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 separate 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 that are 50 percentiles apart.

Keywords: Return Comovement, Financial Flexibility, COVID-19

JEL codes: G12, G32

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1 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 across stocks. The degree of stock return comovement varies considerably over time. Figure 1 plots the time series of stock comovement for the period 2006–2020. The average pairwise correlation in daily stock return residuals—after controlling for the five factors in Fama and French (2015), henceforth FF5—typically fluctuates between 1% and 10% for the firms in the S&P 500 index. However, average correlation peaked in periods characterized by shocks to firms' financial flexibility, such as the start of the financial crisis following the bankruptcy of Lehman Brothers in September 2008 and the outbreak of the COVID-19 crisis in March 2020. In this paper, 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.

[Insert figure 1 around here]

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 two 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 firms' characteristics, such as size, market-to-book, and leverage. To the best of our knowledge, this is the first paper to study stock comovement within an investment-based model with rich debt dynamics.

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

We test the predictions of the model 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, which represented 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. non-financial 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 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 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

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

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

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 at the same time 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. By doing so, we are able to isolate 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 had a significant impact on 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 post-outbreak period. However, we find that this increase was driven by the subsample of firms with the highest degree of similarity in financial flexibility.[5] 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 post-outbreak level of stock comovement for firms with the highest degree of similarity in financial flexibility was ten times larger than the average stock comovement of other firms in the pre-outbreak 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,

[4]We set the pre-COVID period to be between January 1, 2020 and March 10, 2020, and the COVID period between March 11, 2020 and April 30, 2020. As a reference date for the start of the COVID-19 period, we use March 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 Fahlenbrach, Rageth, and Stulz (2021), Ramelli and Wagner (2020), and De Vito and Gómez (2020).

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 that the results are consistent 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 paper 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 paper 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, Sapriza, and Zhang (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 et al. (2022) also introduce shocks to collateralizable assets in a structural corporate finance model to study the 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, but do not examine the cross-sectional variation in pairwise return correla-

[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 of stocks, rather than individual ones, 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 are 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 2.1.4.

tions. 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 corporate real estate 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 the returns 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 paper, 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, a large body of literature provides evidence on how the sensitivity of stock returns to common factors relates to the cross-section of expected returns (see, for example, Harvey, Liu, and Zhu 2016), while fewer studies focus on the correlation in stock return residuals. For example, De Bodt, Eckbo, and Roll (2021) show how shocks to industry competition affect comovement in stock return residuals for rival firms, after filtering out the effect of the common risk factors in Fama and French (2015). 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, Shleifer, and Wurgler (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 the 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 (2022) show the implications of using heterogeneous benchmarks to assess the performance of

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

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, namely financial flexibility, predicts future correlation in stock returns.

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

The remainder of the paper is structured as follows. In section II, we introduce the setup of the model, discuss the equilibrium, and present the numerical results and main model's 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.

2 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 main empirical predictions of the model in terms of stock comovement.

2.1 Setup of the Model

We build on the model in Livdan, Sapriza, and Zhang (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 in a parsimonious way, as our model only features the key characteristics—endogenous choice of investment, leverage, aggregate and firm-specific shocks to profitability, and shocks to collateralizable assets—that are necessary to derive the predictions that we will test in the empirical analysis on stock comovement in section 3.

2.1.1 Technology and Investment

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

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

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 law of motion of the aggregate productivity shock is

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

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,

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

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_t^x and ε_{jt}^z are i.i.d. standard-normal shocks, ε_t^x is independent of ε_{jt}^z, and ε_{jt}^z and ε_{lt}^z are independent for $j \neq l$.

The firm accumulates capital according to

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

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

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

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

2.1.2 Stochastic Discount Factor

Following Zhang (2005) and Livdan, Sapriza, and Zhang (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 two periods, x_t and x_{t+1}, and is given by

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

$$\gamma_t = \gamma_0 + \gamma_1 x_t, \tag{7}$$

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

2.1.3 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 the risk-free interest rate, r_{ft}. We assume that the firm can use as collateral both its capital stock, k, and its non-operating 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

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

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, Sapriza, and Zhang (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 2.2.3 below), 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

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

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

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

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

2.1.4 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, like in our model, affect directly collateral value, while Catherine et al. (2022) quantify the effects of the existence of collateral constraints on aggregate output and total factor

[9] As in Catherine et al. (2022), we assume that non-operating 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 3.1, in which identification relies on the presence of local shocks to an important component of collateralizable assets, namely corporate real estate assets.

productivity. Moreover, several papers document that shocks to collateral values affect corporate investment in the data (e.g., Lamont 1997, Gan 2007, and Chaney, Sraer, and Thesmar 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 of using a continuous-time setting. One of the main advantages is that, depending on how tractable the model is, 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), it is unlikely that a closed-form solution would be possible even if one reformulated the model in a continuous-time setting.

2.2 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.

2.2.1 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

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

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

[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 adjustment costs of capital. 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.

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

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

and

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

respectively.

2.2.2 Expected Returns

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

$$R_{jt+1} = \frac{V_{jt+1}}{V_{jt} - d_{jt}}. \qquad (16)$$

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

$$\beta_{jt} = -\mathbf{Cov}[M_{t+1}, R_{jt+1}]/\mathbf{Var}[M_{t+1}], \qquad (17)$$

price of risk $\chi_t = \mathbf{Var}[M_{t+1}]/\mathbf{E}[M_{t+1}]$, and 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}.

2.2.3 Measures of Financial Flexibility

We define two model-implied measures of financial flexibility. The first one follows the definition of shadow price of new debt in Livdan, Sapriza, and Zhang (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, ν_{jt}, is given by

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

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

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

where b_{jt+1} is the amount of debt to be repaid in the next period and $s(1-\delta)k_{jt+1}+\mathbf{E}[\exp(p_{jt+1})|p_{jt}]H$ is the debt capacity, i.e. the maximum amount of debt that the firm can raise. This measure simply captures the distance between the firm's debt usage and debt limit.

2.2.4 Calibration

To provide economic intuition for the policy functions of the model and generate empirical predictions in terms of stock return comovement, in this subsection we perform the model calibration. 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 Online Appendix. 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, time length, and frequency of the simulated sample are comparable to those of the real-data sample that we use in the empirical section of the paper (see section 3.1.1 for the details on data construction).

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

Panel A in table 1 reports the calibration parameters. Whenever possible, we take the parameter values directly from the literature to be able to compare our results with the ones in previous papers. In particular, several parameter values are from Livdan, Sapriza, and Zhang (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).

[Insert table 1 around here]

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 in 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 non-operating 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 in table 1 compares several moments simulated from the model to their counterparts in the real data. Overall, the model does a good job matching real-data asset pricing moments that are of key interest in the paper, but that are not 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, and the model generates an average

[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:

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

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 $\sigma_p = 0.08$.

3.2% pairwise correlation in one-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 positive serial correlation in investment and profitability; and the correlation coefficients of investment with Tobin's Q and with leverage have the same signs as in the real data.

2.2.5 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 (subplot 2.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 (2.C), and to even issue costly external equity (2.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).

[Insert figure 2 around here]

[13] See section 2.3 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 the ones reported by Hackbarth and Johnson (2015): market Sharpe ratio of 0.39 and average firm Sharpe ratio of 0.23 for the period 1960–2009.

[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.

Figure 3 plots the optimal policies against the firm-specific productivity shock z, for different levels of price p. Because productivity is positively autocorrelated, when z is high the firm has better expected investment opportunities for the next period, so the investment rate is high (subplot 3.A). To finance its investment needs, the company increases book leverage (3.B) and uses up all its free debt capacity (3.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 that the firm can raise is an increasing function of z: higher productivity implies higher capital in the next period, k', which can be used as collateral (see equation 8). In figure 3, this effect is even more evident for 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.

