Resilience and Asset Pricing in COVID-19 Disaster

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Abstract

The COVID-19 pandemic potentially affected stock prices in two, not mutually exclusive ways: discount rates and cash flows. This paper concentrates on the second and analyzes it through the lens of an asset pricing model. It shows how workplace resilience and financial resilience interacted and significantly affected asset prices. The model-based equity premium is increasing in the probability of disaster. Results suggest the significant amplification of workplace resilience by financial resilience. Specifically, the dividend growth of low-resilience firms is significantly more responsive to workplace flexibility and suffers more severely than that of high-resilience firms.

Keywords: financial resilience, workplace resilience, dynamic functional principal components, Markov-Switching, COVID-19 disaster, equity premium.

JEL classification: C23, C24, C38, G11, G12, Q51, Q54.

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1 Introduction

COVID-19 has profoundly affected the economy and induced tremendous uncertainty in financial markets. Governments adopted different kinds of social distancing policies to control the pandemic spread, especially in the first wave and the fever period of COVID (February to April 2020). These social distancing rules and lockdowns effectively influenced the working environment and firms' performance (among all Koren and Peto, 2020). Fast-growing literature asserts that firms with less labor constraint in the lockdown-restricted situation featured better performance (Bretscher et al., 2020), as firms with more flexibility in their workforce are expected to be less financially vulnerable in such situations since they are less likely to face additional costs due to lockdowns and social distancing rules. Koren and Peto (2020) propose different dimensions of firms' workplace flexibility that played an important role in their cost of production as well as asset price fluctuations in response to the COVID-19 shock (Pagano et al., 2023).

In theory, COVID-19 can affect stock prices through two not mutually independent channels: discount rates and cash flows. Pagano et al. (2023) focus mainly on the impact of the increase in perceived risk on expected excess returns (first channel). Back to the story of COVID, industries saw huge business disruption due to social distancing and lockdowns as a consequence of pathological pandemic disaster that affected the cost of production and especially the output of firms with less flexibility in their workplace. In such a turmoil market, conservative investors care mostly about the price of an equity claim to the output of such firms as risky assets which is exactly the expected future cash flows. Daadmehr (2024) shows that risks related to firm's working environment, including the impact of communication mode, teamwork and physical presence, which a firm is exposed to can create heterogeneity in expected cash flows. According to Stulz (2024), managing such risks as a consequences of COVID pandemic crisis, can potentially affect firm's value. This paper concentrates on the second channel and in a novel work, quantifies the expected cash flows not just to fill the gap in risk management literature but to show how the impact of COVID-19 and corporate resilience can transmit from cash flows to expected returns. The characterization of resilience heterogeneity in expected cash flow sheds light on how this paper bridges a gap and links the real part of the economy, where exogenous COVID-19 triggered, to the financial market.

This paper analyzes the asset price implications of the COVID-19 crisis including its impact on the economy and firms' production costs, in the context of a model with: i) a fictitious representative investor with Epstein-Zin-Weil preferences who may prefer early resolution of uncertainty in disasters[1]. ii) an exogenous dividend stream sensitive to the consequences of the COVID-19 disaster and to its contractionary effects on the real part of the economy. This study considers the cross-sectional time-varying impact of COVID-19 on the dividend stream as the interaction of two components: the cross-sectional firm-level impact of workplace resilience and the time-varying impact of aggregate economic contraction, as a control for macro time-effect of COVID-19. Specifically, it shows that the dividend growth of low workplace-resilient firms is significantly more sensitive to workplace resilience and suffers more severely than that of high workplace-resilient firms.

On the other hand, the impact of corporate financials is quite confusing during the COVID outbreak. Firms started raising capital just because of cash flow dry-up fears or to be capable enough to overcome difficulties during the first wave. Meanwhile, the provided credit, especially in small firms could affect capital structure and increase the leverage. Consequently, firms' financial characteristics such as capital structure and liquidity also played an important role in firms' performance and were considerably influenced by a wide range of policies adopted in response to COVID-19 from corporate policies to public policies, including bank loan guarantees and additional mitigation packages e.g. the Paycheck Protection Program, PPP loans (Fahlenbrach et al., 2021; Pagano and Zechner, 2022). This suggests that these characteristics may have also contributed to amplifying the degree of corporate

[1]This type of preferences could better capture the investors' preference in an uncertain situation like COVID-19. The results of the calibration exercise approve this although the Euler equation is a general form of power utility function with a specific version of EZ preferences.

resilience and as a result, the response of asset prices (Daadmehr, 2024).

