BANK OF CANADA
BANQUE DU CANADA

Staff Working Paper/Document de travail du personnel—2022-24

Last updated: December 14, 2022

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

by Pablo Ottonello[1] and Wenting Song[2]

[1] Department of Economics
University of Michigan
National Bureau of Economic Research
pottonel@umich.edu

[2] Canadian Economic Analysis Department
Bank of Canada
wsong@bankofcanada.ca

DOI: https://doi.org/10.34989/swp-2022-24 | **ISSN** 1701-9397

Acknowledgements

We thank Michael Bauer, Simon Gilchrist, Marco Grotteria, Juan Herreño, John Leahy, Jesse Schreger and participants at various seminars and conferences for useful comments and suggestions. Caitlin Hegarty and Hanna Onyshchenko provided excellent research assistance. The views expressed herein are those of the authors and not necessarily those of the Bank of Canada.

Abstract

We provide empirical evidence on the effects of surprises about financial intermediaries' net worth on the overall economy based on a high-frequency identification strategy. We measure financial shocks with changes in the market value of large US intermediaries' net worth in a narrow window around their earnings announcements. Using these shocks, we estimate that a surprise decline of 1% in intermediaries' net worth leads to a 0.2%–0.4% decrease in the market value of nonfinancial firms. These effects are more pronounced for firms with high default risk and low liquidity, and when the aggregate net worth of intermediaries is low.

Topics: Asset pricing; Business fluctuations and cycles; Credit and credit aggregates; Financial institutions; Financial markets; Financial system regulation and policies; Monetary and financial indicators

JEL codes: E44, G01, G21, G23, G24, G32

Résumé

Nous fournissons des résultats empiriques concernant les effets sur l'économie globale de nouvelles inattendues liées à la valeur nette d'intermédiaires financiers. Pour ce faire, nous employons une stratégie d'identification des chocs financiers à l'aide de données de haute fréquence. Nous mesurons ces chocs en fonction des variations de la valeur de marché d'importants intermédiaires américains survenant dans un court laps de temps autour de l'annonce de leurs résultats. À l'aide des chocs relevés, nous estimons qu'une baisse inattendue de 1 % de la valeur nette des intermédiaires entraîne une diminution de 0,2 à 0,4 % de la valeur de marché des sociétés non financières. Ces effets sont plus prononcés pour les sociétés qui présentent un risque de défaillance élevé et une faible liquidité, et aussi quand la valeur nette globale des intermédiaires est faible.

Sujets : Crédit et agrégats du crédit; Cycles et fluctuations économiques; Évaluation des actifs; Indicateurs monétaires et financiers; Institutions financières; Marchés financiers; Réglementation et politiques relatives au système financier

Codes JEL : E44, G01, G21, G23, G24, G32

1. Introduction

What effect do financial intermediaries have on the macroeconomy? The history of financial crises suggests that news about intermediaries' net worth plays a key role in driving economic downturns (see, for example, Bernanke, 1983; Reinhart and Rogoff, 2009a; Gertler and Gilchrist, 2018). Motivated by these episodes, this paper provides empirical evidence on the role of intermediaries based on a high-frequency (HF) identification strategy to measure the aggregate effects of "financial shocks" (i.e., surprises about intermediaries' net worth).

We begin by measuring financial shocks with the changes in large U.S. intermediaries' net worth in a narrow window around their earnings announcements. In the spirit of the HF event-study approach to identifying monetary policy shocks (surveyed by Nakamura and Steinsson, 2018a), our empirical strategy exploits the fact that earnings announcements cause a discontinuity in the information released around these events about individual intermediaries' net worth.

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

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

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

2. Data

Our measure of financial shocks 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 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 2014.[2] We focus on these types of intermediaries because their direct involvement in lending activities in the economy renders them more likely to be linked to the macroeconomy, which is our main focus of analysis. Table 1 details the set of 18 financial intermediaries selected using our main criteria, together with the period in which they are included in our analysis. Table 1 also shows that financial intermediaries in our sample represent 67% of the total equity of U.S. depository institutions, measured by the Federal Reserve's Flow of Funds. Therefore, our sample is based on large financial institutions, whose individual changes in net worth are likely to represent a significant change in the net worth of the entire financial sector.[3] In our period of analysis, we obtain 870 announcements of earnings, with roughly four per institution–year.

We study the effects on nonfinancial firms using intraday stock prices of the S&P 500 constituent securities, also obtained from the HF TAQ database. Our main analysis focuses

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

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

[3]Gabaix and Koijen (2020) discuss how idiosyncratic shocks to large players in the economy that affect aggregates constitute powerful instruments. Appendix A discusses the importance of granularity for identifying the effects of financial shocks in an illustrative theoretical framework.

Table 1: Financial Intermediaries Included in the Sample

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

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

on the movements of these nonfinancial constituents in a narrow window that matches that of financial shocks. We complement this analysis with additional daily indices data from FRED and Bloomberg—the S&P 500 Ex-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.

We also study the effect of financial shocks on the corporate bond market using several data sources. First, we use daily data on U.S. corporate bond indices from the Intercontinental Exchange Bank of America (ICE BofA), obtained from FRED.[4] Our analysis covers

[4]The choice of daily frequency takes into account the less liquid nature of bond markets as well as the

a wide range of ratings from investment grade to high yield. Second, we study the effects on excess bond premia, developed by Gilchrist and Zakrajšek (2012) and extended to daily frequency by Gilchrist, Wei, Yue and Zakrajšek (2021), which measures risk premia as the residuals from projecting firms' bond spreads on their probabilities of default using Merton's 1974 model. Third, we study the within-firm effects of financial shocks by using individual bond-level data from the constituents of corporate bond indices. For each of these bonds, we have information on option-adjusted spreads and bond characteristics from the ICE BofA; transaction-level data in the secondary market from the Trade Reporting and Compliance Engine (TRACE); and the share of bonds (at the CUSIP level) held by each reporting financial institution from Bloomberg. Appendix Tables B.1b and B.2 report descriptive statistics for bond data.

3. Measuring High-Frequency Financial Shocks

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

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

where t is the time of an announcement for financial intermediary i (expressed in minutes within a day); $P_{i,t}$ is the stock price of institution i at time t; Δ^+ and Δ^- control the size of the window around the announcement; and $\theta_{i,q(t)}$ is the market capitalization of institution i as a share of the total market capitalization of institutions in our sample in the quarter $q(t)$ before announcement. For announcements made within trading hours,[5] we select $\Delta(t)^-$ to be 20 minutes before the announcement and $\Delta(t)^+$ to be 40 minutes after the announcement, following Nakamura and Steinsson (2018b) for monetary policy shocks. For announcements that occur after trading hours, we compute the financial shock as the change between the closing and opening log prices. Given that our measure is more precise

day-end settlement time of major participants (such as mutual funds).

[5] 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.

for announcements made within trading hours, we create two measures of financial shocks: a "narrow" measure that includes only this type of announcement and a "broad" one that includes both types of shocks. Appendix Figure B.1 illustrates our HF-identified shocks with four graphical examples. Panels (a) and (b) show two shocks that occur inside trading hours, with their magnitudes corresponding to median positive and negative shocks inside trading hours; Panels (c) and (d) illustrate shocks that occur outside of trading hours.

Appendix Table B.3 reports descriptive statistics for the narrow measure of financial shocks. The first column shows the HF changes in log prices of reporting institutions around their earnings announcements. All statistics are displayed in percent. On average, the price changes of reporting institutions are close to zero, with a standard deviation of 2.7%. Median positive and negative shocks are close to 1%. The third column shows descriptive statistics of HF financial shocks—which, as shown in (1), weight each change in log price of reporting institutions by their market share. Weighting overall reduces the magnitude of the shocks, resulting in a standard deviation of 0.30% and median positive and negative shocks of 0.06% and −0.08%, respectively. We also report changes in the financial sector around earnings announcements. The second column reports the unweighted sum of HF changes in the log prices of all sample intermediaries included in the sample around an earnings announcement, and the fourth column reports the sum weighted by market share. Shocks based on all sample intermediaries are similarly centered around zero and have amplified median positives and negatives and greater volatility compared with the baseline financial shocks.

Content of the shocks Appendix C conducts a set of exercises to examine the content of our measure of financial shocks. 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.

The second exercise shows that financial shocks are not linked systematically to information available at the moment of earnings releases. For this, 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.

