this channel, Appendix Figure B.2 shows that shocks to the market value of an earnings-releasing intermediary leads to a 0.19% increase in the market value of other nonreleasing intermediaries. This can arise, for example, if an intermediary's positive earnings surprise leads investors to revise upwards the earnings expectations of other intermediaries that are scheduled to report earnings.

study framework. First, Appendix C.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, financial shocks are not linked systematically to information available at the moment of earnings releases. Appendix C.2 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.

Next, Appendix C.3 studies the relationship between financial shocks within a quarter by computing the standard deviation and autocorrelation of the n-th financial shock in the quarter. The analysis shows no systematic differences in stock price changes between the first intermediaries to report earnings and those that report subsequently.

Lastly, the financial press disseminates information contained in intermediaries' earnings announcements to market participants. Appendix C.4 conducts textual analyses on news articles from the *Wall Street Journal* to understand how the financial press interprets intermediaries' earnings: 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' core business areas, and narratives constructed in the articles attribute stock price movements to earnings performance relative to forecasts and attribute earnings results to bank-specific factors.

3.2. Heteroskedasticity-based identification

Our second empirical strategy is a heteroskedasticity-based identification strategy (developed by Rigobon, 2003; Rigobon and Sack, 2004), which relaxes the identifying assumption from the event-study approach in two dimensions. First, it allows for unobserved common shocks (unrelated to the release of earnings of intermediaries) that affect both nonfinancial firms' outcomes and financial intermediaries' stock prices in the narrow window around earnings announcements. Second, it allows for feedback effects from nonfinancial firms' outcomes to financial intermediaries' stock prices. For this strategy, consider the following simultaneousequation model (following Rigobon and Sack, 2004; Hébert and Schreger, 2017):

$$\Delta p_{\mathrm{N},t} = \alpha_{\mathrm{N}} + \gamma \Delta p_{\mathrm{F},t} + \lambda_N F_t + \varepsilon_{\mathrm{N},t}, \tag{2}$$

$$\Delta p_{\mathrm{F},t} = \alpha_{\mathrm{F}} + \eta \Delta p_{\mathrm{N},t} + \lambda_F F_t + \varepsilon_{\mathrm{F},t}, \tag{3}$$

where $p_{\mathrm{N},t}$ and $p_{\mathrm{F},t}$ are the log market values of nonfinancial firms and financial intermediaries; F_t is an unobserved factor that affects both financial and nonfinancial market values; and $\varepsilon_{\mathrm{N},t}$ and $\varepsilon_{\mathrm{F},t}$ are shocks to these values, which are uncorrelated with each other, the unobserved factor, or over time. The coefficient of interest, γ, measures the impact of changes in the market value of financial intermediaries on the market value of nonfinancial firms.

Unlike the event-study framework, 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 them with nonevents, defined as the times in which nonfinancial firms in the S&P 500 release earnings. For time t when either financial or nonfinancial firms release earnings, we measure $\Delta p_{\mathrm{F},t}$ with the change in the log value-weighted index of intermediaries' stock prices in a 60-minute window and $\Delta p_{\mathrm{N},t}$ with the change in the log value-weighted index of nonfinancial firms' stock prices in the same window.[10] We estimate the coefficient of interest, γ, following the instrumental variable approach 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.[11]

The identifying assumption for the heteroskedasticity-based identification is that the variance of intermediaries' stock prices is larger during earnings-announcement event times than in nonevent times, while those of nonfinancial firms are the same during both earnings releases of financial intermediaries and nonevent times. To validate this assumption, we report in Appendix C.5 the volatility of the stock prices of financial intermediaries and nonfinancial firms during event and nonevent windows. These moments show that the variance in financial intermediaries' stock prices during their earnings announcements increases by substantially more than that of nonfinancial firms during those events, which is consis-

[10]The 60-minute event window matches the frequency from the event-study framework.

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

tent with the fact that intermediaries' earnings announcements contain more information about financial intermediaries than about nonfinancial firms. In contrast, variance in the stock price of nonfinancial firms remains the same during both the event times of financial intermediaries' earnings releases and nonevent times.

4. The Aggregate Effects of News about Intermediaries' Net Worth

4.1. Stock markets

Baseline results We begin by analyzing how news about intermediaries' net worth affects nonfinancial firms' stock prices. Panel (a) in Table 3 reports results from the event study, using stock prices of nonfinancial constituent firms in the S&P 500 Index. Column (1) shows the results from estimating the baseline model (1), which indicate that a 1% financial shock leads to a 0.25% change in the market value of nonfinancial firms.[12] Column (2) shows that controlling for business-cycle variables—output, employment, and a recession indicator—affects neither the estimated elasticity nor the standard errors.

Panel (b) in Table 3 shows results from the heteroskedasticity-based identification, which imposes weaker identifying assumptions than the event-study framework by allowing for common factors that affect financial and nonfinancial firms. The estimated coefficients indicate that a 1% change in intermediaries' market value of the net worth of the financial intermediaries in our sample leads to a 0.36% change in the market value of nonfinancial firms.

The last two columns of Panel (a) facilitate comparison of estimates from the event-study and heteroskedasticity-based approaches. We estimate a variant of the event-study regression (1), in which we replace the financial shock $v_{\mathrm{F},t}$ (based only on earnings-releasing financial intermediaries) with $\Delta p_{\mathrm{F},t}$, the change in the market value of all intermediaries in

[12] Re-expressing the effects in terms of earnings surprises, we estimate in Appendix Table C.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 \$0.14 trillion) and that of nonfinancial firms in the S&P 500 by 7.8% (or \$0.62 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.

Table 3: Effects of News about Financial Net Worth on Nonfinancial Market Values

(a) Event-Time

	(1)	(2)		(3)	(4)
	Releasing Intermediaries			**All Intermediaries**	
$v_{\mathrm{F},t}$	0.245**	0.240**	$\Delta p_{\mathrm{F},t}$	0.190***	0.190***
	(0.104)	(0.110)		(0.052)	(0.052)
R^2	0.012	0.012		0.029	0.030
Observations	173,475	173,475		171,313	171,313
Macro controls	no	yes		no	yes
Cusip FE	yes	yes		yes	yes
Double-cl. SE	yes	yes		yes	yes

(b) Heteroskedasticity-Based

	(5)	(6)
	All Intermediaries	
$\Delta p_{\mathrm{F,t}}$	0.363***	0.363***
	(0.027)	(0.028)
95% CI	[0.299, 0.415]	[0.299, 0.415]
Observations	1,373	1,373
Macro controls	no	yes

Notes: Columns 1 and 2 in Panel (a) estimate the event-time regression in (1): $\Delta y_{jt} = \alpha_j + \beta v_{\mathrm{F},t} + u_{jt}$, where Δy_{jt} is the HF log price change of a nonfinancial S&P 500 constituent stock j; $v_{\mathrm{F},t}$ is 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 in Panel (a) estimate a variant of (1): $\Delta y_{jt} = \alpha_j + \gamma \Delta p_{\mathrm{F},t} + u_{jt}$, where $\Delta p_{\mathrm{F},t}$ is an HF shock constructed using the price changes of all sample intermediaries and provides estimates that are more comparable to heteroskedasticity-based estimates. Standard errors in Panel (a) are two-way clustered at shock and CUSIP levels and reported in parentheses. Panel (b) reports the heteroskedasticity-based estimator for γ from the bivariate model (3) implemented with an instrumental variable approach. First-stage F-statistics are 423 and 421 for Columns 5 and 6, respectively. Standard errors and confidence intervals are computed with stratified bootstrap, as described in the text.
* ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

our sample.[13] Columns (3) and (4) report an estimated elasticity of 0.2, which is slightly smaller than the baseline estimate, while the R^2 doubles that of the baseline.[14] Importantly,

[13]Specifically, we estimate $\Delta y_{it} = \alpha_j + \gamma \Delta p_{\mathrm{F},t} + \varepsilon_{jt}$. Under this specification, the regressor $\Delta p_{\mathrm{F},t}$ uses the change in the market value of all financial intermediaries in our sample. Because of the larger set of intermediaries, interpreting the estimates as causal requires stronger identifying assumptions than those from our baseline event-study model (1). Insofar as common unobserved factors within the narrow window of earnings releases leads to a positive comovement between the stock price of nonreleasing financial intermediaries and nonfinancial firms, the reported coefficient represents an upper bound on the estimates.

[14]To understand this lower estimated coefficient, recall that, as stated in Section 3.1, Appendix Figure B.2

the estimates obtained under the event-study approach appear to be below those obtained under the heteroskedasticity-based approach, which suggests that the stronger identifying assumptions from the event-study approach do not lead overall to an upward bias (see Rigobon and Sack, 2004, for more detailed analysis of this comparison).[15] Based on this, we will use the financial shocks $v_{\mathrm{F},t}$ in the rest of the paper, which lead to simpler implementation in other empirical models considered below (e.g., external-instrument vector autoregression to study the effects of financial shocks on macroeconomic variables, analyzed in Section 4.3).

Robustness analysis In Appendix D, 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 D.1 uses as the dependent variable S&P 500 nonfinancial constituents' log changes in net worth weighted by their market value 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 D.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 D.3 shows that the effects of financial shocks are robust and stronger if we instead use a broader measure of financial shocks, which includes announcements made outside of trading hours. A related concern is that intermediaries may strategically release worse earnings outside of trading hours. Appendix Figure D.1 plots realized earnings results against the hours of earnings announcements and shows no evidence of strategic timing.

shows that shocks to the market value of an earnings-releasing intermediary lead to a 0.2% increase in the market value of other nonreleasing intermediaries.

[15] A full comparison of the two identification strategies, for different weightings and frequencies, is reported in Appendix Table B.5.

Fourth, Appendix Table D.4 accounts for systematic comovements between financial and nonfinancial stocks. We estimate the time-varying beta between the S&P 500 Ex-Financials and S&P 500 Financials 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.

Finally, the effects we document of large financial intermediaries on the rest of the economy motivate a natural implementation of the granular-instrumental-variable (GIV) strategy developed by Gabaix and Koijen (2020). Appendix Table D.5 estimates the effects of financial net worth on nonfinancial net worth, instrumented with the GIV of the time-varying difference between size-weighted and equal-weighted changes in intermediaries' market values. Both the magnitude and statistical significance of the estimates under the GIV strategy are in line with those from our baseline event-study regressions.

Placebo tests We also conduct two placebo exercises to provide evidence for our interpretation of the event-time results. The first exercise, shown in Appendix Figure B.3, shows 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 pre-trends. 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 impacts 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 3.1 for financial shocks, but focus on the earnings announcements of nonfinancial firms included in the Dow Jones Industrial Average. Appendix Table B.3b shows the results of estimating the event-time regression but using the shock to nonfinancial firms instead of the financial shock. Results yield a baseline estimate that is negative, not statistically significant, and unstable across specifications. To render the shocks further comparable, Appendix Table

B.3c 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 exhibit an effect similar to that of financial shocks.[16]

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 $\Delta \log y_t^{-s} = \alpha + \beta v_t^s + u_{st}$ for each sector $s \in \{\text{energy, materials, ...}\}$, where v_t^s is the placebo shock and y_t^{-s} is the equity index that excludes the placebo shock sector. Appendix Table B.4 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.