[Insert figure 3 around here]

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

2.3 Model Predictions

In this section, we set up the empirical strategy to analyze the predictions of the model in terms of stock return comovement, which is the main focus of the paper. 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 in a similar way, 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 higher stock comovement.

To test this hypothesis, we define stock comovement, denoted by $\rho_{ij,t}$, as the pairwise correlation in one-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.

2.3.1 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 paper. To construct measures of pairwise similarity in financial flexibility, we sort all firms in the simulated panel into percentiles according to their level of financial flexibility (defined in subsection 2.2.3 either as the shadow price of new debt, ν_{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, $SAMEFINFLEX_{ij,t}$, 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 100$^{\text{th}}$ percentile) to zero (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, $SAMEFINFLEX_{ij,t}$, computed using the shadow price

[16]Notice that, as shown in section 2.2.2, 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 2.2.4, we simulate 50 panels of 1,200 firms each. The results reported in this section correspond to the average across these panels of firms.

of new debt in subplot 4.A and the free debt capacity in subplot 4.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]

[Insert figure 4 around here]

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 following multivariate regression:

$$\rho_{ij,t+1} = \alpha + \beta \cdot SAMEFINFLEX_{ij,t} + \Gamma \cdot X_{ij,t} + \epsilon_{ij,t}, \tag{20}$$

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 of these variables, 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 two 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.

[Insert table 2 around here]

[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, so that there is a small number of observations with low *SAMEFINFLEX*. For example, 1.98% of pairs in our simulated sample have *SAMEFINFLEX=-1*, while only 0.02% have *SAMEFINFLEX=-99*.

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 one-percentile increase in similarity in terms of financial flexibility between two 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.

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 both by positive or negative shocks to collateral or profitability. To see this, consider two 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 two firms diverges following the shock: firm A has higher financial flexibility than firm B, causing a decrease in *SAMEFINFLEX* for the two 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.

2.3.2 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 zero, 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 that there are no shocks to the value of collateralizable assets, that is, $p_{jt} = 0$ for all t and j, similar to Livdan, Sapriza, and Zhang (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, Sapriza, and Zhang (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 subsection 3.1.2). 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, two 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, Sapriza, and Zhang (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, but 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 for our predictions.

To the best of our knowledge, this is the first paper to show that similarity in firm characteristics

[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.

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, Eckbo, and Roll 2021). 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.

3 Empirical Results

In this section, we develop two empirical strategies to test the effect of financial flexibility on stock return comovement in the real data. The first one employs variation in the market value of corporate real estate 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.

3.1 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 non-operating collateralizable assets is equal to $\mathbf{E}\big[\exp(p_{jt+1})|p_{jt}\big]H$, it varies over time as a function of the price p, and it affects directly the maximum amount of debt capacity (c.f. equation 8). The main determinant of collateralizable assets for actual firms is represented by corporate real estate 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 corporate real estate 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 2.3 (equation

[20]See section 3.1.1 for data construction.

20):

$$\rho_{ij,t+1} = \alpha + \beta \cdot SAMEFINFLEX_{ij,t} + \Gamma \cdot X_{ij,t} + \epsilon_{ij,t}.$$

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 two firms in the pair. The market value of real estate assets, $REValue^l_{it}$, is the ratio of the market value of the corporate real estate assets that firm i owns in location l in year t to lagged PPE.[22] Finally, we include a set of control variables, $X_{ij,t}$, which we describe in the next subsection.

When estimating the comovement regression in the real data, a possible source of endogeneity could be due to the presence of an omitted variable that affects at the same time real estate prices and the comovement of stock returns across firms, such as an unobserved local economic shock. To address this endogeneity concern, we employ the instrumental variable (IV) approach developed in Himmelberg, Mayer, and Sinai (2005) and Mian and Sufi (2011), who use the following equation to predict real estate prices P^l_t for location l at time t:

$$P^l_t = \alpha^l + \delta_t + \gamma \cdot Elasticity^l \cdot IR_t + u^l_t, \tag{21}$$

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

[21]The five factors proposed by Fama and French (2015) 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, $REValue^l_{it}$, we follow procedures that are standard in the literature. See the Online Appendix for details.

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, that is, in areas where real estate prices will increase the most.

In our application, the main variable of interest, $SAMEFINFLEX_{ij,t}$, is measured as a non-linear transformation of the corporate real estate asset values of the pair of firms i and j. To deal with pair-level observations, we adapt the identification approach of Himmelberg, Mayer, and Sinai (2005) and Mian and Sufi (2011) by instrumenting $SAMEFINFLEX_{ij,t}$ 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

$$\mu_{ij,t} = PR\left[-\left|Elasticity^l \times REValue^l_{i0} - Elasticity^m \times REValue^m_{j0}\right| \times IR_t\right], \tag{22}$$

where $PR[\cdot]$ denotes the percentile ranking, l and m are the MSAs in which firms i and j are located, respectively, and following Cvijanović (2014) we include $REValue^l_0$, the market value of corporate real estate assets for the firm in the initial year of the sample.[23] We implement our instrumental variable approach by using two-stage least squares (2SLS) to estimate equation (20). Moreover, we exclude pairs of firms that are 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 three 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 corporate real estate assets on stock returns through the appreciation of the value of these assets. This is due to the fact that the value of corporate real estate assets equals the present value of their future rents (see, for example, Ling and Archer 2012 and Geltner et al. 2001). Therefore, the positive effect related to an increase in corporate real estate prices

[23] As explained in the Online Appendix, 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.

compensates in expectation the negative effect due to the subsequent increase in imputed rents in the future. 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.

3.1.1 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 standard in the corporate finance literature, we omit financial firms, utilities, not-for-profit and governmental firms as well as firms with missing values of PPE or total assets. Accounting data is 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 five Fama and French (2015) factors (see footnote 21). In robustness tests, we also compute four alternative measures of return residuals: using only the market (CAPM) factor; accounting for the three factors in Fama and French (1993) and the momentum factor of Carhart (1997); and augmenting the FF5 model with the *Quality-Minus-Junk* factor in Asness, Frazzini, and Pedersen (2019) and with the *Betting-Against-Beta* factor in Frazzini and Pedersen (2014).[24]

The independent variable of main interest in our analysis is similarity in financial flexibility among firms, $SAMEFINFLEX_{ij,t}$. 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 property, plant, and equipment (PPE).[25] To do so, we obtain residential real estate indices from the Federal Housing Finance Association (FHFA) at the MSA level, and construct the market value of corporate real estate assets following standard procedures in the

[24] We obtain the Fama and French (2015), Fama and French (1993), and Carhart (1997) daily return factors from Ken French's website. Data on the *Quality-Minus-Junk* and *Betting-Against-Beta* factors are from Andrea Frazzini's webpage.

[25] Welch (2020) criticizes the common practice of using the same scaling variable for the dependent and independent variables in a regression, pointing to the paper by Chaney, Sraer, and Thesmar (2012), in which the dependent variable is capital expenditure scaled by the lagged PPE and the main independent variable is market value of real estate assets scaled by lagged PPE. This problem does not arise in our case, because the dependent variable is constructed from stock returns, while the main independent variable is based on accounting data.

literature (c.f. Kumar and Vergara-Alert 2020, see the Online Appendix 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 2.3): *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 two firms in the pair, respectively.