Some recent papers shed light on the amplification impact of corporate financials on asset prices in the COVID-19 period (Ramelli and Wagner, 2020 and Daadmehr, 2024) and find significant resilience-heterogeneity in expected returns by introducing a new "composite-financial resilience" index containing both workplace flexibility and "financial-based resilience" (Daadmehr, 2024). As a piece of novelty, this paper provides a simple example as evidence of the amplification effect and shows that cross-sectional and time-varying corporate financials can potentially amplify the overall effect of the exogenous COVID-19 consequences, consistent with the evidence that better-financed firms before and during the COVID-19, can better overcome the side effects of the lockdown and related COVID-mitigation restrictions (Fahlenbrach et al., 2021; Daadmehr, 2024). Then, it quantifies "financial resilience", to capture the footprints of the impact of a wide range of different policies on firms' financial status.

This paper proposes a new asset pricing model with COVID-19 disaster embedding workplace resilience and financial resilience to investigate and track the impact of firms' characteristics on asset pricing implications. The novelty of this paper is directly related to how it quantifies the consequences of the exogenous COVID-19 crisis on the dividend stream that affects asset prices depending on these two kinds of firms' resilience. In other words, it clarifies how resilience practically contributes to the asset pricing and characterizes the resilience-heterogeneous equity premium, by providing tractable formulas, which is increasing in disaster probability.

In line with Daadmehr (2024), this paper shows that the effect of firms' financial resilience significantly amplifies the impact of workplace resilience and aggregate economic contraction due to COVID-19. The novel proposed exogenous dividend stream and its estimation provide an opportunity to compare the impact of firms' financial resilience and workplace resilience. Meanwhile, the estimated dividend growth highlights that the heterogeneous effect of workplace resilience is dominant although the impact of firms' financial resilience is statistically significant which proves the necessity of "financial resilience" characterization. The novel application of

Dynamic Functional Principal Component Analysis (DFPCA) enables to distinguish not only the main time-varying elements of financial resilience but also those that create significant cross-sectional variation. Finally, this paper empirically proves that valuation, liquidity, and solvency ratios have key roles in firms' financial resilience and the corresponding amplification of workplace resilience. The results of this part shed light on possible corporate policies.

The paper is structured as follows. Section 2 clarifies how this paper contributes to the literature and postpones the introduction on intuitions of resilience to Section 3. The model of the economy and the assumptions about the firm-level exogenous dividend stream are presented in Section 4. The solution of the model appears in Section 5, where the closed form of resilience-heterogeneous equity premium is presented. The results on both the effect of COVID-19 macroeconomic contraction and the estimated dividend stream are included in Section 6. The paper proposes the main ingredients of financial resilience components in Section 7 and then concludes.

2 Contribution to literature

As the main novelty of this paper is to investigate resilience heterogeneity in expected cash flows and its role in asset pricing, this paper contributes to two main strands of literature: i) corporate resilience and the impact of COVID-19 on cross-section of stock returns, and ii) Asset pricing models with rare events.

From one side, this paper tries to talk about the impact of workplace resilience and financial resilience as an overall indicator of firms' financial status. Since the COVID-19 emergence, many studies have started to explain about flexibility of firms or industries in such a pandemic crisis, specifically in response to health mitigation policies, social distancing rules, and lockdowns (among all Koren and Peto, 2020; Dingel and Neiman, 2020; and Hensvik et al., 2020). This paper contributes to these studies more from asset pricing perspectives rather than corporate resilience and considers workplace resilience in the spirit of Koren and Peto

(2020). As a key feature, this paper uses the data on workplace resilience and explains how and to what extent it significantly contributes to the asset pricing model for COVID time.