The previous subsection shows that the effects of financial shocks survive even after removing the systematic comovements between financial and nonfinancial firms. This subsection shows that placebo shocks based on large nonfinancial firms do not generate the same pervasive effects as financial shocks. Together, they provide convincing evidence that financial net worth affects the net worth of nonfinancial firms, and thus supports a causal interpretation of the baseline effects observed in Table 3.

4.2. Bond markets

We estimate the effect of financial shocks on bond spreads using Jordà's 2005 local projections:

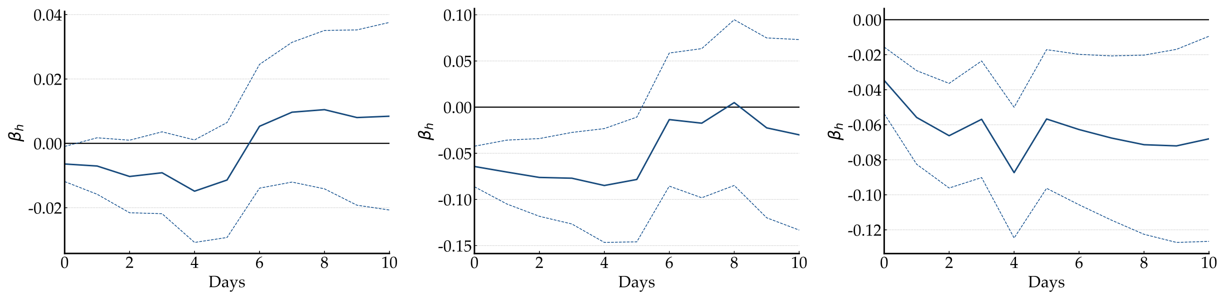
$$\Delta_h z_t = c_h + \beta_h v_{\mathrm{F},t} + u_t, \tag{4}$$

where z_t is the bond spread of interest; $v_{\mathrm{F},t}$ is the broad measure of financial shocks to match the daily frequency of bond indices; and β_h estimates the semi-elasticity of corporate bonds to financial shocks for horizon h.

[16] 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. Appendix Table C.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 News about Financial Net Worth 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 $\Delta_h z_t = c_h + \beta_h v_{\mathrm{F},t} + u_t$. 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. $v_{\mathrm{F},t}$ denotes the broad measure of financial shocks. Dotted lines represent 90% confidence intervals.

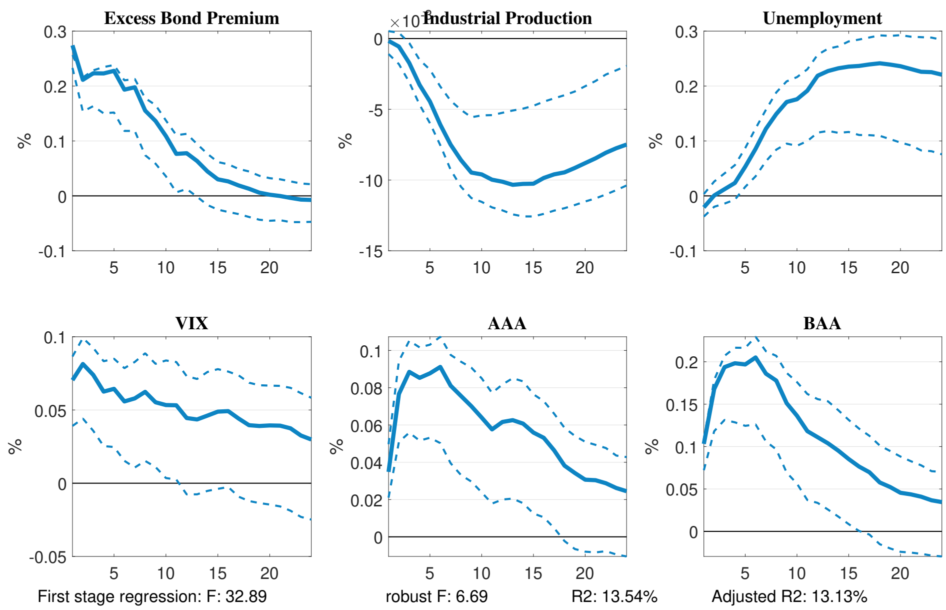
Panels (a) and (b) in Figure 1 show that declines in the market value of intermediaries lead to higher spreads for firms. Although the benchmark spreads for both investment-grade and high-yield bonds are affected, high-yield bond spreads rise more substantially in response to a negative financial shock: A 1% negative financial shock results in an increase of 6 to 10 basis points for high-yield bonds. Panel (c) 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 a 1% negative financial shock that results in an increase of 4 to 10 basis points in the excess bond premium.

4.3. The macroeconomy

Finally, we study the effects of financial shocks on macroeconomic outcomes. For this analysis, we turn to longer horizons at monthly frequency instead of the high frequency our analysis has so far focused on.

Our econometric model is an external-instrument vector autoregression (Stock and Watson, 2012; Mertens and Ravn, 2013; Gertler and Karadi, 2015) that consists of the excess bond premium (EBP), log industrial production, unemployment rate, log VIX index, and the spreads between AAA- and BAA-rated bonds and 10-year treasury yields. Using HF financial shocks as the external instrument for the EBP, we identify the effects of financial shocks on macroeconomic outcomes through affecting firms' borrowing costs. The first stage

Figure 2: Financial Shocks and Aggregate Responses



Notes: This figure reports the impulse responses to a one-standard-deviation financial shock to the supply of credit estimated in an external-instrument VAR. The VAR consists of the excess bond premium, log industrial production, unemployment rate, log VIX index, and the spreads between AAA- and BAA-rated bonds and 10-year treasury yields, with the excess bond premium instrumented by HF financial shocks. Dashed lines represent 90% bootstrapped confidence intervals.

isolates variation in firms' borrowing costs as a result of shocks to financial intermediaries, which allows us to estimate the effects of financial shocks on the macroeconomy in the second stage. The sample for this analysis starts in January 1973, when the EBP data became available, and ends in January 2020, before the onset of the Covid pandemic. We aggregate HF financial shocks to monthly frequency to match the remaining macro series.[17]

Figure 2 presents the impulse responses to a one-standard-deviation financial shock. The first panel shows that the EBP rises on impact by 30 basis points, and thus represents an increase in firms' borrowing costs. The F-statistic from the first stage is 33, which is above the threshold suggested by Stock, Wright and Yogo (2002) to rule out possible weak instruments. Financial shocks have significant effects on long-run macroeconomic outcomes.

[17] This analysis uses financial shocks as an instrument for the borrowing costs of nonfinancial firms. Evidence from the bond market in Section 4.2 shows that financial shocks lead to a decrease in the EBP. We analyze in Section 5.1 that the component of financial shocks that tends to comove negatively with borrowing costs is the one that primarily affects the credit supply (v_{CS}, see Section 5.1 for details). Therefore, we use this decomposed component of financial shocks as our main measure of financial shocks in this analysis for its validity as an instrument. Appendix Figure D.2 re-estimates the VAR using total HF shocks (v_{F}) and finds a similar pattern in impulse responses but a lower F-statistic in the first stage.

The next panels show that industrial production declines and remains depressed by 1 basis point for over a year; long-run unemployment rises and shows little sign of recovery; macro uncertainty remains elevated at around 5 basis points for a year; and firms face higher borrowing costs in bond markets, with a bigger effect on riskier firms.

5. Evidence on Transmission Mechanisms

This section studies how financial shocks transmit to the rest of the economy. Section 5.1 uses sign restrictions to decompose the effects of financial shocks into components related to credit supply and demand. Section 5.2 provides supportive evidence of the role of intermediaries' net worth, and Section 5.3 discusses the role of firms' financial positions by examining their heterogeneous responses to financial shocks.

5.1. A decomposition between credit supply and demand channels

From the perspective of credit markets, there are two broad types of channels through which financial shocks can affect nonfinancial firms: channels that primarily affect credit supply and move lending and borrowing costs in opposite directions; and those that primarily affect credit demand and move lending and borrowing costs in the same direction. Appendix A includes illustrations of how different shocks can impact credit demand and supply. On one hand, positive news about intermediaries' net worth (for example, due to a positive return on their investments) implies an increase in their funds available to lend, which boosts the credit supply and lowers borrowing costs. Similarly, positive news about the net worth of the intermediaries in our sample could lead to a decrease in the risk aversion of other investors participating in credit markets (e.g., institutional investors), and further increase the supply of funds. On the other hand, positive news about intermediaries' net worth can also be associated with optimistic news about the future productivity or demand faced by nonfinancial firms, and thus increase their demand for credit and raise interest rates.

These observations suggest that we can decompose the relative strength of the two types of channels using sign-restriction methods (e.g., as developed by Cieslak and Schrimpf, 2019; Jarociński and Karadi, 2020, for decomposing monetary shocks). Formally, we decompose financial shocks into orthogonal shocks that primarily affect credit supply ($\boldsymbol{v}_{\text{CS}}$) and primarily affect credit demand ($\boldsymbol{v}_{\text{CD}}$) as

$$\boldsymbol{v}_{\text{F}} = \boldsymbol{v}_{\text{CS}} + \boldsymbol{v}_{\text{CD}}, \tag{5}$$

where each series is a vector of length T. The sign restrictions are that v_{CS} is negatively correlated with changes in interest rates, Δy, and v_{CD} is positively correlated with changes in interest rates. That is, the decomposition satisfies

$$\begin{bmatrix} \boldsymbol{v}^{\text{F}} & \Delta \boldsymbol{y} \end{bmatrix} = \begin{bmatrix} \boldsymbol{v}_{\text{CS}} & \boldsymbol{v}_{\text{CD}} \end{bmatrix} \begin{bmatrix} 1 & - \\ 1 & + \end{bmatrix} \tag{6}$$

$$\boldsymbol{v}_{\text{CS}}^{'} \boldsymbol{v}_{\text{CD}} = 0 \tag{7}$$

$$\text{var}(\boldsymbol{v}_{\text{CS}}) + \text{var}(\boldsymbol{v}_{\text{CD}}) = \text{var}(\boldsymbol{v}_{\text{F}}). \tag{8}$$

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 credit supply and one that conveys information about credit demand—and by no other shocks. Second, sign restrictions on the comovements between financial shock price movements and interest rates are satisfied.