In addition, $X_{ij,t}$ contains variables that have been shown in the previous literature to be significant determinants of stock comovement (see Antón and Polk 2014). The first one is *SAMEMOM*, which is 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 two 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 one 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 zero otherwise.

Finally, as mentioned above, to address the potential endogeneity problem of local real estate prices, we follow Himmelberg, Mayer, and Sinai (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 in Saiz (2010). These measures capture the amount of developable land in each MSA and are estimated by processing satellite-generated data on 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 exhibits the summary statistics for the variables that we use in our empirical analysis. Moreover, the table provides summary statistics on additional variables which are informative about our sample, such as profitability, cash holdings, and the growth ratio of assets and sales.

[Insert table 3 around here]

3.1.2 Results

To study the relationship between financial flexibility and stock comovement in our sample, we start from a bivariate analysis similar to the one performed in section 2.3. 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, $SAMEFINFLEX_{ij,t}$, based on the market value of corporate real estate 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.[26] This change (1.3%) represents a 163% increase in average stock comovement, and its magnitude is comparable to the results obtained in the 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).

[Insert figure 5 around here]

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 3.1.1. 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 four factors of Fama and French (1993) and Carhart (1997), and columns [7]-[10] account for the five Fama and French (2015) factors. For comparison purposes, in columns [1] and [2] we report the estimation results using the simulated data.[27]

[26] 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*.

[27] In columns [1]-[2], we use free debt capacity as a measure of financial flexibility. Results based on the shadow

[Insert table 4 around here]

Overall, the OLS coefficient for *SAMEFINFLEX* is positive and significant across all specifications (columns [3] to [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*), 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 instrumental variable μ (equation 22), using FF5 residuals to compute stock comovement.[28] 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 one 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.

3.1.3 Robustness Tests

To check the validity of our empirical results for different subsamples of firms, we re-estimate 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 on the validity of the instrumental variable and on the presence of

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price of new debt are qualitatively similar and are available upon request from the authors. The specifications in columns [1]-[2] of Table 4 are similar to those in columns [3]-[4] in Table 2, but we add the size controls to maintain consistency in the regression specification between the real and simulated data samples.

[28] The estimates of the first-stage regressions are available upon request.

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 two subsamples of firms in the top and bottom three deciles of the Tobin's Q distribution.[29] Columns [1]-[2] of Table 5 present the regression results for the two subsamples. Consistent with our hypothesis, we find that the coefficient associated with *SAMEFINFLEX* is three times larger for the subsample of firms with better investment opportunities.

[Insert table 5 around here]

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 three deciles of firms' age distribution.[30] 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 et al. (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

[29] 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, namely firm age and net leverage. Following Almeida and Campello (2007), we define Tobin's Q as (AT+(PRCC$\times$ CSHO) – CEQ – TXDB)/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.

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

positive and significant also for mature firms, for which the effect of the variables that determine the choice of location is less relevant, mitigates the concerns about a potential selection effect.[31]

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.[32] Column [5] of Table 5 presents the regression results for the subsample of firms in the bottom three deciles of net leverage, while column [6] shows the results for firms in the top three 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 two 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 five factors proposed by Fama and French (2015). 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 two robustness tests that control for additional potential determinants of stock returns. First, we compute the return residuals by adding the *Quality-Minus-Junk* (QMJ) factor of Asness, Frazzini, and Pedersen (2019) to the five-factor model of Fama and

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

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

French (2015). 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 *Betting-Against-Beta* (BAB) factor proposed by Frazzini and Pedersen (2014). The BAB factor is long on leveraged low-beta assets and short on high-beta assets.

The results of the comovement regressions using these six-factor models are reported in the Online Appendix. 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.[33]

Instrument Validity. One potential concern regarding the validity of our instrument, which is based on the market value of corporate real estate, is that land availability and land-use regulations could be correlated with 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 including these interaction terms and are available from the authors upon request.

Fixed Unobserved Heterogeneity. Finally, we address the potential presence of time-invariant unobserved heterogeneity affecting stock comovement between pairs of firms. To do so, in table 6 we estimate 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.

[Insert table 6 around here]

[33] In a recent paper, Grieser, Lee, and Zekhnini (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, Lee, and Zekhnini (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 3.2).

3.2 Empirical Strategy 2: COVID-19 Event Study

The outbreak of the COVID-19 pandemic was an unexpected event for the global economy. Managers and policy makers 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 five risks in the ranking of the World Economic Forum's 2020 Global Risk Report were all related to environmental events.[34] 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, Fahlenbrach, Rageth, and Stulz (2021) and Ramelli and Wagner (2020) find that firms with higher financial flexibility experienced a lower decrease in stock returns following the outbreak of the pandemic.[35]

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

$$\begin{aligned}\rho_{ij,t} =& \beta_1 \cdot COVID19_t + \beta_2 \cdot SAMEFINFLEX_{ij} \\ &+ \beta_3 \cdot SAMEFINFLEX_{ij} \times COVID19_t + \Gamma \cdot X_{ij} + \epsilon_{ij,t}\end{aligned} \tag{23}$$

where $\rho_{ij,t}$ is the correlation between each stock pair's daily FF5 return residuals, and *COVID19* is an indicator variable that takes value zero for the "pre-COVID period" between January 1, 2020 and March 10, 2020, and one for the "COVID period" between March 11, 2020 and April 30, 2020.[36]

[34]See https://www.weforum.org/reports/the-global-risks-report-2020.

[35]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 et al. (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 et al. (2020) and Davis, Hansen, and Seminario-Amez (2020).

[36]We choose the COVID period to start from March 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 using February 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 February 24, 2020 and end on March 23, 2020, the last day before the market reacted to the economic stimulus announced by the Federal Reserve and Federal Open Market Committee.

As the market value of corporate real estate assets is not available for the time period of this sample, in this section 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).[37] The set of controls, X_{ij}, includes the same variables as the previous analysis in section 3.1.[38] 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 December 2019.

The sample for the COVID-19 event study includes all active firms in Compustat for which 2019 year-end annual accounting data is 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 3.1.1. In addition, we exclude stocks with prices of less than one 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 Online Appendix.

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.

[Insert table 7 around here]

The main coefficient of interest in the event study is the one associated with the interaction term between the *COVID19* indicator variable and *SAMEFINFLEX*, β_3. Column [3] of Table 7 shows the estimation results for the full regression specification in equation (23): the estimated β_3

[37]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 Fahlenbrach, Rageth, and Stulz (2021), Ramelli and Wagner (2020), and De Vito and Gómez (2020).

[38]The only difference compared to section 3.1 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*.

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 similarity in financial flexibility on stock comovement, we replace the variable $SAMEFINFLEX_{ij}$ in equation (23) with $DSAMEFINFLEX_{ij}$, a dummy variable that equals one if firms i and j have a difference of up to thirty percentiles in the distribution of financial flexibility, and zero otherwise.[39] The results reported in column [5] of Table 7 indicate that the group of firms with 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 for the control group in the pre-COVID period (0.21%), in the COVID period the level of stock comovement for firms with the highest degree of similarity in financial flexibility was ten times larger. Finally, in contrast with the results in column [3] using *SAMEFINFLEX*, in column [5] the coefficient associated with the COVID-19 indicator 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 3.1, 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 two 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). Panel A of figure 6 plots the average correlation for the two groups between the first week of January 2020 and the last week of April 2020, as well as their 95% confidence intervals. This graph shows that the correlation for the two groups

[39] 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 upon request.

moved in parallel until the week starting on February 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 two groups started diverging substantially.