Meanwhile, this paper takes into account financial resilience since fast-growing literature has already emphasized the importance of corporate financials on asset prices in response to a wide range of public and corporate policies (Ramelli and Wagner, 2020; Ding et al., 2021; Fahlenbrach et al., 2021; Pagano and Zechner, 2022). Daadmehr (2024) compares these two intuitions of resilience and provides a measure of corporate resilience, called the composite-financial resilience index, applicable in pandemic times. This cross-sectional measure allows to categorization of assets into more risky and less risky groups and enables investors to manage their resources. She provides different evidence of resilience heterogeneity in expected returns and expected future cash flows that can potentially originate from workplace resilience and financial resilience as an additional source of variation. This paper deviates from Daadmehr (2024) and quantifies cross-sectional "time-varying" financial resilience although the aim is not to propose an index. Contrary to the major part of these studies in corporate finance, this paper proposes a mechanism to estimate mixed specification for exogenous dividend stream as an expected future cash flow. Since there is neither empirical study on the link between these two kinds of resilience nor theoretical work or background, this paper (Subsection 3.2) starts with simple empirical evidence to motivate the characterization of the exogenous dividend stream as a bridge between these two kinds of resilience.

According to the literature, it is noteworthy to mention the impact of the possibility of disaster and clarify on macro time-effect of the exogenous COVID-19 pandemic as a third source of variation. Among all, Gourio (2012), Gabaix (2012), and Wachter (2013) declare the time-varying probability of disaster that generates covariation in equity premium. Ghaderi et al. (2022) develop the literature and consider the gradually unfolding disasters. They explain that investors are not aware of the true state of the economy and introduce a Bayesian learning framework showing that updating investors' beliefs captures the effect of slowly unfolding disasters, as prices truly react to the consumption decline. They show that updating the agent's belief accords with the true state of the economy. This paper deviates from Ghaderi et al. (2022) by considering disaster states as bad times of the economy. It empirically proves COVID-19 has a tremendous impact on the economy and captures the impact of disaster and controls the time variation of expected cash flows for macroeconomic sensitivity to COVID-19 using the Markov-switching approach. As opposed to Wachter and Zhu (2019) who use the jump Poisson process to capture low and high intensity of disaster that defines disaster states based on two high and low amount of disaster intensity, and apply Markov-switching simulation to investigate the impact of learning in asset pricing of rare disasters, this study considers disaster states as the bad times of the economy and "estimates" the probability of disaster, states and the duration of regimes based on monthly GDP.

From an asset pricing perspective, this paper uses the general framework proposed by Barro (2006) but with a special case of EZ preferences. Contrary to Barro (2006) who proposes economic contraction due to rare events as a "random variable" and calibrates it, this paper considers it as a "stochastic process" and provides an estimation for each month, using the Markov switching approach. The empirical analysis on this part shows that dividend growth was significantly sensitive to the overall economic contraction due to the COVID-19 phenomenon, with a conditional probability of 2 percent, in line with Barro (2006) who calibrates the disaster probability parameter. Another main difference is directly related to the idea of resilience.

"Resilience" in Asset Pricing:

In asset pricing literature, many studies introduce resilience in the rare disaster framework. Gabaix (2012) considers a deterministic aggregate consumption growth in the absence of disaster, however, consumption growth is magnified by a positive macroeconomic recovery rate when a disaster occurs. He presents an asset-specific dividend process magnified by a positive rate of surviving in a disaster period. The definition of time-varying "resilience" in his paper is an increasing function of asset-specific surviving rate. In the framework he proposed, resilience is a linearity-generating process that sees shock uncorrelated with disaster occurrence. Since the definition of resilience highly depends on the type of disaster, this paper, as opposed to Gabaix (2012), considers cross-sectional workplace resilience due to the natural feature of the COVID-19 pandemic and its effect on the workforce and firm's costs through social distancing rules and lockdowns (similar to Pagano et al., 2023 and Daadmehr, 2023).