We perform the decomposition using Givens rotation matrices, closely following the algorithm developed by Jarocinski (2020). To ensure that our findings are not sensitive to the method used to impose sign restrictions, we alternatively perform the decomposition using a Householder transformation developed by Arias, Rubio-Ramírez and Waggoner (2018) and a simple "poor man's sign restrictions" proposed by Jarociński and Karadi (2020). Among the set of admissible structural shocks that satisfy the sign restrictions, we use median shocks as v_{CS} and v_{CD}. Appendix E provides further details on the procedures.

Given that the theoretical argument motivating the empirical decomposition (presented in Appendix A) centers around the component of borrowing costs unrelated to default risk, we decompose financial shocks based on their correlation with the excess bond premium (EBP; Gilchrist *et al.*, 2021, described in more detail in Section 2), which measures financing costs in the absence of default risks. To match the daily frequency of the EBP, we use the broad measure of HF financial shocks that include earnings announcements outside of trading hours for the decomposition.

Using the decomposed shocks, we then examine the importance of each channel by estimating

$$\Delta y_t = \alpha + \beta_{\text{CS}} v_{\text{CS,t}} + \beta_{\text{CD}} v_{\text{CD,t}} + u_t, \tag{9}$$

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

Panel (a) in Table 4 shows that the credit-supply channel is the dominant channel through which financial shocks affect the rest of the economy. The estimated semi-elasticity of the credit demand channel is also positive, albeit not statistically significant, which suggests that information about nonfinancial firms' investment opportunities potentially contained in intermediaries' earnings releases does not drive the observed effects of financial shocks.

5.2. The role of intermediaries' net worth

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 investigate the importance of aggregate conditions in the transmission of financial shocks. We decompose the effects of financial shocks on nonfinancial firms by estimating

$$\Delta y_{jt} = \alpha_j + \beta_w \cdot v_{\text{F},t} \mathbb{1}(N_t > \bar{N}_t) + \beta_u \cdot v_{\text{F},t} \mathbb{1}(N_t < \bar{N}_t) + \Gamma' Z_t + u_{jt}, \tag{10}$$

where $v_{\text{F},t} \mathbb{1}(N_t < \bar{N}_t)$ 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-filtered trend $\bar{v}_t$) 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.

Panel (b) of Table 4 shows that the impact of financial shocks is driven 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 that drives 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).

Within-firm variation Next, we provide further evidence on the importance of intermediaries' net worth by exploiting within-firm variation. Firms frequently have a large number of bonds outstanding, which provides an ideal laboratory for us to compare the prices of bonds issued by the same firm and with similar characteristics but held by different financial intermediaries.

We study within-firm variation by estimating the local projection

$$\Delta_h z_{k(j)it} = \alpha_{jt} + \gamma_h \pi_{k(j)it} v_{\mathrm{F},t} + \Gamma' Z_{jt} + u_{jith}, \tag{11}$$

where $\Delta z_{k(j)it}$ is cumulative changes in bond k's option-adjusted spreads over h days; $v_{\mathrm{F},t}$ is the HF financial shock around intermediary i's earnings announcement; $\pi_{k(j)it}$ is the share of bond k issued by firm j held by intermediary i in the quarter preceding 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 $\pi_{k(j)it}$, a categorical variable for bond ratings, remaining maturity, trailing average, and month-to-date changes in spreads. We estimate (11) 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 are most exposed to financial shocks.

Panel (c) of Table 4 rejects the null hypothesis that the observed effects are not influenced by a direct net worth channel from financial intermediary releasing their earnings.[18] The estimated marginal coefficient is negative and statistically significant, which indicates that within a firm, bonds that have more substantial holdings by an earnings-releasing intermediary have a larger sensitivity in absolute value to financial shocks. These results are consistent with financial shocks' 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, 2022).

[18] Appendix Figure B.4 reports the full dynamics of responses for horizons $h = 1, \cdots, 10$ and conducts an additional robustness test that includes controls for bond liquidity. Table 4 only reports the estimates for $h = 5$ due to space constraints.

5.3. The role of nonfinancial 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 estimating how nonfinancial firms' financial positions (leverage, credit risk, and liquidity) affect their responses to financial shocks using the model

$$\Delta y_{jt} = \alpha_j + \alpha_{sq} + \beta v_{\mathrm{F},t} + \gamma v_{\mathrm{F},t} x_{jt} + \Gamma' Z_{jt} + u_{jt}, \tag{12}$$

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; $v_{\mathrm{F},t}$ is the HF financial shock; x_{jt} is an indicator variable that equals 1 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: firm characteristic x_{jt}, lagged sales growth, lagged size, lagged current assets as a share of total assets, and an indicator for fiscal quarter. We interact financial shocks with the indicator variable, x_{jt}, for a firm's financial positions. The coefficient of interest, γ, measures how the effect of financial shocks depends on a firm's financial position.[19] We report both the average responses to financial shocks (β) and the marginal responses that depend on financial positions (γ). Standard errors are two-way clustered by firm and shock.

Panel (d) of Table 4 shows that firms' financial positions indeed 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.

Interestingly, dimensions of firms' heterogeneity in the response to financial shocks differ from those in response to the monetary policy shocks documented in previous literature. To

[19] 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). 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.

facilitate this comparison, Appendix Table B.6 reports the heterogeneous responses of firms in our sample for high-frequency monetary policy shocks, constructed 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. In contrast, firms with lower credit ratings appear to be the most responsive to financial shocks.

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. Then, to study the effects of financial shocks on the aggregate economy, we exploit the granularity of financial shocks that stem from the considerable size of U.S. publicly traded financial intermediaries. 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. In addition, financial shocks have lasting effects on the macroeconomy.

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 models aimed at understanding the role of financial intermediaries in determining the aggregate transmission of shocks. We leave the combination of models with these empirical estimates for future research.

Table 4: Transmission Channels of News about Financial Intermediaries' Net Worth

	Average Effect	Interaction Effect	Adj. R^2	Obs.	Fixed Effects	Standard Errors
(a) Credit supply and demand channels						
dependent var.: S&P 500 ex-financial index						
average	0.759***		0.042	492	-	heterosk.-
	(0.206)					robust
credit supply channel		1.276***	0.068	492	-	heterosk.-
		(0.305)				robust
credit demand channel		0.067				
		(0.389)				
(b) Aggregate state dependency						
dependent var.: S&P 500 constituents						
average	0.245**		0.008	173,475	cusip	double-
	(0.104)					clustered
well capitalized		0.017	0.011	173,475	cusip	double-
		(0.113)				clustered
undercapitalized		0.269**				
		(0.105)				
(c) Within-firm variation						
dependent var.: CCC bonds						
average	-0.155**		0.635	9,587	bond×qtr,	double-
	(0.071)				firm×bank	clustered
by bond holdings		-0.537***	0.806	9,212	firm×shock	double-
		(0.131)				clustered
(d) Firms' heterogeneous financial positions						
dependent var.: S&P 500 constituents						
high leverage	0.240***	0.015	0.025	750,260	sector×qtr,	double-
	(0.090)	(0.133)			firm	clustered
invt-grade credit ratings	0.362***	-0.088**	0.040	162,281	sector×qtr,	double-
	(0.133)	(0.043)			firm	clustered
high liquidity	0.250***	-0.006	0.025	750,241	sector×qtr,	double-
	(0.087)	(0.015)			firm	clustered

Notes: Panel (a) estimates (9): $\Delta y_t = \alpha + \beta_{\mathrm{CS,t}} v_{\mathrm{CS,t}} + \beta_{\mathrm{CD}} v_{\mathrm{CD}} + u_t$, where $v_{\mathrm{CS,t}}$ is the shock to the supply of credit and $v_{\mathrm{CD,t}}$ is the shock to the demand for credit. $v_{\mathrm{CS,t}}$ and $v_{\mathrm{CD,t}}$ are decomposed using sign restrictions as described in Section 5.1. Panel (b) estimates (10): $\Delta y_{jt} = \alpha_j + \beta_w v_{\mathrm{F},t} \mathbb{1}(v_{\mathrm{F},t} > \bar{v}_t) + \beta_u v_{\mathrm{F},t} \mathbb{1}(v_{\mathrm{F},t} < \bar{v}_t) + \Gamma' Z_t + u_{jt}$, where $v_{\mathrm{F},t}$ is the HF shock; $\mathbb{1}(v_{\mathrm{F},t} < \bar{v}_t)$ is an indicator variable for dates on which the market value of intermediaries' net worth is below its HP trend $\bar{v}_t$; and Z_t is a vector of macro controls including output, payrolls, a recession indicator, and their interaction terms with the financial shocks. Panel (c) estimates (11): $\Delta_h z_{k(j)it} = \alpha_{jt} + \gamma_h \pi_{k(j)it} v_{\mathrm{F},t} + \Gamma' Z_{jt} + u_{jith}$, where the dependent variable is cumulative changes in bond k's option-adjusted spreads over 5 days; and $\pi_{k(j)it}$ is the share of bond k issued by firm j held by intermediary i in the quarter proceeding its earnings announcement in period t. Panel (d) estimates (12): $\Delta y_{jt} = \alpha_j + \alpha_{sq} + \beta v_{\mathrm{F},t} + \gamma v_{\mathrm{F},t} x_{jt} + \Gamma' Z_{jt} + u_{jt}$, where x_{jt} is an indicator variable for firms with high leverage, investment-grade credit rating, or high liquidity. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

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Online Appendix

A. An Illustrative Theoretical Framework

In this section, we consider a model to motivate and interpret our empirical analysis. We utilize this model to discuss the various channels through which financial shocks can impact nonfinancial firms.

A.1. Environment

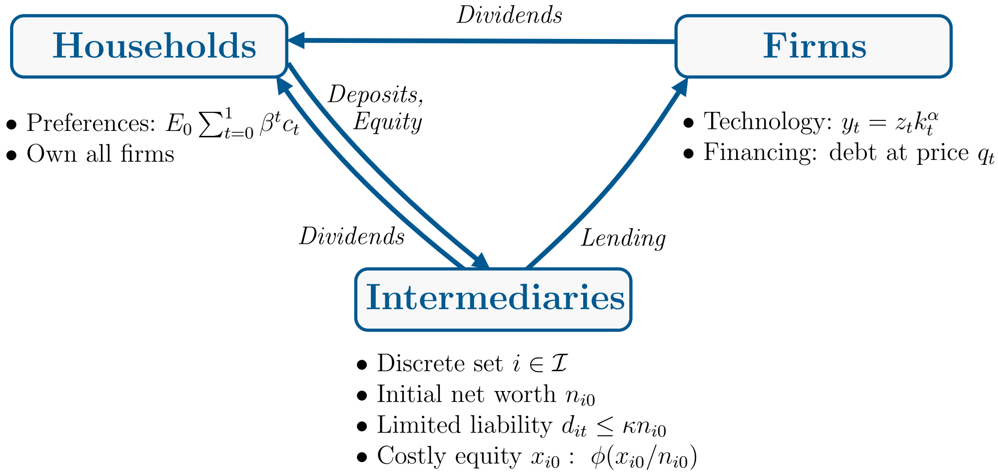
There are two periods: $t = 0, 1$; and two goods: final and capital goods. The economy is populated by a unit mass of identical households and nonfinancial firms and a discrete set of intermediaries indexed by $i \in \mathcal{I}$. Figure A.1 summarizes the model economy.