[Insert figure 6 around here]

Second, we perform a multivariate analysis in order to test whether the conclusions from the univariate analysis of correlation trends are robust to controlling for the determinants of comovement. In particular, we re-estimate equation (23) substituting the COVID-19 indicator with dummies for each week. In Panel 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 zero until the week starting on February 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 April 30 to June 10, 2020 (columns [6] and [7] of table 7) and September 10, 2020 (columns [8] and [9]), which correspond to a 3- and 6-month window 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*.

3.3 External Validity

In this subsection, we perform two 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.

3.3.1 Cross-Country Evidence

We extend our analysis of the determinants of stock comovement for U.S. companies in section 3.1 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 is obtained from Datastream, while financial data comes from Compustat Global. Due to data constraints, as in section 3.2 we use net leverage (net debt/total assets) to construct the variable *SAMEFINFLEX*. 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 six countries, although its magnitude varies considerably—for example, the coefficient for firms in Japan is double compared to the one for firms in Great Britain.[40]

[Insert table 8 around here]

3.3.2 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 for our analysis for two reasons. First, as shown in figure 1, stock comovement spiked following the bankruptcy of Lehman Brothers in September 2008. Second, during this period firms experienced a significant negative shock to credit (see, for example, Duchin, Ozbas, and Sensoy 2010 and Campello, Graham, and Harvey 2010). To study the link between financial flexibility and stock comovement around the bankruptcy of Lehman Brothers, we estimate the following regression:

$$\begin{aligned}\rho_{ij,t} =& \beta_1 \cdot LEHMAN\ BANKRUPTCY_t + \beta_2 \cdot SAMEFINFLEX_{ij} \\ &+ \beta_3 \cdot SAMEFINFLEX_{ij} \times LEHMAN\ BANKRUPTCY_t + \Gamma \cdot X_{ij} + \epsilon_{ij,t},\end{aligned} \tag{24}$$

[40] 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.

where *LEHMAN BANKRUPTCY* is an indicator variable that takes value zero for the three months preceding bankruptcy (June 15, 2008 to September 14, 2008) and one for the post-bankruptcy period (between September 15, 2008, the day when Lehman Brothers filed for Chapter 11 bankruptcy protection, and December 14, 2008). The definitions of all other variables are the same as in the COVID-19 event study in section 3.2, and the controls are based on firm characteristics as of December 2007.[41]

The regression results in column [1] of Table 9 show a significant increase in stock comovement during Lehman Brothers' post-bankruptcy 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 one if the firms in a pair have a difference of less than 30 percentiles in the distribution of net leverage. The results 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 two most recent global crises.

[Insert table 9 around here]

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, *SAMEFINFLEX*, measures the degree of similarity in financial flexibility across firms. As discussed in section 2.3, 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 nature: economic, such as drops in aggregate demand, and financial, such as large systematic increases in

[41] We use the same data sources as the COVID-19 event study. The Online Appendix reports the summary statistics for the sample.

credit risk premia (see, for example, Duchin, Ozbas, and Sensoy 2010 and 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 of each aggregate shock that took place during the crises on stock comovement, the event study design allows us to estimate the combined effect of these shocks on comovement through financial flexibility.

3.4 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 four-step approach both to model-generated and real data.[42] 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 one-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 as the dependent variable the pairwise correlation in excess returns over the year, and as independent variables the measures of similarity in firm characteristics, 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 two 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

[42] For the real data, we use the same sample of U.S. stocks considered in section 3.1. 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).

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 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 in Sharpe ratios.

[Insert table 10 around here]

4 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 two firms increases with the level of similarity in their financial flexibility.

We test the implications of the model on a sample of US firms for the period 1993 to 2018. Our empirical strategy relies on shocks to the market value of corporate real estate 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.

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Figure 1: **Average Pairwise Stock Comovement Among S&P500 firms.** This figure shows the average pairwise correlation of FF5 daily stock return residuals among firms in the S&P500 index for each month between January 2006 and July 2020.

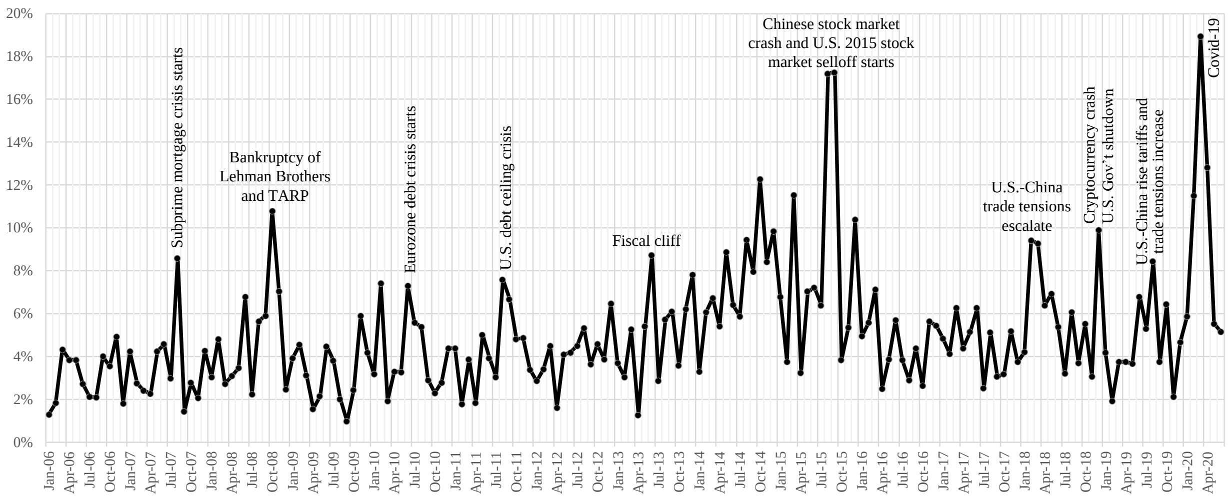


Figure 2: **Optimal Policies as Functions of Capital.** This figure shows the optimal investment rate i' (panel A), leverage $\frac{b'}{k+H}$ (panel B), debt capacity ξ (panel C), and equity issuance rate $\frac{-e}{k+H}$ (panel D) as functions of the firm's current capital level k, for different levels 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 2.2.4 provides the details of the calibration, which is based on the parameter values reported in panel A of table 1.