This paper deviates from Pagano et al. (2023) in two aspects: First, it uses data on workplace resilience (in the spirit of Koren and Peto, 2020) rather than considering it as a parameter in the model. Moreover, this study considers workplace resilience, affecting the dividend stream cross-sectionally, and quantifies the cross-sectional time-varying impact of corporate financials as an additional part called financial resilience. Second, it provides the monthly estimates for disaster probability rather than theoretical intuition for the probability of disaster as a parameter in the model. It is also noteworthy to emphasize that this paper provides an empirical test as a prerequisite for having a particular definition of disaster state and the corresponding probabilities based on the intrinsic feature of COVID-19 and Poisson distribution as Daadmehr (2023) theoretically proposes. The striking difference is directly related to the role of the estimated Markov switching process as a control for the macro time-effect of COVID-19, a necessary part as Barro (2006) declares.

This paper demonstrates the dominant heterogeneous effect of workplace resilience showing that the dividend growth for low-resilience firms is more responsive to workplace resilience than that of high-resilience firms. Meanwhile, the impact of cross-sectional time-varying financial resilience is not negligible and significantly amplifies the impact of COVID-19 on firms' production growth as well as dividend stream. Section 3 briefly introduces these two intuitions of resilience and provides some pieces of initial evidence of amplification which sheds light on the characterization of dividend stream as expected cash flows.

3 Resilience

This paper tries to investigate how resilience affects asset price fluctuations in the COVID-19 pandemic. At first glance, it seems little a bit tricky to clarify "resilience". Due to the pathological feature of the COVID-19 pandemic and its severe impact on the labor force and workplace that leads to huge business disruption, this paper considers workplace resilience as a capacity to absorb the disturbance in the COVID-19 outbreak.

3.1 Workplace resilience

After the emergence of COVID-19, many studies started to interpret to what extent firms' performance depends on communication restrictions and social distancing rules (among all Dingel and Neiman, 2020; Koren and Peto, 2020; Hensvik et al., 2020). Many of them try to propose a measure of workplace flexibility. Koren and Peto (2020) provide a theory-based measure for the dependency of US businesses on human interaction, based on three dimensions of occupation: teamwork intensive, customer facing, and physical presence. Their model of communication reveals the sensitivity of production costs to an increase in face-to-face interaction and determines firms with less efficient performance from home. They explain the impact of face-to-face communication on costs of production, introduce the average 'affected share', and interpret that a higher firm's affected share implies less flexibility towards social distancing restrictions during the COVID-19 pandemic.

The important feature of workplace resilience is that the resilience of firms depends on their own workplace characteristics and flexibility towards the new social distancing rules and lockdown policies which is not implied by the workplace-resilience of other firms. Despite all the prominent features of this resilience measure, Daadmehr (2024) shows the shortcoming of this kind of resilience to exhibit 'significant' resilience-heterogeneity in the firm's implied discount rate as the proxy for expected return.

3.2 Is workplace resilience adequate enough?

Although the necessity and adequacy of workplace resilience are fully investigated by Daadmehr (2024) using several empirical evidence, Figure 1 shows the evolution of analysts' expectation of future cash flows for high- and low-resilience[2] firms in the spirit of Koren and Peto (2020) in the first panel. They propose a proxy called "affected share" to show to what extent businesses rely on human interaction. From the analysts' point of view, low-resilience firms experienced lower expected cash flows[3] than high-resilience firms. The first panel reveals that aggregate expectations reflect more the earnings expectation of low-resilience firms, especially before and during the fever period of COVID-19, and suggests that workplace resilience can be potentially an important source of heterogeneity in firms' expected cash flows.

Although this type of resilience accords with the pandemic type of crisis and shows to what extent firms can survive when their productivity is affected by human loss (Koren and Peto, 2020), the financial status of firms may provide a kind of flexibility for firms to handle additional production costs. On top of all the evidence provided by Daadmehr (2024), the second panel of Figure 1 shows analysts' expectations of future cash flows separately for high- and low-levered firms and provides evidence about the importance of capital structure and firms' leverage on the evolution of expected earnings. This panel exhibits that not only did earnings expectations decline more for high-levered firms but also this decline for high-levered firms was persistent and associated with higher oscillations in the following fiscal years. This is consistent with much previous evidence that firms with less strong balance sheets experienced greater difficulties during and after the fever period of COVID-19, such as Pettenuzzo et al. (2022) who show how leverage and cash-holdings are related to the performance of firms, especially those with less profitability and lower revenue growth.

