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Stock Comovement and Financial Flexibility

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Abstract

We develop a dynamic model of corporate investment and financing, in which shocks to the value of collateralizable assets generate variation in firms' debt capacity. We show that the degree of similarity among firms' financial flexibility forecasts cross-sectional variation in return correlation. We test the implications of the model with firm-level data in two empirical analyses using i) an instrumental variable approach based on shocks to the value of collateralizable corporate assets and ii) the outbreak of the COVID-19 crisis as an event study. We find that firms in the same percentile of the cross-sectional distribution of financial flexibility have 62% higher correlation in stock-return residuals than firms 50 percentiles apart.

I. Introduction

The extent to which stock prices move together is a core issue in asset pricing and portfolio management, as it determines the ability of investors to diversify risk

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across stocks. The degree of stock-return comovement varies considerably over time. Figure 1 plots the time series of stock comovement for the period of 2006 to 2020. The average pairwise correlation in daily stock-return residuals – after controlling for the 5 factors in Fama and French (FF5) (2015) – typically fluctuates between 1% and 10% for the firms in the S&P 500 index. However, the average correlation peaked in periods characterized by shocks to firms' financial flexibility, such as the start of the financial crisis following the Lehman Brothers bankruptcy in Sept. 2008 and the outbreak of the COVID-19 crisis in Mar. 2020. In this article, we show that firms' financial flexibility – defined as the ability to raise capital to finance investment when needed – is indeed a key determinant of stock-return comovement.

To study the effect of financial flexibility on stock comovement, we formulate a dynamic asset-pricing model of corporate investment and financing with heterogeneous firms that face borrowing constraints determined by the value of their collateralizable assets. Building on the model by Livdan, Sapriza, and Zhang (2009), we introduce firm-specific shocks to the value of collateralizable assets and, as a consequence, to firms' debt capacity and financial flexibility. Positive shocks to the value of collateralizable assets allow firms to increase leverage to finance their investment needs.[1] The resulting higher rates of investment are reflected in firms' cash flows and stock returns. Due to this collateral channel, stock-return comovement arises among firms with similar values of pledgeable assets. Thus, our model's main prediction is that the correlation between the stock returns of 2 firms increases with the similarity in the level of their debt capacity.

The model allows us to illustrate how endogenous comovement in stock-return residuals arises from similarity in financial flexibility as well as in other firm characteristics, such as size, market-to-book, and leverage. To the best of our knowledge, this is the first article to study stock comovement within an investment-based model with rich debt dynamics.

We test the model's predictions using a sample of publicly traded U.S. firms in Compustat. To do so, we implement two main empirical strategies. First, we use an instrumental variable (IV) to generate exogenous variation in firms' financial flexibility. Second, we perform an event study using the outbreak of the COVID-19 crisis, a large and unexpected shock to firms' financial flexibility.

For our first empirical strategy, we use data from 1993 to 2018 and rely on the value of corporate real estate (CRE) assets to measure the degree of firms' financial flexibility. CRE assets are an important component of firms' collateralizable assets: in 2018, U.S. nonfinancial corporations owned \$13.1 trillion in real estate, which represented 31% of total firm assets.[2] Moreover, previous research has documented how variation in the value of CRE assets affects firms' debt capacity and, as a consequence, their investment (Chaney, Sraer, and Thesmar (2012)) and leverage (Cvijanović (2014)) policies. Based on this evidence, we use the market value of CRE assets to proxy for firms' financial flexibility, and sort firms into percentiles

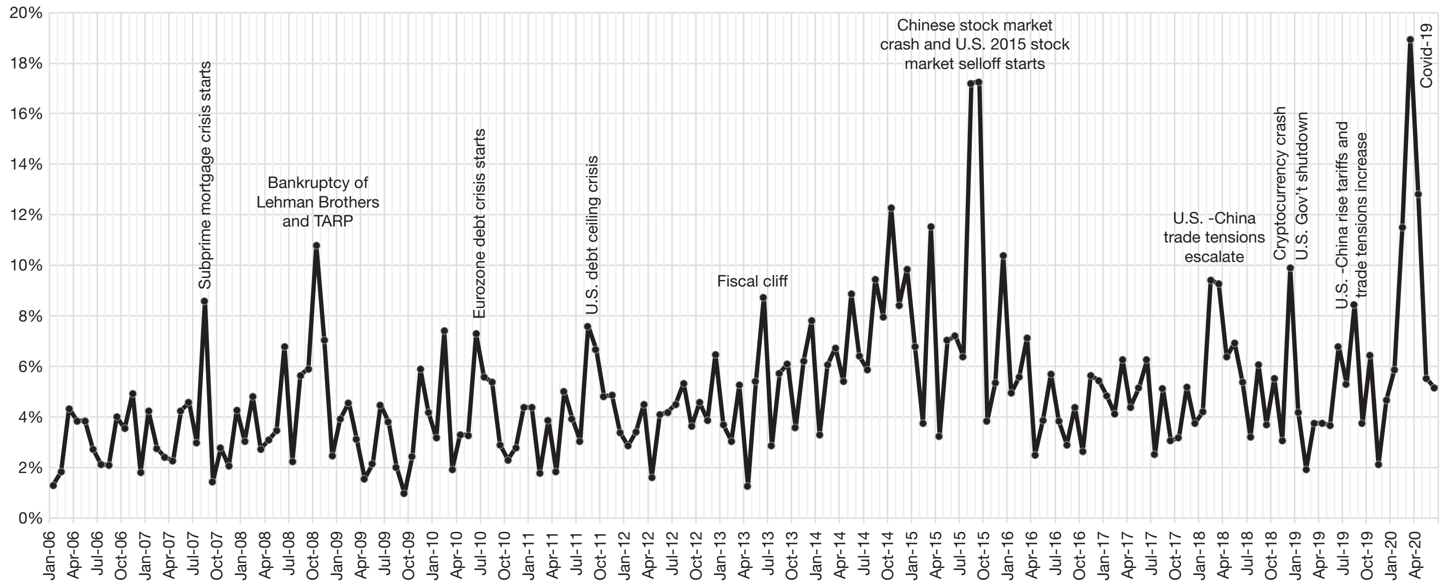
[1]Similarly, negative shocks to collateral value reduce debt capacity and may lead to lower investment rates.

[2]*Source:* Federal Reserve Board of Governors, Table B.103 of the Financial Accounts of the United States, 2019.

FIGURE 1

Average Pairwise Stock Comovement Among S&P500 Firms

Figure 1 shows the average pairwise correlation of Fama and French (2015) daily stock return residuals among firms in the S&P500 index for each month between Jan. 2006 and July 2020.



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according to the value of their CRE holdings to measure their similarity in terms of financial flexibility.

We find that the average within-year pairwise correlation in FF5 monthly stock return residuals among firms in the same percentile of lagged financial flexibility is 0.5% ($50 \times 0.01\%$) higher than among firms with a difference of 50 percentiles. Thus, the effect of financial flexibility is sizable, as this estimate represents 62% of the average correlation in return residuals (0.8%) for the portfolio of firms with a 50-percentile difference.[3] Our finding of a positive relationship between similarity in financial flexibility and stock comovement is robust to multivariate analyses that control for several dimensions of similarity across firms, as well as to using alternative factor models to compute stock-return residuals, and to introducing fixed effects to control for time-invariant unobserved heterogeneity at the firm-pair level. Moreover, we perform the same regression analysis using data simulated from the calibrated model and show that the empirical results are consistent with the model's predictions. We also provide evidence that the results hold for different groups of firms – splitting the sample according to firms' availability of investment opportunities, age, and net leverage – and across the business cycle.

To establish a causal effect of financial flexibility on stock-return comovement, we address a potential source of endogeneity that may affect our empirical analysis, namely the presence of an omitted variable. Specifically, an unobserved local economic shock could affect the value of a firm's CRE assets, its stock returns, and its return correlation with other firms. To address this endogeneity issue, we adapt the IV approach developed by Himmelberg, Mayer, and Sinai (2005) and Mian and Sufi (2011) to our specific problem. In particular, we instrument local real estate prices using the interaction between the supply elasticity of the local real estate market and nationwide aggregate long-term interest rates. This method isolates the variation in local real estate prices that is orthogonal to the potentially omitted local economic shock. The results of the IV regressions confirm the positive effect of similarity in firms' financial flexibility on stock-return comovement.

As a second empirical test, we perform an event study of stock comovement around the start of the COVID-19 crisis. The outbreak of the COVID-19 pandemic in early 2020 significantly impacted the revenues of many firms and affected their ability to raise financing. To quantify the effect of this shock on stock comovement through firms' financial flexibility, we analyze the change in pairwise FF5-stock-return-residual correlation in the weeks around the outbreak of the COVID-19 pandemic.[4] Our results show that stock comovement increased significantly in the postoutbreak period. However, we find that this increase was driven by the subsample of firms with the highest degree of similarity in financial flexibility.[5]

[3]This magnitude corresponds to the most conservative estimate obtained from the IV approach described below.

[4]We set the pre-COVID period between Jan. 1, 2020, and Mar. 10, 2020, and the COVID period between Mar. 11, 2020, and Apr. 30, 2020. As a reference date for the start of the COVID-19 period, we use Mar. 11, when the World Health Organization declared the COVID-19 outbreak a pandemic. In robustness tests, we use alternative dates for the start and the end of the COVID-19 period. The results are qualitatively unchanged.

[5]For the COVID-19 event study, we use net leverage as a measure of financial flexibility, similar to recent papers that analyze the financial effects of the pandemic, such as De Vito and Gómez (2020), Ramelli and Wagner (2020), and Fahlenbrach, Rageth, and Stulz (2021).

In particular, these firms had 1.02% higher correlation in FF5 stock return residuals before the COVID-19 outbreak than other firms. After the outbreak, this difference in comovement doubled to 2.08%. Overall, the postoutbreak level of stock comovement for firms with the highest degree of similarity in financial flexibility was 10 times larger than the average stock comovement of other firms in the preoutbreak period (0.21%).

In a series of tests, we investigate the robustness of the empirical results and their external validity outside the time period and geographical region considered in our main analyses. First, we estimate comovement regressions using data for several developed economies, and find that our conclusions extend to firms located outside the United States. Although to a different degree, similarity in financial flexibility is positively and significantly associated with stock comovement for firms based in Great Britain, Japan, France, Germany, Italy, Spain, and most of the other countries considered. Second, we use the 2008 financial crisis as an alternative event study to the COVID-19 outbreak and find consistent results across the two crisis periods. Finally, while our main analyses focus on comovement in stock-return residuals, we provide evidence that financial flexibility is also related to comovement in expected excess returns, return volatility, and Sharpe ratios.

Our article contributes to the theoretical literature on stock comovement by showing how correlation in return residuals can arise within a dynamic asset-pricing model, even in the absence of behavioral biases. Previous research has identified two broad classes of theories for stock comovement: theories based on rational expectations, in which comovement in stock returns reflects firms' sensitivities to common factors affecting fundamentals (i.e., expected future cash flows and discount rates), and theories that rely on the presence of irrational investors and limits to arbitrage.[6] Our article relates to the first class of theories, and especially to the literature that studies dynamic asset-pricing models in the presence of frictions to corporate investment and financing. Our model builds upon the discrete-time setup of Livdan et al. (2009), who incorporate collateral constraints on debt into an asset-pricing model with heterogeneous firms.[7] Compared to their paper, our model includes firm-specific shocks to the value of collateral, an assumption that allows us to analyze the effect of exogenous variation in financial flexibility on stock comovement. Catherine, Chaney, Huang, Sraer, and Thesmar (2022) also introduce shocks to collateralizable assets in a structural corporate-finance model to study the

[6]This classification follows Barberis, Shleifer, and Wurgler (2005), who further divide the second group of theories into the "category view" (investors allocate funds across easy-to-follow categories, rather than individual stocks, to simplify their portfolio choice), the "habitat view" (transaction costs or other market frictions cause investors to trade only a limited number of all available stocks), and the "information-diffusion view" (news is incorporated faster in the price of some stocks, such as those belonging to a stock market index, than in the price of others). As it is hard to separate empirically between the category and habitat views, subsequent papers such as Greenwood (2008) and Chen, Singal, and Whitelaw (2016) refer to these two theories jointly as an "asset-class effect." For portfolio-choice models that feature asset-class effects, see, for example, Barberis and Shleifer (2003) and DeMarzo, Kaniel, and Kremer (2004).

[7]Instead of using a discrete-time framework, a possible alternative would be to build upon continuous-time real options models of investment and asset prices, such as Hackbarth and Johnson (2015). See discussion in Section II.A.4.

effect of collateral constraints on aggregate output and total factor productivity, but they do not investigate the asset-pricing implications of financial flexibility. Other models with endogenous debt financing (e.g., Gomes and Schmid (2010)) focus on the analysis of average stock returns without examining the cross-sectional variation in pairwise return correlations. Finally, some papers incorporate real estate into an asset-pricing framework. For example, Lustig and Van Nieuwerburgh (2005) find that a decrease in the collateral value of housing increases household exposure to idiosyncratic risk, as well as the market price of risk. Tuzel (2010) studies the relationship between CRE holdings and the cross-section of stock returns in a model with no financial frictions and finds that the returns of firms with a high ratio of real estate over total assets are higher than those of firms with a low ratio. Nevertheless, no prior study uses the collateral properties of corporate assets to analyze the drivers of stock-return comovement. To summarize our theoretical contribution, this is the first article, to the best of our knowledge, to study the determinants of comovement in stock-return residuals within a neoclassical rational-expectations model of firms' investment and financing.

On the empirical side, evidence from a large body of literature suggests how the sensitivity of stock returns to common factors relates to the cross-section of expected returns (see, e.g., Harvey, Liu, and Zhu (2016)), while fewer studies focus on the correlation in stock-return residuals. For example, De Bodt, Eckbo, and Roll (2022) show how shocks to industry competition affect comovement in stock-return residuals for rival firms, after filtering out the effect of the common FF5 risk factors. Previous research has also highlighted several sources of excessive comovement that appear to be unrelated to fundamentals and that are consistent with the second class of theories mentioned above. Barberis et al. (2005) show that stocks in the S&P 500 index comove with other members of the index.[8] Pirinsky and Wang (2006) find that the stocks of firms located in the same city tend to move together. Green and Hwang (2009) provide evidence of comovement for similarly priced stocks. Eun, Wang, and Xiao (2015) show that culture affects the correlation between investors' trading activity, which leads to higher (lower) stock-price comovement in culturally tight (loose) and collectivistic (individualistic) countries. Pindyck and Rotemberg (1993), Kumar and Lee (2006), Chordia, Goyal, and Tong (2011), Kumar, Page, and Spalt (2013), and Antón and Polk (2014), among others, provide evidence on the link between stock comovement and demand from institutional and retail investors. Raffestin (2017) finds that bonds that change rating classes start comoving more with the bonds in the new class. Buffa and Hodor (2023) show the implications of using heterogeneous benchmarks to assess the performance of asset managers on stock comovement. Our contribution to the empirical literature on comovement is to show how similarity across firms in one of the key determinants of corporate financial policies, financial flexibility, predicts future correlation in stock returns.

While the main focus of the article is on stock comovement, our model generates several predictions on the link between collateral constraints and corporate policies. In particular, the model predicts that firms receiving a positive shock to

[8]For other papers that study comovement using stock market indexes as an asset class, see Vijh (1994), Greenwood and Sosner (2007), Greenwood (2008), Boyer (2011), and Claessens and Yafeh (2013).

collateralizable assets invest more, increase leverage, and can afford higher equity payouts. These predictions are supported by evidence from existing empirical studies showing that, after a positive shock to collateral, firms increase investment (Gan (2007), Chaney et al. (2012)), leverage (Cvijanović (2014)), and payout flexibility (Kumar and Vergara-Alert (2020)), and decrease cash reserves (Chen, Harford, and Lin (2017)).

The remainder of the article is structured as follows: Section II sets up the model, discusses the equilibrium, and presents the numerical results and main model predictions. In Section III, we describe the firm-level data, show the results of our empirical analyses, and perform several robustness and external validity tests. Section IV concludes.

II. Model

In this section, we set up a dynamic model of investment and financing with infinitely lived firms in discrete time, solve for the equilibrium policy functions and stock returns, and derive the model's main empirical predictions in terms of stock comovement.

A. Model Setup

We build on the model in Livdan et al. (2009) by introducing firm-specific shocks to collateral value. This extension allows us to study the endogenous correlation in stock returns among firms that receive different shocks to the value of their collateralizable assets and, as a consequence, to their financial flexibility. We do so parsimoniously as our model features only the key characteristics – endogenous choice of investment, leverage, aggregate and firm-specific shocks to profitability, and shocks to collateralizable assets – necessary to derive the predictions we will test in the empirical analysis on stock comovement in Section III.