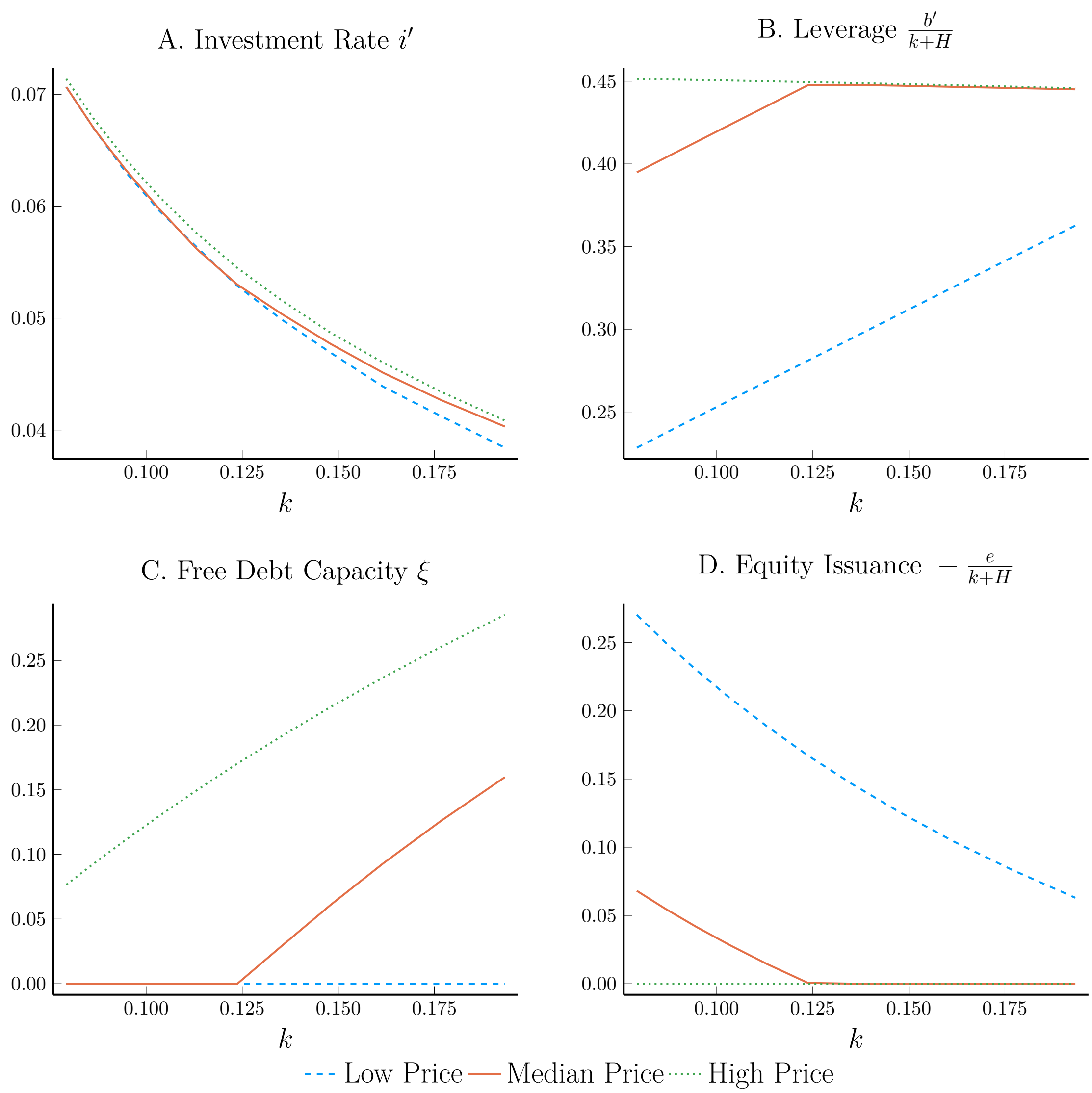


Figure 3: **Optimal Policies as Functions of Idiosyncratic Productivity.** This figure summarizes the optimal investment rate i' (panel A), leverage $\frac{b'}{k+H}$ (panel B), debt capacity ξ (panel C), and equity issuance rate $\frac{-e}{k+H}$ (panel D) as functions of the firm's current productivity 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 2.2.4 provides the details of the calibration, which is based on the parameter values reported in panel A of table 1.

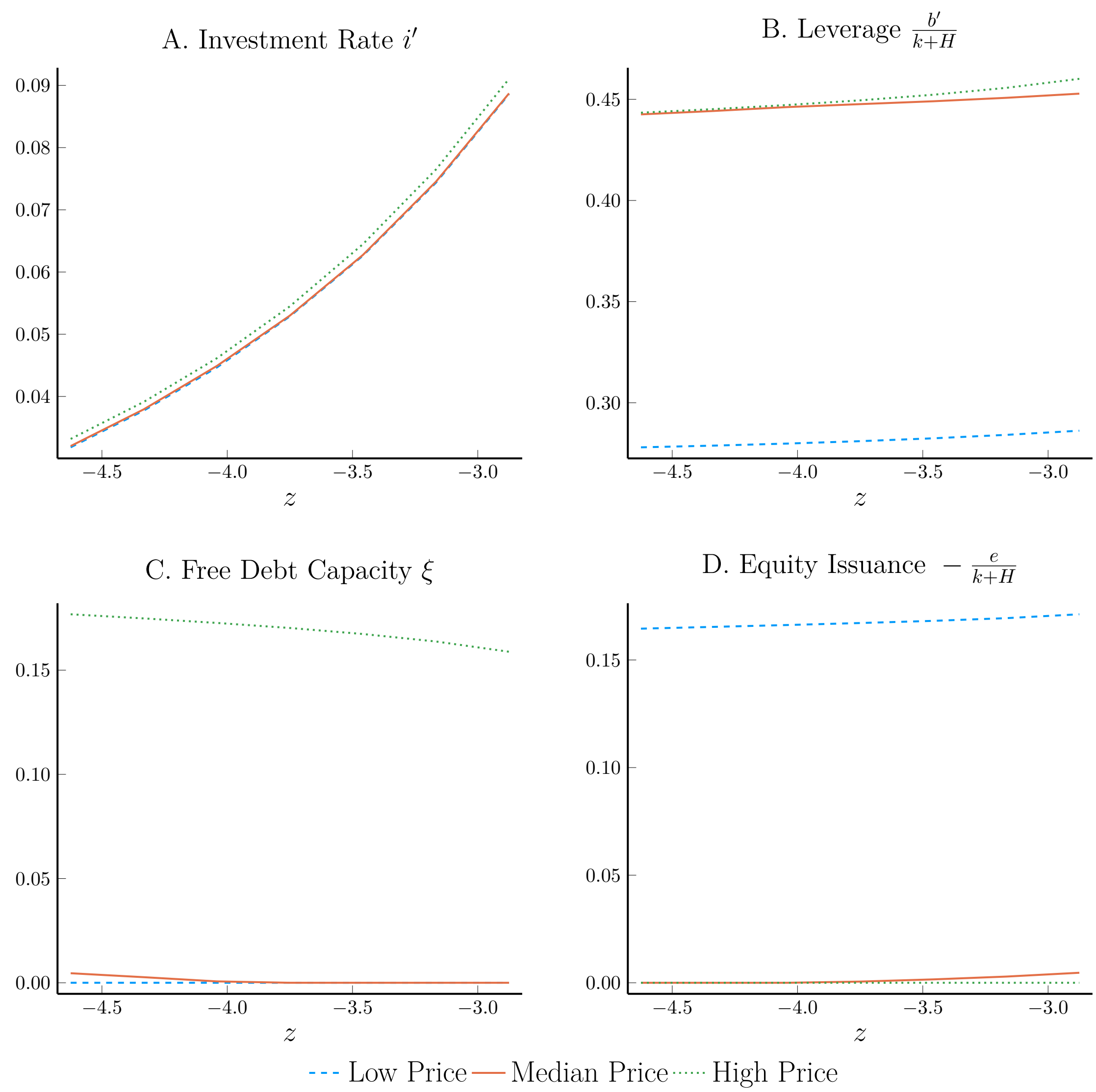
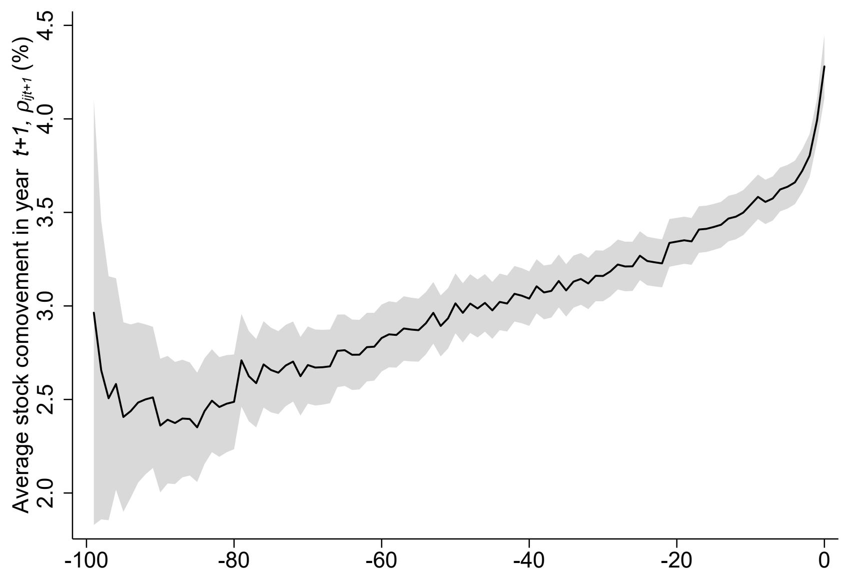
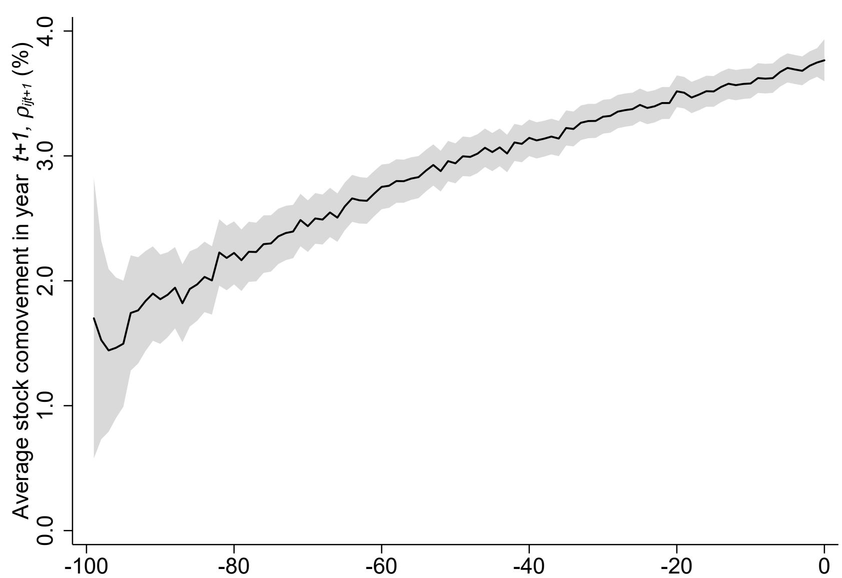