Finally, Appendix C.3 reports the volatility of the stock prices of financial intermediaries and nonfinancial firms during event windows that include intermediaries' earnings announcements and compares it with the volatility during nonevent windows. These moments show that the volatility of financial intermediaries' stock prices during their earnings announcements increases by substantially more than that of nonfinancial firms during those events, which is consistent with the fact that intermediaries' earnings announcements contain more information about financial intermediaries than about nonfinancial firms. Based on this, in our empirical analysis in the next section we conduct a heteroskedasticity-based identification. This can be conducted even if common factors affect both intermediaries and nonfinancial firms during their earnings announcements, as long as the variance of intermediaries' stock prices is larger during earnings-announcement events than on nonevent dates. In contrast, the variance in stock price of nonfinancial firms is the same during both the event dates of financial intermediaries' earnings releases and nonevent dates.

4. The Aggregate Effects of Financial Shocks

Theoretical background We now study the aggregate effects of the HF financial shocks. From a theoretical perspective, there are two main channels linking surprises about intermediaries' net worth to the aggregate economy (see Appendix A). First, theories in which a decline in the net worth of financial intermediaries (driven, for example, by a negative realization of returns on their investments) leads to contraction in the supply of funds for nonfinancial firms and a decline in nonfinancial firms' investment and market value (e.g., Gertler and Kiyotaki, 2010; He and Krishnamurthy, 2012, 2013; Brunnermeier and Sannikov, 2014; Maggiori, 2022, and references therein). In these models, the strength of this effect is governed by the degree of financial frictions faced by intermediaries. Therefore, analyzing the effects of financial shocks can be informative of the degree of financial frictions faced by financial intermediaries. Second, news about financial intermediaries' net worth might contain information about productivity or demand faced by nonfinancial firms. Similar to the Fed's "information effect" that Romer and Romer (2000) and Nakamura and Steinsson (2018b) document in the context of monetary policy shocks, investors may view financial intermediaries as a bellwether of the broader economy. We first provide evidence on the aggregate effects of financial shocks in this section, before studying the relative strength of these two channels in Section 5.

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

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

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

Table 2 reports the main results of estimating the aggregate effects of financial shocks. The baseline result in the first column of Panel (a) shows that a 1% change in the net worth of financial intermediaries leads to a 0.3% change in the net worth of nonfinancial firms.[6] Controlling for business-cycle variables—output, employment, and a recession indicator—affects neither the estimated elasticity nor the standard errors, as shown in the second column.

[6] 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 2: Effects of Financial Shocks on the Market Value of Nonfinancial Firms

(a) Event-Time

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

(b) Heteroskedasticity-Based

	(5)	(6)
	All Intermediaries	
Fin shock (narrow)	0.360***	0.361***
SE	(0.028)	(0.028)
95 percent CI	[0.296, 0.412]	[0.295, 0.412]
Observations	1,281	1,281
Macro controls	no	yes

Notes: Panel (a) estimates variants of the event-time regression in (2): $\Delta y_{jt} = \alpha_j + \beta \varepsilon_t^{\mathrm{F}} + u_{jt}$, where Δy_{jt} is the HF log price change of a nonfinancial S&P 500 constituent stock j; $\varepsilon_t^{\mathrm{F}}$ is the narrow measure of the HF financial shock; and α_j is a CUSIP fixed effect. Macro controls include output, employment, and an indicator variable for recession. Columns 3 and 4 replace $\varepsilon_t^{\mathrm{F}}$ with a HF shock constructed using the price changes of all sample intermediaries, as described in the main text, whose estimate is more comparable to heteroskedasticity-based estimates. Standard errors are two-way clustered at shock and CUSIP levels and reported in parentheses. Panel (b) reports the heteroskedasticity-based estimator for β from the bivariate model (3) implemented with an instrumental variable framework. First-stage F-statistics are 423 and 421 for columns 5 and 6, respectively. Standard errors and confidence intervals are computed with statefied bootstrap, as described in the text. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

News released through the earnings announcements of these granular intermediaries can potentially influence the net worth of other intermediaries that have yet to report earnings; Appendix Figure B.2 shows that shocks to the market value of an earnings-releasing intermediary lead to a 0.2% increase in the market value of other nonreleasing intermediaries. In the third and fourth columns of Panel (a), we account for these effects and alternatively measure the financial shock based on the price changes of all sample intermediaries (i.e., $\varepsilon_t^{\mathrm{F}} = \sum_{i \in \mathcal{I}_q} \theta_{i,q(t)} (\log P_{i,t+\Delta^+} - \log P_{i,t-\Delta^-})$, where $\mathcal{I}_q$ denotes the set of intermediaries reporting earnings in quarter q). As with the baseline shocks, changes in financial net worth lead to changes in the net worth of nonfinancial firms. The estimated elasticity of 0.2 is slightly smaller than the baseline estimate, which reflects a smaller role of nonreleasing intermediaries in the rest of the economy.

Heteroskedasticity-based identification A potential concern about the event-time approach is that factors unrelated to the release of earnings of intermediaries may ultimately be related to the stock prices of nonfinancial firms, even within a narrow window around earnings announcements. We allow for this possibility by conducting an alternative estimation using a heteroskedasticity-based identification strategy (Rigobon, 2003; Rigobon and Sack, 2004). This strategy can be conducted even in the presence of common factors that affect the market values of both intermediaries and nonfinancial firms, as long as the variance of intermediaries' stock prices 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 conduct the estimation based on heteroskedasticity for the same 60-minute event window that matches the frequency from the event-time analysis, we consider the bivariate model

$$\begin{aligned} \Delta\nu_t^{\mathrm{F}} &= \alpha\Delta y_t + \Phi' Z_t + e_t \\ \Delta y_t &= \beta\Delta\nu_t^{\mathrm{F}} + \Gamma' Z_t + u_t, \end{aligned} \tag{3}$$

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

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

We estimate the coefficient of interest, β, following the instrumental variable implementation developed by Rigobon and Sack (2004). Standard errors and confidence intervals use the bootstrap procedure developed by Hébert and Schreger (2017) to correct for small-sample bias.[7]

Panel (b) in Table 2 shows the results from estimating the effects of financial shocks on nonfinancial firms using a heteroskedasticity-based approach. The elasticity is estimated to be 0.4 and statistically significant. To compare estimates from the event-time and heteroskedasticity-based approaches, we include in the third and fourth columns the event-time regressions with financial shocks based on the price changes of all sample intermediaries and not just the reporting intermediary. A full comparison of the two identification strategies, for different weightings and frequency, is reported in Appendix Table B.6. Although weaker assumptions are imposed, the effects of financial shocks identified through heteroskedasticity are stronger than the event-study estimates, which suggests that our baseline results based on event-time analysis provide a lower bound on the impact of financial shocks.

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 values at the beginning of the quarter. The estimated impact, at 0.2, is slightly smaller than the equal-weighted benchmark, which suggests that the financial shocks have a stronger effect on smaller firms. The table also reports the effect on the broad S&P 500 Index, measured through the exchange-traded fund SPDR at high frequency, similar to the baseline estimates in terms of both economic magnitude and statistical significance.

Second, these effects do not depend on the frequency of analysis or the set of nonfinancial firms. Appendix Table 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;

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

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 the broad measure of financial shocks, including announcements made outside of trading hours. A related concern is that intermediaries may strategically release worse earnings outside of trading hours. Appendix Figure D.1 plots the realized earnings results against the hours of earnings announcements and shows no evidence of the strategic timing.

Fourth, Appendix Table D.4 accounts for the 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 in 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 the 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, demonstrates that the HF shocks do not have an effect on the market value of nonfinancial firms during the days before the shock, which suggests that the effects are not driven by 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 for financial shocks but focus on the earnings announcements of nonfinancial firms included in the Dow Jones index. Appendix Table B.4b shows the results of estimating the event-time regression but using the shock to nonfinancial firms instead of the financial shock. Results indicate a baseline estimate that is negative, not statistically significant, and unstable across specifications (e.g., has a negative point estimate when we use the narrow version of the shocks but a positive point estimate with a broad version of the shocks). To render the shocks further comparable, Appendix Table B.4c restricts the number of Dow Jones firms used in placebo shocks to equal the number of financial intermediaries included in financial shocks, keeping the top nonfinancial firms by market value. Again, placebo shocks do not display an effect similar to that of financial shocks.[8]