1. Technology and Investment

The after-tax operating profits for firm j in period t are given by

$$(1) \qquad \pi_{jt} = (1-\tau)\exp\left(x_t + z_{jt}\right)k_{jt}^{\alpha},$$

where τ is the corporate tax rate, x_t denotes the aggregate productivity shock, z_{jt} is a firm-specific productivity shock, k_{jt} denotes the firm's stock of capital, and $\alpha \in (0,1)$ captures the curvature of the profit function. The aggregate productivity shock's law of motion is

$$(2) \qquad x_t = \rho_x x_{t-1} + \sigma_x \varepsilon_t^x,$$

where $\rho_x \in (0,1)$ is the persistence parameter, and σ_x is the standard deviation of innovations to aggregate productivity. The firm-specific productivity shock follows an AR(1) process,

(3) $$z_{jt} = (1-\rho_z)\bar{z} + \rho_z z_{jt-1} + \sigma_z \varepsilon^z_{jt},$$

where $\rho_z \in (0,1)$ is the persistence of idiosyncratic productivity, σ_z is the standard deviation of the innovations to firm-specific productivity, and $\bar{z}$ is a scaling parameter. Both ε^x_t and ε^z_{jt} are IID standard-normal shocks, ε^x_t is independent of ε^z_{jt}, and ε^z_{jt} and ε^z_{lt} are independent for $j \neq l$.

The firm accumulates capital according to

(4) $$k_{jt+1} = (1-\delta)k_{jt} + i_{jt+1}k_{jt},$$

where i_{jt+1} is the investment rate and δ is the depreciation rate of capital. As in Zhang (2005), the firm incurs asymmetric and quadratic capital-adjustment costs, defined by

(5) $$\text{Adj}\left(i_{jt+1}, k_{jt}\right) = \frac{a_P \mathbf{1}\{i_{jt+1} \geq 0\} + a_N \mathbf{1}\{i_{jt+1} < 0\}}{2} i^2_{jt+1} k_{jt},$$

where a_P and a_N capture adjustment costs for investment and disinvestment, respectively, and $\mathbf{1}\{\cdot\}$ denotes the indicator function.

2. Stochastic Discount Factor

Following Zhang (2005) and Livdan et al. (2009), we assume that the stochastic discount factor from period t to $t+1$, M_{t+1}, is a function of the aggregate productivity shocks in the 2 periods, x_t and x_{t+1}, and is given by

(6) $$\log(M_{t+1}) = \log\eta + \gamma_t(x_t - x_{t+1}),$$

(7) $$\gamma_t = \gamma_0 + \gamma_1 x_t,$$

where $\eta \in (0,1)$ is a time-preference parameter, and $\gamma_0 > 0$ and $\gamma_1 < 0$ are risk-aversion parameters.

3. Financing and Shocks to Financial Flexibility

Firms can finance their operations with internally generated cash flows or by raising debt or external equity. Each firm can issue one-period debt, secured by collateral, at a risk-free interest rate, r_{ft}. We assume that the firm can use as collateral both its capital stock, k, and its nonoperating collateralizable assets, H, as in Liu, Wang, and Zha (2013) and Catherine et al. (2022). As a result, the face value of debt to be repaid in period $t+1$, b_{jt+1}, is limited by the collateral constraint

(8) $$b_{jt+1} \leq s(1-\delta)k_{jt+1} + \mathbf{E}\left[\exp\left(p_{jt+1}\right)|p_{jt}\right]H,$$

where $\exp(p_{jt+1})$ denotes the price of collateralizable assets for firm j in period $t+1$, and the parameter s determines the fraction of capital that the firm can use as collateral. The log price of collateralizable assets follows the stochastic process

$$p_{jt} = \rho_p p_{jt-1} + \sigma_p \varepsilon^p_{jt}, \tag{9}$$

where $\rho_p \in (0,1)$, $\sigma_p > 0$, $\varepsilon^p_{jt} \sim N(0,1)$, ε^p_{jt} is independent of ε^x_t for all t, and ε^p_{jt} and ε^p_{lt} are independent for $j \neq l$. We model the choice of debt under collateral constraints similar to Livdan et al. (2009), and Catherine et al. (2022), as opposed to the models with defaultable debt such as Hennessy and Whited (2007) and Gomes and Schmid (2010), because we are interested in studying how fluctuations in financial flexibility, which is determined by the presence of collateral constraints (see discussion in Section II.B.3), affect stock comovement.[9] The sum of equity payout, investment, and capital-adjustment costs must equal the cash flows generated by profits and debt-financing activities, as described by the cash flow identity

$$e_{jt} + i_{jt+1}k_{jt} + \mathrm{Adj}\left(i_{jt+1}, k_{jt}\right) = \pi_{jt} + \tau\delta k_{jt} + \frac{b_{jt+1}}{1+(1-\tau)r_{ft}} - b_{jt}, \tag{10}$$

where e_{jt} is the equity payout. When $e_{jt} \geq 0$, the firm makes distributions to shareholders, and when $e_{jt} < 0$, the firm issues external equity. Issuing equity is costly, and distributions to shareholders net of external financing costs are

$$d_{jt} = e_{jt} - \mathbf{1}\left\{e_{jt} < 0\right\}\left(-\lambda e_{jt}\right), \tag{11}$$

where $\lambda > 0$ is a linear equity-issuance-cost parameter.

4. Discussion

The main novelty of our theoretical framework is to introduce shocks to the value of collateralizable assets into a dynamic asset-pricing model with heterogeneous firms that face investment and financing frictions. By doing so, we are able to study the effects on stock comovement of exogenous variation in collateral values, controlling for other potential sources of comovement, such as shocks to investment opportunities – captured in the model by the profitability shocks (equations (2) and (3)) – and similarity in firm characteristics, such as size and leverage. Several theoretical papers have highlighted the role of the "collateral channel" in determining firms' decisions and, ultimately, macroeconomic aggregates. Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) show how the presence of collateral constraints for the borrower amplifies the effects of productivity shocks on investment. Jermann and Quadrini (2012) study the macroeconomic implications of financial shocks that, as in our model, directly affect collateral value, while Catherine et al. (2022) quantify the effects of the existence of collateral constraints on aggregate output and total factor productivity. Moreover, several papers document that shocks to collateral values affect corporate investment

[9] As in Catherine et al. (2022), we assume that nonoperating collateralizable assets, H, are fixed, so that fluctuations in their value are fully determined by exogenous firm-specific shocks to their price, p. We do so to be consistent with the empirical analysis in Section III.A, in which identification relies on the presence of local shocks to an important component of collateralizable assets, namely corporate real estate assets.

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in the data (e.g., Lamont (1997), Gan (2007), and Chaney et al. (2012)), providing empirical support for the existence of a collateral channel.

While we develop our dynamic model within a discrete-time framework, one could also investigate stock comovement in a continuous-time setting. The latter approach is standard in contingent-claims models, such as real-options models of investment (see Dixit and Pindyck (1994),[10] asset prices (e.g., Carlson, Fisher, and Giammarino (2004), Cooper (2006), and Hackbarth and Johnson (2015)), and capital structure (Leland (1994), Hackbarth, Miao, and Morellec (2006), and Strebulaev (2007)). As discussed in Strebulaev and Whited (2012), there are advantages and disadvantages to using a continuous-time setting. One of the main advantages is that, depending on the model's tractability, it is often possible to characterize the solution analytically. In our case, however, since the model includes a rich set of features (idiosyncratic and aggregate productivity shocks, shocks to collateral value, and endogenous firm size and leverage), a closed-form solution is not likely to be possible even if one reformulated the model in a continuous-time setting.

B. Equilibrium, Calibration, and Numerical Results

We now define the equilibrium conditions of the model, discuss alternative model-implied measures of financial flexibility, describe the details of the calibration, and characterize the policy functions for investment and financing implied by the model.

1. Value Maximization

The equity value of the firm, V_{jt}, is the present value of all future cash flows to shareholders, d_{jt}, discounted by the stochastic discount factor. The Bellman equation for the firm's problem is

$$V(x,z,p,b,k) = \max_{b',k'} d(x,z,p,b,k,b',k') + \mathbf{E}[M'V(x',z',p',b',k')|x,z,p], \tag{12}$$

$$\text{s.t. } b' \le s(1-\delta)k' + \mathbf{E}[\exp(p')|p]H, \tag{13}$$

where we omit time and firm subscripts for ease of notation and use primes to denote state variables for period $t+1$. Equity and dividend payouts are given by

$$e(x,z,p,b,k,b',k') = (1-\tau)\exp(x+z)k^{\alpha} + \tau\delta k - i'k - \text{Adj}(i',k) + \frac{b'}{1+(1-\tau)r_f} - b \tag{14}$$

and

$$d(x,z,p,b,k,b',k') = e - \mathbf{1}\{e<0\}(-\lambda e), \tag{15}$$

respectively.

[10]A common assumption in canonical real-options models such as McDonald and Siegel (1986) is investment irreversibility. Our model features costly reversibility, by assuming asymmetric convex capital-adjustment costs. Notice that, for high values of the adjustment-cost parameter for disinvestment, a_N, the firm will find it unprofitable to reduce its capital stock, approximating the case of pure investment irreversibility.

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2. Expected Returns

As in Zhang (2005), the firm's stock return is defined as

$$R_{jt+1} = \frac{V_{jt+1}}{V_{jt} - d_{jt}}. \tag{16}$$

The conditional expected return for the firm in a given period must be such that $\mathbf{E}\left[R_{jt+1}\right] = \left(1 + r_{ft}\right) + \beta_{jt}\chi_t$, with quantity of risk

$$\beta_{jt} = -\mathbf{cov}\left[M_{t+1}, R_{jt+1}\right] / \mathbf{var}[M_{t+1}], \tag{17}$$

price of risk $\chi_t = \mathbf{var}[M_{t+1}] / \mathbf{E}[M_{t+1}]$, and the risk-free rate $r_{ft} = \frac{1}{\mathbf{E}[M_{t+1}]} - 1$, where the expectations, variances, and covariances are conditional on the information in period t. Importantly, notice that β_{jt}, which captures the firm's exposure to systematic risk, varies over time and across firms, as it depends on the firm-specific state variables: z_{jt}, p_{jt}, b_{jt}, and k_{jt}.

3. Measures of Financial Flexibility

We define 2 model-implied measures of financial flexibility. The first follows the definition of the shadow price of new debt in Livdan et al. (2009), which corresponds to the Lagrange multiplier associated with the collateral constraint in equation (13). For firm j in time t, the shadow price of new debt, v_{jt}, is given by

$$v_{jt} = \frac{\tau r_{ft}}{\left(1 + (1-\tau) r_{ft}\right)\left(1 + r_{ft}\right)} + \frac{\lambda \mathbf{1}\left\{e_{jt} < 0\right\}}{1 + (1-\tau) r_{ft}} - \mathbf{E}\left[M_{t+1}\left(\lambda \mathbf{1}\left\{e_{jt+1} < 0\right\}\right)\right]. \tag{18}$$

This expression reflects the benefits and costs of one extra unit of debt to be repaid in the next period, in terms of tax shields and equity issuance costs.[11] The first component of equation (18) represents the tax shield generated by debt. The second component accounts for the fact that, by raising debt, the firm can reduce issuing external equity in the current period if any, which incurs the associated cost λ. However, the firm will have to repay the unit of debt in the next period, and to do so it may have to issue more equity. The third component of equation (18) represents the expected present value of this equity-issuance cost. Overall, the higher the shadow price of debt, the more financially constrained the firm is.

The second measure of financial flexibility is the free debt capacity of firm j in time t, ξ_{jt}, defined as

$$\xi_{jt} = 1 - \frac{b_{jt+1}}{s(1-\delta)k_{jt+1} + \mathbf{E}\left[\exp(p_{jt+1}) | p_{jt}\right] H}, \tag{19}$$

where b_{jt+1} is the amount of debt to be repaid next period and $s(1-\delta)k_{jt+1} + \mathbf{E}\left[\exp(p_{jt+1}) | p_{jt}\right] H$ is the debt capacity (i.e., the maximum amount of debt that

[11]See Appendix A of Livdan et al. (2009) for the derivation of the shadow price of new debt. In particular, their equation A4 corresponds to our equation (18), except that in our model debt also implies a tax shield.

the firm can raise). This measure simply captures the distance between the firm's debt usage and its debt limit.

4. Calibration

To provide economic intuition for the model's policy functions and generate empirical predictions in terms of stock-return comovement, we perform the model calibration in this subsection. Since the model does not have a closed-form solution, we solve it by value-function iteration. We provide a detailed explanation of the solution algorithm in the Supplementary Material. To compute the moments for calibration, we simulate 50 panels, each consisting of 1,200 firms over 25 years, at a monthly frequency. The size, duration, and frequency of the simulated sample are comparable to those of the real-data sample we use in the empirical section (see Section III.A.1 for the details on data construction).

Panel A of Table 1 reports the calibration parameters. Whenever possible, we take the parameter values directly from the literature to compare our results with those in previous papers. In particular, several parameter values are from Livdan et al. (2009): The persistence ρ_x and standard deviation σ_x of the aggregate productivity shock, the time-preference parameter η, the risk-aversion parameters γ_0 and γ_1, the persistence ρ_z and volatility parameter σ_z of the firm-specific productivity shock, the scaling parameter $\bar{z}$, the curvature of the profit function α, the capital depreciation rate δ, and the capital-adjustment-cost parameters a_P and a_N. The corporate tax rate τ is taken from Belo, Lin, and Yang (2018).

We calibrate the remaining parameters as follows: The linear equity-issuance cost, λ, is set to 0.05, which generates a 7% frequency of equity issuance in the simulated data to approach the 9% frequency reported by Gomes and Schmid (2010). The collateral-constraint parameter, s, is set to 0.3, which generates 22.15% average book leverage in the simulated data, compared to 27.4% in our data sample. The amount of nonoperating collateralizable assets H is set to 0.13, which implies a 14.9% average ratio of collateralizable assets to total assets in the simulated data, close to the 14% average ratio of real estate assets over total assets reported in Catherine et al. (2022). To calibrate the persistence, ρ_p, and standard deviation, σ_p, of the price of collateralizable assets, we match the serial correlation and standard deviation of the residuals estimated from a first-order autoregression of the market value of collateralizable assets on its lagged value.[12]

Panel B of Table 1 compares several moments simulated from the model to their counterparts in the real data. Overall, the model does a good job matching the real-data asset-pricing moments that are of key interest in the article, but that are not

[12]The proxy for collateralizable assets is the ratio of the market value of corporate real estate holdings to lagged property, plant, and equipment. The panel autoregression includes year and firm fixed effects. Since the regression is estimated from annual data, we use the following formula to convert the parameters into a monthly frequency:

$$p_{jt} = \rho_p p_{jt-1} + \sigma_p \varepsilon_{jt}^p = \rho_p^2 p_{jt-2} + \rho_p \sigma_p \varepsilon_{jt-1}^p + \sigma_p \varepsilon_{jt}^p = \cdots = \rho_p^{12} p_{jt-12} + \sum_{l=0}^{11} \rho_p^l \sigma_p \varepsilon_{jt-l}^p.$$

The coefficient estimates obtained at the annual frequency are 0.8187 for the persistence parameter and 0.2539 for the variance. Therefore, the parameters at the monthly frequency are $\rho_p = 0.9835$ and $\sigma_p = 0.08$.

TABLE 1

Model Parameters and Moments

Table 1 reports the calibration parameters and the main moments generated from the model. In Panel A, we provide the value, source, and description for each parameter in the model. LSZ and BLY stand for Livdan et al. (2009) and Belo et al. (2018), respectively. In Panel B, we report selected moments on stock prices, operating statistics, and correlations between key variables of interest computed using the model-generated and real data. In the model, the market-to-book ratio is defined as $(V+b)/(k+H)$, profitability as $e^{x+z}k^{\alpha}/(k+H)$, and book leverage as $b/(k+H)$. Section III.A.1 provides the details on the sample construction and the definitions of the variables for the real-data sample.