Figure 4: **Stock Comovement as a Function of Similarity in Financial Flexibility for the Simulated Sample.** This figure shows the average pairwise stock comovement in year $t+1$, $\rho_{ij,t+1}$, as a function of pairwise similarity in financial flexibility in year t, $SAMEFINFLEX_{ij,t}$, in the simulated sample. Stock comovement is defined as the pairwise correlation in one-factor (CAPM) return residuals. Stock returns are simulated at a monthly frequency for 50 panels of 1,200 firms and 25 years each. $SAMEFINFLEX_{ij,t}$ is defined using the shadow price of new debt ν_{jt} in subplot A, and the free debt capacity ξ_{jt} in subplot B. Details of the construction of $SAMEFINFLEX_{ij,t}$ are provided in section 2.3. Section 2.2.4 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.



A. *SAMEFINFLEX* $_{ijt}$ based on the shadow price of new debt in year *t*, ν_{jt}



B. *SAMEFINFLEX* $_{ijt}$ based on free debt capacity in year *t*, ξ_{jt}

Figure 5: **Stock Comovement as a Function of Similarity in Financial Flexibility for the Real Data Sample.** This figure 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 ($REValue$) in year t. Return residuals are calculated accounting for the FF5 factors. $SAMEFINFLEX_{ij,t}$ is measured as the negative of the absolute value of the difference in the $REValue$ percentiles for firms i and j in year t. Data sources and sample construction are described in section 3.1.1 and the Online Appendix. The shaded areas represent the 95%-level confidence intervals.

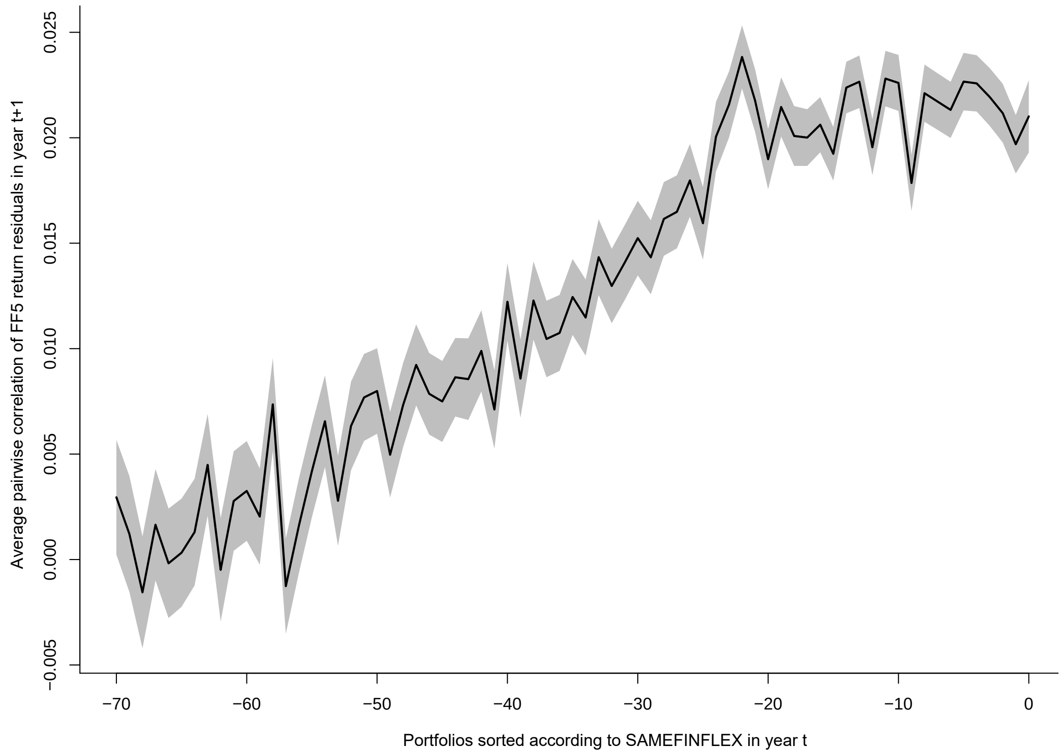
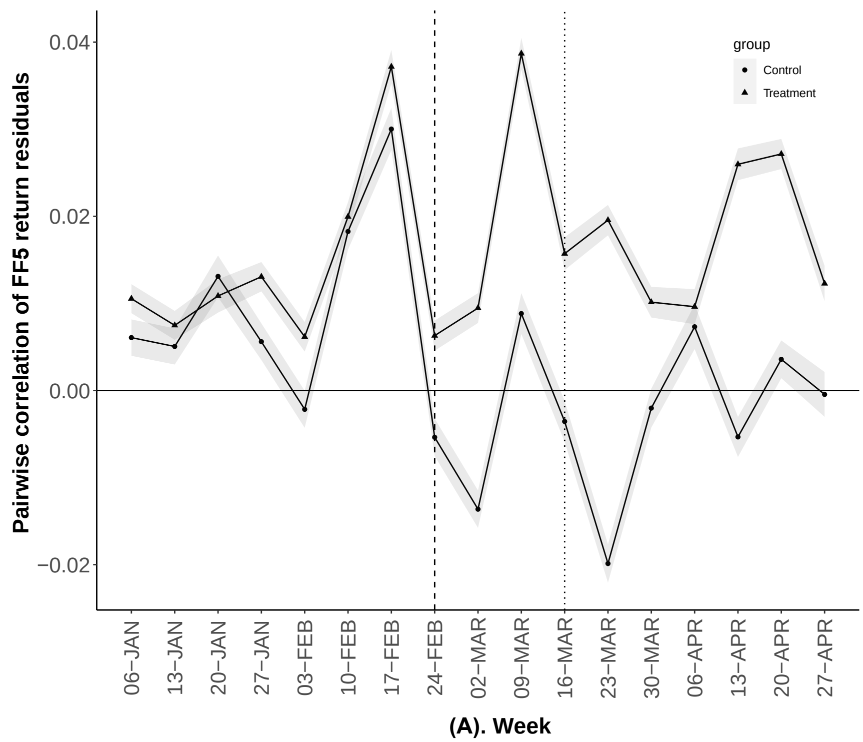