[2]Term "resilience" without mentioning its type, refers to workplace intuition of resilience.

[3]This paper considers analysts' earnings expectation as a proxy for future cash flows, following Daadmehr (2024), Landier and Thesmar (2020).

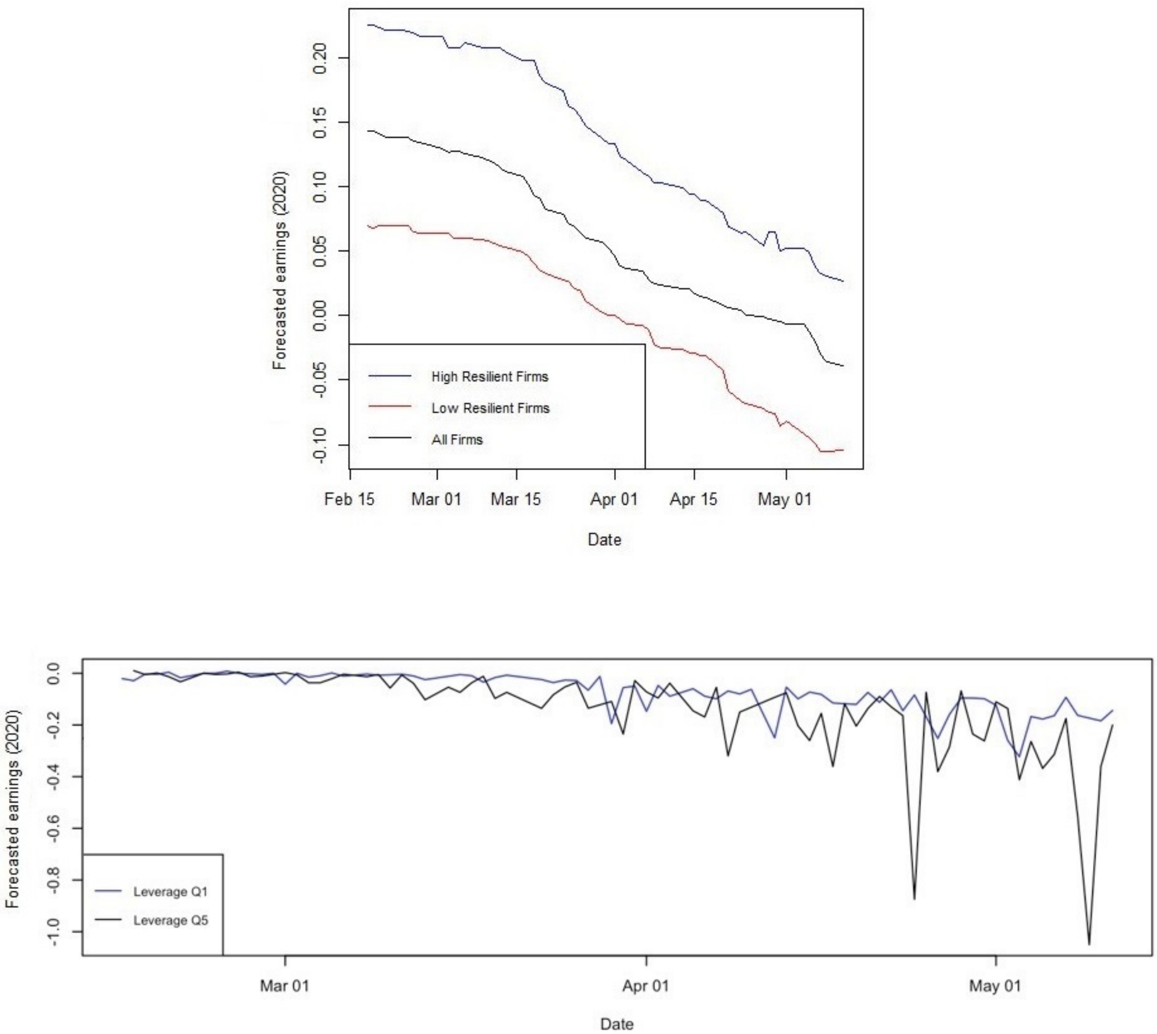

Figure 1: **The evolution of expected future cash flows in the fever period of COVID-19 (the impact of workplace resilience and leverage):** First panel shows the standardized earnings expectation $(Ex_tEPS_{i,2020} - EPS_{i,2019})/EPS_{i,2019}$ of high- and low-resilience firms, in the sense of workplace flexibility, for current fiscal year of 2020. $Ex_tEPS_{i,2020}$ stands for earnings expectation of firm i at time t (similar to Landier and Thesmar, 2020; Daadmehr, 2024; Koren and Peto, 2020). Firms with 'affected share' less than 40 are assigned to the high-resilience group and ones with greater than 65 are assigned to the low-resilience one. The second panel shows the standardized earnings expectations of firms with different levels of leverage. Firms with higher leverage than the 80th percentile are assumed high-levered (Q5) and firms with the lower than 20th percentile are the low-levered ones (Q1). Data source: Compustat/CRSP merged, WRDS for fundamentals, and Refinitiv-Eikon (Thomson Reuters) I/B/E/S forecasts for daily consensus analysts' earnings.

Each panel of this figure emphasizes that workplace resilience and firms' corporate financials 'separately' can potentially explain heterogeneity in expected cash flows.