Panel A. Parameters

Parameter	Value	Source	Description
s	0.3	Calibrated	Collateral-constraint parameter of capital
H	0.13	Calibrated	Nonoperating collateralizable assets
ρ_p	0.9835	Calibrated	Persistence of the log price of collateralizable assets
σ_p	0.08	Calibrated	Conditional std. dev. of log price of collateralizable assets
λ	0.05	Calibrated	Linear equity-issuance cost
ρ_x	0.983	LSZ	Persistence of aggregate productivity shock
σ_x	0.0023	LSZ	Conditional std. dev. of aggregate productivity shock
η	0.994	LSZ	Time-preference parameter
γ_0	50	LSZ	Risk-aversion parameter
γ_1	−1,000	LSZ	Risk-aversion parameter
ρ_z	0.96	LSZ	Persistence of idiosyncratic productivity shock
σ_z	0.10	LSZ	Conditional std. dev. of the idiosyncratic productivity shock
$\overline{z}$	−3.75	LSZ	Scaling parameter for idiosyncratic productivity
α	0.65	LSZ	Curvature of the profit function
δ	0.01	LSZ	Capital depreciation rate
a_P	15	LSZ	Capital-adjustment cost for positive investment
a_N	150	LSZ	Capital-adjustment cost for negative investment
τ	0.2	BLY	Corporate tax rate

Panel B. Moments

Statistic	Model	Data
Stock price statistics		
Average monthly return	0.0109	0.0110
Average pairwise correlation in CAPM residuals	0.0319	0.0370
Market Sharpe ratio	0.4472	0.5134
Average firm Sharpe ratio	0.3740	0.1209
Average market-to-book ratio	1.9244	2.0450
Operating statistics		
Average investment rate	0.1208	0.1230
Average profitability	0.2660	0.1752
Average book leverage	0.2215	0.2740
Correlations		
Serial correlation of investment rate	0.6853	0.5570
Serial correlation of profitability	0.7051	0.8102
Correl. investment rate with Tobin's Q	0.7898	0.2490
Correl. investment rate with lagged leverage	−0.2743	−0.1465

used as targets for calibration: average monthly returns are 1.09% in the simulated data compared to 1.1% in the real data. The average simulated market-to-book ratio is 1.9 compared to 2 in the real sample. The model generates an average 3.2% pairwise correlation in 1-factor (CAPM) monthly return residuals compared to 3.7% in the real data.[13] The model-implied market Sharpe ratio, 0.45, is close to the value in the data, 0.51, while the model overshoots the average firm Sharpe ratio (0.37 in the model compared to 0.12 in the data).[14] The model also fits the data well in terms of operating statistics. The average investment rate is 12.1% in the model and 12.3% in the data. The model generates a positive serial correlation between

[13]See Section II.C for details on the construction of pairwise correlations of stock-return residuals in the simulated data.

[14]For comparison, our model produces estimates that are closer to those reported by Hackbarth and Johnson (2015): market Sharpe ratio of 0.39 and average firm Sharpe ratio of 0.23 for the period of 1960 to 2009.

investment and profitability. The correlation coefficients of investment with Tobin's Q and with leverage have the same signs as in the real data.

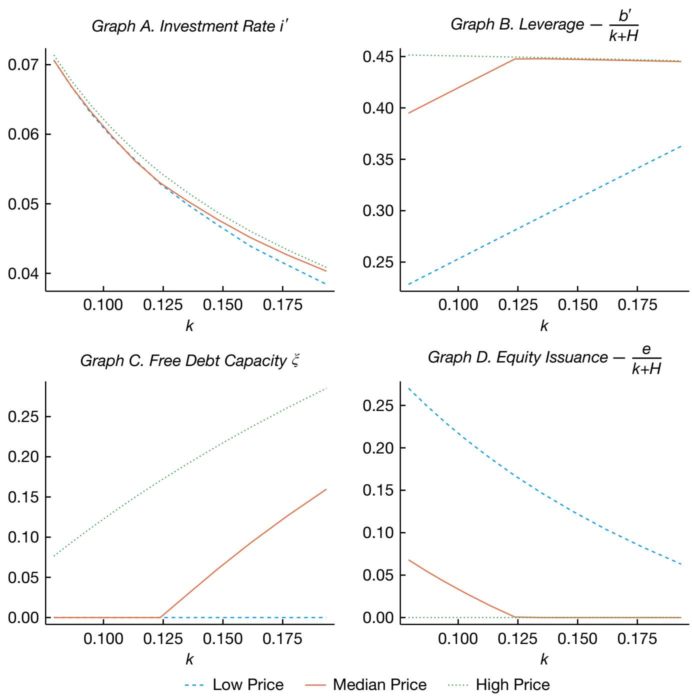
5. Policy Functions and Economic Mechanism

Next, we present the equilibrium policy functions from the calibrated model and analyze the economic mechanism that drives our results. Figure 2 shows the optimal investment rate (i'), book leverage ($\frac{b'}{k+H}$), free debt capacity (ξ), and equity-issuance rate ($\frac{-e}{k+H}$) against the capital stock (k) for different levels of the price of collateralizable assets (p).[15] Consider the policy functions at the median level of p (solid lines in the graphs). Due to the assumption of decreasing returns to scale, the investment rate monotonically decreases as a function of capital (Graph A). For low levels of k, the marginal value of capital is high. To grow in size, the firm is willing to exhaust all its debt capacity (Graph C), and to even issue costly external equity

FIGURE 2

Optimal Policies as Functions of Capital

Figure 2 shows the optimal investment rate (i'; Graph A), leverage ($\frac{b'}{k+H}$; Graph B), debt capacity (ξ; Graph C), and equity-issuance rate $\left(\frac{-e}{k+H}\right.$; Graph D) as functions of the firm's current capital level k for different levels of the price of collateralizable assets p. In each graph, we set the idiosyncratic and aggregate productivity shocks, z and x, respectively, to their steady-state values and keep fixed the value of debt b. Section II.B.4 provides the details of the calibration, which is based on the parameter values reported in Panel A of Table 1.



[15]In Figures 2 and 3, we scale next-period debt (b') with the current-period capital (k) to highlight the effects of the state variables on optimal debt policy in isolation from their impact on the choice of capital for the next period, k'. In the remainder of our analysis, we adopt the standard definition of leverage, which uses contemporaneous debt and capital values.

(Graph D). As k increases, the marginal value of capital decreases, and the debt usage and equity-issuance rate decline.

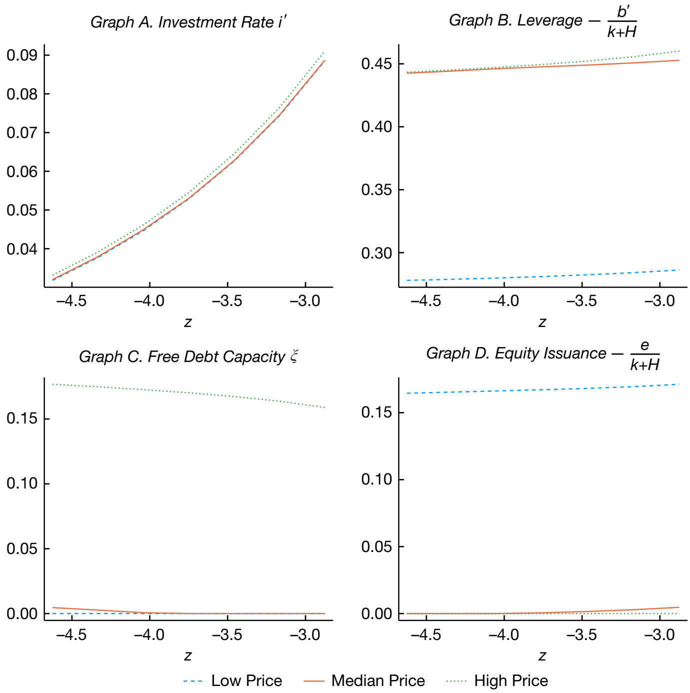
The price of collateralizable assets, p, plays an important role in shaping the firm's investment and financing policies. Because p is persistent over time, a high price in the current period implies a high expected price in the next period, which means that the company has a high debt capacity (see equation (8)). Hence, high prices expand the availability of debt financing for the firm through the collateral channel and stimulate investment, resulting in higher leverage and investment rates, and lower equity issuance (see dotted lines in the graphs).

Figure 3 plots the optimal policies against the firm-specific productivity shock, z, for different levels of price, p. Because productivity is positively autocorrelated, the firm has better-expected investment opportunities for the next period when z is high, so the investment rate is high (Graph A). To finance its investment needs, the company increases book leverage (Graph B) and uses up all its free debt capacity (Graph C). Notice that book leverage $\left(\frac{b'}{k+H}\right)$ increases even when the firm hits the collateral constraint, because the maximum amount of debt the firm can raise is an increasing function of z: Higher productivity implies higher capital in the

FIGURE 3

Optimal Policies as Functions of Idiosyncratic Productivity

Figure 3 summarizes the optimal investment rate (i'; Graph A), leverage ($\frac{b'}{k+H}$; Graph B), debt capacity (ξ; Graph C), and equity-issuance rate ($\frac{-e}{k+H}$; Graph D) as functions of the firm's current productivity shock, z, for different levels of the price of collateralizable assets, p. In each graph, we set the aggregate productivity shock, x, to its steady-state value and keep fixed the value of capital (k) and debt (b). Section II.B.4 provides the details of the calibration, which is based on the parameter values reported in Panel A of Table 1.



next period, k', which can be used as collateral (see equation (8)). In Figure 3, this effect is even more evident in the case of low prices of collateralizable assets (p; dashed line). In this case, the company uses all of its debt capacity for any level of z, and raises external equity to finance investment, but book leverage monotonically increases in z.

Overall, Figures 2 and 3 highlight the effects on the policy functions of changes to the value of the collateral constraint, which depends on the level of prices, p. Firms with high p can borrow more, so they are less constrained in their investment policies. These firms invest more, have higher leverage, and lower equity issuance. These model predictions are consistent with findings from previous empirical studies, which document that firms experiencing positive shocks to the value of their collateralizable assets increase their investment (Gan (2007), Chaney et al. (2012)), leverage (Cvijanović (2014)), and payouts to equity holders (Kumar and Vergara-Alert (2020)).

C. Model Predictions

In this section, we set up the empirical strategy to analyze the model's predictions in terms of stock-return comovement, which is the main focus of the article. The model predicts that firms with similar levels of the state variables – capital, debt, value of collateralizable assets, and profitability shocks – will invest and choose their financing policies similarly, as shown in the policy-function Figures 2 and 3. Because firms' exposures to systematic risk, captured by β_{jt} (equation (17)), depend directly on firms' investment and financing policies (see equations (12) and (16)), we expect that similarity in the value of the state variables translates into similarity in equity returns and in greater stock comovement.

To test this hypothesis, we define stock comovement, denoted by $\rho_{ij,t}$, as the pairwise correlation in 1-factor stock-return residuals between firm i and j in year t.[16] To obtain realizations of $\rho_{ij,t}$, we simulate the model using the calibrated parameters in Table 1 at a monthly frequency for 25 years.[17] Using the simulated panel of stock returns, we compute the realized monthly returns on the market portfolio, defined as the value-weighted portfolio of all stocks. We then estimate the stock-return residuals for each firm in a given year from a regression of the firm's monthly excess returns on the market portfolio's excess returns. Finally, for each firm pair, ij, we obtain $\rho_{ij,t}$ by computing the correlation coefficient of the monthly return residuals in year t.

1. Firm Characteristics and Stock Comovement

We start our analysis of the relationship between the similarity in firm characteristics and stock comovement by focusing on financial flexibility, the explanatory variable of main interest in the article. To construct measures of pairwise

[16]Notice that, as shown in Section II.B.2, a one-factor model with time-varying risk exposures, β_{jt}, holds in our setup. However, as measures of stock comovement in the literature are based on stock residuals obtained from factor models with fixed risk exposures over time, we base our analysis on a one-factor model with constant β_j at the firm level. This corresponds to estimating an unconditional CAPM.

[17]As described in Section II.B.4, we simulate 50 panels of 1,200 firms each. The results reported in this section correspond to the average across these panels of firms.

similarity in financial flexibility, we sort all firms in the simulated panel into percentiles according to their level of financial flexibility (defined in Section II.B.3 as either the shadow price of new debt, v_{jt}, or the free debt capacity, ξ_{jt}) at the end of year t. For each pair of firms i and j, we then compute the negative of the absolute value of the difference in financial flexibility percentile rankings. The resulting variable, $\text{SAMEFINFLEX}_{ij,t}$, is increasing in the similarity of financial flexibility between firms i and j in year t, and can take values from -99 (when one firm in the pair belongs to the first percentile, and the other to the 100th percentile) to 0 (for firms in the same percentile). We follow this procedure to construct our measure of similarity across firms to be consistent with previous papers on stock comovement (see Antón and Polk (2014)).

Figure 4 plots the average simulated pairwise stock comovement in year $t+1$, $\rho_{ij,t+1}$, as a function of similarity in financial flexibility in year t, $\text{SAMEFINFLEX}_{ij,t}$, computed using the shadow price of new debt in Graph A and the free debt capacity in Graph B. We find that when firms are more similar in terms of financial flexibility, their stock comovement in the subsequent year is higher. In particular, firms in the same percentile of financial flexibility according to the shadow price of new debt have an average pairwise correlation of return residuals of 4.28% in the next year (3.77% using the measure based on free debt capacity), compared to 3.01% (2.94%) for firms with a difference of 50 percentiles in the distribution of financial flexibility.[18]

The results from the bivariate analysis shown in Figure 4 are consistent with our conjecture that pairwise similarity in firm characteristics, captured in the model by similar values of the state variables, predicts higher stock comovement for the pair of firms. To isolate the effect of financial flexibility on stock comovement from the confounding effects caused by similarity in other firm characteristics, we estimate the regression

$$\rho_{ij,t+1} = \alpha + \beta \times \text{SAMEFINFLEX}_{ij,t} + \Gamma \times X_{ij,t} + \epsilon_{ij,t}, \tag{20}$$

where the set of pairwise control variables $X_{ij,t}$ consists of similarity in firm size k (SAMESIZE), market-to-book ratio $\frac{V+b}{k+H}$ (SAMEMB), and leverage $\frac{b}{k+H}$ (SAMELEVERAGE). To compute each variable, we follow the same procedure used to construct SAMEFINFLEX: In year t, we rank firms into percentiles of the relevant variable, and we then compute the negative of the absolute value of the difference in percentiles for each pair of firms i and j.

Table 2 shows the estimation results, following different specifications of regression equation (20). In the first 2 columns, we use the shadow price of new debt to construct the variable SAMEFINFLEX, while in the third and fourth columns the measure of financial flexibility is free debt capacity. In all specifications, we include year-fixed effects to control for variation in aggregate productivity, x.

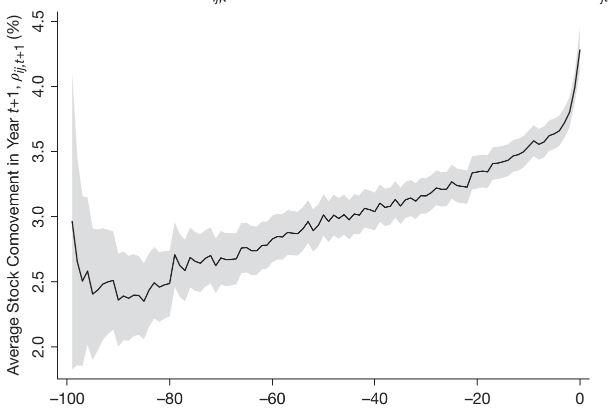
[18]These differences in average stock comovement are statistically significant, as can be seen in Figure 4, which plots the 95% confidence intervals for the mean in the shaded areas. Notice that the confidence intervals are wider for lower values of SAMEFINFLEX, because the number of observations decreases as the difference in percentiles increases; there are few observations with low SAMEFINFLEX. For example, 1.98% of pairs in our simulated sample have SAMEFINFLEX $= -1$, while only 0.02% have SAMEFINFLEX $= -99$.

FIGURE 4

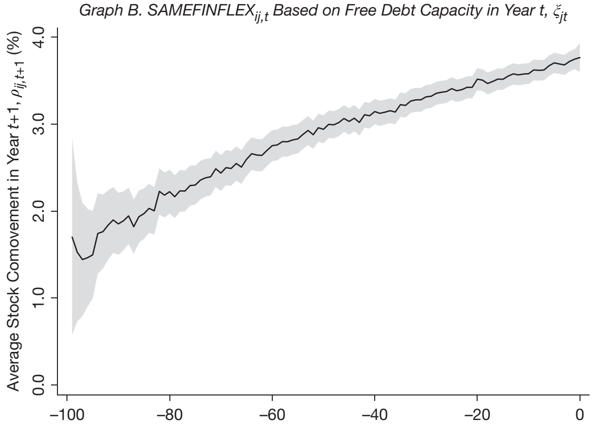
Stock Comovement as a Function of Similarity in Financial Flexibility for the Simulated Sample

Figure 4 shows the average pairwise stock comovement in year $t+1$, $\rho_{ij,t+1}$, as a function of pairwise similarity in financial flexibility in year t, SAMEFINFLEX$_{ij,t}$, in the simulated sample. Stock comovement is defined as the pairwise correlation in 1-factor (CAPM) return residuals. Stock returns are simulated at a monthly frequency for 50 panels of 1,200 firms for 25 years each. SAMEFINFLEX$_{ij,t}$ is defined using the shadow price of new debt (ν_{jt}) in Graph A, and the free debt capacity (ξ_{jt}) in Graph B. Details of the construction of SAMEFINFLEX$_{ij,t}$ are provided in Section II.C. Section II.B.4 provides the details of the simulation, which is based on the calibrated parameters reported in Panel A of Table 1. The shaded areas represent the 95%-level confidence intervals.