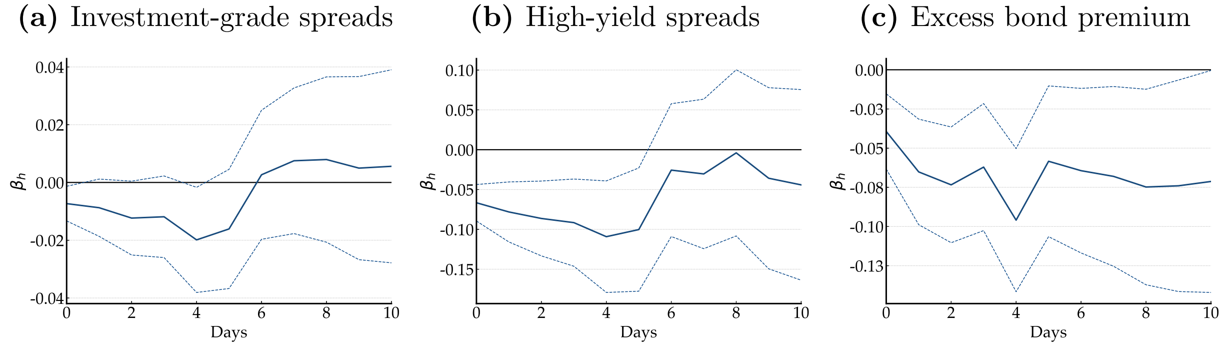
Furthermore, we construct HF placebo shocks for each of the 10 nonfinancial sectors in the S&P 500. As in the procedure for financial shocks, we collect precise dates and times for nonfinancial firms' earnings releases and compute their log price changes in a narrow 60-minute window around the announcement,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

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

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

[8] 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 Financial Shocks on Corporate Bonds



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

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

Panels (a) and (b) in Figure 1 show that declines in the market value of intermediaries 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% decline in the market value of intermediaries 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% decline in the market value of intermediaries resulting in an increase of 4 to 10 basis points in the excess bond premium.

5. Inspecting the Transmission Mechanism

Given the aggregate importance of financial shocks, we now study how they transmit to the rest of the economy. We provide supportive evidence on four potential channels: the financial system's overall conditions, nonfinancial firms' financial positions, the information effect of financial shocks, and the net worth of financial intermediaries.

Aggregate state dependency Empirical evidence on the role of financial intermediaries in the macroeconomy often comes from analyzing episodes of financial crises (Reinhart and Rogoff, 2009b; Chodorow-Reich, 2014; Huber, 2018). Motivated by this evidence, we begin by investigating the importance of aggregate conditions in the transmission of financial shocks. We decompose the effects of financial shocks depending on whether the financial system is undercapitalized (i.e., when the market value of intermediaries' net worth is below its HP trend).

Panel (a) of Table 3 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 driving the aggregate effects of intermediaries in the economy is the overall condition of the financial system (as stressed, for instance, by Gertler and Kiyotaki, 2010).

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 documenting how nonfinancial firms' financial positions (leverage, credit risk, and liquidity) affect their responses to financial shocks. Appendix E.1 contains details of our empirical model, which mirrors the specifications used for studying the heterogeneous transmission of monetary shocks.[9]

Panel (b) of Table 3 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

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

from those in response to the monetary policy shocks documented in previous literature. To facilitate this comparison, Appendix Table B.7 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; this is in contrast to firms with lower credit ratings being the most responsive to financial shocks.

Information effects As mentioned in the theoretical background section (and further detailed in Appendix A), financial earnings may convey information about the productivity or demand faced by nonfinancial firms. We now decompose the information contained in the HF shocks into information about intermediaries' net worth and information about nonfinancial firms' investment opportunities. In the spirit of sign-restriction methods developed by Cieslak and Schrimpf (2019) and Jarociński and Karadi (2020) for decomposing monetary shocks, we disentangle these two channels by exploiting the comovements of interest rates and stock prices around earnings announcements. Appendix E.2 contains details of our empirical model: On one hand, positive news about intermediaries' net worth raises lenders' *supply* of funds and leads to a lower interest rate. On the other hand, positive news about nonfinancial firms' investment opportunities raises borrowers' *demand* for funds and leads to a higher interest rate. Appendix A.4 formalizes this idea and illustrates in Figure A.3 the opposite directions in which borrowing rates react following shocks in these two channels. Imposing the aforementioned sign restrictions and measuring interest rates in the absence of default risk using excess bond premia (EBP, in Gilchrist and Zakrajšek, 2012), we decompose the financial shocks into two orthogonal components: a lenders' net-worth shock and a borrowers' information shock.

Panel (c) of Table 3 shows that intermediaries' net worth remains the dominant channel through which financial shocks affect the rest of the economy. The estimated semi-elasticity of borrowers' information 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.

The role of intermediaries' net worth Finally, 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

$$\Delta_h z_{k(j)it} = \alpha_{jt} + \gamma_h \theta_{k(j)it} \varepsilon_t^{\mathrm{F}} + \Gamma' Z_{jt} + u_{jith}, \tag{5}$$

where $\Delta z_{k(j)it}$ is cumulative changes in bond k's option-adjusted spreads over h days; $\varepsilon_t^{\mathrm{F}}$ is the narrow HF financial shock around intermediary i's earnings announcement; $\theta_{k(j)it}$ is the share of bond k issued by firm j held by intermediary i in the quarter proceeding its earnings announcement in period t; α_{jt} is a firm-by-shock fixed effect; and Z_{jt} is a vector of bond controls that includes bond holdings $\theta_{k(j)it}$, a categorical variable for bond ratings, remaining maturity, trailing average, and month-to-date changes in spreads. We estimate (5) 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 (d) of Table 3 rejects the null hypothesis that the observed effects of financial intermediaries are entirely driven by information specific to nonfinancial firms.[10] 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' having an effect on the security prices of nonfinancial firms through financial intermediaries' net worth, which under short-term trading frictions can translate into different prices for bonds with similar risk (see Morelli, Ottonello and Perez, 2021).

[10] Appendix Figure B.4 reports the full dynamics of responses for horizons $h = 1, \cdots, 10$ and conducts additional robustness of including controls for bond liquidity. Table 3 reports the estimates for $h = 5$ due to space constraint.

Table 3: Transmission Channels of Financial Shocks

	Average Effect	Interation Effect	Adj. R^2	Obs.	Fixed Effects	Standard Errors
(a) Aggregate state dependency						
dependent var.: S&P 500 constituents						
average	0.291** (0.140)		0.009	104,167	cusip	double-clustered
well capitalized		0.098 (0.233)	0.015	104,167	cusip	double-clustered
undercapitalized		0.294** (0.142)				
(b) Firms' heterogenous financial positions						
dependent var.: S&P 500 constituents						
high leverage	0.252** (0.108)	0.024 (0.018)	0.023	598,572	sector×qtr, firm	double-clustered
invt-grade credit ratings	0.330** (0.142)	-0.075* (0.043)	0.039	162,267	sector×qtr, firm	double-clustered
high liquidity	0.283** (0.109)	-0.038** (0.015)	0.023	598,530	sector×qtr, firm	double-clustered
(c) Information effect						
dependent var.: S&P 500 ex-financial index						
average	0.910*** (0.228)		0.062	344	-	heterosk.-robust
net-worth channel		1.306*** (0.341)	0.078	344	-	heterosk.-robust
information channel		0.382 (0.431)				
(d) Intermediaries' net worth (within-firm variation)						
dependent var.: CCC bonds						
average	-0.155** (0.071)		0.635	9,587	bond×qtr, firm×bank	double-clustered
by bond holdings		-0.537*** (0.131)	0.806	9,212	firm×shock	double-clustered

Notes: Panel (a) estimates $\Delta y_{jt} = \alpha_j + \beta_w \varepsilon_t^{\mathrm{F}} \mathbb{1}(\varepsilon_t^{\mathrm{F}} > \bar{\varepsilon}_t) + \beta_u \varepsilon_t^{\mathrm{F}} \mathbb{1}(\varepsilon_t^{\mathrm{F}} < \bar{\varepsilon}_t) + \Gamma' Z_t + u_{jt}$, where $\varepsilon_t^{\mathrm{F}}$ is the narrow HF shock; $\mathbb{1}(\varepsilon_t^{\mathrm{F}} < \bar{\varepsilon}_t)$ is an indicator variable for dates on which the market value of intermediaries' net worth is below its HP trend $\bar{\varepsilon}_t$; and Z_t is a vector of macro controls including output, payrolls, a recession indicator, and their interaction terms with the financial shocks. Panel (b) estimates (7): $\Delta y_{jt} = \alpha_j + \alpha_{sq} + \beta \varepsilon_t^{\mathrm{F}} + \gamma \varepsilon_t^{\mathrm{F}} x_{jt} + \Gamma' Z_{jt} + u_{jt}$, where x_{jt} is an indicator variable for firms with high leverage, investment-grade credit rating, or high liquidity. Panel (c) estimates (12): $\Delta y_t = \alpha + \beta_{\mathrm{lender}} \varepsilon_{\mathrm{lender}} + \beta_{\mathrm{borrower}} \varepsilon_{\mathrm{borrower}} + u_t$, with $\varepsilon_{\mathrm{lender}}$ and $\varepsilon_{\mathrm{borrower}}$ decomposed using sign restrictions as described in Appendix E.2. Panel (d) estimates (5): $\Delta_h z_{k(j)it} = \alpha_{jt} + \gamma_h \theta_{k(j)it} \varepsilon_t^{\mathrm{F}} + \Gamma' Z_{jt} + u_{jith}$, where the dependent variable is cumulative changes in bond k's option-adjusted spreads over 5 days; and $\theta_{k(j)it}$ is the share of bond k issued by firm j held by intermediary i in the quarter proceeding its earnings announcement in period t. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

6. Concluding Remarks

In this paper, we propose a new measure of financial shocks based on HF changes in the market value around intermediaries' earnings announcements. 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.