Figure 6: **Test of Parallel Trends.** Panel A plots the average within-week pairwise correlation of FF5 stock-return residuals, $\rho_{ij,t}$ for the treatment ($DSAMEFINFLEX$=1) and control ($DSAMEFINFLEX$=0) groups around the outbreak of the COVID-19 pandemic in early 2020. $DSAMEFINFLEX_{ij}$ is an indicator variable that equals one if firms i and j have a difference of up to thirty percentiles in the distribution of financial flexibility (measured as the net leverage of the firm in December 2019), and zero otherwise. Panel 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 3.2.



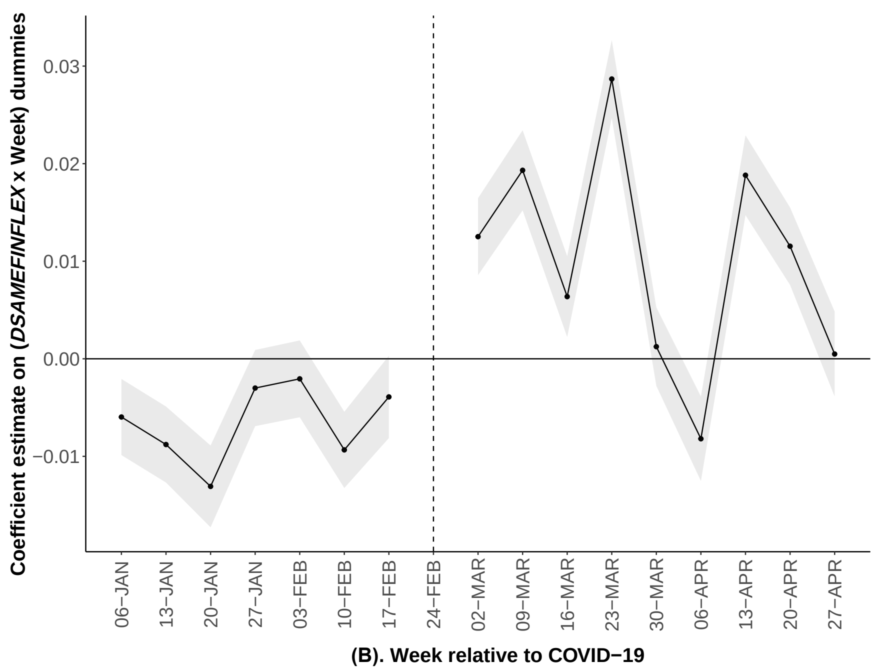


Table 1: **Model Parameters and Moments.** This table reports the calibration parameters and the main moments generated from the model. In panel A, we provide the value, source, and description for each parameter in the model. LSZ and BLY stand for Livdan, Sapriza, and Zhang (2009) and Belo, Lin, and Yang (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 the 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 3.1.1 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	Non-operating 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	-1000	LSZ	Risk-aversion parameter
ρ_z	0.96	LSZ	Persistence of idiosyncratic productivity shock
σ_z	0.10	LSZ	Conditional std. dev. of idiosyncratic productivity shock
$\bar{z}$	-3.75	LSZ	Scaling parameter for idiosyncratic productivity
α	0.65	LSZ	Curvature of the profit function
δ	0.01	LSZ	Depreciation rate of capital
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

	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

Table 2: **Regression Analysis of Stock Comovement in the Simulated Sample.** This table 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 one-factor (CAPM) return residuals between firm 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 firm 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 2.2.4 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 2.3.2: the Modigliani and Miller (1958) economy ("MM"), the Livdan, Sapriza, and Zhang (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% level, respectively.

	Shadow Price		Free Debt Capacity			Free Debt Capacity	
	Full [1]	Full [2]	Full [3]	Full [4]	MM [5]	LSZ [6]	Symmetric [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
Observations	17,265,600	17,265,600	17,265,600	17,265,600	17,265,600	17,265,600	17,265,600
Adjusted R^2	0.0001	0.0010	0.0002	0.0010	0.0005	0.0017	0.0016

Table 3: **Summary Statistics of the Real Data Sample.** This table 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 3.1.1 and the Online Appendix. *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 FF5 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. *REValue* is the ratio of the market value of real estate assets normalized by lagged PPE. *DSTATE*, *DINDEX*, and *DLISTING* are dummy variables that take value one if the two 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, 25^{th} and 75^{th} percentiles, and number of observations.

	Mean	Median	Std. Dev.	p25	p75	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 earnings	-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
REValue	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

Table 4: **Regression Analysis of Stock Comovement in the Real Data Sample.** This table reports the OLS and 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 four-factor model that includes the three factors in Fama and French (1993) plus the momentum factor in Carhart (1997) (4F, columns $[5]-[6]$), or the five factors in Fama and French (2015) (FF5, 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 (*REValue*) percentile ranking for the firms in a pair in year t, while 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* $\times$ *SIZE2*, *SAMEMOM*, *NUMSIC*, *DSTATE*, *DINDEX*, and *DLISTING*. Details of the construction of the real data sample and variable definitions can be found in section 3.1.1. Section 2.2.4 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% level, 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 [1]	OLS [2]	OLS [3]	OLS [4]	OLS [5]	OLS [6]	OLS [7]	OLS [8]	IV [9]	IV [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 $\times$ *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
Observations	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

Table 5: **Robustness Tests: Sample Splits.** This table 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 five factors in Fama and French (2015) (FF5). The independent variable of main interest is *SAMEFINFLEX*, which is defined as the negative of the absolute value of the difference in real estate market value (*REValue*) percentile ranking for the firms in a pair in year t. Columns [1] and [2] show the results for the two 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] 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 3.1.1. 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% level, respectively.

	Correlation of FF5 residuals							
	Investment Opportunities		Firm Age		Net Leverage		Real Estate Boom & 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
Observations	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

Table 6: **Robustness Tests: Fixed Unobserved Heterogeneity.** This table provides pairwise fixed effects panel regressions of stock return comovement. Column [1]-[4] provide the results for the simulated data and column [5]-[8] 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 five factors in Fama and French (2015) (FF5) in the real data. The independent variable of main interest is *SAMEFINFLEX*, which is defined as the negative of the absolute value of the difference in percentile rankings of shadow price of debt (column [1]-[2]), free debt capacity (columns [3]-[4]), and real estate market value (*REValue*) (columns [5]-[8]) for the firms in a pair in year t. For the real data, column [5]-[6] present the OLS regression results, and column [7]-[8] present the 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* $\times$ *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 3.1.1. Section 2.2.4 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% level, respectively.