Graph A. SAMEFINFLEX$_{ij,t}$ Based on the Shadow Price of New Debt in Year t, ν_{jt}



Graph B. SAMEFINFLEX$_{ij,t}$ Based on Free Debt Capacity in Year t, ξ_{jt}



The estimated coefficients for SAMEFINFLEX are positive and significant across all specifications, and the magnitudes are similar across the two measures of financial flexibility. More specifically, the results show that a 1-percentile increase in similarity in terms of financial flexibility between 2 firms predicts a 0.01% higher stock comovement in the subsequent year after controlling for similarity in other firm characteristics. In addition, the estimated coefficients for the other explanatory variables (SAMESIZE, SAMEMB, and SAMELEVERAGE) are all positive and significant, confirming that higher similarity in each of the firms' characteristics leads to higher stock return comovement.

TABLE 2

Regression Analysis of Stock Comovement in the Simulated Sample

Table 2 reports the OLS estimates of the stock comovement regression in equation (20). The dependent variable is stock comovement, $\rho_{ij,t+1}$, defined as the pairwise correlation in 1-factor (CAPM) return residuals between firms i and j in year $t+1$. SAMEFINFLEX, SAMESIZE, SAMEMB, and SAMELEVERAGE are measures of pairwise similarity in firm characteristics, each constructed by sorting firms into percentiles according to the value of the relevant variable at the end of year t, and computing the negative of the absolute value of the difference in percentile rankings for firms i and j. SAMEFINFLEX is constructed using the shadow price of new debt (ν_{jt}) in columns 1 and 2, and the free debt capacity (ξ_{jt}) in columns 3, 4, 6, and 7. SAMESIZE is based on firm capital, k_{jt}. SAMEMB is computed using the market-to-book ratio, defined in the model as $(V_{jt}+b_{jt})/(k_{jt}+H)$. SAMELEVERAGE is calculated using the book leverage ratio, $b_{jt}/(k_{jt}+H)$. For each model simulation, we generate 50 panels of 1,200 firms for 25 years at a monthly frequency. Section II.B.4 provides the details of the simulation. In columns 1–4, we report the regression results of samples generated by our baseline model ("Full"), according to the parameter values reported in Panel A of Table 1. In columns 5–7, we report the regression results of samples generated in the counterfactual experiments described in Section II.C.2: The Modigliani and Miller (1958) economy ("MM"), the Livdan et al. (2009) economy ("LSZ"), and our model with symmetric capital adjustment costs ($a_P = a_N = 50$, "Symmetric"), respectively. All statistics are averaged over the 50 simulated samples. T statistics are reported in parentheses. Standard errors are clustered at the stock-pair level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Shadow Price		Free Debt Capacity			Free Debt Capacity	
	Full	Full	Full	Full	MM	LSZ	Symmetric
	1	2	3	4	5	6	7
SAMEFINFLEX	0.0001***	0.0001***	0.0002***	0.0001***		0.0002***	0.0001***
	(40.84)	(19.78)	(53.55)	(28.66)		(46.78)	(17.86)
SAMESIZE		0.0001***		0.0001***	0.0002***	0.0003***	0.0001***
		(35.29)		(40.41)	(48.66)	(50.01)	(25.09)
SAMEMB		0.0004***		0.0004***	0.0002***	0.0005***	0.0005***
		(103.12)		(100.13)	(58.67)	(125.40)	(146.45)
SAMELEVERAGE		0.0001***		0.0001***		−0.0002***	0.0001***
		(11.13)		(5.86)		(−32.69)	(26.74)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	17,265,600	17,265,600	17,265,600	17,265,600	17,265,600	17,265,600	17,265,600
Adj. R^2	0.0001	0.0010	0.0002	0.0010	0.0005	0.0017	0.0016

Finally, when interpreting the results of the comovement regressions, it is important to recall that SAMEFINFLEX measures the degree of *similarity* in financial flexibility between firms. Changes in SAMEFINFLEX between pairs of firms can be caused by either positive or negative shocks to collateral or profitability. To see this, consider 2 firms (A and B) with the same initial degree of financial flexibility. Firm A experiences a *positive* shock to collateral value, while Firm B's collateral value remains unchanged. In this case, the financial flexibility of the 2 firms diverges following the shock: Firm A has greater financial flexibility than Firm B, causing a decrease in SAMEFINFLEX for the 2 firms. However, notice that an equivalent decrease in SAMEFINFLEX can also happen if Firm A experiences a *negative* shock to collateral value, which makes Firm A's financial flexibility lower than Firm B's.

2. Counterfactual Experiments

To better understand the drivers of stock comovement, we perform the following counterfactual experiments. First, we consider an investment model without financial frictions. In particular, we assume that the equity-issuance-cost parameter, λ, is 0, and that there are no tax benefits associated with debt (i.e., $\tau = 0$). This first counterfactual corresponds to a Modigliani and Miller (1958) economy, in which capital structure does not affect firm value. Second, we reintroduce financial frictions, setting λ and τ to their original values in Table 1 but assuming no shocks to the value of collateralizable assets: $p_{jt} = 0$ for all t and j, similar to Livdan et al.

(2009). For each of these counterfactuals, we estimate the stock comovement regression (equation (20)) in the simulated data.

The regression estimates for these counterfactual experiments are reported in Table 2. Column 5 corresponds to the Modigliani–Miller economy. The results show that, in a standard dynamic model in which firms face shocks to investment opportunities, similarity in firm characteristics (i.e., SAMESIZE and SAMEMB) is positively associated with stock comovement, even in the absence of financial frictions.

In the second counterfactual, which corresponds to a Livdan et al. (2009) economy, the model generates a positive and significant SAMEFINFLEX coefficient, even without shocks to the collateral value (column 6).[19] However, we find that such a model generates a negative SAMELEVERAGE coefficient, which is not consistent with the empirical evidence (cf. later results in Section III.A.2). In contrast, when we also account for shocks to collateral value in the full model (column 4), we are able to rationalize positive coefficients on both SAMEFINFLEX and SAMELEVERAGE. The intuition for this result is the following. In the model without shocks to collateral value, in any given period, 2 firms with the same size, profitability, and (most importantly) leverage have the same distance to the collateral constraint and, therefore, the same level of financial flexibility. Instead, in the full model, shocks to the collateral value introduce an additional layer of heterogeneity across firms, which breaks the tight link between leverage and financial flexibility in the Livdan et al. (2009) model.

Finally, our model features asymmetric capital-adjustment costs (see equation (5)). To verify whether this asymmetry in costs has a relevant impact on the predicted link between similarity in financial flexibility and stock comovement, we perform a third counterfactual experiment. Specifically, we solve the baseline model using the parameters in Panel A of Table 1 while assuming that the positive and negative capital-adjustment-cost parameters have the same magnitude ($a_P = a_N$), so that there are no cost asymmetries between investing and divesting. We then estimate the comovement regression (equation (20)) using the simulated data from this counterfactual, and report the results in column 7 of Table 2. We find that the coefficient for SAMEFINFLEX has the same magnitude as the one estimated for the baseline model with asymmetric adjustment costs (column 4). Therefore, we conclude that asymmetries in capital-adjustment costs do not play a major role in our predictions.

To the best of our knowledge, this is the first article to show that similarity in firm characteristics is associated with future stock comovement using a dynamic asset-pricing model with rational expectations and financial frictions. This theoretical prediction is supported by the empirical findings in previous papers that estimate stock comovement regressions similar to equation (20) (e.g., Antón and Polk (2014), Grieser, Lee, and Zekhnini (2020), and De Bodt et al. (2022)). On the empirical side, our contribution to this literature is to study the link between similarity in financial flexibility and stock comovement, which we document in the next section.

[19]In this counterfactual experiment, the variable SAMEFINFLEX is based on free debt capacity, ξ. The results are qualitatively unchanged when using the shadow price of new debt, ν.

III. Empirical Results

In this section, we develop 2 empirical strategies to test the effect of financial flexibility on stock-return comovement in the real data. The first employs variation in the market value of CRE assets, an important component of collateralizable assets, as a proxy for changes in firms' financial flexibility. The second strategy uses the outbreak of the COVID-19 pandemic as a shock to firm revenues and, hence, financial flexibility. We then corroborate the results obtained from these empirical analyses, performing several robustness and external validity tests.

A. Empirical Strategy 1: Shocks to the Value of Collateralizable Assets

Our first empirical strategy is based on using shocks to collateralizable asset values to generate variation in similarity of financial flexibility across firms. In the model, the market value of nonoperating collateralizable assets is equal to $\mathbf{E}\left[\exp(p_{jt+1})|p_{jt}\right]H$. This value varies over time as a function of the price p, and it directly affects the maximum debt capacity (cf. equation (8)). The main determinant of collateralizable assets for actual firms is represented by CRE assets, which in our sample are on average 77% of net property, plant, and equipment (PPE).[20] Therefore, in the empirical analysis of this section, we employ shocks to the value of CRE assets to measure variation in firms' debt capacity and, hence, financial flexibility.

To examine the effect of firms' similarity in financial flexibility on pairwise return correlation, we estimate in the real data the stock comovement regression presented in Section II.C (equation (20)):

$$\rho_{ij,t+1} = \alpha + \beta \times \text{SAMEFINFLEX}_{ij,t} + \Gamma \times X_{ij,t} + \epsilon_{ij,t}.$$

To measure pairwise stock comovement ($\rho_{ij,t+1}$) in the real data, we compute the realized correlation between each stock pair's monthly FF5 return residuals.[21] Financial flexibility is measured as the market value of firms' real estate assets scaled by lagged PPE. Therefore, in this first empirical test, SAMEFINFLEX is defined as the negative of the absolute value of the difference in real estate market-value percentile ranking across the 2 firms in the pair. The market value of real estate assets, RE_VALUE^{l}_{it}, is the ratio of the market value of the CRE assets firm i owns in location l in year t to lagged PPE.[22] Finally, we include a set of control variables, $X_{ij,t}$, described in the next subsection.

When estimating the comovement regression in the real data, a source of endogeneity could be the presence of an omitted variable that affects real estate prices and the comovement of stock returns across firms at the same time, such as an unobserved local economic shock. To address this endogeneity concern, we employ

[20]See Section III.A.1 for data construction.

[21]The FF5 factors are MARKET, SIZE, BOOK_TO_MARKET, PROFITABILITY, and INVESTMENT. By using the correlation of FF5 return residuals – instead of raw returns – as our dependent variable, we remove the effect of similarity across firms in the exposure to these factors. In robustness tests presented in the next sections, we compute return residuals using alternative factor models.

[22]To compute the market value of real estate assets, RE_VALUE^{l}_{it}, we follow standard procedures in the literature. See the Supplementary Material for details.

the IV approach developed by Himmelberg et al. (2005) and Mian and Sufi (2011), who use the following equation to predict real estate prices $\left(P_t^l\right)$ for location l at time t:

$$P_t^l = \alpha^l + \delta_t + \gamma \times \text{ELASTICITY}^l \times \text{IR}_t + u_t^l, \tag{21}$$

where ELASTICITY^l is the elasticity of housing supply at the Metropolitan Statistical Area (MSA) level, IR_t is the nationwide real interest rate at which banks refinance their home loans, α^l is a location (MSA) fixed effect, and δ_t captures macroeconomic fluctuations in real estate prices. The economic intuition behind the use of the interaction between ELASTICITY^l and IR_t as an instrumental variable is the following. A decrease in interest rates leads to higher demand for real estate, which translates into higher real estate prices. The price increase is larger in areas where the amount of developable land is scarce and, thus, housing supply is less elastic. Therefore, because of the collateral channel described in our model, the increase in debt capacity will be higher for firms with real estate assets located in areas with more inelastic housing supply (i.e., in areas where real estate prices will increase the most).

In our application, the main variable of interest, $\text{SAMEFINFLEX}_{ij,t}$, is measured as a nonlinear transformation of the CRE asset values of the pair of firms, i and j. To deal with pair-level observations, we adapt the identification approach of Himmelberg et al. (2005) and Mian and Sufi (2011) by instrumenting $\text{SAMEFINFLEX}_{ij,t}$ with the pairwise similarity in the interaction between the elasticity of local housing supply and the aggregate interest rate. More precisely, our instrumental variable is defined as

$$\mu_{ij,t} = \text{PR}\left[-|\text{ELASTICITY}^l \times \text{RE\_VALUE}_{i0}^l - \text{ELASTICITY}^m \times \text{RE\_VALUE}_{j0}^m| \times \text{IR}_t\right], \tag{22}$$

where $\text{PR}[\cdot]$ denotes the percentile ranking, and l and m are the MSAs in which firms i and j are located, respectively. Following Cvijanović (2014), we include RE_VALUE_0^l, the market value of CRE assets for the firm in the initial year of the sample.[23] We implement our IV approach using 2-stage least squares (2SLS) to estimate equation (20). Moreover, we exclude pairs of firms located in the same MSA, so that $l \neq m$, to be able to exploit differences in the elasticity of housing supply across locations.

The variable $\mu_{ij,t}$ is a valid instrument for our empirical strategy for 3 reasons. First, the IV regression has a strong first stage, because exogenous variation in real estate prices, captured by the interaction between the local housing supply elasticity and the aggregate interest rate, generates dispersion in real estate values and, thus, in the similarity between the value of collateralizable assets for pairs of firms located in different MSAs. Second, the exclusion restriction is met because the interaction between the amount of developable land at the MSA level and the nationwide interest rate is exogenous to stock-return comovement. Finally, there is no mechanical effect of an increase in the value of CRE assets on stock returns through the

[23]As explained in the Supplementary Material, because of constraints on the availability of data to compute the market value of real estate assets, the initial year in our sample is 1993.

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appreciation of the value of these assets. This is due to the fact that the value of CRE assets equals the present value of their future rents (see, e.g., Geltner, Miller, Clayton, and Eichholtz (2001), Ling and Archer (2012)). Therefore, the positive effect related to an increase in CRE prices compensates in expectation for the negative effect due to the subsequent increase in imputed future rents. Consistent with this argument, Quan and Titman (1997) find no empirical relation between changes in real estate values, nor rental changes, and stock returns in the United States.

1. Data

To implement our empirical strategy, we use the universe of publicly traded firms headquartered in the U.S. available in Compustat and CRSP from 1993 to 2018. As is standard in the corporate finance literature, we omit financial firms, utilities, not-for-profits, and governmental firms as well as firms with missing values of PPE or total assets. Accounting data are obtained from Compustat while stock returns come from the CRSP monthly files.

To compute stock comovement – the dependent variable, $\rho_{ij,t}$, in regression equation (20) – we form all the possible pairs of stocks in our sample at the beginning of a given year and compute the pairwise correlation of their monthly stock-return residuals. For our main results, we calculate return residuals by discounting the effect of the FF5 factors (see footnote 21). In robustness tests, we also compute 4 alternative measures of return residuals: Using only the market (CAPM) factor, accounting for the 3 factors in Fama and French (1993) and the momentum factor of Carhart (1997), and augmenting the FF5 model with the *Quality-Minus-Junk* (QMJ) factor in Asness, Frazzini, and Pedersen (2019) and with the *Betting-Against-Beta* (BAB) factor in Frazzini and Pedersen (2014).[24]

The independent variable of main interest in our analysis is similarity in financial flexibility among firms, $\text{SAMEFINFLEX}_{ij,t}$. Since our empirical strategy is based on shocks to the value of firms' collateralizable assets, we measure financial flexibility as the market value of firms' real estate assets scaled by lagged PPE. To do so, we obtain residential real estate indices at the MSA level from the Federal Housing Finance Agency and construct the market value of CRE assets following standard procedures in the literature (cf. Kumar and Vergara-Alert (2020), see the Supplementary Material for details).

The set of controls, $X_{ij,t}$, includes the same measures of pairwise similarity in firm characteristics that we used in the regression for simulated data (Section II.C): SAMESIZE, SAMEMB, and SAMELEVERAGE, which in the data are measured as the negative of the absolute value of the difference in firm size (total assets, Compustat item AT), market-to-book ratio (market value of equity – defined as the annual price close, PRCC, times the number of common shares outstanding, CSHO – plus total liabilities, LT, plus preferred stock, PSTKL, minus deferred taxes, TXDI, all scaled by AT), and leverage (total debt, DLTT + DLC, divided by AT) percentile ranking across the 2 firms in the pair, respectively.