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

References

Adrian, T., Etula, E. and Muir, T. (2014). Financial intermediaries and the cross-section of asset returns. *Journal of Finance*, **69** (6), 2557–2596.

Amiti, M. and Weinstein, D. E. (2011). Exports and financial shocks. *Quarterly Journal of Economics*, **126** (4), 1841–1877.

Anderson, G. and Cesa-Bianchi, A. (2020). Crossing the credit channel: Credit spreads and firm heterogeneity. *Bank of England Working Paper*.

Bernanke, B. S. (1983). Nonmonetary effects of the financial crisis in the propagation of the Great Depression. *American Economic Review*, **73** (3), 257–276.

— (2018). The real effects of disrupted credit: Evidence from the global financial crisis. *Brookings Papers on Economic Activity*, **2018** (2), 251–342.

— and Kuttner, K. N. (2005). What explains the stock market's reaction to Federal Reserve policy? *Journal of Finance*, **60** (3), 1221–1257.

Breiman, L. (2001). Random forests. *Machine Learning*, **45** (1), 5–32.

Brunnermeier, M. K. and Sannikov, Y. (2014). A macroeconomic model with a financial sector. *American Economic Review*, **104** (2), 379–421.

Chodorow-Reich, G. (2014). The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis. *Quarterly Journal of Economics*, **129** (1), 1–59.

Chordia, T. and Shivakumar, L. (2006). Earnings and price momentum. *Journal of Financial Economics*, **80** (3), 627–656.

Christiano, L. J., Eichenbaum, M. S. and Trabandt, M. (2015). Understanding the Great Recession. *American Economic Journal: Macroeconomics*, **7** (1), 110–67.

—, Motto, R. and Rostagno, M. (2014). Risk shocks. *American Economic Review*, **104** (1), 27–65.

Cieslak, A. and Schrimpf, A. (2019). Non-monetary news in central bank communication. *Journal of International Economics*, **118**, 293–315.

Cochrane, J. H. and Piazzesi, M. (2002). The Fed and interest rates—a high-frequency identification. *American Economic Review*, **92** (2), 90–95.

Cook, T. and Hahn, T. (1989). The effect of changes in the federal funds rate target on market interest rates in the 1970s. *Journal of Monetary Economics*, **24** (3), 331–351.

Coval, J. and Stafford, E. (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics*, **86** (2), 479–512.

Gabaix, X. and Koijen, R. S. (2020). Granular instrumental variables. *National Bureau of Economic Research*.

Gertler, M. and Gilchrist, S. (2018). What happened: Financial factors in the Great Recession. *Journal of Economic Perspectives*, **32** (3), 3–30.

— and — (2019). The channels of financial distress during the Great Recession: Some evidence on the aggregate effects. *Working Paper, Columbia University*.

— and Kiyotaki, N. (2010). Financial intermediation and credit policy in business cycle analysis. *Handbook of Monetary Economics*, **3** (11), 547–599.

Gilchrist, S., Wei, B., Yue, V. Z. and Zakrajšek, E. (2021). The term structure of the excess bond premium: Measures and implications. *Atlanta Federal Reserve*, (12-2021).

— and Zakrajšek, E. (2012). Credit spreads and business cycle fluctuations. *American Economic Review*, **102** (4), 1692–1720.

Gomes, J. F. (2001). Financing investment. *American Economic Review*, **91** (5), 1263–1285.

Gorodnichenko, Y. and Weber, M. (2016). Are sticky prices costly? Evidence from the stock market. *American Economic Review*, **106** (1), 165–99.

Gürkaynak, R. S., Sack, B. P. and Swanson, E. T. (2004). Do actions speak louder than words? The response of asset prices to monetary policy actions and statements. *FEDS Working Paper*.

He, Z., Kelly, B. and Manela, A. (2017). Intermediary asset pricing: New evidence from many asset classes. *Journal of Financial Economics*, **126** (1), 1–35.

— and Krishnamurthy, A. (2012). A model of capital and crises. *Review of Economic Studies*, **79** (2), 735–777.

— and — (2013). Intermediary asset pricing. *American Economic Review*, **103** (2), 732–70.

— and — (2018). Intermediary asset pricing and the financial crisis. *Annual Review of Financial Economics*, **10**, 173–197.

Hébert, B. and Schreger, J. (2017). The costs of sovereign default: Evidence from Argentina. *American Economic Review*, **107** (10), 3119–45.

Hennessy, C. A. and Whited, T. M. (2007). How costly is external financing? Evidence from a structural estimation. *Journal of Finance*, **62** (4), 1705–1745.

Herreño, J. (2020). The aggregate effects of bank lending cuts. *Working Paper, Columbia University*.

Huber, K. (2018). Disentangling the effects of a banking crisis: Evidence from German firms and counties. *American Economic Review*, **108** (3), 868–98.

Jarocinski, M. (2020). Central bank information effects and transatlantic spillovers.

Jarociński, M. and Karadi, P. (2020). Deconstructing monetary policy surprises—the role of information shocks. *American Economic Journal: Macroeconomics*, **12** (2), 1–43.

Jeenas, P. (2019). Firm balance sheet liquidity, monetary policy shocks, and investment dynamics. *Working Paper*.

Jermann, U. and Quadrini, V. (2012). Macroeconomic effects of financial shocks. *American Economic Review*, **102** (1), 238–71.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, **95** (1), 161–182.

Khan, A. and Thomas, J. K. (2013). Credit shocks and aggregate fluctuations in an economy with production heterogeneity. *Journal of Political Economy*, **121** (6), 1055–1107.

Khwaja, A. I. and Mian, A. (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, **98** (4), 1413–42.

Kilian, L. and Lütkepohl, H. (2017). *Structural vector autoregressive analysis*. Cambridge University Press.

Kuttner, K. N. (2001). Monetary policy surprises and interest rates: Evidence from the fed funds futures market. *Journal of Monetary Economics*, **47** (3), 523–544.

Maggiori, M. (2022). International macroeconomics with imperfect financial markets. In G. Gopinath, E. Helpman and K. Rogoff (eds.), *Handbook of International Economics: International Macroeconomics, Volume 6*, *Handbook of International Economics*, vol. 6, Elsevier, pp. 199–236.

McCracken, M. W. and Ng, S. (2016). FRED-MD: A monthly database for macroeconomic research. *Journal of Business & Economic Statistics*, **34** (4), 574–589.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, **29** (2), 449–470.

Morelli, J. M., Ottonello, P. and Perez, D. J. (2021). Global banks and systemic debt crises. *National Bureau of Economic Research*.

Nakamura, E. and Steinsson, J. . (2018a). Identification in macroeconomics. *Journal of Economic Perspectives*, **32** (3), 59–86.

— and Steinsson, J. . (2018b). High-frequency identification of monetary non-neutrality: The information effect. *Quarterly Journal of Economics*, **133** (3), 1283–1330.

Ottonello, P. and Winberry, T. (2020). Financial heterogeneity and the investment channel of monetary policy. *Econometrica*, **88** (6), 2473–2502.

Reinhart, C. M. and Rogoff, K. S. . (2009a). *This time is different*. Princeton University Press.

— and Rogoff, K. S. . (2009b). The aftermath of financial crises. *American Economic Review*, **99** (2), 466–72.

Rigobon, R. (2003). Identification through heteroskedasticity. *Review of Economics and Statistics*, **85** (4), 777–792.

— and Sack, B. (2004). The impact of monetary policy on asset prices. *Journal of Monetary Economics*, **51** (8), 1553–1575.

Romer, C. D. and Romer, D. H. (2000). Federal Reserve information and the behavior of interest rates. *American Economic Review*, **90** (3), 429–457.