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 finance their investment only 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.*, 2022). 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

$$\max_{d_{i1}, a_{f1}, a_{i1}} \; c_0 + \beta \mathbb{E}_0 c_1 \tag{13}$$

$$\text{s.t.} \quad c_0 + p_{f0} a_1 + \sum_{i \in \mathcal{I}} p_{i0} a_{i1} + d_1 = \; y_0 + \pi_{f0} + p_{f0} + \sum_{i \in \mathcal{I}} (\pi_{i0} + p_{i0})$$

$$c_1 = \; \pi_{f1} a_1 + \sum_{i \in \mathcal{I}} a_{i1} \pi_{i1} + R_d d_1,$$

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

$$R_d = \frac{1}{\beta}, \qquad p_{f0} = \beta \mathbb{E}_0 \pi_{f1}, \qquad p_{i0} = \beta \mathbb{E}_0 \pi_{i1}, \tag{14}$$

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

$$\max_{k_1\geq 0, b_1, \pi_{f0}\geq 0} \pi_{f0} + \beta \mathbb{E}_0 \pi_{f1} \tag{15}$$

$$\text{s.t. } \pi_{f0} = q_0 b_1 - k_1$$

$$\pi_{f1} = z_1 k_1^{\alpha} - b_1,$$

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

$$\frac{1}{q_0} = \mathbb{E}_0 z_1 \alpha k_1^{\alpha-1}, \tag{16}$$

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

$$\max_{x_{i0}, b_{i1}} \pi_{i0} + \beta \pi_{i1} \tag{17}$$

$$\text{s.t. } \pi_{i0} = -x_{i0}\left(1 + \mathbb{1}_{\{x_{i0}>0\}} \phi\left(\frac{x_{i0}}{n_{i0}}\right)\right),$$

$$\pi_{i1} = b_{i1} - R_d d_{i1},$$

$$q_0 b_{i1} = n_{i0} + x_{i0} + d_{i1},$$

$$d_{i1} \leq \kappa n_{i0},$$

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

$$1 + 2\phi\left(\frac{x_{i0}}{n_{i0}}\right) = \beta R_d + \mu_i \tag{18}$$

$$\beta R_d + \mu_i = \beta \frac{1}{q_0}, \tag{19}$$

with complementary slackness condition

$$(d_{i1} - \kappa n_{i0})\mu_i = 0, \tag{20}$$

where μ_i denotes the Lagrange multiplier associated with the limited liability constraint of intermediary i. Equation (18) 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 (19) implies that intermediaries equate the marginal cost of external finance with the return on lending. Note that (18) and (19) 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 (13); nonfinancial firms' allocations solve (15); and financial intermediaries' allocations solve (17).

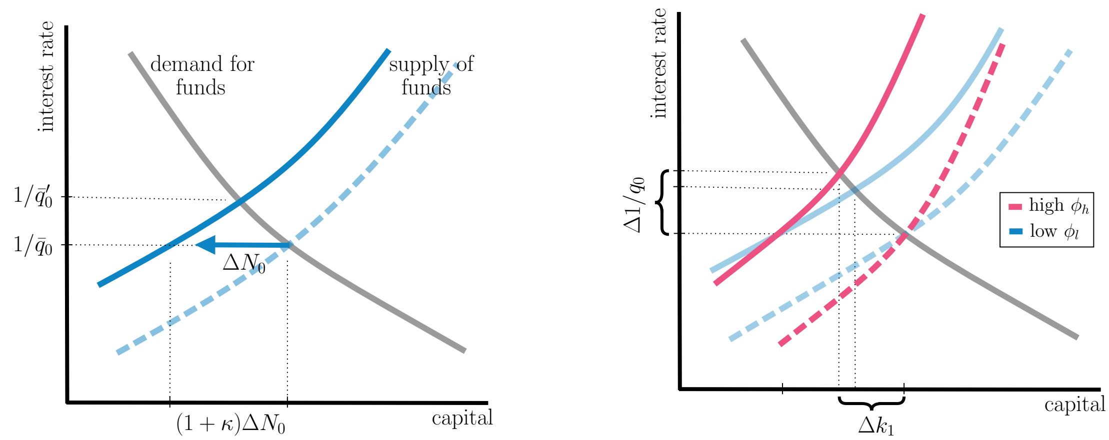
ii. Asset markets clear—i.e., $b_1 = \sum_{i\in\mathcal{I}} b_{i1}$, $d_1 = \sum_{i\in\mathcal{I}} d_{i1}$, $a_{f1} = 1$, and $a_{i1} = 1$ for all i.

We represent the equilibrium of the model using a demand–supply-of-funds scheme (similar to that developed by Morelli *et al.*, 2022). On the side of intermediaries, we focus 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*:

$$\mathcal{K}^s(q_0, N_0, \phi) = N_0(1 + \kappa + \mathcal{X}(q_0, \phi)), \tag{21}$$

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

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

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 implies a relationship between capital and interest rates, which we label the *aggregate demand for funds*: $\mathcal{K}^d(q_0) = (q_0 \mathbb{E}_0 z_1 \alpha)^{\frac{1}{1-\alpha}}$. This relationship between the demand for 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 depicts the equilibrium capital and interest rates as the intersection between the aggregate supply of and demand for 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.

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 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 regarding the degree of financial frictions faced by intermediaries. We next discuss in more detail the link between the model experiment and the empirical analysis.

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 (14) 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 (14) 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 more likely to satisfy this condition.

A.5. Extending the model to incorporate additional channels

We now extend the model to incorporate additional channels that might drive the empirical results. Using the demand–supply-of-funds scheme from Figure A.2, it is helpful to distinguish between additional channels that primarily affect the supply of funds and those that affect the demand of funds, as in our empirical decomposition in Section 5.1.

Credit supply Our baseline model features a direct channel through which changes in the net worth of the releasing financial intermediary impact the supply of funds (as illustrated in Figure A.2). Our empirical estimates can also be driven by other (indirect) channels through which financial shocks affect credit supply. For instance, news about an intermediary's net worth can reveal information about the state of the financial sector. In our framework, this can occur if the decline in $n_{\iota 0}$ is associated with higher costs of raising external financing for financial intermediaries (i.e., an increase in the parameter ϕ). This is illustrated in Panel (b) of Figure A.2, which shows that such an increase steepens the credit supply curve and amplifies the initial contraction in net worth. In addition, in a version of our model where lending is risky, news about a lower intermediary's net worth can be associated with an increase in investors' risk aversion. This can lead to a contraction of the credit supply beyond that induced by changes in net worth, or even in the absence of direct channels of net worth affecting credit supply.

Credit demand We can also extend our model to incorporate credit demand channels. For example, surprises about intermediaries' net worth can contain information about nonfinancial firms' expected productivity, i.e., $\frac{\partial \mathbb{E}_0 z_1}{\partial n_{\iota 0}} \geq 0$. 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-for-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 for 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 credit supply and credit demand channels. For a contraction in intermediaries' initial aggregate net worth N_0, all channels we discussed contribute to a contraction in nonfinancial firms' investment and market value. However, the overall effects on borrowing costs are indeterminate and depend on the relative strength of each channel. Panel (b) represents the case in which credit supply channels dominate and, consistent with our empirical analysis, borrowing costs increase in response to a negative financial shock.

Link to empirical decomposition Figures A.2 and A.3 show that shocks that negatively affect credit supply and credit demand have the same sign on nonfinancial firms' market value but opposite effects on borrowing costs, which exhibit a negative comovement with nonfinancial firms' value for the credit supply channel and positive comovement with nonfinancial firms' value for the credit demand channel. This motivates our empirical strategy in Section 5.1 to decompose the channels through which financial shocks affect the economy. Given that the theoretical argument motivating the decomposition centers on the component of borrowing costs unrelated to default risk, 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 unrelated to their probability of default.

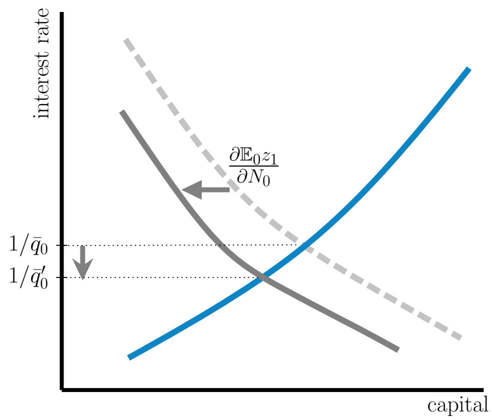
A.6. Proofs

Proof of Proposition 1.

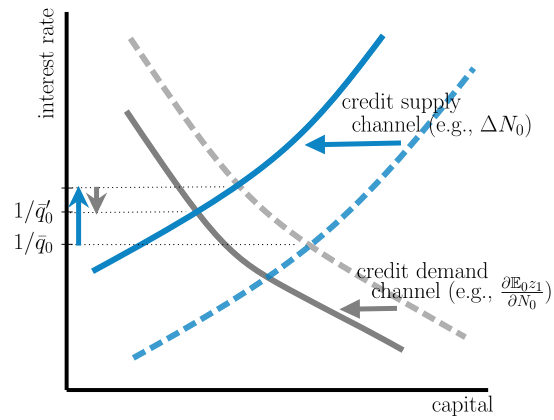
Proof. First, if $\phi = 0$, then intermediaries' optimality conditions (18) and (19) imply that $q_0 = \beta$. Nonfinancial firms' optimality condition (16) implies that $1 = \beta \mathbb{E}_0 z_1 \alpha k_1^{\alpha-1}$, meaning that $\frac{\partial k_1}{\partial N_0} = 0$.