[24]We obtain the FF5, Fama and French (1993), and Carhart (1997) daily return factors from Ken French's website. Data on the QMJ and BAB factors are from Andrea Frazzini's web page.

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In addition, $X_{ij,t}$ contains variables shown in the previous literature to be significant determinants of stock comovement (see Antón and Polk (2014)). The first is SAMEMOM, the negative of the absolute value of the difference in momentum percentile ranking across the two stocks in the pair. Second, because we expect stocks of firms in similar industries to comove more, we measure industry similarity as the number of consecutive SIC digits, beginning with the first digit, that are equal for a given pair of stocks, NUMSIC. Since financial flexibility depends on firms' size (see equation (8)), we also control for SIZE1 and SIZE2, which are defined as the normalized rank-transform of the percentile size (total assets) of the 2 firms in the pair. SIZE1 (SIZE2) represents the larger (smaller) firm in the pair. We also control for the interaction between these normalized size rankings. Finally, to capture important similarity between the two stocks in a pair, we control for DSTATE, DINDEX, and DLISTING, which are indicator variables that assume a value of 1 if the firms are headquartered in the same state, are included in the S&P500 index, and are listed on the same stock exchange, respectively, and 0 otherwise.

Finally, as mentioned above, to address the potential endogeneity problem of local real estate prices, we follow Himmelberg et al. (2005) and Mian and Sufi (2011) and instrument local real estate prices using the interaction of long-term interest rates and local housing supply elasticity. We use the local housing supply elasticities provided by Saiz (2010). These measures capture the amount of developable land in each MSA and are estimated by processing satellite-generated data on the elevation and presence of water bodies. As a measure of long-term interest rates, IR_t, we use the "contract rate on 30-year, fixed-rate conventional home mortgage commitments" from the Federal Reserve website.

Table 3 presents the summary statistics for the variables we use in our empirical analysis. Moreover, the table provides informative summary statistics on additional variables in our sample, such as profitability, cash holdings, and the growth ratio of assets and sales.

2. Results

To study the relationship between financial flexibility and stock comovement in our sample, we start from a bivariate analysis similar to that performed in Section II.C. Figure 5 shows the average pairwise correlation of FF5 stock-return residuals, $\rho_{ij,t+1}$, as a function of our measure of pairwise similarity in financial flexibility, $\mathrm{SAMEFINFLEX}_{ij,t}$, based on the market value of CRE assets. Consistent with the predictions from the model (Figure 4), average stock comovement increases in SAMEFINFLEX, growing from 0.8% for firms with a difference of 50 percentiles in the distribution of financial flexibility to 2.1% for firms in the same percentile.[25] This change (1.3%) represents a 163% increase in average stock comovement, and its magnitude is comparable to the results obtained in the

[25]Stock comovement is not significantly different from zero for pairs of firms with more than 70 percentiles of difference in the distribution of financial flexibility. This is partly due to the fact that, as discussed in footnote 18 above, the number of firm-pair observations increases in SAMEFINFLEX, so that the confidence intervals are wider for lower values of SAMEFINFLEX.

TABLE 3

Summary Statistics of the Real-Data Sample

Table 3 provides the summary statistics for the data sample that uses the market value of real estate assets to measure financial flexibility. Data sources and sample construction are described in Section III.A.1 and the Supplementary Material. RETURN is the monthly stock return obtained from CRSP. EXCESS_RETURN is the difference between RETURN and the risk-free rate. $\rho_{ij,t}$ is the correlation, computed for each year t, between the monthly return residuals for stocks i and j in a pair. Return residuals are computed either using the Fama and French (FF5) (2015) factors, or just the market factor (CAPM). RETAINED_EARNINGS is computed as the ratio of retained earnings to book value of assets. BOOK_LEVERAGE is the sum of short-term and long-term debt normalized by book value of assets. ASSET_GROWTH is the growth rate of total assets. FIRM_SIZE is defined as the book value of total assets. MARKET_TO_BOOK_RATIO is the market value of equity plus the book value of assets minus the book value of equity, all divided by the book value of assets. SALES_GROWTH measures the growth rate of firm revenues. PROFITABILITY equals operating income divided by book value of assets. CASH_HOLDINGS account for cash and short-term securities. AGE is the number of years since the firm first appeared in the Compustat database. RE_VALUE is the ratio of the market value of real estate assets normalized by lagged property plant and equipment. DSTATE, DINDEX, and DLISTING are dummy variables that take value 1 if the 2 firms in a pair are headquartered in the same state, are included in the S&P500 index, and are listed on the same stock exchange, respectively. For each variable, we report the mean, median, standard deviation, 25th and 75th percentiles, and number of observations.

	Mean	Median	Std. Dev.	p25	p75	No. of Obs.
RETURN	0.011	0.010	0.059	−0.014	0.034	22,282
EXCESS_RETURN	0.009	0.008	0.060	−0.017	0.031	22,282
$\rho_{ij,t}$ (FF5 residuals)	0.014	0.011	0.314	−0.211	0.237	5,591,712
$\rho_{ij,t}$ (CAPM residuals)	0.037	0.037	0.311	−0.185	0.260	5,591,712
RETAINED_EARNING	−0.309	0.121	1.189	−0.354	0.370	28,893
BOOK_LEVERAGE	0.274	0.212	0.323	0.048	0.374	29,082
ASSET_GROWTH	0.091	0.043	0.323	−0.053	0.166	26,536
FIRM_SIZE ($ million)	2,725	169	12,995	29	970	29,158
MARKET_TO_BOOK_RATIO	2.045	1.497	1.555	1.104	2.297	26,240
SALES_GROWTH	0.244	0.063	4.000	−0.032	0.182	26,192
PROFITABILITY	−0.003	0.070	0.265	−0.009	0.121	29,063
CASH_HOLDINGS ($ million)	240	11	1,420	2	66	29,153
AGE (years)	21.728	19.000	14.133	10.000	32.000	29,219
RE_VALUE	0.768	0.290	1.123	0.000	1.028	23,469
DSTATE	0.028	0.000	0.164	0.000	0.000	6,947,713
DINDEX	0.013	0.000	0.113	0.000	0.000	6,947,713
DLISTING	0.428	0.000	0.495	0.000	1.000	6,947,713

simulated data (1.3% increase in stock comovement using the measure of similarity in financial flexibility based on the shadow price of new debt, and 0.8% using free debt capacity).

To account for the effect of similarity in firm characteristics other than financial flexibility, we estimate equation (20) including the control variables described in Section III.A.1. Table 4 presents the results. For robustness, we use alternative factor models to compute the pairwise correlation in stock-return residuals: Columns 3–4 discount only for the market factor (CAPM), columns 5–6 include the 4 factors of Fama and French (1993) and Carhart (1997), and columns 7–10 account for the FF5 factors. For comparison purposes, columns 1 and 2 report the estimation results using the simulated data.[26]

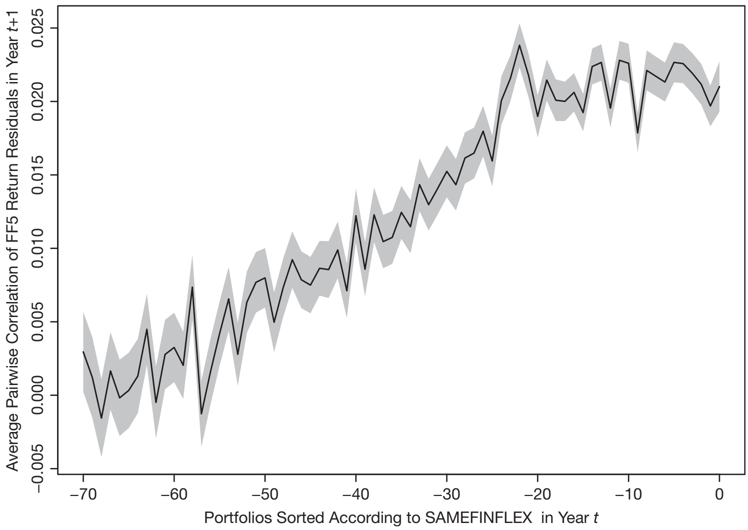
Overall, the OLS coefficient for SAMEFINFLEX is positive and significant across all specifications (columns 3–8), confirming that similarity in financial flexibility is associated with higher pairwise return correlation in the subsequent year. This result is robust to controlling for firm similarity along several characteristics, such as the market-to-book ratio (SAMEMB), momentum (SAMEMOM),

[26]In columns 1–2, we use free debt capacity as a measure of financial flexibility. Results based on the shadow price of new debt are qualitatively similar and are available from the authors. The specifications in columns 1–2 of Table 4 are similar to those in columns 3–4 of Table 2, but we add the size controls to maintain consistency in the regression specification between the real and simulated-data samples.

FIGURE 5

Stock Comovement as a Function of Similarity in Financial Flexibility for the Real-Data Sample

Figure 5 shows the average pairwise correlation of monthly stock-return residuals, $\rho_{ij,t+1}$, computed for each *ij* pair of firms in year $t+1$, as a function of the similarity in firms' financial flexibility, SAMEFINFLEX$_{ij,t}$, measured using the market value of firms' real estate assets (RE_VALUE) in year t. Return residuals are calculated accounting for the Fama and French (FF5) (2015) factors. SAMEFINFLEX$_{ij,t}$ is measured as the negative of the absolute value of the difference in the RE_VALUE percentiles for firms i and j in year t. Data sources and sample construction are described in Section III.A.1 and the Supplementary Material. The shaded area represents the 95%-level confidence interval.



size (SAMESIZE), leverage (SAMELEVERAGE), industry (NUMSIC), state (DSTATE), inclusion in the S&P 500 index (DINDEX), and stock exchange in which the company is listed (DLISTING).

In columns 9 and 10, we report the estimated coefficients of the 2SLS regressions based on the IV μ (equation (22)), using FF5 residuals to compute stock comovement.[27] The results are in line with those obtained from the OLS regressions, though the magnitude of the coefficient associated with SAMEFINFLEX is smaller. In particular, the coefficient reported in column 10 implies that a 1-percentile increase in similarity among firms' financial flexibility results in higher correlation in stock-return residuals of 0.01% – compared to the 0.02% OLS estimate in column 8 – after controlling for other sources of similarity across firms. Therefore, according to the IV results, the average comovement for firms in the same percentile of financial flexibility is 1.3%, which is 62% higher than the average comovement for firms with 50 percentiles of difference in financial flexibility (0.8%, cf. Figure 5). Finally, the regression coefficients are comparable in terms of sign and magnitude to those obtained from the model-simulated data (columns 1 and 2), both for the main variable of interest, SAMEFINFLEX, and in general for the other controls.

[27]The estimates of the first-stage regressions are available from the authors.

TABLE 4

Regression Analysis of Stock Comovement in the Real-Data Sample

Table 4 reports the OLS and instrumental variable (IV) estimates of the stock comovement regression specified in equation (20). The dependent variable is the pairwise correlation, $\rho_{ij,t+1}$, computed for year $t+1$, between the monthly return residuals for stocks *i* and *j* in a pair. Return residuals are computed using either the market factor (CAPM, columns 1–4), a 4-factor model that includes the 3 factors in Fama and French (1993) plus the momentum factor in Carhart (1997), 4F, columns 5–6), or the 5 factors in Fama and French (FF5) ((2015), columns 7–10). The independent variable of main interest is SAMEFINFLEX, which is defined in the real data as the negative of the absolute value of the difference in real estate market value (RE_VALUE) percentile ranking for the firms in a pair in year *t*. In the simulated data, SAMEFINFLEX is based on free debt capacity. Columns 1–2 report the results using model-simulated data, while columns 3–10 report the results using real data. Columns 1–8 report the results of OLS regressions and columns 9–10 the results of the IV estimation. The instrument in the first stage is the interaction of housing supply elasticity with the aggregate real interest rate (see equation (22)). Columns 4, 6, 8, and 10 control for similarity in firm characteristics, captured by the variables SAMESIZE, SAMEMB, SAMELEVERAGE, SIZE1, SIZE2, SIZE1 × SIZE2, SAMEMOM, NUMSIC, DSTATE, DINDEX, and DLISTING. Details of the construction of the real-data sample and variable definitions can be found in Section III.A.1. Section II.B.4 provides the details of the simulation, which is based on the parameter values reported in Panel A of Table 1. All columns control for year-fixed effects. Standard errors are clustered at the stock-pair level. *T*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Correlation of CAPM Residuals (Simulated Data)		Correlation of CAPM Residuals (Real Data)		Correlation of 4F Residuals (Real Data)		Correlation of FF5 Residuals (Real Data)			
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	IV	IV
	1	2	3	4	5	6	7	8	9	10
SAMEFINFLEX	0.0002***	0.0001***	0.0003***	0.0002***	0.0004***	0.0002***	0.0004***	0.0002***	0.0003***	0.0001***
	(53.55)	(28.51)	(66.60)	(39.61)	(83.38)	(51.14)	(84.01)	(51.46)	(29.39)	(13.88)
SAMESIZE		0.0001**		−0.0001***		0.0001***		0.0001		0.0001
		(2.49)		(−4.48)		(3.62)		(1.63)		(0.81)
SAMEMB		0.0003***		0.0003***		0.0002***		0.0002***		0.0002***
		(98.22)		(44.43)		(36.31)		(37.28)		(37.72)
SAMELEVERAGE		0.0001***		0.0001***		0.0001***		0.0001***		0.0001***
		(5.85)		(9.01)		(13.64)		(14.10)		(15.01)
SIZE1		−0.0033***		−0.0211***		−0.0096***		−0.0098***		−0.0102***
		(−9.56)		(−71.88)		(−32.22)		(−32.89)		(−34.10)
SIZE2		0.0002		0.0145***		0.0063***		0.0077***		0.0084***
		(0.65)		(48.93)		(20.96)		(25.81)		(27.73)
SIZE1 × SIZE2		0.0019***		−0.0006***		0.0049***		0.0046***		0.0052***
		(14.57)		(−4.73)		(26.40)		(24.70)		(27.06)
SAMEMOM				0.0001***		0.0002***		0.0002***		0.0002***
				(14.91)		(28.79)		(25.30)		(25.45)
NUMSIC				0.0068***		0.0066***		0.0065***		0.0066***
				(33.58)		(31.85)		(31.48)		(32.22)
DSTATE				0.0031***		0.0019**		0.0018**		0.0018**
				(3.68)		(2.29)		(2.14)		(2.18)
DINDEX				0.0101***		0.0726***		0.0716***		0.0713***
				(7.65)		(53.76)		(53.28)		(53.09)
DLISTING				0.0045***		0.0066***		0.0067***		0.0072***
				(15.21)		(22.07)		(22.48)		(23.99)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	17,265,600	17,265,600	5,591,712	5,145,143	5,591,712	5,145,143	5,591,712	5,145,143	5,591,712	5,145,143
R^2	0.0002	0.0011	0.0055	0.0097	0.0027	0.0059	0.0037	0.0069	0.0012	0.0044

3. Robustness Tests

To check the validity of our empirical results for different subsamples of firms, we reestimate the stock-comovement regression in equation (20) by splitting our sample across several dimensions: Tobin's Q, firm age, net leverage, and during periods of real estate booms and busts. We then test the robustness of our results using alternative factor models to compute return residuals. Finally, we address potential concerns about the validity of the IV and the presence of fixed unobserved heterogeneity across pairs of firms.

Investment Opportunities

We examine if the stock returns of firms that have better investment opportunities comove more. In our model, a positive shock to the value of collateralizable assets has a direct effect on firms' investment (see Figure 3) and, as a consequence, on stock returns. This effect is larger for firms with better investment opportunities. The reason is that loosening the collateral constraint is more valuable for firms that can put the additional funds to better use. Hence, we expect that similarity in financial flexibility should have a larger effect on stock comovement for firms with better investment opportunities.

To test this hypothesis empirically, we proxy for investment opportunities using Tobin's Q, and we estimate the comovement regression (equation (20)) for the 2 subsamples of firms in the top and bottom 3 deciles of Tobin's Q distribution.[28] Columns 1–2 of Table 5 present the regression results for the 2 subsamples. Consistent with our hypothesis, we find that the coefficient associated with SAMEFINFLEX is 3 times larger for the subsample of firms with better investment opportunities.

Firm Age

We address the concern that only mature firms drive the relationship between financial flexibility and stock-return comovement. Columns 3–4 of Table 5 show that our results remain robust when we divide the sample into the top and bottom 3 deciles of the firms' age distribution.[29] Indeed, the estimated coefficient associated with SAMEFINFLEX is positive and statistically significant for young as well as mature firms.