Siriwardane, E. N. (2019). Limited investment capital and credit spreads. *Journal of Finance*, **74** (5), 2303–2347.

Zou, H. and Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, **67** (2), 301–320.

Online Appendix

A. An Illustrative Theoretical Framework

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

A.1. Environment

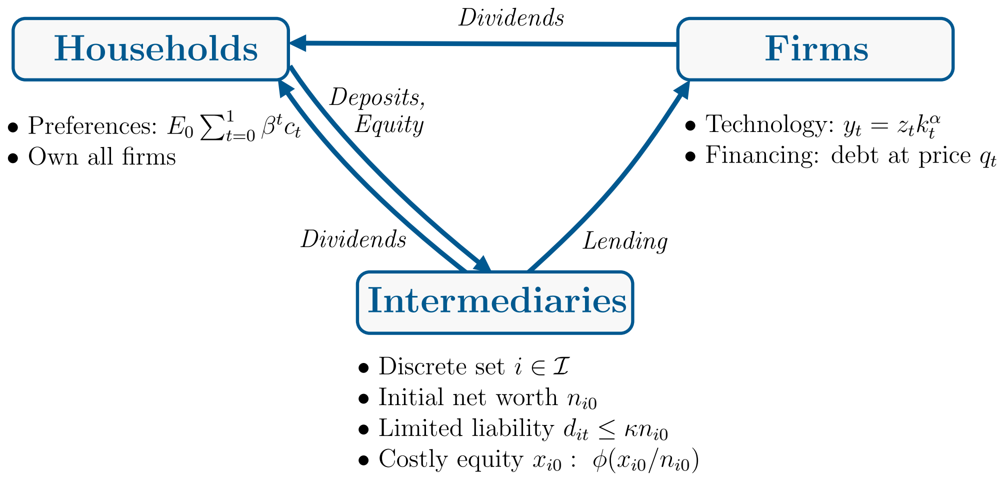
There are two periods: $t = 0, 1$; and two goods: final and capital goods. The economy is populated by a unit mass of identical households and nonfinancial firms and a discrete set of intermediaries indexed by $i \in \mathcal{I}$. Figure A.1 summarizes the model economy.

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

Nonfinancial firms have access to a technology to produce final goods in period 1 using capital input—$y_t = z_t k_t^{\alpha}$, where z_t is an aggregate productivity shock with a bounded support—and to a linear technology to accumulate capital goods out of the final good. Capital fully depreciates after production. Firms cannot raise equity and can 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.*, 2021). On the deposit side, intermediaries face limited liability constraints, which link their deposits to their net worth: $d_{i1} \leq \kappa n_{i0}$, with $\kappa \geq 0$. On the equity side, intermediaries face a cost to raise equity $\phi \left(\frac{x_{i0}}{n_{i0}} \right)$. As in the quantitative corporate finance literature (e.g., Gomes, 2001; Hennessy and Whited, 2007), these costs are designed to capture flotation costs, adverse-selection premia, and other costs associated with raising external finance. The parameter $\phi \geq 0$ governs the degree of intermediaries' frictions to raise external finance and is a key object in our analysis. The case of $\phi = 0$ corresponds to a frictionless case that is isomorphic to an economy in which households directly finance firms.

Figure A.1: Model Economy



A.2. 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*

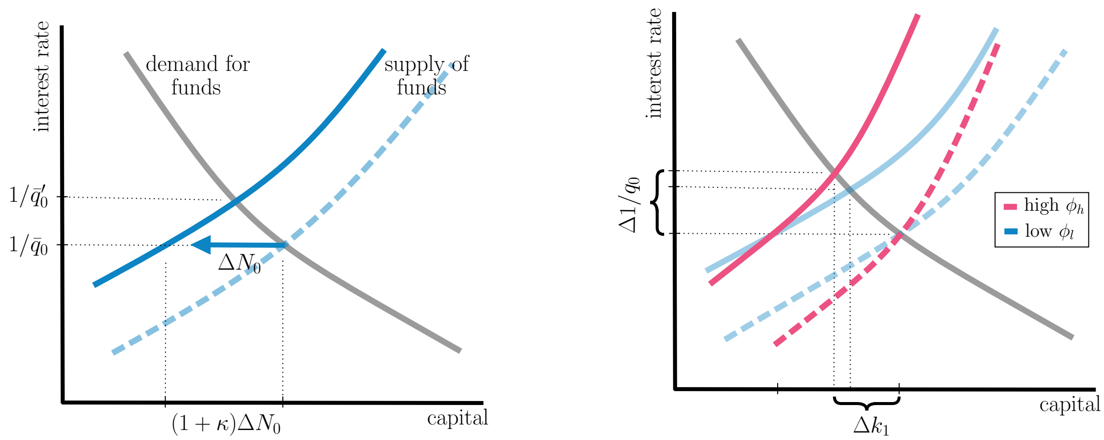
i. Given prices, allocations of households, firms, and financial intermediaries solve their respective problems.

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

We represent the equilibrium of the model using a demand–supply-of-funds scheme (similar to that developed by Morelli *et al.*, 2021). On the side of intermediaries, 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*:

$$\mathcal{K}^s(q_0, N_0, \phi) = N_0(1 + \kappa + \mathcal{X}(q_0, \phi)), \tag{6}$$

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

where $\mathcal{K}^s(q_0, N_0, \phi) = q_0 \sum_{i\in\mathcal{I}} b_{i0}$; $N_0 = \sum_{i\in\mathcal{I}} n_{i0}$ denotes aggregate net worth; and $\mathcal{X}(q_0, \phi) = \frac{1}{2\phi}\left(\beta\frac{1}{q_0} - 1\right)$. The relationship between the supply of funds and interest rates is upward sloping for $\phi > 0$ (i.e., $\frac{\partial\mathcal{K}^s(q_0,N_0,\phi)}{\partial(1/q_0)} > 0$) because, in this case, intermediaries face an upward-sloping cost to raise external finance (governed by ϕ), which implies that to supply more funds, the returns on lending must be larger. On the side of firms, the Euler equation for capital 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 represents the equilibrium capital and interest rates as the intersection between the aggregate supply of and demand for funds.

A.3. 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 $\phi \to 0$.*

This discussion suggests that analyzing the macroeconomic effects of idiosyncratic financial shocks—as we do in our empirical analysis—is highly informative on the degree of financial frictions faced by intermediaries. We next discuss 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: If we combine households' first-order conditions 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 households' first-order conditions 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 $\frac{1}{\beta}$.

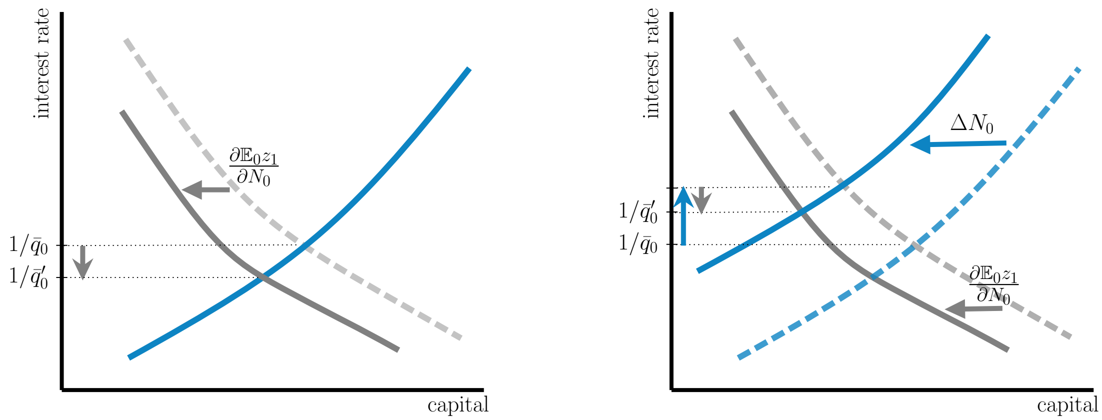
The model experiment can be used to further discuss the identifying assumptions used in our empirical analysis to estimate the effects of financial shocks on the real economy. First, in the model, changes in individual intermediaries' net worth affect the aggregate net worth (i.e., $\frac{\partial N_0}{\partial n_{\iota 0}} > 0$). 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 changes in intermediaries' net worth. For this reason, our empirical analysis focuses on changes in intermediaries' market value in a narrow window around their earnings announcement, which is likely to satisfy this condition.