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

Figure A.3: Asset Price Comovements for the Credit Supply and Demand Channels



(a) Credit Demand Channel



(b) Credit Supply and Credit Demand Channels

bind ($\mu_i > 0$ for all i). From (18), in such equilibria, all intermediaries raise the same external finance relative to their net worth $\chi_0 \equiv \frac{x_{i0}}{n_{i0}}$. Combining (16) and (21), 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

$$\mathcal{K}(k_1, N_0, \phi) = k_1 - N_0(1 + \kappa + \frac{1}{2\phi}\left(\beta \mathbb{E}_0 z_1 \alpha k_1^{\alpha-1} - 1\right)). \tag{22}$$

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 (18), intermediaries do not raise external finance (i.e., $x_{i0} = 0$ for all i); and by (19), $q_0 = \beta$. 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 (16) $\frac{1}{\beta} = z_1^* \alpha (k_1^*)^{\alpha-1}$. 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 (16) $\frac{1}{\beta} = \hat{z}_1 \alpha (\hat{k}_1)^{\alpha-1}$. 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: Descriptive Statistics for Equity and Bonds

(a) Daily Returns of Equity Indices

	Release	Nonrelease	All Days
SP500 Ex-Financial			
Mean	0.01	0.03	0.02
	(0.05)	(0.02)	(0.02)
Std Deviation	1.24	1.20	1.20
	(0.03)	(0.01)	(0.01)
Observations	635	5,655	6,290
SML			
Mean	0.05	0.03	0.03
	(0.06)	(0.02)	(0.02)
Std Deviation	1.51	1.47	1.48
	(0.04)	(0.01)	(0.01)
Observations	635	5,654	6,289
Russell			
Mean	0.04	0.02	0.02
	(0.06)	(0.02)	(0.02)
Std Deviation	1.60	1.53	1.53
	(0.04)	(0.01)	(0.01)
Observations	635	5,654	6,291

(b) Daily Changes in Bond Spreads

	Release	Non-Release	All Days
Excess bond premium			
Mean	-0.27	-0.00	-0.03
	(0.37)	(0.12)	(0.11)
Std Deviation	8.31	7.91	7.95
	(0.27)	(0.08)	(0.08)
Observations	492	4,441	4,933
Investment grade			
Mean	-0.13	0.03	0.01
	(0.10)	(0.03)	(0.03)
Std Deviation	2.60	2.64	2.64
	(0.07)	(0.02)	(0.02)
Observations	634	5,992	6,626
High yield			
Mean	-0.75	0.11	0.03
	(0.42)	(0.13)	(0.12)
Std Deviation	10.62	10.10	10.15
	(0.30)	(0.09)	(0.09)
Observations	634	5,992	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: Panel (a) 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. Panel (b) 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" refers to days with earnings releases by financial intermediaries in the sample; "Nonrelease Days" refers to days without earnings releases; "All Days" includes both release days and nonrelease days. Standard errors are in parentheses.

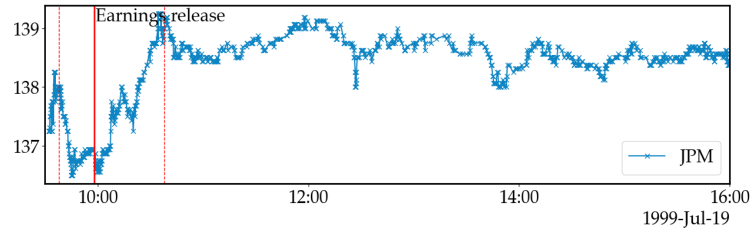
Table B.2: Bond Holdings by Intermediary

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

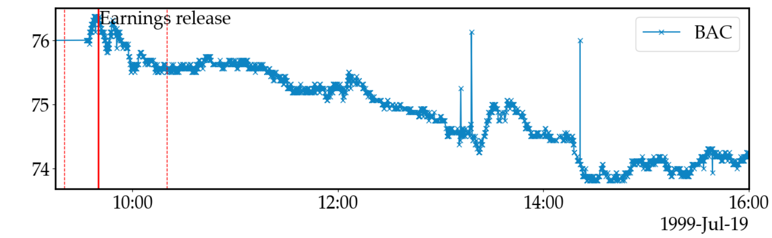
Notes: This table shows descriptive statistics for the shares of bonds held by financial intermediaries, displayed in percent. The set of bonds includes bonds rated CCC or lower in ICE issued by firms with at least 10 bonds outstanding.

Figure B.1: Construction of Financial Shocks

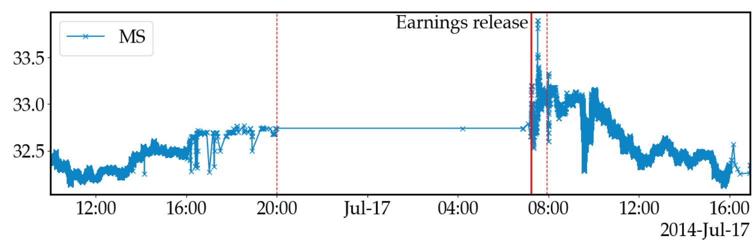
(a) Median Positive Shock (Inside Regular Trading Hours)



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



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



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

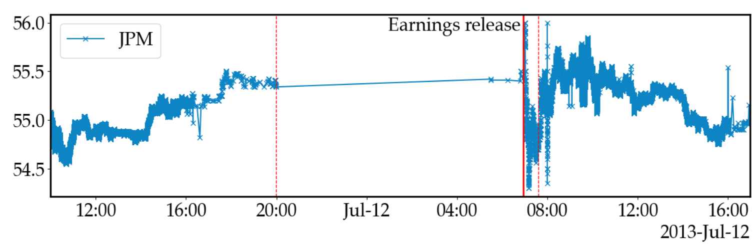
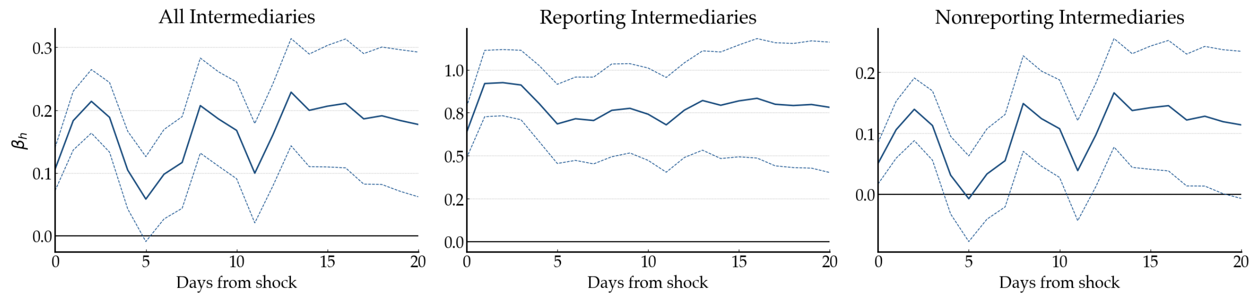
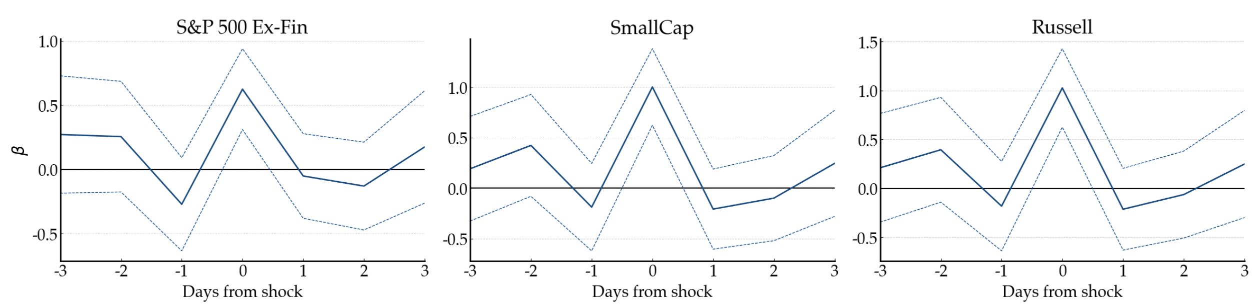


Figure B.2: The Effect of Financial Shocks on the Financial Sector's Net Worth



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 $\Delta \log y_{t+j} = c + \beta v_{\mathrm{F,t}} + u_t$. 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.3: Financial Shocks vs. Placebo Dow Jones Shocks

(a) Financial Shocks

	SP500 Ex-Fin	**SmallCap**	**Russell**	**Obs**
$v_{\mathrm{F,t}}$ (narrow measure)	0.741***	1.196***	1.263***	390
	(0.199)	(0.250)	(0.260)	
Macro controls	0.720***	1.116***	1.185***	390
	(0.200)	(0.250)	(0.261)	
Broad measure	0.624***	1.000***	1.028***	635
	(0.157)	(0.189)	(0.200)	

(b) Placebo Dow Jones Nonfinancial Shocks

	SP500	**SmallCap**	**Russell**	**Obs**
$v_{\mathrm{NF,t}}$ (narrow measure)	-0.026	-0.230	-0.227	801
	(0.189)	(0.234)	(0.241)	
Macro controls	-0.030	-0.226	-0.226	801
	(0.190)	(0.235)	(0.242)	
Broad measure	0.287*	0.105	0.135	1146
	(0.169)	(0.201)	(0.208)	

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

	SP500	**SmallCap**	**Russell**	**Obs**
$v_{\mathrm{NF,t}}$ (narrow measure)	-0.018	-0.150	-0.146	554
	(0.152)	(0.193)	(0.198)	
Macro controls	0.003	-0.114	-0.110	554
	(0.153)	(0.194)	(0.199)	
Broad measure	0.224	0.099	0.126	831
	(0.146)	(0.175)	(0.180)	

Notes: This table shows results from estimating $\Delta \log y_t = \alpha + \beta v_{\mathrm{F,t}} + u_t$, where $\Delta \log y_t$ is the daily log change in one of the following indices: S&P 500 Ex-Financials, S&P SmallCap 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, Alcoa, Altria, Philip Morris, Apple, Amgen, 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, Raytheon, Salesforce, Sears, Texaco, Union Carbide, United Technologies, UnitedHealth, Verizon, Visa, Walgreens, Walmart, Walt Disney, and Westinghouse. Panel (c) shows placebo tests with HF shocks generated based on 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.4: Effects of HF Placebo Shocks with S&P 500 Nonfinancial Firms

Dependent Variables	**Placebo Sectors**	**Effects of Placebo Shocks**
SP500 Ex-Energy Index	Energy	-0.724
		(0.611)
SP500 Ex-Materials Index	Materials	-1.219
		(0.956)
SP500 Ex-Industrials Index	Industrials	0.509
		(1.131)
SP500 Ex-Consumer Discretionary Index	Consumer Discretionary	0.315
		(0.658)
SP500 Ex-Consumer Staples Index	Consumer Staples	0.191
		(0.518)
SP500 Ex-Healthcare Index	Healthcare	1.166
		(0.875)
SP500 Ex-Information Technology Index	Information Technology	0.166
		(0.813)
SP500 Ex-Communication Services Index	Communication Services	0.177
		(0.365)
SP500 Ex-Utilities Index	Utilities	-1.487
		(1.246)
SP500 Ex-Real Estate Index	Real Estate	1.497
		(1.457)

Notes: This table reports the effects of placebo HF shocks. For each nonfinancial sector s of the S&P 500, the placebo HF shock v_t^s is constructed following the procedure for HF financial shocks described in Section 4. The specification estimated is $\Delta \log y_t^{-s} = \alpha + \beta v_t^s + u_{st}$ for each sector $s \in$ {energy, materials, information technology, ...}, where v_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. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