Through this test, we also address the potential self-selection bias due to firms choosing their locations based on unobservable variables that may be correlated with financial flexibility. Almazan, De Motta, Titman, and Uysal (2010) argue that the effect of variables that may influence a firm's original choice of location becomes less important over time. Therefore, our finding that the SAMEFINFLEX coefficient is positive and significant also for mature firms, for which the effect of the

[28]We calculate deciles of the cross-sectional distribution of Tobin's Q for every year in the sample. We follow a similar procedure to compute the deciles of the variables used in the other sample-split exercises in this section, firm age, and net leverage. Following Almeida and Campello (2007), we define Tobin's Q as $(\mathrm{AT}+(\mathrm{PRCC}\times\mathrm{CSHO})-\mathrm{CEQ}-\mathrm{TXDB})/\mathrm{AT}$, where the Compustat items are defined as follows: AT is total assets, PRCC is the annual price close, CSHO is the number of common shares outstanding, CEQ is the book value of common equity, and TXDB are deferred taxes.

[29]Firm age is computed using the first year of inclusion in the Compustat sample.

TABLE 5

Robustness Tests: Sample Splits

Table 5 reports the OLS estimates of the stock-comovement regression specified in equation (20) for different subsamples of firms. The dependent variable is the pairwise correlation, $\rho_{ij,t+1}$, computed for year $t+1$, between the monthly return residuals for stocks i and j in a pair. Return residuals are computed using the 5 factors in Fama and French (FF5) (2015). The independent variable of main interest is SAMEFINFLEX, defined as the negative of the absolute value of the difference in real estate market value (RE_VALUE) percentile ranking for the firms in a pair in year t. Columns 1 and 2 show the results for the 2 subsamples of firms with high (top 30%) and low (bottom 30%) Tobin's Q, respectively. Columns 3 and 4 show the results for similar sample splits based on firm age, and columns 5 and 6 are based on net leverage. Columns 7 and 8 report the results when estimating the stock-comovement regression for the period of increasing real estate prices (2001–2006) and decreasing real estate prices (2007–2011), respectively. All columns control for SAMESIZE, SAMEMB, SAMELEVERAGE, SIZE1, SIZE2, SIZE1 × SIZE2, SAMEMOM, NUMSIC, DSTATE, DINDEX, and DLISTING, and year-fixed effects. Details of the construction of the real-data sample and variable definitions can be found in Section III.A.1. Standard errors are clustered at the stock-pair level. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Correlation of FF5 Residuals							
	Investment Opportunities		Firm Age		Net Leverage		Real Estate Boom and Bust Periods	
	Worse	Better	Young	Mature	Low	High	2001–2006	2007–2011
	1	2	3	4	5	6	7	8
SAMEFINFLEX	0.0001***	0.0003***	0.0002***	0.0002***	0.0002***	0.0001***	0.0002***	0.0001**
	(7.69)	(18.33)	(18.91)	(11.24)	(14.92)	(7.31)	(16.18)	(1.97)
SAMESIZE	0.0002***	0.0001***	0.0002***	−0.0001	0.0001	0.0001	0.0003***	0.0003***
	(3.77)	(2.83)	(5.10)	(−0.01)	(0.99)	(0.17)	(7.15)	(4.74)
SAMEMB	0.0002**	0.0003***	0.0002***	0.0003***	0.0003***	0.0004***	0.0002***	0.0004***
	(2.29)	(3.92)	(15.51)	(16.02)	(14.18)	(16.41)	(16.04)	(18.20)
SAMELEVERAGE	0.0001	0.0001***	0.0001***	0.0002***	−0.0001	0.0001**	0.0001***	0.0001***
	(0.27)	(3.85)	(3.06)	(7.10)	(−1.29)	(2.09)	(3.61)	(2.92)
SIZE1	−0.0100***	−0.0115***	−0.0050***	−0.0095***	−0.0156***	−0.0102***	0.0004	−0.0025
	(−10.09)	(−10.92)	(−6.13)	(−9.06)	(−14.13)	(−9.75)	(0.38)	(−1.58)
SIZE2	0.0073***	0.0081***	0.0043***	0.0146***	0.0043***	0.0100***	−0.0013	−0.0007
	(7.29)	(7.89)	(5.85)	(12.63)	(3.76)	(9.18)	(−1.43)	(−0.45)
SIZE1 × SIZE2	0.0026***	0.0016***	0.0052***	0.0015**	0.0032***	0.0040***	−0.0009*	−0.0098***
	(3.80)	(2.70)	(10.11)	(2.16)	(4.25)	(5.41)	(−1.73)	(−12.37)
SAMEMOM	0.0001***	0.0002***	−0.0001	0.0006***	0.0001	0.0001***	0.0003***	0.0001***
	(4.76)	(8.02)	(−1.03)	(23.92)	(1.13)	(5.00)	(17.53)	(4.03)
NUMSIC	0.0053***	0.0111***	0.0058***	0.0144***	0.0082***	0.0114***	0.0087***	0.0159***
	(7.02)	(20.13)	(13.25)	(20.40)	(16.72)	(13.43)	(16.85)	(18.86)
DSTATE	−0.0029	0.0056*	−0.0012	0.0045*	0.0095***	0.0047	0.0016	0.0099***
	(−1.08)	(1.86)	(−0.62)	(1.76)	(3.36)	(1.59)	(0.78)	(2.89)
DINDEX	0.0318***	0.1371***	0.0107	0.0673***	0.0285*	0.0995***	0.0607***	0.0560***
	(3.78)	(40.01)	(0.99)	(36.28)	(1.82)	(26.17)	(21.48)	(14.22)
DLISTING	0.0040***	0.0153***	0.0018***	0.0117***	0.0082***	0.0073***	0.0012	0.0066***
	(4.18)	(14.66)	(2.59)	(11.59)	(8.57)	(6.98)	(1.54)	(5.35)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	457,093	468,179	944,816	529,201	506,795	414,053	795,466	323,236
R^2	0.0131	0.0146	0.0032	0.0410	0.0054	0.0182	0.0040	0.0045

variables that determine the choice of location is less relevant, mitigates the concerns about a potential selection effect.[30]

Net Leverage

We assess the robustness of our findings for firms with high versus low net leverage, defined as the ratio of net debt to total assets.[31] Column 5 of Table 5 presents the regression results for the subsample of firms in the bottom 3 deciles of

[30]Although in this test, we split firms based on age and not number of years in the same headquarters location, Pirinsky and Wang (2006) find that less than 2.4% of the Compustat firms changed their headquarters' location between 1992 and 1997.

[31]We compute net debt as short-term debt plus long-term debt minus cash holdings (Compustat items DLC + DLTT − CHE).

net leverage, while column 6 shows the results for firms in the top 3 deciles. The coefficient of interest, SAMEFINFLEX, remains positive and statistically significant for both subsamples.

Real Estate Booms and Busts

In the regressions presented in Table 4, we control for the impact of aggregate time-varying determinants of stock comovement by including year-fixed effects. However, the effect of similarity in financial flexibility on stock comovement could only be relevant during certain phases of the business cycle. To verify this hypothesis, we estimate the stock-comovement regression for 2 separate periods in our sample: The period of increasing real estate prices between 2001 and 2006, denoted as the "boom" period, and the period of decreasing prices between 2007 and 2011, the "bust" period. Columns 7 and 8 of Table 5 show that the coefficient for SAMEFINFLEX is positive and statistically significant for both the boom and the bust periods. This result confirms that financial flexibility is an important determinant of stock comovement across the whole business cycle.

Alternative Factor Models

A potential concern for our empirical results could be the existence of firm-specific characteristics that affect returns, but are not captured by the 5 factors proposed by FF5. To the extent that these omitted characteristics are correlated with firms' financial flexibility, they could generate an inconsistent estimate of the coefficient of interest in the stock-comovement regressions.

To address this concern, we perform 2 robustness tests that control for additional potential determinants of stock returns. First, we compute the return residuals by adding the QMJ factor of Asness et al. (2019) to the 5-factor model of FF5. The QMJ factor is constructed based on firms' profitability level and growth, and most importantly the variable SAFETY, which captures firms' risk of financial distress. Second, the presence of leverage constraints for investors could drive their demand for stocks with high risk, such as those of firms with low financial flexibility. To deal with this issue, we compute return residuals using the BAB factor proposed by Frazzini and Pedersen (2014), which is long on leveraged low-beta assets and short on high-beta assets.

The results of the comovement regressions using these 6-factor models are reported in the Supplementary Material. For both tests, we find that the sign and magnitude of the coefficient on SAMEFINFLEX are in line with the ones obtained using the FF5 return residuals.[32]

[32]In a recent paper, Grieser et al. (2020) raise concerns about the potential for omitted factors in return-comovement regressions based on excess returns and groupings according to firm characteristics, such as those in Pirinsky and Wang (2006). However, Grieser et al. (2020) point out that this concern is less relevant in studies that control for similarity in observable characteristics, such as in our paper, an approach that they call "intensity-based tests." Moreover, to address the residual concern about an omitted variable, we implement the IV test based on the market value of corporate real-estate assets, and perform an event study using as a shock the outbreak of the COVID-19 pandemic (see Section III.B).

Instrument Validity

One potential concern regarding the validity of our instrument, which is based on the market value of CRE, is that land availability and land-use regulations could be correlated with the local demand for real estate assets (see Davidoff (2016)). In this case, the instrument would not isolate the supply-driven variation in real estate prices. Following Davidoff (2016), we address this issue by controlling for the interaction of the elasticity of housing supply and year dummies in both the first- and second-stage IV regressions. The results are robust to include these interaction terms and are available from the authors.

Fixed Unobserved Heterogeneity

Finally, we address the potential presence of time-invariant unobserved heterogeneity affecting stock comovement between pairs of firms. To do so, Table 6 presents estimates of the comovement regression in equation (20) including fixed effects for firm pairs, both for the simulated data (columns 1–2 using the shadow price of new debt, and columns 3–4 using free debt capacity) and for the real data (columns 5 and 6 report the fixed effects estimates, and 7 and 8 show the results of the IV regressions). The coefficient of interest, associated with SAMEFINFLEX, remains positive and statistically significant in all specifications, both for the simulated and the real data.

B. Empirical Strategy 2: COVID-19 Event Study

The outbreak of the COVID-19 pandemic was an unexpected event for the global economy. Managers and policymakers largely ignored the risk coming from infectious diseases, and focused instead their attention on economic and climate-change-related risks, as exemplified by the fact that the top 5 risks in the ranking of the World Economic Forum's 2020 Global Risk Report were all related to environmental events (see https://www.weforum.org/reports/the-global-risks-report-2020). In addition to being unanticipated, the pandemic outbreak and subsequent lockdown had a substantial economic and financial impact on companies, by affecting, in turn, their revenues, profits, financial flexibility, and stock returns. Recent empirical studies illustrate this point by showing that the impact of COVID-19 on stock returns was significantly different depending on the degree of firms' financial flexibility. For example, Ramelli and Wagner (2020) and Fahlenbrach et al. (2021) find that firms with higher financial flexibility experienced a smaller decrease in stock returns following the pandemic's outbreak.[33]

In summary, the outbreak of COVID-19 represents an exogenous, unexpected, and significant shock to firms' economic and financial prospects. In this section, we perform an event study around the COVID-19 shock as a second empirical test of

[33]For the effects of the pandemic on financial flexibility, see also De Vito and Gómez (2020), who estimate the impact of the COVID-19 cash crunch on firms' liquidity, and Ding, Levine, Lin, and Xie (2021), who show that the reduction in stock prices following the pandemic was smaller for firms with higher cash balances, more profits, and less debt. For evidence on the impact of COVID-19 on firms' stock returns, see also Albuquerque, Koskinen, Yang, and Zhang (2020) and Davis, Hansen, and Seminario-Amez (2021).

TABLE 6

Robustness Tests: Fixed Unobserved Heterogeneity

Table 6 provides pairwise fixed-effects panel regressions of stock-return comovement. Columns 1–4 provide the results for the simulated data, and columns 5–8 present results for the real data. The dependent variable is the pairwise correlation, $\rho_{ij,t+1}$, computed for year $t+1$, between the monthly return residuals for stocks i and j in a pair. $\rho_{ij,t+1}$ is constructed using CAPM residuals in the simulated data and using the 5 factors in Fama and French (2015) in the real data. The independent variable of main interest is SAMEFINFLEX, defined as the negative of the absolute value of the difference in percentile rankings of the shadow price of debt (columns 1–2), free debt capacity (columns 3–4), and real estate market value (RE_VALUE; columns 5–8) for the firms in a pair in year t. For the real data, columns 5–6 present the OLS regression results, and columns 7–8 present the instrumental variable (IV) regression results. columns 2, 4, 6, and 8 control for similarity in firm characteristics, captured by the variables SAMESIZE, SAMEMB, SAMELEVERAGE, SIZE1, SIZE2, and SIZE1 × SIZE2. Columns 6 and 8 also control for SAMEMOM, NUMSIC, DSTATE, DINDEX, and DLISTING. Details of the construction of the real-data sample and variable definitions can be found in Section III.A.1. Section II.B.4 provides the details of the simulation, which is based on the parameter values reported in Panel A of Table 1. All the columns include stock-pair fixed effects and year fixed effects. Standard errors are clustered at the stock-pair level. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Model				Data			
	Shadow Price		Free Debt Capacity		OLS		IV	
	1	2	3	4	5	6	7	8
SAMEFINFLEX	0.0001*** (29.33)	0.0001*** (20.17)	0.0001*** (39.47)	0.0001*** (25.17)	0.0004*** (65.94)	0.0003*** (39.27)	0.0002*** (15.79)	0.0001*** (6.95)
SAMESIZE		−0.0001*** (−6.6)		−0.0001*** (−5.8)		0.0001*** (4.11)		0.0001*** (3.05)
SAMEMB		0.0003*** (82.18)		0.0003*** (79.48)		0.0002*** (30.62)		0.0002*** (30.94)
SAMELEVERAGE		0.0001*** (8.63)		0.0001*** (4.67)		0.0001*** (13.08)		0.0001*** (14.01)
SIZE1		−0.005*** (−12.3)		−0.0051*** (−12.47)		−0.0080*** (−20.03)		−0.0085*** (−21.11)
SIZE2		0.0033*** (8)		0.0034*** (8.21)		0.0077*** (19.11)		0.0089*** (21.33)
SIZE1 × SIZE2		0.0003* (1.87)		0.0003** (2.12)		0.0039*** (15.98)		0.0046*** (18.33)
SAMEMOM						0.0002*** (26.49)		0.0002*** (26.75)
NUMSIC						0.0074*** (26.98)		0.0076*** (27.77)
DSTATE						0.0026** (2.38)		0.0027** (2.45)
DINDEX						0.0696*** (44.23)		0.0692*** (43.94)
DLISTING						0.0064*** (16.25)		0.0070*** (17.62)
Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	17,265,600	17,265,600	17,265,600	17,265,600	4,824,163	4,339,046	4,824,163	4,339,046
R^2 (within)	0.0001	0.0007	0.0001	0.0007	0.0013	0.0050	0.0010	0.0048

the effects of financial flexibility on stock comovement. To do so, we estimate the following regression:

$$\rho_{ij,t} = \beta_1 \times \text{COVID\_19}_t + \beta_2 \times \text{SAMEFINFLEX}_{ij} + \beta_3 \times \text{SAMEFINFLEX}_{ij} \times \text{COVID\_19}_t + \Gamma \times X_{ij} + \epsilon_{ij,t}, \tag{23}$$

where $\rho_{ij,t}$ is each stock pair's correlation in daily FF5 return residuals, and COVID19 is an indicator variable that takes value 0 for the "pre-COVID period" between Jan. 1, 2020, and Mar. 10, 2020, and 1 for the "COVID period" between Mar. 11, 2020, and Apr. 30, 2020.[34] As the market value of CRE assets is not

[34]We choose the COVID period to start from Mar. 11, 2020, because this is the day when the World Health Organization (WHO) announced the COVID-19 outbreak as a pandemic. The results are robust to

available for the time period of this sample, we construct our measure of similarity in financial flexibility, SAMEFINFLEX, using net leverage, defined as the ratio of net debt (short-term debt, Compustat item DLC, plus long-term debt, DLTT, minus cash holdings, CHE) to total assets (AT).[35] The set of controls, X_{ij}, includes the same variables as the previous analysis in Section III.A.[36] Finally, both SAMEFINFLEX_{ij} and the control variables in X_{ij} are measured using data for the pair of firms i and j as of Dec. 2019.