A.4. Extending the model for a borrowers' information channel

So far, our model has focused on the intermediaries' net worth channel in the transmission of financial shocks. This section extends our model to include a borrowers' information channel, as we consider in our empirical analysis of Section E.2. For this, we assume that surprises about intermediaries' net worth can potentially contain information about nonfinancial firms' expected productivity, i.e., $\frac{\partial \mathbb{E}_0 z_1}{\partial n_{\iota 0}} = \varphi \geq 0$.

Panel (a) of Figure A.3 represents the effect of the borrowers' information channel on the equilibrium investment and interest rates. A contraction in the initial aggregate net worth N_0 is associated with a lower expected productivity for nonfinancial firms, which shifts the demand-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 the intermediaries' net worth channel from the previous section, which shifts the supply curve. For a contraction in intermediaries' initial aggregate net worth N_0, both channels contribute to a contraction of nonfinancial firms' investment and market value. The overall effects on interest rates are indeterminate, depending on the relative strength of each channel, governed by the degree of intermediaries' financial frictions ϕ and the information content

Figure A.3: Asset Price Comovements for the Intermediaries' Net Worth Channel and Borrowers' Information Channel



(a) Borrowers' Infomation Channel

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

of financial shocks φ. Panel (b) represents the case in which the effect of intermediaries' balance sheet dominates and, consistent with our empirical analysis, interest rates increase in response to a negative financial shock.

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

B. Additional Tables and Figures

Table B.1: Descriptive Statistics for Equity and Bonds

(a) Daily Returns of Equity Indices

	Release	Nonrelease	All Days
S&P 500 Ex-Financials			
Mean	-0.03	0.03	0.02
	(0.06)	(0.02)	(0.02)
Std Deviation	1.32	1.12	1.14
	(0.04)	(0.01)	(0.01)
Observations	486	5,048	5,534
SmallCap 600			
Mean	0.03	0.03	0.03
	(0.07)	(0.02)	(0.02)
Std Deviation	1.58	1.39	1.41
	(0.05)	(0.01)	(0.01)
Observations	486	4,603	5,089
Russell 2000			
Mean	0.02	0.02	0.02
	(0.08)	(0.02)	(0.02)
Std Deviation	1.70	1.46	1.48
	(0.05)	(0.01)	(0.01)
Observations	486	4,603	5,089

(b) Daily Changes in Bond Spreads

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

Notes: 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.

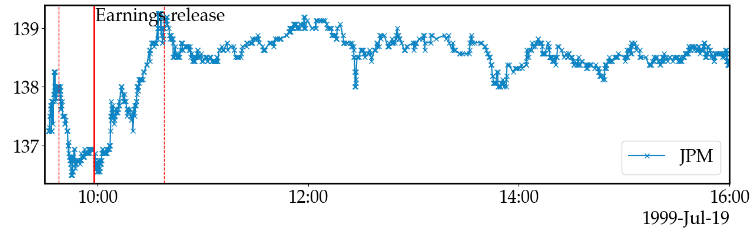
Table B.2: Bond Holdings by Intermediary

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					

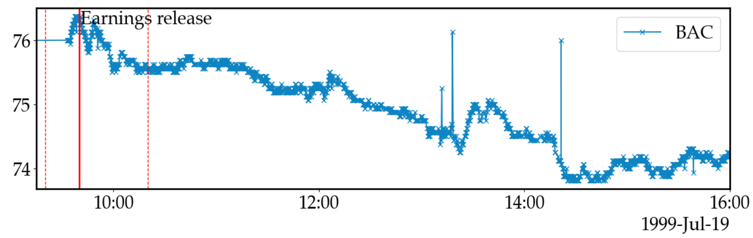
Notes: This table shows descriptive statistics for the shares of bonds held by financial intermediaries, displayed in percent. The set of bonds includes bonds rated CCC or lower in ICE issued by firms with at least 10 bonds outstanding.

Figure B.1: Construction of Financial Shocks

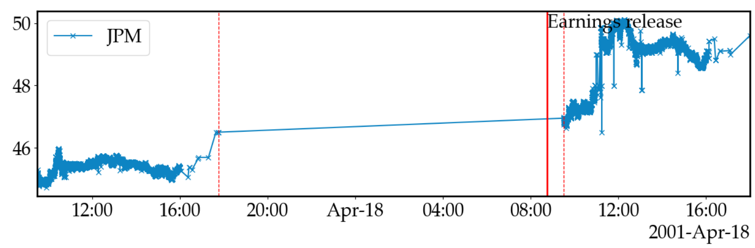
(a) Median Positive Shock (Inside Regular Trading Hours)



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



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



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

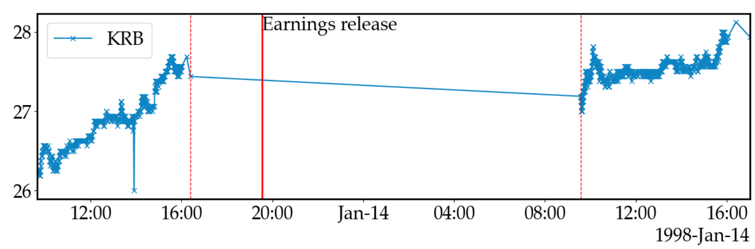
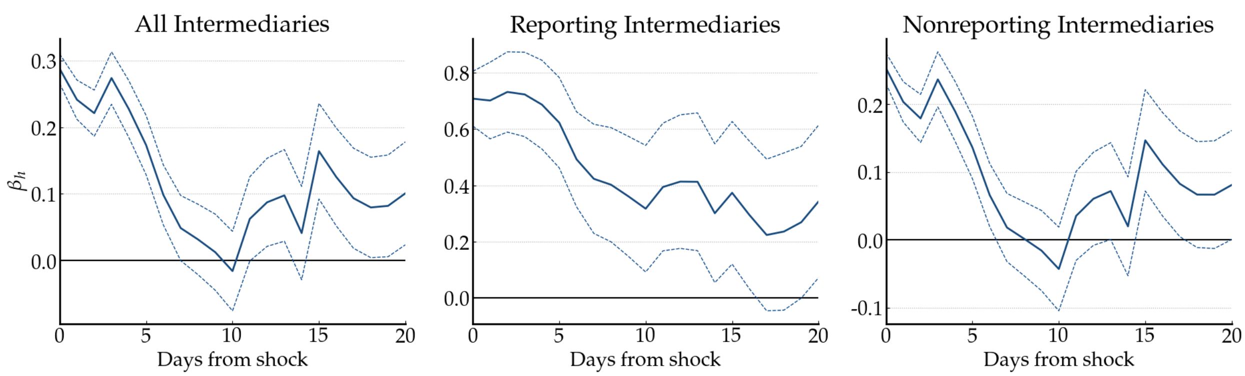


Table B.3: Financial Shocks

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

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

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.

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

(a) Financial Shocks

	S&P 500 Ex-Fin	**SmallCap**	**Russell**	**Obs**
Narrow	0.924***	1.348***	1.453***	272
	(0.241)	(0.296)	(0.313)	
Macro controls	0.908***	1.276***	1.381***	272
	(0.243)	(0.299)	(0.316)	
Broad	0.720***	1.085***	1.124***	486
	(0.179)	(0.213)	(0.229)	

(b) Placebo Dow Jones Nonfinancial Shocks

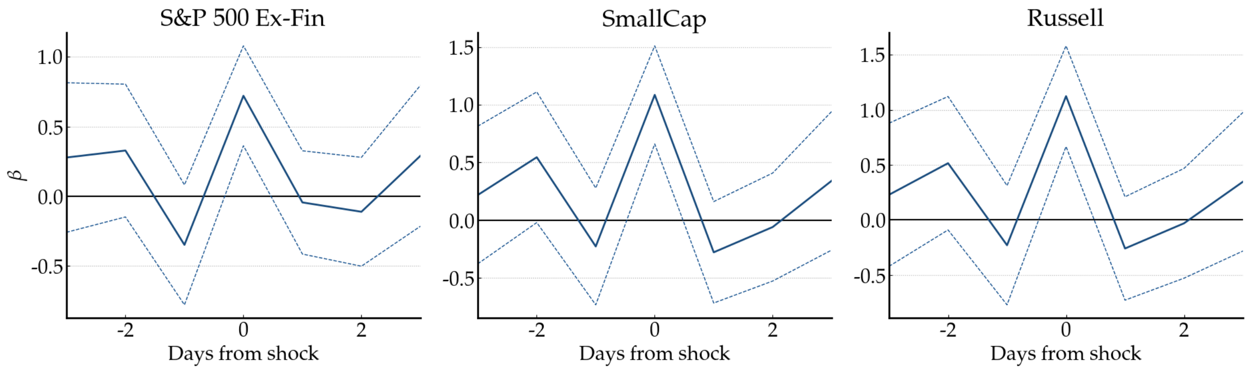
	S&P 500	**SmallCap**	**Russell**	**Obs**
Narrow	-0.205	-0.557*	-0.513	546
	(0.272)	(0.330)	(0.346)	
Macro controls	-0.158	-0.506	-0.462	546
	(0.272)	(0.329)	(0.345)	
Broad	0.334	0.064	0.135	877
	(0.220)	(0.256)	(0.268)	