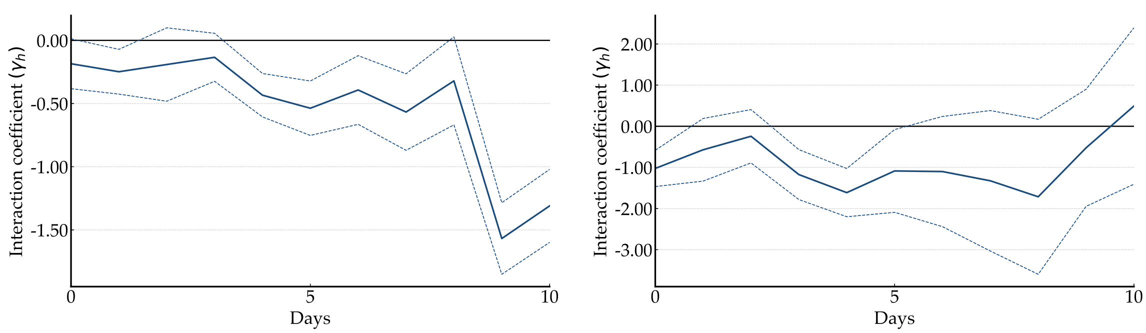
Table B.5: Comparison of Event-time and Heteroskedasticity-based Identification

Fin Shock	**Freq**	**Dependent Variable**	**Freq**	**OLS**	**Heteroske-dasticity**
Reporting intermediaries	60-min	S&P 500 nonfin constituents (equal weighted)	60-min	0.245** (0.104)	- -
All intermediaries	60-min	S&P 500 nonfin constituents (equal weighted)	60-min	0.190*** (0.052	0.410*** (0.027)
All intermediaries	60-min	S&P 500 nonfin constituents (value weighted)	60-min	0.186*** (0.050)	0.362*** (0.027)
All intermediaries	60-min	S&P 500 index ETF	60-min	0.151*** (0.025)	0.372*** (0.026)
All intermediaries	60-min	S&P 500 nonfin index	daily	0.538*** (0.079)	- -
All intermediaries	daily	S&P 500 nonfin index	daily	- -	0.434*** (0.022)

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 dependent variables. A specification that is infeasible for an identification strategy is omitted. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Figure B.4: Within-firm Variation

(a) Baseline Controls **(b)** Additional Liquidity Controls



Notes: This figure reports estimates of γ_h from $\Delta_h z_{k(j)it} = \alpha_{jt} + \gamma_h \pi_{k(j)it} v_{\mathrm{F},t} + \Gamma' Z_{jt} + u_{jith}$, where $\Delta_h z_{k(j)it}$ is cumulative changes in bond option-adjusted spreads; v_t^{F} is the HF shock; $\pi_{k(j)it}$ 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 $\pi_{k(j)it}$, 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.

Table B.6: 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)
Fin shock	0.247***	0.240***	0.362***	0.250***
	(0.079)	(0.090)	(0.133)	(0.087)
Fin shock × Characteristic		0.015	-0.088**	-0.006
		(0.014)	(0.043)	(0.015)
Adjusted R^2	0.025	0.025	0.040	0.025
Observations	750,260	750,260	162,281	750,241
Firm controls	no	yes	yes	yes
Firm FE	yes	yes	yes	yes
Quarter-sector FE	yes	yes	yes	yes
Double-clustered SE	yes	yes	yes	yes

Notes: This table reports results from estimating

$$\Delta y_{jt} = \alpha_j + a_{sq} + \beta_M v_{\mathrm{M},t} + \gamma_M(\mathbb{1}_{x_{jt}} v_{\mathrm{M},t}) + \Gamma' Z_{jt} + u_{jt} \quad \text{(monetary)}$$
$$\Delta y_{jt} = \alpha_j + \alpha_{sq} + \beta_F v_{\mathrm{F},t} + \gamma_F(\mathbb{1}_{x_{jt}} v_{\mathrm{F},t}) + \Gamma' Z_{jt} + u_{jt} \quad \text{(financial)}$$

where $v_{\mathrm{M},t}$ and $v_{\mathrm{F},t}$ denote 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. The HF financial shock, $v_{\mathrm{F},t}$, is constructed as described in the text. The HF monetary shock, $v_{\mathrm{M},t}$, is constructed based on changes in federal funds futures in a 60-minute window around a Federal Open Market Committee announcement, as in Gorodnichenko and Weber (2016). 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. The dependent variable, Δy_{jt}, is log changes in firms' stock prices in the corresponding 60-minute window around the monetary/financial announcement. 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 and follow S&P's definition of investment grade as BBB or better and speculative grade as BB or worse. Standard errors are two-way clustered at shock and firm level and reported in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

C. Content of HF Financial Shocks

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

C.1. Unexpected earnings and financial shocks

Figure C.1 depicts 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 C.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.

Figure C.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, as defined in the text.

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

	Financial Shocks	**Placebo Shocks**
Earnings surprises	0.217^{***} (0.032)	0.233^{***} (0.069)
R^2	0.040	0.010
Obs.	1,109	1,150

Notes: This table reports 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. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

C.2. 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

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

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.[20]

As Gentzkow *et al.* (2019) argue, the benefits of regression trees from nonlinearity and high-order interactions lessen 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 elastic net estimator is defined

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

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 with 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

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

where $\bar{y}_t$ is the rolling-mean forecast computed on a window that matches the model-estimation window and $\hat{y}_{m,t}$ is the forecast from the model. R^2_{oos} 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 C.2. Random-forest forecasts with both macro and financial predictors have negative R^2_{oos}, 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 C.2: Out-of-sample R^2 of Predictions of Financial Shocks

	Macro	**Financial**
Random forest	−15.7%	−16.9%
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 1 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 that matches 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.

C.3. Relationship of financial shocks within quarters

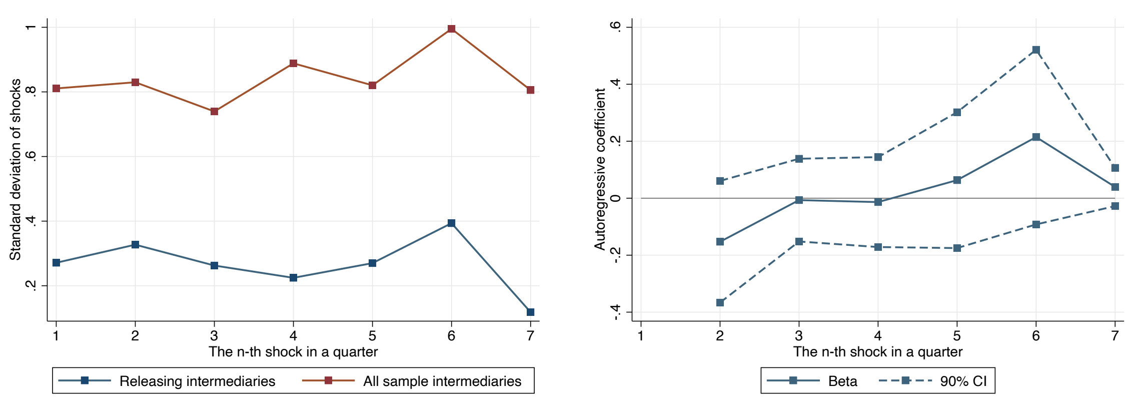
Panel (a) in Figure C.2 reports the standard deviation of the n-th financial shocks in a quarter, with the financial shocks based on earnings-releasing intermediaries in blue and those based on all sample intermediaries in red. Stock price movements around the first financial earnings announcements in a quarter display variation similar to that of movements around subsequent announcements, which suggests that variation in the news content contained in financial announcements does not depend on the order of the scheduled announcements.

Panel (b) reports the correlation of shocks within a quarter. We estimate the autocorrelation of the n-th financial shocks in quarter q by regressing $v_{\mathrm{F},q(n)} = c_n + \beta_n v_{\mathrm{F},q(n-1)} + u_{n,q}$ and report the point estimates for β_n's along with their 90% confidence intervals. We find no evidence of autocorrelation in financial shocks. The autoregressive coefficients are statistically indistinguishable from zero, regardless of whether earnings are announced first or subsequently in a quarter.

Figure C.2: Relationship of Financial Shocks Within Quarters

(a) Standard Deviation

(b) Autoregressive Coefficient



Notes: Panel (a) reports the standard deviation for the n-th financial shock in a quarter. Panel (b) reports the regression coefficents, β_n, from estimating $v_{\mathrm{F},q(n)} = c_n + \beta_n v_{\mathrm{F},q(n-1)} + u_{n,q}$ for the n-th financial shock in quarter q.

C.4. Textual analysis of financial shocks

We conduct three textual analyses to provide evidence that market participants interpret the earnings as being driven by idiosyncratic factors related to intermediaries and not by 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 the dates of articles, names of reporters, and alt text of pictures, to form the corpus for analysis.

C.4.1. 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 of all unique words in a news piece. For robustness, we construct an additional measure of positive sentiment as the percentage of positive minus negative words of all unique words.

Table C.3a 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 C.3b 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.

C.4.2. 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 that have fewer than 3 characters, appear fewer than 5 times, or appear 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 C.3b shows that $K = 3$ is the optimal choice of topic numbers under this criterion.

Figure C.3a reports the topics detected by the LDA model. All three topics center on 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 to macroeconomic fluctuations.