The sample for the COVID-19 event study includes all active firms in Compustat for which 2019 year-end annual accounting data are available. To compute return comovement for the pre- and post-pandemic-outbreak periods, $\rho_{ij,t}$, we obtain stock-price data at the daily frequency from the Compustat-Capital IQ Security Daily database. We apply the same data filters described in Section III.A.1. In addition, we exclude stocks with prices of less than 1 dollar and those with a security type other than "common, ordinary." Since we use net leverage as a measure of financial flexibility, we also drop firms with missing data on cash and short-term investments (Compustat item CHE). The summary statistics for the sample are available in the Supplementary Material.

The regression results are reported in Table 7. Column 1 shows that controlling for similarity across multiple dimensions of firm characteristics, stock comovement increased significantly in the period after the COVID-19 outbreak. This result is consistent with the findings from the univariate analysis of stock comovement for the S&P500 sample in Figure 1. In column 2, we include in the regression our measure of similarity in financial flexibility, SAMEFINFLEX, and find that the associated coefficient is positive and significant.

The main coefficient of interest in the event study, β_3, is associated with the interaction term between the COVID_19 indicator variable and SAMEFINFLEX. Column 3 of Table 7 shows the estimation results for the full regression specification in equation (23): The estimated β_3 coefficient is positive and statistically significant at the 1% level, which implies that the increase in stock comovement following the COVID-19 outbreak was larger for firms with similar levels of financial flexibility.

To test for any nonlinearity in the effect of financial-flexibility similarity on stock comovement, we replace SAMEFINFLEX_{ij} in equation (23) with DSAMEFINFLEX_{ij}, a dummy variable that equals 1 if firms i and j have a difference of up to 30 percentiles in the distribution of financial flexibility, and

using Feb. 24, 2020 (the day in which markets responded to the first substantial rise in COVID-19 cases outside of China), as the start date of the pandemic, and to using weekly correlations based on daily stock returns instead of computing the correlations in daily returns over the full pre- and post-outbreak periods. Moreover, our conclusions are unaffected if we define the COVID-19 period to start on Feb. 24, 2020, and end on Mar. 23, 2020, the last day before the market reacted to the economic stimulus announced by the Federal Reserve and Federal Open Market Committee.

[35]Using net leverage as a measure of financial flexibility is in line with the previous studies on the financial impact of COVID-19, such as De Vito and Gómez (2020), Ramelli and Wagner (2020), and Fahlenbrach et al. (2021).

[36]The only difference compared to Section II.A is that, to estimate equation (23), we drop from the set of controls the similarity in book leverage, SAMELEVERAGE. The reason is that we are already using the closely related variable net leverage, which is equal to book leverage minus the ratio of cash to assets, to measure financial flexibility in SAMEFINFLEX.

TABLE 7

COVID-19, Financial Flexibility, and Stock Comovement

Table 7 reports the results of the stock-comovement regression in equation (23). The dependent variable, $\rho_{ij,t}$, is the pairwise correlation in daily Fama and French (FF5) (2015) return residuals. COVID_19 is an indicator variable with a value of 0 for the period between Jan. 1, 2020, and Mar. 10, 2020, and 1 for the period between Mar. 11, 2020, and Apr. 30, 2020, (columns 1–5); between Mar. 11, 2020, and June 10, 2020, (columns 6–7); and between Mar. 11, 2020, and Sept. 10, 2020, (columns 8–9). SAMEFINFLEX is defined as the negative of the absolute value of the difference in net leverage (net debt/total assets) percentile ranking across the stocks in a pair. Net debt is long- and short-term debt minus cash. DSAMEFINFLEX is an indicator variable with value 1 if the firms in a pair have a difference of less than 30 percentiles in the distribution of net leverage, and 0 otherwise. All the columns control for similarity in firm characteristics, captured by the variables SAMESIZE, SAMEMB, SIZE1, SIZE2, SIZE1 × SIZE2, SAMEMOM, NUMSIC, DSTATE, DINDEX, and DLISTING. All firm characteristics are measured as of Dec. 2019. Section III.B describes data sources and sample construction, and Section III.A.1 provides the definitions of the control variables. Standard errors are clustered at the stock-pair level. *T*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Correlation of FF5 Residuals								
	Post-Covid Window:					Post-Covid Window:		Post-Covid Window:	
	Mar. 11, 2020–Apr. 30, 2020					Mar. 11, 2020–June 10, 2020		Mar. 11, 2020–Sept. 10, 2020	
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	1	2	3	4	5	6	7	8	9
COVID_19	0.0062***	0.0061***	0.0139***	0.0061***	0.0006	0.0154***	−0.0016**	0.0110***	−0.0001
	(12.01)	(11.66)	(16.08)	(11.83)	(0.88)	(20.17)	(2.49)	(15.73)	(−0.17)
SAMEFINFLEX		0.0004***	0.0003***			0.0003***		0.0003***	
		(38.09)	(22.81)			(23.13)		(23.23)	
COVID_19 × SAMEFINFLEX			0.0002***			0.0003***		0.0002***	
			(11.29)			(16.11)		(10.77)	
DSAMEFINFLEX				0.0154***	0.0102***		0.0105***		0.0105***
				(31.36)	(17.10)		(17.59)		(17.70)
COVID_19 × DSAMEFINFLEX					0.0106***		0.0136***		0.0096***
					(10.88)		(15.75)		(12.02)
SAMESIZE	0.0004***	0.0003***	0.0003***	0.0004***	0.0004***	0.0002***	0.0003***	0.0003***	0.0003***
	(33.73)	(28.78)	(28.77)	(30.49)	(30.49)	(22.08)	(24.18)	(26.99)	(28.95)
SAMEMB	0.0001***	0.0002***	0.0002***	0.0001***	0.0001***	0.0002***	0.0002***	0.0002***	0.0002***
	(12.01)	(12.74)	(12.74)	(12.41)	(12.41)	(18.25)	(17.82)	(20.04)	(19.66)
SIZE1	0.0004	0.0004	0.0004	0.0004	0.0004	−0.0004	−0.0004	0.0001	0.0001
	(1.45)	(1.46)	(1.48)	(1.45)	(1.48)	(−1.59)	(−1.62)	(0.43)	(0.42)
SIZE2	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	−0.0001	−0.0001
	(0.39)	(0.40)	(0.40)	(0.39)	(0.39)	(0.47)	(0.50)	(−0.36)	(−0.34)
SIZE1 × SIZE2	0.0005**	0.0005**	0.0005**	0.0005**	0.0005**	−0.0001	−0.0001	−0.0001	−0.0001
	(2.18)	(2.19)	(2.18)	(2.16)	(2.16)	(−0.17)	(−0.16)	(−0.67)	(−0.68)
SAMEMOM	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***
	(37.31)	(36.52)	(36.60)	(36.89)	(36.96)	(38.06)	(38.52)	(42.95)	(43.47)
NUMSIC	0.0218***	0.0212***	0.0212***	0.0214***	0.0214***	0.0228***	0.0230***	0.0223***	0.0225***
	(54.66)	(53.23)	(53.24)	(53.73)	(53.74)	(64.33)	(64.90)	(68.59)	(69.12)
DSTATE	0.0271***	0.0270***	0.0270***	0.0270***	0.0270***	0.0294***	0.0294***	0.0289***	0.0289***
	(23.46)	(23.40)	(23.40)	(23.41)	(23.41)	(28.76)	(28.79)	(30.89)	(30.93)
DINDEX	0.0831***	0.0815***	0.0815***	0.0821***	0.0821***	0.0790***	0.0797***	0.0728***	0.0733***
	(66.65)	(65.35)	(65.35)	(65.85)	(65.85)	(65.46)	(66.00)	(63.93)	(64.43)
DLISTING	0.0083***	0.0067***	0.0067***	0.0072***	0.0072***	0.0094***	0.0100***	0.0095***	0.0099***
	(16.60)	(13.37)	(13.38)	(14.48)	(14.49)	(21.11)	(22.39)	(23.33)	(24.48)
No. of obs.	1,113,843	1,113,843	1,113,843	1,113,843	1,113,843	1,237,108	1,237,108	1,255,305	1,255,305
Adj. R^2	0.0143	0.0156	0.0158	0.0152	0.0153	0.0173	0.0153	0.0188	0.0184

0 otherwise.[37] The results reported in column 5 of Table 7 indicate that the group of firms with the most similar levels of financial flexibility (DSAMEFINFLEX = 1) had 1.02% higher correlation before the COVID-19 shock than firms in the control group (DSAMEFINFLEX = 0). After the COVID-19 outbreak, this difference more than doubled to 2.08%. Thus, compared to the average stock comovement

[37]The results are robust when choosing different threshold percentiles. The regression estimates using 10-, 20-, and 50-percentile thresholds to define the variable DSAMEFINFLEX are available from the authors.

for the control group in the pre-COVID period (0.21%), the level of stock comovement in the COVID period for firms with the highest degree of similarity in financial flexibility was 10 times larger. Finally, in contrast to the results in column 3 using SAMEFINFLEX, the coefficient associated with the COVID-19 indicator in column 5 is not statistically significant. This result implies that the increase in stock comovement during the COVID-19 crisis is driven by the subsample of firms with the highest degree of similarity in terms of financial flexibility.

Overall, the findings from the event study based on the COVID-19 pandemic outbreak confirm the conclusions obtained in Section III.A, which showed that financial flexibility is an important determinant of stock comovement.

Robustness Tests

One potential concern about the results of this COVID-19 event study is the presence of diverging trends between the group of firms with high and low similarity in financial flexibility even before the COVID-19 outbreak. To address this issue, we perform 2 different tests. First, we compute the average correlation of daily FF5 return residuals at the weekly level for the subsample of firm pairs with DSAMEFINFLEX = 1 (the “treatment” group) and for the subsample with DSAMEFINFLEX = 0 (the “control” group). Graph A of Figure 6 plots the average correlation for the two groups between the first week of Jan. 2020 and the last week of Apr. 2020, as well as their 95% confidence intervals. This graph shows that the correlation for the two groups moved in parallel until the week starting on Feb. 24, the day when the stock markets reacted to the first substantial increase in COVID-19 cases outside of China. After this date, the average correlation of the 2 groups started diverging substantially.

Second, we perform a multivariate analysis to test whether the conclusions from the univariate analysis of correlation trends are robust to controlling for the determinants of comovement. In particular, we reestimate equation (23) substituting the COVID-19 indicator with dummies for each week. In Graph B of Figure 6, we plot the coefficients of weekly dummies interacted with DSAMEFINFLEX for this specification. Consistent with the assumption of parallel trends, the regression coefficients are not statistically different from 0 until the week starting on Feb. 24, 2020, while they become positive and significant for the later weeks.

As an additional robustness test, we extend the end date of the post-COVID-19 period from Apr. 30 to June 10, 2020 (columns 6 and 7 of Table 7), and Sept. 10, 2020 (columns 8 and 9), which correspond to 3- and 6-month windows after the outbreak of the COVID-19 pandemic, respectively. We do so to account for the possibility that firms delay their debt-financing response to the crisis by months. We find that the sign and magnitude of the coefficients associated with SAMEFINFLEX and with its interaction with the COVID-19 indicator are very similar using the alternative definitions of the post-COVID period (cf. columns 3, 6, and 8). Moreover, the results in columns 7 and 9 confirm the finding that the increase in stock comovement during the COVID-19 period is mainly driven by firms with the highest degree of similarity in financial flexibility, as measured by the variable DSAMEFINFLEX.

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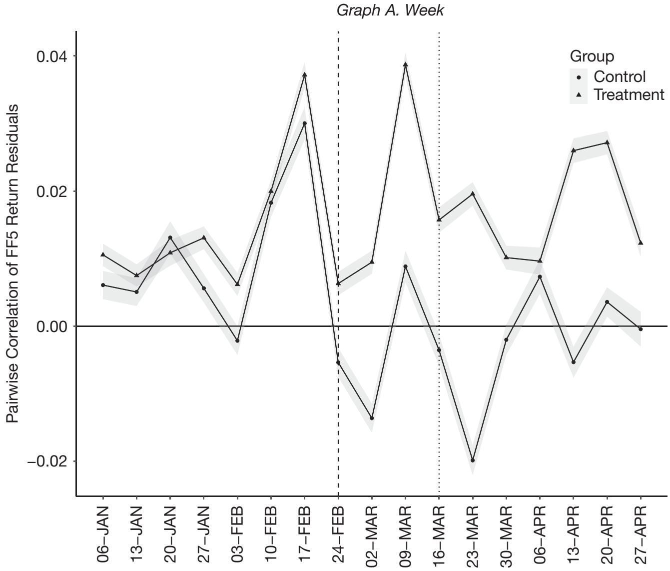
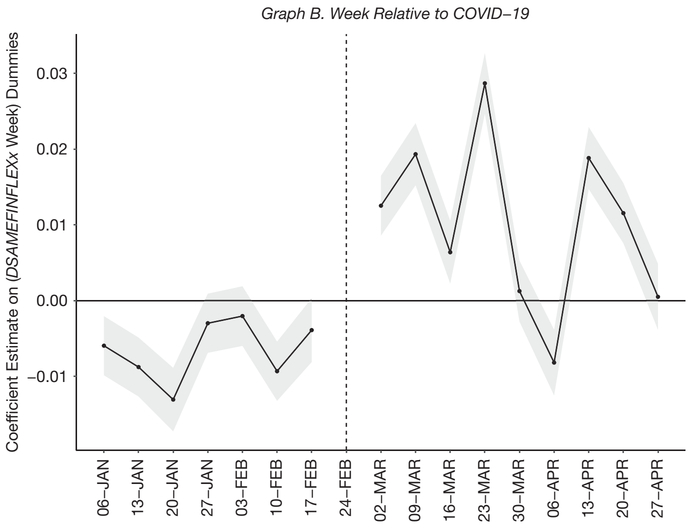
FIGURE 6

Test of Parallel Trends

Graph A of Figure 6 plots the average within-week pairwise correlation of Fama and French (FF5) (2015) stock-return residuals, $\rho_{ij,t}$ for the treatment (DSAMEFINFLEX = 1) and control (DSAMEFINFLEX = 0) groups around the outbreak of the COVID-19 pandemic in early 2020. DSAMEFINFLEX$_{ij}$ is an indicator variable that equals 1 if firms *i* and *j* have a difference of up to 30 percentiles in the distribution of financial flexibility (measured as the net leverage of the firm in Dec. 2019), and 0 otherwise. Graph B shows the coefficient estimates of the interaction terms between DSAMEFINFLEX and weekly dummies in the multivariate stock comovement regression (equation (23)). The details of the sample construction are provided in Section III.B.





C. External Validity

In this subsection, we perform 2 tests of external validity for our empirical results. First, we study the effects of financial flexibility on stock comovement across several developed economies. Second, as an additional event study, we analyze stock comovement around the bankruptcy of Lehman Brothers during the 2008 financial crisis.

1. Cross-Country Evidence

We extend our analysis of the determinants of stock comovement for U.S. companies in Section III.A to a set of developed countries across the world. In particular, we estimate separate stock comovement regressions (equation (20)) for firms listed in Great Britain, Japan, France, Germany, Italy, and Spain. Stock-return data are obtained from Datastream, while financial data comes from Compustat Global. Due to data constraints, we use net leverage (net debt/total assets) to construct the variable SAMEFINFLEX as in Section III.B. Finally, to be consistent with our previous analysis, we include the same set of control variables as for the U.S. data (except for DSTATE and DINDEX, which are specific to U.S. firms), and consider the same period, 1993 to 2018.

The results in Table 8 show that our findings on the determinants of stock comovement using U.S. data extend to other developed economies. Overall, the coefficient of interest on SAMEFINFLEX is positive and significant for all 6 countries, although its magnitude varies considerably (e.g., the coefficient for firms in Japan is twice that for firms in Great Britain).[38]

2. Financial Crisis Event Study

As a second external-validity test, we perform an event study of stock comovement around the collapse of Lehman Brothers, one of the defining moments of the 2008 financial crisis. This event is of particular interest to our analysis for two reasons. First, as shown in Figure 1, stock comovement spiked following the bankruptcy of Lehman Brothers in Sept. 2008. Second, firms experienced a significant negative shock to credit during this period (see, e.g., Campello, Graham, and Harvey (2010), Duchin, Ozbas, and Sensoy (2010)). To study the link between financial flexibility and stock comovement around the bankruptcy of Lehman Brothers, we estimate the following regression:

$$\text{(24)}\quad \begin{aligned}\rho_{ij,t} = {} & \beta_1 \times \text{LEHMAN\_BANKRUPTCY}_t + \beta_2 \times \text{SAMEFINFLEX}_{ij} \\ & + \beta_3 \times \text{SAMEFINFLEX}_{ij} \times \text{LEHMAN\_BANKRUPTCY}_t + \Gamma \times X_{ij} + \epsilon_{ij,t},\end{aligned}$$

where LEHMAN_BANKRUPTCY is an indicator variable that takes value 0 for the 3 months preceding bankruptcy (June 15, 2008, to Sept. 14, 2008) and 1 for the postbankruptcy period (between Sept. 15, 2008, the day when Lehman Brothers

[38]In unreported regressions, we find similar results for Finland, Greece, Netherlands, Norway, Portugal, Sweden, and Switzerland, while there is weaker evidence for Austria, Belgium, Denmark, and Ireland.