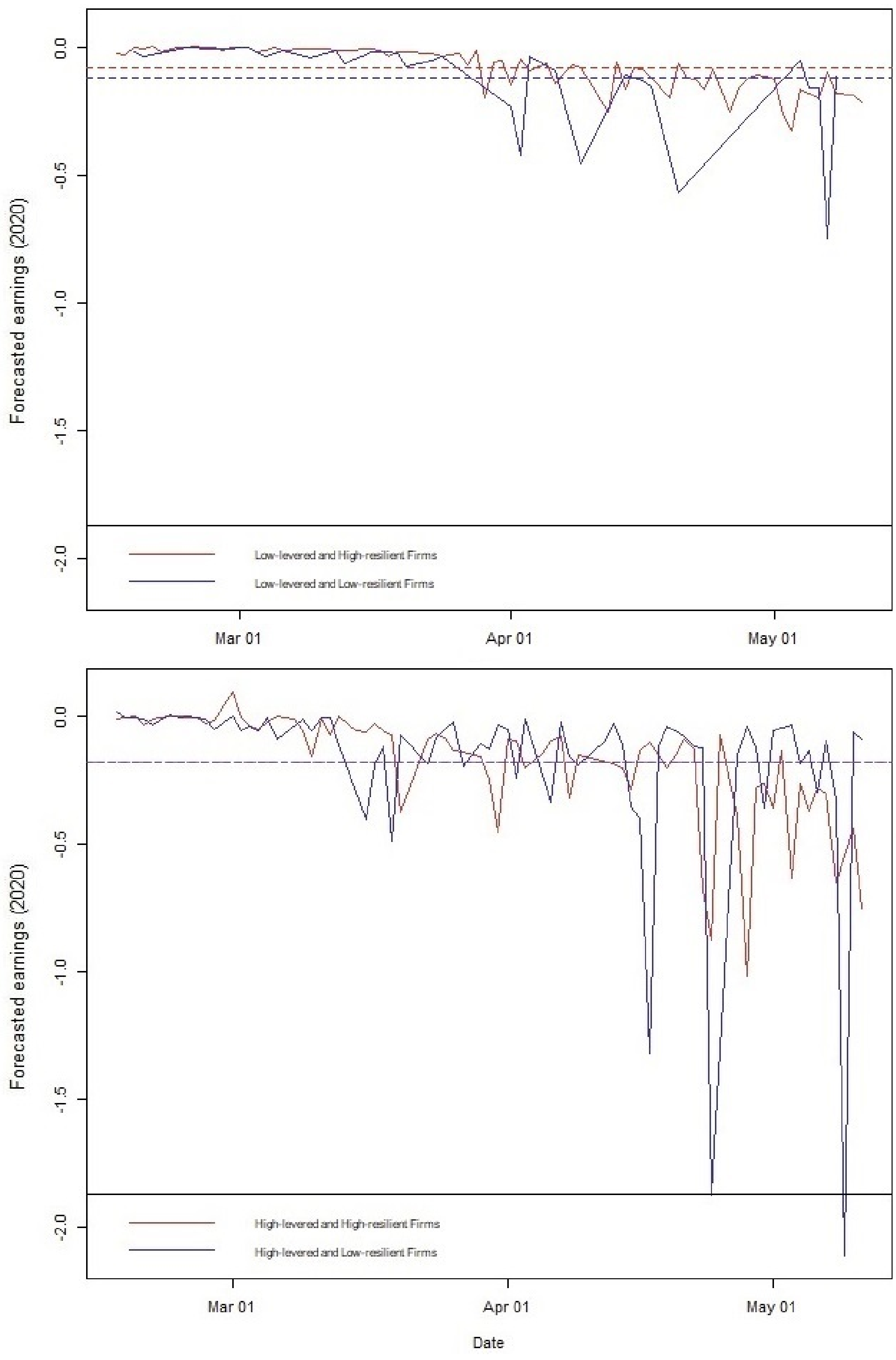

Figure 2: **The evolution of expected future cash flows in the fever period of COVID-19 (amplification effect):** Both panels show the standardized earnings expectation, $(Ex_tEPS_{i,2020} - EPS_{i,2019})/EPS_{i,2019}$ for four groups of firms during the fever period. $Ex_tEPS_{i,2020}$ stands for earnings expectation of firm i at time t for the current fiscal year of 2020. Firms with 'affected share' less than 40 are assigned to the high-resilience group and ones with greater than 65 are assigned to the low-resilience one. Firms with higher leverage than the 80th percentile are assumed high-levered and firms with lower than the 20th percentile are the low-levered ones. The categorization of firms into high- and low-resilience firms in the sense of workplace flexibility, is based on Koren and Peto (2020) and follows Daadmehr (2024). Data source: Compustat/CRSP merged, WRDS for fundamentals, and Refinitiv-Eikon (Thomson Reuters) I/B/E/S forecasts for daily consensus analysts' earnings.

Meanwhile, low workplace-resilience firms would be more capable of handling and managing production costs if they have had already an appropriate financial status. They see less reduction in the average earnings expectations (Daadmehr, 2024); However, analysts were quite pessimistic about the rebound in earnings of these firms with lower financial status as Daadmehr (2024) explains. So, it is crucial to find a mechanism in which these two intuitions jointly affect the expected cash flows as well as the price fluctuations of an equity claim to the output of such firms.