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

	S&P 500	**SmallCap**	**Russell**	**Obs**
Narrow	-0.161	-0.432	-0.392	378
	(0.239)	(0.294)	(0.307)	
Macro controls	-0.096	-0.356	-0.314	378
	(0.239)	(0.291)	(0.305)	
Broad	0.282	0.071	0.134	649
	-0.204	-0.237	-0.247	

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

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



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

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

Dependent Variables	**Placebo Sectors**	**Effects of Placebo Shocks**
S&P 500 Ex-Energy Index	Energy	-0.729
		(0.617)
S&P 500 Ex-Materials Index	Materials	-1.261
		(0.975)
S&P 500 Ex-Industrials Index	Industrials	0.526
		(1.164)
S&P 500 Ex-Consumer Discretionary Index	Consumer Discretionary	0.410
		(0.672)
S&P 500 Ex-Consumer Staples Index	Consumer Staples	0.186
		(0.530)
S&P 500 Ex-Healthcare Index	Healthcare	1.180
		(0.871)
S&P 500 Ex-Information Technology Index	Information Technology	0.371
		(0.994)
S&P 500 Ex-Communication Services Index	Communication Services	0.212
		(1.391)
S&P 500 Ex-Utilities Index	Utilities	-1.536
		(1.289)
S&P 500 Ex-Real Estate Index	Real Estate	1.995
		(1.620)

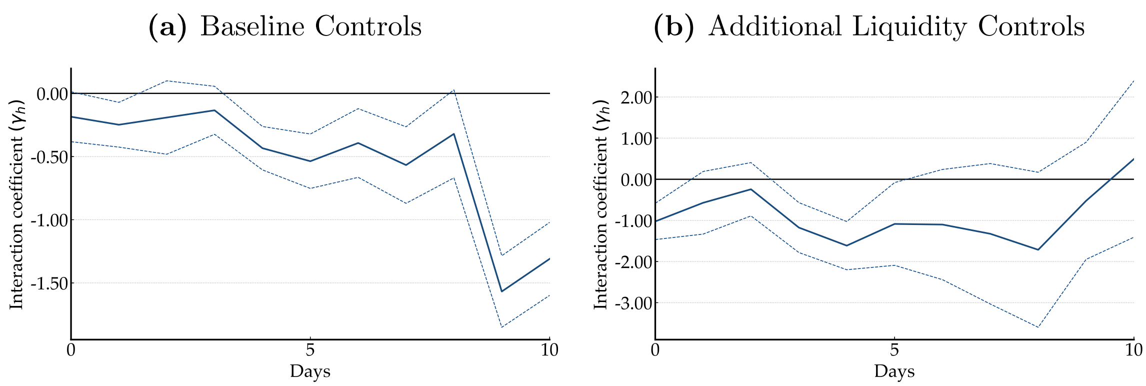
Notes: This table reports the effects of placebo HF shocks. For each nonfinancial sector s of the S&P 500, the placebo HF shock ε_t^s is constructed following the procedure for the narrow measure of HF financial shocks described in Section 3. The specification estimated is $\Delta \log y_t^{-s} = \alpha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

Table B.6: 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	0.291** (0.140)	- -
All intermediaries	60-min	S&P 500 nonfin constituents (equal weighted)	60-min	0.183*** (0.061)	0.408*** (0.027)
All intermediaries	60-min	S&P 500 nonfin constituents (value weighted)	60-min	0.150*** (0.051)	0.360*** (0.028)
All intermediaries	60-min	S&P 500 index ETF	60-min	0.134*** (0.028)	0.370*** (0.027)
All intermediaries	60-min	S&P 500 nonfin index	daily	0.538*** (0.090)	- -
All intermediaries	daily	S&P 500 nonfin index	daily	- -	0.400*** (0.024)

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

Figure B.4: Within-Firm Variation



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

Table B.7: Heterogeneous Firm Responses to Financial and Monetary Shocks

(a) Monetary Shocks

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

(b) Financial Shocks

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

Notes: This table reports results from estimating

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

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

where $\varepsilon_t^{\mathrm{M}}$ and $\varepsilon_t^{\mathrm{F}}$ denote narrow HF financial and monetary shocks, respectively; $\mathbb{1}_{x_{jt}}$ is an indicator variable for high leverage, investment-grade credit ratings, or high liquidity; and Z_{jt} is a vector of firm controls—the firm characteristic $\mathbb{1}_{x_{jt}}$, lagged sales growth, lagged size, lagged current assets as a share of total assets, and an indicator for fiscal quarter. The HF financial shock, $\varepsilon_t^{\mathrm{F}}$, is constructed as described in the text. The HF monetary shock, $\varepsilon_t^{\mathrm{M}}$, 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

C.1. Unexpected earnings and financial shocks

We study the relationship between financial shocks and surprise earnings.[11] 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. Table C.1 estimates the relationship displayed in Figure C.1 with a regression, showing that earnings that are one standard deviation lower than expected from financial intermediaries leads to 0.2% decline in their market values. It also shows that earnings surprises of placebo nonfinancial firms in Dow Jones display a transmission similar to their market values.

Figure C.1: Earnings Surprises and Financial Shocks

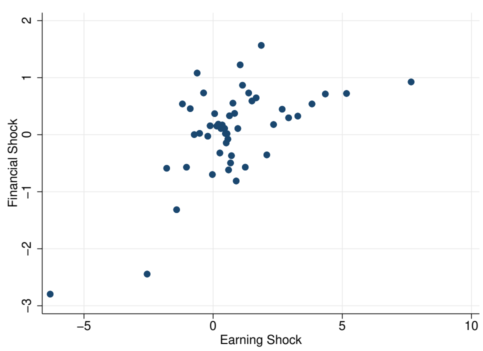


Table C.1: Transmission from Earnings Surprises to Financial Shocks

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

Notes: Figure C.1 shows a binned scatter plot between financial shocks and earnings surprises with 50 bins. Financial shocks are unweighted and constructed as described in the main text. Earnings surprises are measured as standardized unexpected earnings, defined in the text. Table C.1 reports the estimates from regressing unweighted changes in the stock prices of financial intermediaries and placebo nonfinancial firms in Dow Jones. Earnings surprises are measured with standardized unexpected earnings, defined in the text. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

[11]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.

C.2. Predictability of financial shocks

Table C.2 shows that random-forest (Breiman, 2001) forecasts based on large panels of macro (FRED-MD by McCracken and Ng, 2016) and financial predictors perform worse than historical rolling-mean forecasts, which suggests 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	−15.1%	−16.8%
Random-walk benchmark		−5.2%

Notes: This table reports the out-of-sample R^2 of random-forest forecasts based on a large panel of macroeconomic and financial variables compared with the out-of-sample R^2 of random-walk forecasts based on the stock returns one day before the shock. In the first column, macro predictors consist of 126 monthly macroeconomic series constructed by McCracken and Ng (2016) and available through FRED-MD. In the second column, financial predictors consist of daily stock prices of the financial intermediaries in our sample, as well as the S&P 500 and VIX. We first perform variable selection with elastic net (Zou and Hastie, 2005); we set an equal weight between LASSO and ridge regressions and tune the penalty parameter so that the elastic net selects the 20 best predictors. We then use random forests (Breiman, 2001) to form predictions using 48-month rolling windows for macro predictors and quarter rolling windows for financial predictors. Forecastability is assessed with the out-of-sample R^2, defined as $R^2_{\text{oos}} = 1 - \frac{\Sigma_t (y_t - \hat{y}_{m,t})^2}{\Sigma_t (y_t - \bar{y}_t)^2}$, where $\bar{y}_t$ is the rolling-mean forecast computed on a window matching the model-estimation window, and $\hat{y}_{m,t}$ is the forecast from the model. Negative numbers indicate that the forecast underperforms the rolling historical mean of the series.