C.4.3. Narratives

The last textual analysis provides further context for narratives related to 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 *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 C.4 plots the top 30 narratives for each intermediary. On close inspection of the coverage of the three intermediaries, narratives related to 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 C.3: News Sentiment, Earnings Surprises, and Financial Shocks

(a) News Sentiment and Earnings

	(1)	(2)	(3)
	Earnings Surprises		
% Positive	0.800***		
	(0.115)		
% Negative		-0.492***	
		(0.055)	
% (Positive − Negative)			0.459***
			(0.042)
Observations	710	710	710
R^2	0.097	0.088	0.137

(b) News Sentiment and Stock Prices

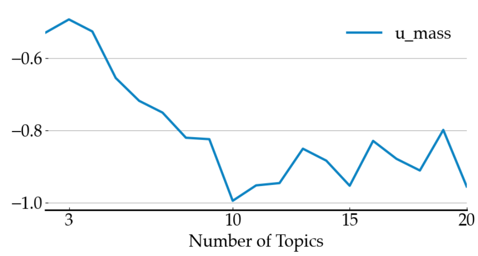
	(1)	(2)	(3)
	Change in Stock Prices		
% Positive	0.432***		
	(0.103)		
% Negative		-0.143*	
		(0.081)	
% (Positive − Negative)			0.179***
			(0.057)
Observations	710	710	710
R^2	0.022	0.006	0.017

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 of all unique words in an article, respectively. Robust standard errors are in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Figure C.3: LDA Topics in Earnings Coverage

(a) LDA Topics

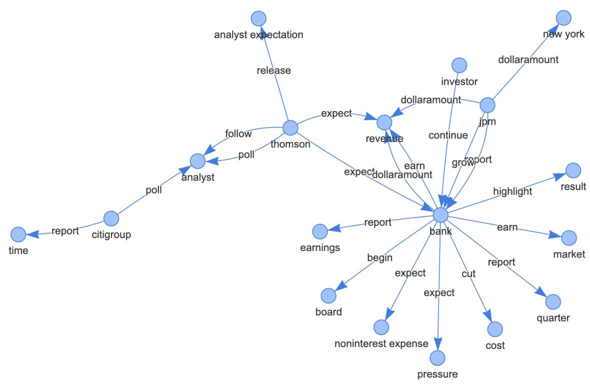
(b) Topic Coherence



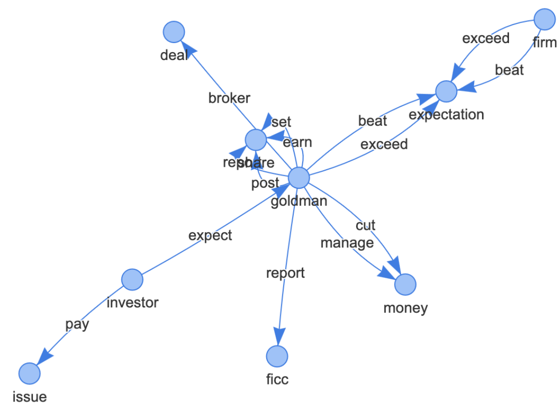
Notes: Panel (a) reports all three topics detected by the LDA model in WSJ articles. A larger font size represents a higher probability of a word or bigram appearing in an article. Panel (b) plots topic coherence measured against the number of topics K. Topic coherence is measured by $u_{\text{mass}}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

Figure C.4: Narratives in Earnings Coverage

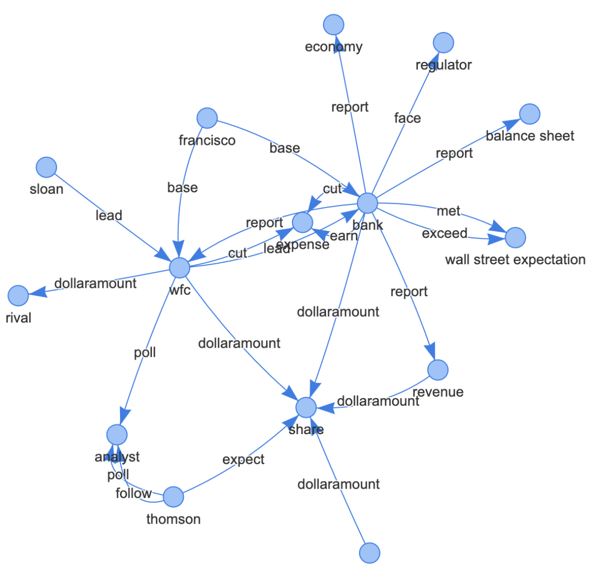
(a) J.P. Morgan



(b) Goldman Sachs



(c) Wells Fargo



C.5. Stock-price volatility for financial intermediaries and nonfinancial firms: Event vs. nonevent days

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

	Financial Intermediaries		Nonfinancial Firms	
	Release	Nonrelease	Release	Nonrelease
Mean of weighted ΔP	0.11	0.05	0.02	0.04
	(0.02)	(0.00)	(0.01)	(0.00)
SD of weighted ΔP	0.74	0.67	0.46	0.42
	(0.02)	(0.00)	(0.01)	(0.00)
Observations	1,104	20,365	1,104	20,365

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.

D. Additional Robustness Analysis

Table D.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:					
$v_{\mathrm{F,t}}$	0.245**	0.240**	0.200***	0.197**	0.203**
	(0.104)	(0.110)	(0.077)	(0.082)	(0.079)
R^2	0.012	0.012	0.005	0.005	0.022
Observations	173,475	173,475	164,132	164,132	517
Macro controls	no	yes	no	yes	yes
Cusip fixed effects	yes	yes	yes	yes	no
Double clustering	yes	yes	yes	yes	no

Notes: This table reports estimates from the event-time regression $\Delta y_{jt} = \alpha_j + \beta v_{\mathrm{F},t} + u_{jt}$ using different weighting for the dependent variable Δy_{jt}. α_j is a CUSIP fixed effect and $v_{\mathrm{F},t}$ is the HF shock. Baseline columns 1 and 2 (same as in Table 3a) estimate the effect of HF financial shocks on equal-weighted log price changes in S&P 500 nonfinancial constituents' stocks. Columns 3 and 4 estimate the effect of 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 levels. 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 D.2: Effects of Financial Shocks (Daily Frequency)

	SP500 Ex-Fin	**SmallCap**	**Russell**	**Obs**
$v_{\mathrm{F,t}}$ (narrow measure)	0.741***	1.196***	1.263***	390
	(0.199)	(0.250)	(0.260)	
Macro controls	0.720***	1.116***	1.185***	390
	(0.200)	(0.250)	(0.261)	
Broad measure	0.624***	1.000***	1.028***	635
	(0.157)	(0.189)	(0.200)	

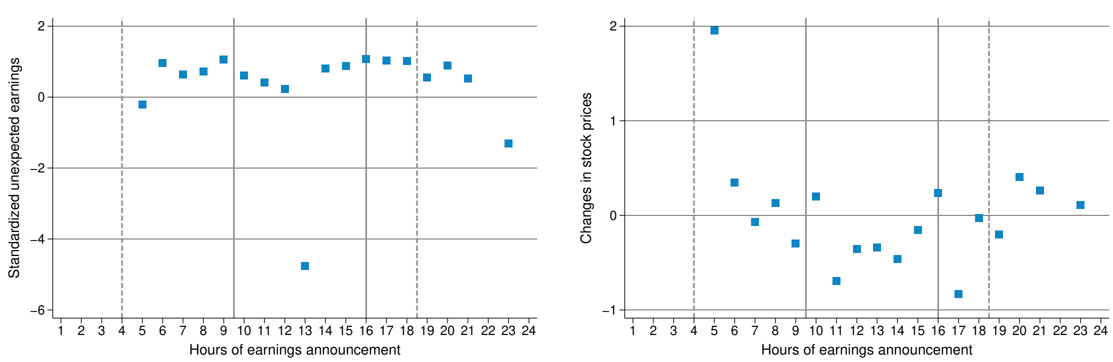
Notes: This table shows results from estimating $\Delta \log y_t = \alpha + \beta v_{\mathrm{F},t} + u_t$, where $\Delta \log y_t$ is the daily log change in one of the following indices: S&P 500 Ex-Financials, S&P SmallCap 600, or Russell 2000; and $v_{\mathrm{F},t}$ is the HF financial shock, described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

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

	(1)	(2)	(3)	(4)	(5)
	Equal-weighted		**Value-weighted**		**HF Index**
Independent variables:					
$v_{\mathrm{F,t}}$ (broad measure)	0.425^{***}	0.435^{***}	0.417^{***}	0.431^{***}	0.458^{***}
	(0.092)	(0.099)	(0.088)	(0.094)	(0.070)
R^2	0.014	0.018	0.004	0.004	0.051
Observations	352,120	352,120	338,066	338,066	1,091
Macro controls	no	yes	no	yes	yes
Cusip fixed effects	yes	yes	yes	yes	no
Double clustering	yes	yes	yes	yes	no

Notes: This table reports estimates from the event-time regression $\Delta y_{jt} = \alpha_j + \beta v_{\mathrm{F},t} + u_{jt}$ using the broad measure of financial shocks which includes earnings announced outside of trading hours. Columns 1 and 2 estimate the effect of broad HF financial shocks on equal-weighted log price changes of S&P 500 nonfinancial constituent 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 levels. 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. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Figure D.1: Earnings Results and Timing of Announcements



(a) Surprise earnings **(b)** Shock price changes

Notes: Panel (a) shows average standardized unexpected earnings by the hour of earnings announcement. Panel (b) shows 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 HF financial shocks are available from TAQ.

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

	(1)	(2)	(3)	(4)
	Releasing Intermediaries		**All Intermediaries**	
$v^{\text{resid}}_{\text{F,t}}$	0.470**	0.462**	0.470**	0.462**
	(0.200)	(0.215)	(0.203)	(0.218)
R^2	0.012	0.013	0.012	0.013
Observations	173,475	173,475	171,313	171,313
Macro controls	no	yes	no	yes
Cusip fixed effects	yes	yes	yes	yes
Double clustering	yes	yes	yes	yes

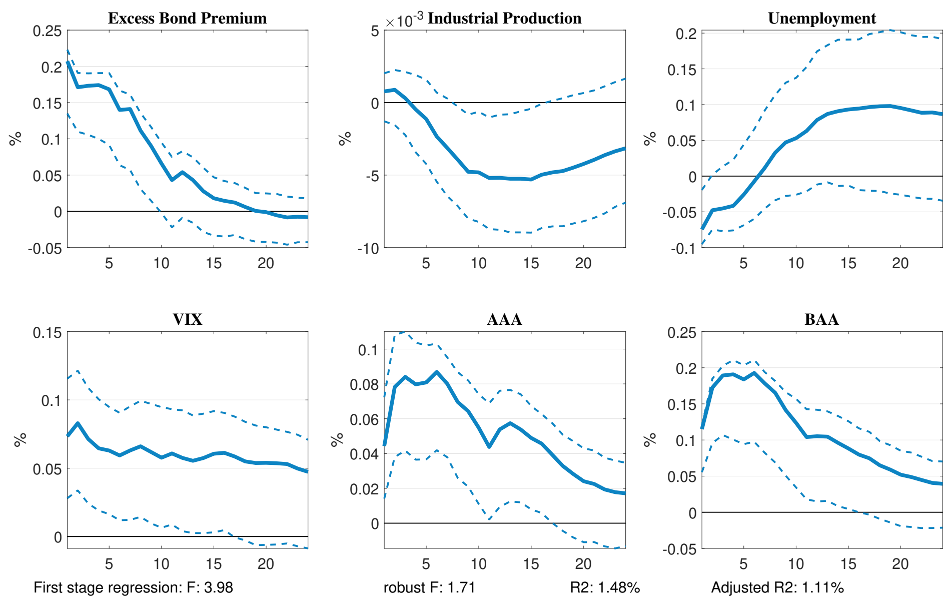
Notes: This table reports results from estimating the baseline event-time regression in (1) with the explanatory variable $v^{\text{resid}}_{\text{F,t}} \equiv v_{\text{F},t} - \hat{\beta}_t v_{\text{F},t}$. The time-varying $\hat{\beta}_t$ is estimated by regressing the daily changes in the S&P 500 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., $\Delta y_t = \alpha + \beta \Delta \nu_t + \varepsilon_t$. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Table D.5: Effects of Financial Firms on Nonfinancial Firms

	(1)	(2)	(3)	(4)
	OLS	**GIV**	**OLS**	**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 $\Delta y_t = \beta \Delta \nu_t + u_t$ under various specifications, where the dependent variable, Δy_t, is the S&P 500 Ex-Financials Daily Index, and the explanatory variable, $\Delta \nu_t$, is the S&P 500 Financials Daily Index. An intermediary's net worth consists of an aggregate factor, η_t, and an idiosyncratic factor, ε_{it}: $\Delta \nu_{it} = \eta_t + \varepsilon_{it}$. GIV is defined as $z_t = \sum_i s_{it} \Delta \nu_{it} - \sum_i \frac{1}{N_t} \Delta \nu_{it}$, where s_{it} is the size weight and $1/N_t$ is the equal weight. 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 the earnings days of intermediaries included in the baseline HF shocks. Column (4) shows the estimate instrumented with GIV using the earnings days of intermediaries included in the baseline HF shocks. Heteroskedasiticy-robust standard errors are reported in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Figure D.2: Aggregate Responses to Financial Shocks



Notes: This figure reports the impulse responses to a one-standard-deviation HF financial shock estimated in an external-instrument VAR. The VAR consists of the excess bond premium, log industrial production, unemployment rate, log VIX index, and the spreads between AAA- and BAA-rated bonds and 10-year treasury yields, with the excess bond premium instrumented by HF financial shocks. Dashed lines represent 90% bootstrapped confidence intervals.