	Model				Data			
	Shadow Price		Free Debt Capacity		OLS		IV	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
SAMEFINFLEX	0.0001***	0.0001***	0.0001***	0.0001***	0.0004***	0.0003***	0.0002***	0.0001***
	(29.33)	(20.17)	(39.47)	(25.17)	(65.94)	(39.27)	(15.79)	(6.95)
SAMESIZE		−0.0001***		−0.0001***		0.0001***		0.0001***
		(-6.6)		(-5.8)		(4.11)		(3.05)
SAMEMB		0.0003***		0.0003***		0.0002***		0.0002***
		(82.18)		(79.48)		(30.62)		(30.94)
SAMELEVERAGE		0.0001***		0.0001***		0.0001***		0.0001***
		(8.63)		(4.67)		(13.08)		(14.01)
SIZE1		−0.005***		−0.0051***		−0.0080***		−0.0085***
		(-12.3)		(-12.47)		(-20.03)		(-21.11)
SIZE2		0.0033***		0.0034***		0.0077***		0.0089***
		(8)		(8.21)		(19.11)		(21.33)
SIZE1 $\times$ *SIZE2*		0.0003*		0.0003**		0.0039***		0.0046***
		(1.87)		(2.12)		(15.98)		(18.33)
SAMEMOM						0.0002***		0.0002***
						(26.49)		(26.75)
NUMSIC						0.0074***		0.0076***
						(26.98)		(27.77)
DSTATE						0.0026**		0.0027**
						(2.38)		(2.45)
DINDEX						0.0696***		0.0692***
						(44.23)		(43.94)
DLISTING						0.0064***		0.0070***
						(16.25)		(17.62)
Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	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

Table 7: **COVID-19, Financial Flexibility and Stock Comovement.** This table reports the results of the stock comovement regression in equation 23. The dependent variable, $\rho_{ij,t}$, is the pairwise correlation in daily FF5 return residuals. *COVID19* is an indicator variable with value zero for the period between January 1, 2020 and March 10, 2020, and one for the period between March 11, 2020 and April 30, 2020 (columns [1]-[5]); between March 11, 2020 and June 10, 2020 (columns [6]-[7]); and between March 11, 2020 and September 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 one if the firms in a pair have a difference of less than 30 percentiles in the distribution of net leverage, and zero 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 December 2019. Section 3.2 describes data sources and sample construction, and section 3.1.1 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% level, respectively.

	Correlation of FF5 Residuals								
	Post Covid Window: March 11, 2020 - April 30, 2020					Post Covid Window: March 11, 2020 - June 10, 2020		Post Covid Window: March 11, 2020 - Sept. 10, 2020	
	OLS [1]	OLS [2]	OLS [3]	OLS [4]	OLS [5]	OLS [6]	OLS [7]	OLS [8]	OLS [9]
COVID19	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)	
COVID19 × *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)
COVID19 × *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)
Observations	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
Adjusted R^2	0.0143	0.0156	0.0158	0.0152	0.0153	0.0173	0.0153	0.0188	0.0184

Table 8: **Cross-Country Evidence.** This table 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 five factors in Fama and French (2015) (FF5). The independent variable of main interest is *SAMEFINFLEX*, which 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 in year t. Net debt is long and short term debt minus cash. All the columns control for *SAMESIZE*, *SAMEMB*, *SIZE1*, *SIZE2*, *SIZE1* $\times$ *SIZE2*, *SAMEMOM*, *NUMSIC*, *DLISTING*, and year fixed effects. Details of the construction of the data sample and variable definitions can be found in section 3.1.1 and 3.3.1. 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% level, respectively.

	Correlation of FF5 Residuals					
	Great Britain	Japan	France	Germany	Italy	Spain
	OLS [1]	OLS [2]	OLS [3]	OLS [4]	OLS [5]	OLS [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 $\times$ *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
Observations	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

Table 9: **2008 Financial Crisis Event Study.** This table reports the results of the stock comovement regression in equation 24. The dependent variable, $\rho_{ij,t}$, is the pairwise correlation in daily FF5 return residuals. *LEHMAN BANKRUPTCY* is an indicator variable with value zero for the period between June 15, 2008 and September 14, 2008, and one for the period between September 15, 2008 and December 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 one if the firms in a pair have a difference of less than 30 percentiles in the distribution of net leverage, and zero otherwise. All the columns control for similarity in firm characteristics, captured by the variables *SAMESIZE*, *SAMEMB*, *SIZE1*, *SIZE2*, *SIZE1* $\times$ *SIZE2*, *SAMEMOM*, *NUMSIC*, *DSTATE*, *DINDEX*, and *DLISTING*. All firm characteristics are measured as of December 2007. Section 3.2 describes data sources and sample construction, and section 3.1.1 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% level, respectively.

	Correlation of FF5 Residuals				
	OLS	OLS	OLS	OLS	OLS
	[1]	[2]	[3]	[4]	[5]
LEHMAN BANKRUPTCY	0.0052***	0.0052***	0.0076***	0.0052***	0.0035***
	(24.97)	(24.92)	(21.64)	(24.94)	(12.11)
SAMEFINFLEX		0.0001***	-0.0001		
		(7.42)	(-0.80)		
LEHMAN BANKRUPTCY $\times$ *SAMEFINFLEX*			0.0001***		
			(8.76)		
DSAMEFINFLEX				0.0014***	-0.0001
				(6.95)	(-0.43)
LEHMAN BANKRUPTCY $\times$ *DSAMEFINFLEX*					0.0031***
					(7.75)
SAMESIZE	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***
	(112.41)	(110.61)	(110.63)	(111.15)	(111.17)
SAMEMB	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(42.99)	(43.35)	(43.34)	(43.26)	(43.26)
SIZE1	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002
	(-1.54)	(-1.54)	(-1.55)	(-1.54)	(-1.55)
SIZE2	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.51)	(0.51)	(0.51)	(0.51)	(0.51)
SIZE1 $\times$ *SIZE2*	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.54)	(0.55)	(0.55)	(0.55)	(0.56)
SAMEMOM	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	(24.95)	(24.83)	(24.86)	(24.89)	(24.91)
NUMSIC	0.0151***	0.0150***	0.0150***	0.0150***	0.0150***
	(97.47)	(97.08)	(97.09)	(97.16)	(97.17)
DSTATE	0.0175***	0.0174***	0.0174***	0.0174***	0.0174***
	(39.24)	(39.04)	(39.05)	(39.07)	(39.08)
DINDEX	0.0395***	0.0393***	0.0393***	0.0394***	0.0394***
	(45.27)	(45.09)	(45.09)	(45.15)	(45.15)
DLISTING	0.0040***	0.0039***	0.0039***	0.0039***	0.0039***
	(18.80)	(18.44)	(18.43)	(18.46)	(18.46)
Observations	4,139,406	4,139,406	4,139,406	4,139,406	4,139,406
Adjusted R^2	0.0107	0.0107	0.0108	0.0107	0.0108

Table 10: **Comovement in Excess Returns, Volatility, and Sharpe Ratios.** This table 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 is generated 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 3.1.1. 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] for the comovement in Sharpe ratios, defined as the ratio between monthly excess return over standard deviation of excess returns. The independent variable of main interest is *SAMEFINFLEX*, which is 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 (*REValue*) (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% level, respectively.

	Model			Data		
	Excess Returns [1]	Std. Dev. [2]	Sharpe Ratios [3]	Excess Returns [4]	Std. Dev. [5]	Sharpe Ratios [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
Observations	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