Figure 2 motivates and suggests the existence of such interaction. It shows the average earnings expectations for four categories of firms: "high workplace-resilience and high-levered" firms, "high workplace-resilience and low-levered" firms, "low workplace-resilience and high-levered" firms, and "low workplace-resilience and low-levered" firms. The evidence emphasizes two prominent impacts of firms' financial status: i) Among low-levered firms, those with a more flexible workforce not only have less reduction in average earnings expectations but also see less severe fluctuations in the following months after the onset (first panel). ii) Higher leverage appears to weaken the benefit of high workplace resilience. The second panel, compared to the first one, suggests that high leverage reduces earnings expectation surplus of high workplace resilience and makes fluctuations more severe. These two pieces of evidence highlight that firms' financial characteristics can potentially magnify the impact of their workplace resilience on expected cash flows.

3.3 Financial resilience

Moreover, back to the story of the impact of a wide range of policies, any financial ratios from any category including e.g. profitability and solvency ratios can be effective on all these associations. This re-motivates to quantify the overall impact of all corporate financials. This paper suggests the machine learning definition for financial resilience based on Dynamic Functional Principal Component Analysis as a solution for such quantification (Subsection 4.2.2). The following sections show how cross-sectional time-varying dynamic functional PCs contribute to the asset pricing model and to what extent financial resilience elements interact at the dividend level (Subsection 4.2) and possibly not only amplify the impact of workplace resilience but also create significant heterogeneity in the dividend growth (Section 6).