E. Details for Shock Decomposition with Sign Restrictions

This section provides details for shock decomposition with sign restrictions in Section 5.1.

E.1. Methodology

We decompose financial shocks into

$$\boldsymbol{v}_{\mathrm{F}} = \boldsymbol{v}_{\mathrm{CS}} + \boldsymbol{v}_{\mathrm{CD}}, \tag{23}$$

where $\boldsymbol{v}$ denotes vectors of length T. We impose sign restrictions whereby v_{CS} is negatively correlated with changes in interest rates, Δy, and v_{CD} is positively correlated with changes in interest rates. That is, the decomposition satisfies

$$\begin{bmatrix}\boldsymbol{v}_{\mathrm{F}} & \Delta \boldsymbol{y}\end{bmatrix} = \begin{bmatrix}\boldsymbol{v}_{\mathrm{CS}} & \boldsymbol{v}_{\mathrm{CD}}\end{bmatrix}\begin{bmatrix}1 & - \\ 1 & +\end{bmatrix} \tag{24}$$

$$\boldsymbol{v}_{\mathrm{CS}}^{'}\boldsymbol{v}_{\mathrm{CD}} = 0 \tag{25}$$

$$\mathrm{var}(\boldsymbol{v}_{\mathrm{CS}}) + \mathrm{var}(\boldsymbol{v}_{\mathrm{CD}}) = \mathrm{var}(\boldsymbol{v}_{\mathrm{F}}). \tag{26}$$

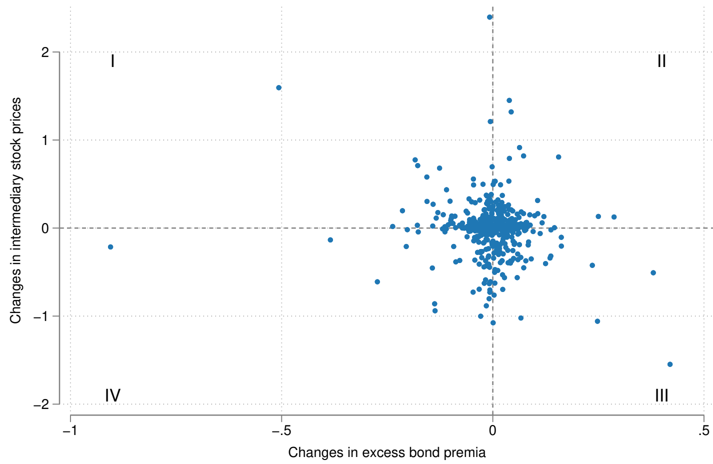
Figure E.1 shows the joint distribution between event-time changes in intermediaries' stock prices and excess bond premia. In quadrants I and III, the comovements between stock prices and the EBP are negative, consistent with the credit supply channel. In quadrants II and IV, the comovements between stock prices and the EBP are positive, consistent with the borrowers' information channel.

E.2. Estimation

Let $M \equiv \begin{bmatrix}\boldsymbol{v}_{\mathrm{F}} & \Delta \boldsymbol{y}\end{bmatrix}$ denote the observed series, $U \equiv \begin{bmatrix}\boldsymbol{v}_{\mathrm{CS}} & \boldsymbol{v}_{\mathrm{CD}}\end{bmatrix}$ denote the structural shocks for which $U'U$ is a diagonal matrix, and C denote the sign restriction matrix. Equation (6) is thus summarized as

$$M = UC. \tag{27}$$

Figure E.1: Scatterplot of event-time changes in stock prices and excess bond premia



To identify the set of matrices C that satisfy the sign restrictions, common approaches include those based on Givens rotation matrices, the Householder transformation, and the so-called "poor man's sign restrictions."[21] To ensure that our results are not sensitive to a specific algorithm, we implement sign restrictions using all three approaches. We use the Givens rotation as our baseline approach, since it is the most tractable in our bivariate system. Results are little changed under the two alternatives.

Givens rotation matrices As in Jarocinski (2020), we construct the structural shocks, U, and the impact matrix, C, as

$$U = QPD \text{ and } C = D^{-1}P'R, \tag{28}$$

where Q is an orthogonal matrix based on QR decomposition of the observed series M, P is a rotation matrix, and D is a scaling matrix to ensure that decomposed shocks add up to the total financial shocks.

Each matrix in (28) is constructed as follows. We first use the QR decomposition to decompose M into two orthogonal components:

$$M = QR, \quad \text{where } Q'Q = I_2, \text{ and } R = \begin{bmatrix} r_{11} > 0 & r_{12} \\ 0 & r_{22} > 0 \end{bmatrix}. \tag{29}$$

[21] Fry and Pagan (2011) show that the Householder transformation and Givens rotation are equivalent. The former enjoys computational advantage in the presence of multiple structural shocks.

Then we rotate the orthogonal components with the matrix P, defined as

$$P = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \quad \text{for } \theta \in [0, 2\pi]. \tag{30}$$

Sign restrictions are imposed on elements of the unscaled impact matrix, $P'R$. The set of angles θ that satisfies sign restrictions is

$$\theta \in \{(0, \arctan\frac{-r_{22}}{r_{12}}) \text{ for all } r_{12} < 0\} \cup \{(\arctan\frac{r_{12}}{r_{22}}, \frac{\pi}{2}) \text{ for all } r_{12} > 0\}. \tag{31}$$

Finally, we scale the set of structural shocks that satisfy sign restrictions, QP, by a diagonal matrix D to ensure that they add up to the total financial shocks. D is specified as

$$D = \begin{bmatrix} r_{11}\cos\theta & 0 \\ 0 & r_{11}\sin\theta \end{bmatrix}. \tag{32}$$

The set of decomposed shocks, U, is set identified. We follow Fry and Pagan (2011) and use the median shocks among the set of admissible shocks as v_{CS} and v_{CD}.

The Householder transformation We alternatively compute C matrices using the algorithm developed by Arias *et al.* (2018) based on the Householder transformation.

As before, we first decompose M into two orthogonal components $M = QR$, where $Q'Q = I_2$ and R is an upper-triangular matrix.

Rather than using the rotation matrix in (30), we construct candidates for P based on the following algorithm. We generate 4,000 random draws of a 2-by-2 real square matrix W from a $N(0, I_2)$ distribution based on an agnostic prior. For each draw, W is decomposed using a QR decomposition into an orthogonal matrix P and an upper-triangular matrix S, whose diagonal elements are normalized to be positive. We normalize the unscaled impact matrix, $P'R$, with the scaling matrix D defined in (32). We maintain draws in which the resulting elements of the impact matrix satisfy the sign restrictions and use the median shocks in the set of admissible shocks.

The poor man's sign restrictions As another robustness, we perform a simple decomposition using "the poor man's sign restrictions" proposed by Jarociński and Karadi (2020). A financial shock, $v_{\mathrm{F},t}$ is classified as a shock to the credit supply if the financial shock and interest rate changes are negatively correlated, i.e., $v_{\mathrm{F},t} \cdot \Delta y_t < 0$. Otherwise, if the financial shock and interest rate changes are positive correlated, then the shock is classified as a shock to the borrowers' information.

Under this method, a given financial shock is classified as either v_{CS} or v_{CD}, but not both. In contrast, a given financial shock can contain both types of shocks under the Givens rotation and the Householder transformation.

Data and regressions We decompose financial shocks based on their correlation with the EBP (from Gilchrist *et al.*, 2021, described in more detail in Section 2), which measures financing costs in the absence of default risks. 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:

$$\Delta y_t = \alpha + \beta_{\mathrm{CS}} v_{\mathrm{CS,t}} + \beta_{\mathrm{CD}} v_{\mathrm{CD,t}} + u_t, \tag{33}$$

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

Results based on sign restrictions with Givens rotation matrices are reported in Panel (c) in Table 4 in the main text. As a robustness test, Table E.1 shows that our results are not sensitive to the methods used to implement sign restrictions. Under alternative implementations with the Householder transformation and the poor man's sign restrictions, the credit supply channel remains the main channel through which financial shocks affect the nonfinancial sector.

Table E.1: Decomposition of financial shocks with sign restrictions

	(1)	(2)	(3)
		SP500 Ex-Fin	
Givens rotation matrix			
Credit-supply channel	1.276***		
	(0.305)		
Credit-demand channel	0.067		
	(0.389)		
The Householder transformation			
Credit-supply channel		1.400***	
		(0.329)	
Credit-demand channel		-0.090	
		(0.432)	
Poor man's sign restrictions			
Credit-supply channel			1.100***
			(0.251)
Credit-demand channel			0.294
			(0.305)
R^2	0.068	0.069	0.053
Observations	492	492	492
Robust SE	yes	yes	yes

Notes: This table reports β_{CS} and β_{CD} from estimating $\Delta y_t = \alpha + \beta_{\mathrm{CS}} v_{\mathrm{CS,t}} + \beta_{\mathrm{CD}} v_{\mathrm{CD,t}} + u_t$, where Δy_t is daily changes in the S&P 500 Ex-Financials Index, v_{CS} is the shock to the supply of credit, and v_{CD} is the shock to the demand for credit. $v_{\mathrm{CS,t}}$ and $v_{\mathrm{CD,t}}$ are decomposed using sign restrictions as specified in the text and implemented using three different methods, which include Givens rotation matrices, the Householder transformation, and the poor man's sign restrictions. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).