C.3. Stock-price volatility for financial intermediaries and nonfinancial firms: Event vs. nonevent days

Table C.3 shows that the volatility of financial intermediaries' stock prices during their earnings announcements increases by substantially more than that 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.3: Summary Statistics for Event and Nonevent Windows

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

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

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:					
Fin shock (narrow)	0.291**	0.292**	0.215**	0.223**	0.235**
	(0.140)	(0.147)	(0.099)	(0.104)	(0.094)
R^2	0.014	0.015	0.006	0.007	0.026
Observations	104,167	104,167	102,058	102,058	341
Macro controls	no	yes	no	yes	yes
CUSIP FE	yes	yes	yes	yes	no
Double-clustered SE	yes	yes	yes	yes	no

Notes: This table reports estimates from the event-time regression $\Delta y_{jt} = \alpha_j + \beta\varepsilon_t^{\mathrm{F}} + u_{jt}$ using different weighting for the dependent variable Δy_{jt}. α_j is a CUSIP fixed effect and $\varepsilon_t^{\mathrm{F}}$ is the narrow HF shock. Baseline columns 1 and 2 (same as in Table 2a) estimate the effect of narrow HF financial shocks on equal-weighted log price changes in S&P 500 nonfinancial constituents' stocks. Columns 3 and 4 estimate the effect of narrow HF financial shocks on the log price changes in S&P 500 nonfinancial constituents' stocks weighted by their market values at the beginning of the quarter. Standard errors in columns 1 through 4 are two-way clustered at shock and CUSIP 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)

	S&P 500 Ex-Fin	**SmallCap**	**Russell**	**Obs**
Narrow	0.924***	1.348***	1.453***	272
	(0.241)	(0.296)	(0.313)	
Macro controls	0.908***	1.276***	1.381***	272
	(0.243)	(0.299)	(0.316)	
Broad	0.720***	1.085***	1.124***	486
	(0.179)	(0.213)	(0.229)	

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

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

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

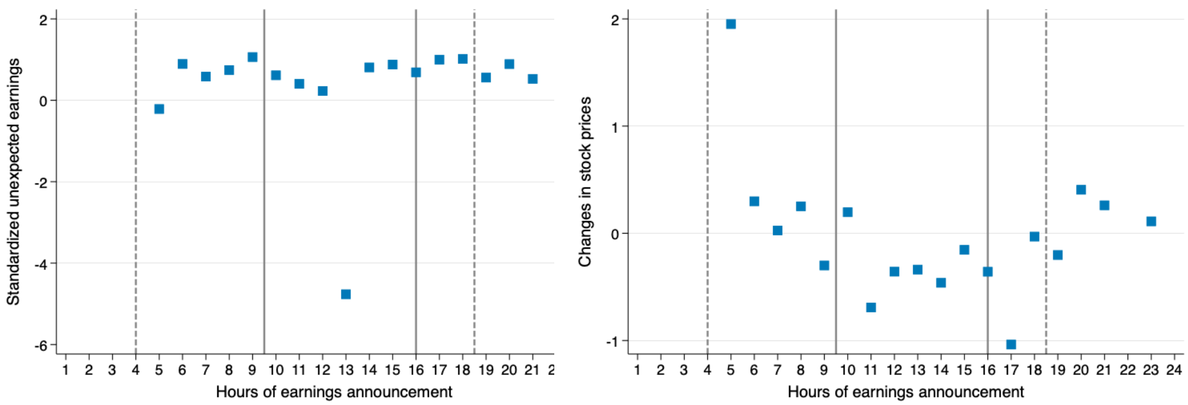
Notes: This table reports estimates from the event-time regression $\Delta y_{jt} = \alpha_j + \beta\varepsilon_t^{\mathrm{F}} + u_{jt}$ using the broad measure of financial shocks, $\varepsilon_t^{\mathrm{F}}$, which includes earnings announced outside of trading hours, described in Section 3. Columns 1 and 2 estimate the effect of broad HF financial shocks on equal-weighted log price changes of S&P 500 nonfinancial constituents stocks. Columns 3 and 4 estimate the effect of broad HF financial shocks on the log price changes in S&P 500 nonfinancial constituents' stocks weighted by their market values at the beginning of the quarter. Standard errors in columns 1 through 4 are two-way clustered at shock and CUSIP 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.4: Controlling for the Systemic Component between Financials and Nonfinancials

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

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

Figure D.1: Earnings Results and Timing of Announcements



(a) Surprise earnings

(b) Shock price changes

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

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

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

Notes: This table shows estimates for β from fitting $\Delta y_t = \beta \Delta \nu_t + u_t$ 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 earnings days of intermediaries included in the baseline HF shocks. Column (4) shows the estimate instrumented with GIV using earnings days of intermediaries included in the baseline HF shocks. Heteroskedasiticy-robust standard errors are reported in parentheses. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

E. Details for Transmission Mechanism

E.1. The role of firm financial heterogeneity

We document how nonfinancial firms' financial positions (leverage, credit risk, and liquidity) affect their responses to financial shocks. In particular, we estimate the model

$$\Delta y_{jt} = \alpha_j + \alpha_{sq} + \beta \varepsilon_t^{\mathrm{F}} + \gamma \varepsilon_t^{\mathrm{F}} x_{jt} + \Gamma' Z_{jt} + u_{jt}, \tag{7}$$

where the dependent variable, Δy_{jt}—as in previous sections—is the log changes in nonfinancial firms' stock prices in the 60-minute window around a financial shock; $\varepsilon_t^{\mathrm{F}}$ is the narrow HF financial shock; x_{jt} is an indicator variable for firms with high leverage, investment-grade credit rating, or high liquidity; α_j is a firm fixed effect; α_{sq} is a sector-by-quarter fixed effect; and Z_{jt} is a vector of firm controls: the firm characteristic x_{jt}, lagged sales growth, lagged size, lagged current assets as a share of total assets, and an indicator for fiscal quarter. The coefficient of interest, γ, measures how the effect of financial shocks depends on a firm's financial position. For this analysis, we expand the sample from S&P 500 nonfinancial constituents to all publicly traded nonfinancial firms in the U.S., which is matched with Compustat firm characteristics. Standard errors are two-way clustered by firm and shock. Results are reported in Panel (b) in Table 3.

E.2. A decomposition of shocks

We decompose the information contained in the HF shocks into information about intermediaries' net worth and information about nonfinancial firms' investment opportunities, in the spirit of sign-restriction strategy approaches developed by Cieslak and Schrimpf (2019) and Jarociński and Karadi (2020) to decompose monetary shocks into a monetary policy shock and a central-bank-information shock. As formalized in Appendix A.4, on the one hand, positive news about intermediaries' net worth is associated with an increase in lenders' supply of funds and should lead to a decline of the EBP; on the other hand, positive news about nonfinancial firms' investment opportunities should be associated with an increase in borrowers' demand for funds and lead to an increase in the EBP.

We decompose the financial shocks based on their correlation with EBP (which measures financing costs in the absence of default risks) as

$$\varepsilon^{\mathrm{F}} = \varepsilon_{\mathrm{lender}} + \varepsilon_{\mathrm{borrower}}, \tag{8}$$

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

$$\begin{bmatrix} \boldsymbol{\varepsilon}^{\text{F}} & \Delta \boldsymbol{y} \end{bmatrix} = \begin{bmatrix} \boldsymbol{\varepsilon}_{\text{lender}} & \boldsymbol{\varepsilon}_{\text{borrower}} \end{bmatrix} \begin{bmatrix} 1 & - \\ 1 & + \end{bmatrix} \tag{9}$$

$$\boldsymbol{\varepsilon}_{\text{lender}}^{'} \boldsymbol{\varepsilon}_{\text{borrower}} = 0 \tag{10}$$

$$\text{var}(\varepsilon_{\text{lender}}) + \text{var}(\varepsilon_{\text{borrower}}) = \text{var}(\varepsilon^{\text{F}}). \tag{11}$$

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

$$\Delta y_t = \alpha + \beta_{\text{lender}} \varepsilon_{\text{lender}} + \beta_{\text{borrower}} \varepsilon_{\text{borrower}} + u_t, \tag{12}$$

where the dependent variable is the daily changes in the S&P 500 Ex-Financials Index. Results are reported in Panel (c) in Table 3.

[12] We perform the decomposition using a Givens rotation. See Kilian and Lütkepohl (2017) and Jarocinski (2020) for details on estimating structural VAR under sign restrictions with a Givens rotation matrix. The decomposition in (9) is set identified. Following Jarocinski (2020), we select the unique rotation such that the share of variance explained by the lenders' financing shock is equivalent to the variance share from the "poor man's sign restrictions" approach—that is, $\text{var}(\varepsilon_{\text{lender}})/\text{var}(\varepsilon^{\text{F}}) = 0.38$. Under the alternative approach, a shock is classified as either a lenders' shock or a borrowers' information shock. It is classified as a lenders' shock if it is negatively correlated with the excess bond premium and a borrowers' information shock otherwise.