TABLE 8

Cross-Country Evidence

Table 8 reports the OLS estimates of the stock-comovement regression specified in equation (20) for major developed countries other than the United States. The dependent variable is the pairwise correlation, $\rho_{ij,t+1}$, computed for year $t+1$, between the monthly return residuals for stocks i and j in a pair. Return residuals are computed using the 5 factors in Fama and French (FF5) (2015). The main independent variable of interest is SAMEFINFLEX, defined as the negative of the absolute value of the difference in net leverage (net debt/total assets) percentile ranking across the stocks in a pair in year t. Net debt is long- and short-term debt minus cash. All the columns control for SAMESIZE, SAMEMB, SIZE1, SIZE2, SIZE1 × SIZE2, SAMEMOM, NUMSIC, DLISTING, and year-fixed effects. Details of the construction of the data sample and variable definitions can be found in Sections III.A.1 and III.C.1. Standard errors are clustered at the stock-pair level. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Correlation of FF5 Residuals					
	Great Britain	Japan	France	Germany	Italy	Spain
	OLS	OLS	OLS	OLS	OLS	OLS
	1	2	3	4	5	6
SAMEFINFLEX	0.00009***	0.00017***	0.00006***	0.00012***	0.00013***	0.00012***
	(23.99)	(102.40)	(7.36)	(12.43)	(5.89)	(2.81)
SAMESIZE	0.0006***	0.0013***	0.0002***	0.0004***	0.0001	0.0007***
	(49.57)	(176.16)	(7.27)	(8.65)	(1.40)	(4.13)
SAMEMB	0.0003***	0.0003***	0.0002***	0.0003***	0.0002***	0.0003***
	(67.52)	(190.36)	(19.63)	(27.52)	(7.29)	(7.46)
SIZE1	0.0140***	0.0366***	0.0007	0.0085***	−0.0040**	0.0053
	(42.62)	(186.79)	(1.08)	(6.66)	(−2.51)	(1.35)
SIZE2	0.0002	−0.0072***	0.0140***	0.0115***	0.0112***	0.0056
	(0.62)	(−38.45)	(21.83)	(9.52)	(7.28)	(1.44)
SIZE1 × SIZE2	0.0032***	0.0011***	0.0033***	0.0123***	0.0043***	0.0052***
	(21.72)	(14.69)	(9.70)	(22.98)	(5.44)	(3.21)
SAMEMOM	0.0002***	0.0004***	0.0002***	0.0006***	0.0002***	0.0003***
	(61.08)	(243.06)	(19.15)	(50.83)	(9.67)	(6.59)
NUMSIC	0.0089***	0.0202***	0.0131***	0.0092***	0.0188***	0.0211***
	(73.21)	(333.04)	(49.33)	(31.19)	(22.22)	(15.08)
DLISTING	0.0062***	0.0183***	0.0118***	0.0251***	0.0698***	0.0086**
	(22.17)	(141.37)	(2.89)	(53.34)	(22.70)	(2.00)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	14,536,855	70,879,468	2,880,822	2,285,610	402,138	121,603
R^2	0.0090	0.0280	0.0143	0.0130	0.0428	0.0346

filed for Chapter 11 bankruptcy protection, and Dec. 14, 2008). The definitions of all other variables are the same as in the COVID-19 event study in Section III.B, and the controls are based on firm characteristics as of Dec. 2007.[39]

The regression results in column 1 of Table 9 show a significant increase in stock comovement during Lehman Brothers' postbankruptcy period, controlling for similarity along several firm characteristics. The regression specification in column 2 includes SAMEFINFLEX, and we find that the associated coefficient is positive and significant. Column 3 presents the estimates for the full regression specification in equation (24). The positive coefficient β_3 on the interaction term implies that the post-Lehman-bankruptcy increase in stock comovement was larger for firms with higher similarity in financial flexibility. Finally, to test for nonlinear effects in the variable of interest, we replace SAMEFINFLEX with the indicator variable DSAMEFINFLEX, which takes value 1 if the firms in a pair have a difference of less than 30 percentiles in the distribution of net leverage. The results

[39]We use the same data sources as the COVID-19 event study. The Supplementary Material reports the summary statistics for the sample.

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TABLE 9

2008 Financial Crisis Event Study

Table 9 reports the results of the stock comovement regression in equation (24). The dependent variable, $\rho_{ij,t}$, is the pairwise correlation in daily Fama and French (FF5) (2015) return residuals. LEHMAN_BANKRUPTCY is an indicator variable with a value of 0 for the period between June 15, 2008, and Sept. 14, 2008, and 1 for the period between Sept. 15, 2008, and Dec. 14, 2008. SAMEFINFLEX is defined as the negative of the absolute value of the difference in net leverage (net debt/total assets) percentile ranking across the stocks in a pair. Net debt is long- and short-term debt minus cash. DSAMEFINFLEX is an indicator variable with value 1 if the firms in a pair have a difference of less than 30 percentiles in the distribution of net leverage, and 0 otherwise. All the columns control for similarity in firm characteristics, captured by the variables SAMESIZE, SAMEMB, SIZE1, SIZE2, SIZE1 × SIZE2, SAMEMOM, NUMSIC, DSTATE, DINDEX, and DLISTING. All firm characteristics are measured as of Dec. 2007. Section III.B describes data sources and sample construction and Section III.A.1 provides the definitions of the control variables. Standard errors are clustered at the stock-pair level. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Correlation of FF5 Residuals				
	OLS	OLS	OLS	OLS	OLS
	1	2	3	4	5
LEHMAN_BANKRUPTCY	0.0052*** (24.97)	0.0052*** (24.92)	0.0076*** (21.64)	0.0052*** (24.94)	0.0035*** (12.11)
SAMEFINFLEX		0.0001*** (7.42)	−0.0001 (−0.80)		
LEHMAN_BANKRUPTCY × SAMEFINFLEX			0.0001*** (8.76)		
DSAMEFINFLEX				0.0014*** (6.95)	−0.0001 (−0.43)
LEHMAN_BANKRUPTCY × DSAMEFINFLEX					0.0031*** (7.75)
SAMESIZE	0.0005*** (112.41)	0.0005*** (110.61)	0.0005*** (110.63)	0.0005*** (111.15)	0.0005*** (111.17)
SAMEMB	0.0002*** (42.99)	0.0002*** (43.35)	0.0002*** (43.34)	0.0002*** (43.26)	0.0002*** (43.26)
SIZE1	−0.0002 (−1.54)	−0.0002 (−1.54)	−0.0002 (−1.55)	−0.0002 (−1.54)	−0.0002 (−1.55)
SIZE2	0.0001 (0.51)	0.0001 (0.51)	0.0001 (0.51)	0.0001 (0.51)	0.0001 (0.51)
SIZE1 × SIZE2	0.0001 (0.54)	0.0001 (0.55)	0.0001 (0.55)	0.0001 (0.55)	0.0001 (0.56)
SAMEMOM	0.0001*** (24.95)	0.0001*** (24.83)	0.0001*** (24.86)	0.0001*** (24.89)	0.0001*** (24.91)
NUMSIC	0.0151*** (97.47)	0.0150*** (97.08)	0.0150*** (97.09)	0.0150*** (97.16)	0.0150*** (97.17)
DSTATE	0.0175*** (39.24)	0.0174*** (39.04)	0.0174*** (39.05)	0.0174*** (39.07)	0.0174*** (39.08)
DINDEX	0.0395*** (45.27)	0.0393*** (45.09)	0.0393*** (45.09)	0.0394*** (45.15)	0.0394*** (45.15)
DLISTING	0.0040*** (18.80)	0.0039*** (18.44)	0.0039*** (18.43)	0.0039*** (18.46)	0.0039*** (18.46)
No. of obs.	4,139,406	4,139,406	4,139,406	4,139,406	4,139,406
Adj. R^2	0.0107	0.0107	0.0108	0.0107	0.0108

in column 5 confirm the significant increase in stock comovement after the collapse of Lehman Brothers for firms with the highest degree of similarity in financial flexibility.

Overall, the results from the Lehman Brothers event study are consistent with those obtained in the COVID-19 event study, indicating that similarity in financial flexibility has been an important determinant of stock comovement in the 2 most recent global crises.

A final comment on the interpretation of the results from the two event studies is in order. It is important to notice that the main variable of interest in our analysis,

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SAMEFINFLEX, measures the degree of similarity in financial flexibility across firms. As discussed in Section II.C, similarity in firm characteristics, such as financial flexibility, translates into similarity in firms' investment and leverage policies, in their exposure to systematic shocks, and ultimately in stock comovement. During the financial and COVID-19 crises, firms experienced aggregate shocks of different natures: economic, such as drops in aggregate demand, and financial, such as large systematic increases in credit-risk premia (see, e.g., Duchin et al. (2010), Nozawa and Qiu (2021), for evidence on spreads during the 2008 financial crisis and the COVID-19 crisis, respectively). While we cannot identify separately the effect on stock comovement of each aggregate shock that took place during the crises, the event study design allows us to estimate the combined effect of these shocks on comovement through financial flexibility.

D. Comovement in Sharpe Ratios

So far, we have analyzed the determinants of comovement in stock-return residuals after filtering out expected returns, as captured by the FF5 or alternative factor models. However, it is natural to ask whether similarity in financial flexibility is also related to comovement in excess returns, return volatilities, and Sharpe ratios. To answer this question, we apply a 4-step approach to both model-generated and real data.[40] First, for each year, we compute the monthly stock returns in excess of the risk-free rate. Second, for each month, we compute the standard deviation of excess returns using a 1-year-forward rolling window. Third, for each firm, we compute the ratio between monthly excess returns and the standard deviation of returns. Fourth, we estimate the comovement regression in equation (20) using the pairwise correlation in excess returns over the year as the dependent variable, and the measures of similarity in firm characteristics as independent variables, computed at the beginning of the year. We do the same for the correlation in return volatilities and in Sharpe ratios between firm pairs.

We expect the coefficients on SAMEFINFLEX to be positive in the comovement regressions using excess returns and return volatility. The reason is that, if 2 firms are alike in terms of financial flexibility, they should have similar return distributions. The regression results obtained using the simulated data from the model (columns 1 and 2 of Table 10) are in line with this hypothesis. When analyzing comovement in Sharpe ratios, it is important to notice that the sign of the coefficient associated with SAMEFINFLEX could be either positive or negative, depending on whether the impact of SAMEFINFLEX on comovement in expected excess returns (the numerator of the Sharpe ratio) is stronger than the effect on comovement in return volatility (the denominator). Column 3 shows that, in the model, the coefficient on SAMEFINFLEX is positive, implying that the effect on the numerator of the Sharpe ratio dominates the effect on the denominator. The results obtained from the real data (columns 4–6) are in line with the predictions

[40]For the real data, we use the same sample of U.S. stocks considered in Section III.A. The simulated data is generated after solving the model according to the parameters reported in Panel A of Table 1 and using free debt capacity as a measure of financial flexibility (the results are qualitatively unchanged using the shadow price of new debt).

TABLE 10

Comovement in Excess Returns, Volatility, and Sharpe Ratios

Table 10 provides the regression results of comovement in excess returns, volatility of returns, and Sharpe ratios. Columns 1–3 provide the results for the simulated data and columns 4–6 for the real data. The simulated data are generated by solving the model with the parameters reported in Panel A of Table 1, and using free debt capacity as a measure of financial flexibility. The real-data sample is described in Section III.A.1. Columns 1 and 4 report the estimates of comovement regressions for excess returns for simulated and real data, respectively, where the dependent variable is the correlation in monthly excess returns between firm *i* and firm *j* in year *t*. Columns 2 and 5 report the results of similar regressions for the comovement in the standard deviation of excess returns, computed for each month using a 1-year-forward rolling window, and columns 3 and 6 report the comovement in Sharpe ratios, defined as the ratio between monthly excess return over standard deviation of excess returns. The main independent variable of interest is SAMEFINFLEX, defined as the negative of the absolute value of the difference in percentile rankings of free debt capacity (columns 1–3), and real estate market value (RE_VALUE) (columns 4–6), for the firms in a pair. All the columns control for similarity in firm characteristics, captured by the variables SAMESIZE, SAMEMB, SAMELEVERAGE, SIZE1, SIZE2, and SIZE1 × SIZE2. Columns 4–6 also control for SAMEMOM, NUMSIC, DSTATE, DINDEX, and DLISTING. All the columns include year-fixed effects. Standard errors are clustered at the stock-pair level. *T*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Model			Data		
	Excess Returns	Std. Dev.	Sharpe Ratios	Excess Returns	Std. Dev.	Sharpe Ratios
	1	2	3	4	5	6
SAMEFINFLEX	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	(3.21)	(4.99)	(5.6)	(20.76)	(4.98)	(19.28)
SAMESIZE	−0.0001***	−0.0001***	−0.0001***	0.0001***	−0.0001	0.0001***
	(−4.34)	(−4.28)	(−6.1)	(6.06)	(−0.87)	(6.86)
SAMEMB	0.0001***	0.0001	0.0002***	0.0002***	0.0002***	0.0002***
	(8.67)	(0.97)	(44.87)	(42.49)	(18.67)	(37.77)
SAMELEVERAGE	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	(16.39)	(13.37)	(3.44)	(5.88)	(6.67)	(6.34)
SIZE1	−0.0001***	−0.0001***	−0.0001***	−0.0041***	0.0041***	−0.0029***
	(−9.99)	(−11.22)	(−12.24)	(−14.72)	(8.43)	(−10.46)
SIZE2	0.0003	0.0001	0.0007***	0.0278***	0.0131***	0.0276***
	(1.5)	(0.36)	(3.33)	(99.18)	(27.10)	(98.05)
SIZE1 × SIZE2	−0.0001	0.0001	0.0006***	0.0012***	0.0030***	0.0008***
	(−0.43)	(0.44)	(5.53)	(6.75)	(10.12)	(4.65)
SAMEMOM				−0.0001***	0.0003***	−0.0001***
				(−10.48)	(34.55)	(−12.24)
NUMSIC				0.0086***	0.0026***	0.0085***
				(45.30)	(8.04)	(44.20)
DSTATE				−0.0007	0.0012	−0.0009
				(−0.84)	(0.87)	(−1.14)
DINDEX				0.0301***	0.0246***	0.0304***
				(25.27)	(12.20)	(25.60)
DLISTING				0.0088***	0.0092***	0.0092***
				(31.71)	(19.10)	(33.07)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	17,265,600	17,265,600	17,265,408	5,647,883	5,965,417	5,596,768
R^2	0.0002	0.0001	0.0003	0.0485	0.0149	0.046

from the model. In summary, the regression results show that similarity in financial flexibility is positively correlated with comovement in excess returns, in the standard deviation of returns, and Sharpe ratios.

IV. Conclusions

We document the role of firms' financial flexibility as a determinant of stock-return comovement. To do so, we first develop a dynamic model of corporate investment and financing with heterogeneous firms, in which shocks to the value of collateralizable assets provide exogenous variation in debt capacity. We show that, in equilibrium, the correlation in stock returns between 2 firms increases with the level of similarity in their financial flexibility.

We test the implications of the model on a sample of U.S. firms for the period of 1993 to 2018. Our empirical strategy relies on shocks to the market value of CRE assets – which represent a substantial fraction of firms' collateralizable assets – to generate exogenous variation in firms' debt capacity and, therefore, financial flexibility. Consistent with the predictions of the model, we find that pairs of stocks with more-similar levels of financial flexibility exhibit higher stock correlation, after controlling for exposure to systematic return factors and several other dimensions of similarity across firms. We confirm the conclusions of this analysis in a second empirical test, in which we perform an event study around the outbreak of the COVID-19 pandemic.

Our novel results on the link between financial flexibility and stock comovement have important implications for investors. For example, our insights can be used to set up new trading strategies that exploit the information in the collateral value of corporate assets and its effect on stock correlation to generate portfolio excess returns. Moreover, our findings provide new insights for regulators and policymakers. For instance, an implication of our results is that, to the extent that monetary policy and banking macroprudential regulations affect firms' financial flexibility, they may have unintended consequences on comovement in the stock markets and, therefore, affect the extent to which investors can diversify the risk of their equity portfolios. We leave the analysis of these issues to future research.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109022001338.

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