4 Model and Data

This section introduces the standard asset pricing framework with the exogenous dividend stream embedding the impact of COVID-19 on firms' productivity. It clarifies how the paper quantifies resilience as well as how it controls the macro time-effect of economic contraction. The data description is presented at the end of the corresponding subsections.

4.1 The economy

The COVID-19 pandemic caused huge business disruption due to social distancing rules and lockdowns that almost all governments imposed. Specifically, firms in some industries were affected even much more because they were not really flexible in their workforce or they could not run tasks in the hybrid mode, simply because such tasks needed more human interaction or face-to-face communication with a higher physical presence. All these increased the cost of production and affected the output of such low (workplace) resilient firms. This situation created a sort of additional uncertainty in the market, which is quite important from an asset pricing perspective. For a representative consumer (investor), it is important to know what happened to the price of an equity claim to the output of these firms.

Following Mehra and Prescott (1985) and Barro (2006), this paper considers recursive preferences of Epstein and Zin (1989) and Weil (1989) for representative-consumer Lucas' fruit-tree model of asset pricing with exogenous stochastic dividend stream[4]. Based on Campbell (1993) with total wealth at the beginning of t+1, $W_{t+1} = W_t - C_t$ as an intertemporal budget constraint and $M_{t+1} = \beta^{*\theta}(\frac{C_{t+1}}{C_t})^{\frac{-\theta}{\psi}}$ as the stochastic discount factor with time

[4]Implicitly, it assumes C_t is equal to production (all output is consumed at each time) and the risky asset pays $D_t = C_t$, which is a claim to aggregate consumption in each period t.

discount β^*; in partial equilibrium, the standard Euler equation is[5]:

$$1 = E_t[\beta^{*\theta}(\frac{C_{t+1}}{C_t})^{\frac{-\theta}{\psi}} R_{i,t+1}]. \tag{1}$$

4.2 Exogenous dividend stream

To clarify how resilience plays a role in the model, based on the initial evidence presented in Figure 2 and in line with evidence on the amplification effect (Daadmehr, 2024), this paper defines the multiplicative form for the dividend level:

$$D_{i,t+1} = D_{it}exp(FR_{it})\varphi_i^\delta(\hat{\eta}_t^s)^\alpha, \tag{2}$$

where $\varphi_i^\delta(\hat{\eta}_t^s)^\alpha$ captures the consequences of the COVID-19 disaster through not only the cross-sectional impact of this disaster on firms' production, called workplace resilience, φ_i^δ but also the time-varying aggregate economic contraction, $(\hat{\eta}_t^s)^\alpha$; Moreover, FR_{it} refers to financial resilience, which is a linear combination of some functions of firm's corporate financials. These terms are defined in the following subsections. The exogenous dividend growth for firm i at time t is:

$$\Delta ln(D_{it}) = FR_{it} + \delta ln(\varphi_i) + \alpha ln(\hat{\eta}_t^s) + \varepsilon_{it}. \tag{3}$$

Aside from ε_{it} which is normally distributed error term with mean zero and variance σ_ε^2, in this paper, the impact of exogenous COVID-19 disaster is multiplicative in the level although it is additive in the growth rate. This implies that the effect of this crisis on the stock price can

[5]Equation 1 is the simplified version of Equation 13 in Campbell (1993), with constant gross simple return on wealth invested from period t to period t+1, as an additional assumption for being able to solve model analytically (Appendix). This can be considered realistic due to two separate pieces of evidence: 1) as Ghaderi et al. (2022) show wealth-to-consumption ratio varies almost not significantly by time-varying beliefs. 2) wealth-to-consumption ratio varies with interest rates (Lustig et al., 2013) and interest rates did not affect neither market crash nor market rebound in COVID time (Cox et al., 2020). Moreover, the model and calibration exercise are in line with Barro (2009) who fully explains that the EZW framework ends up as simple as the power-utility setting, and it accords with a broader set of asset-pricing facts.

be multiplicative, while that on returns may not be so. In what follows, a full interpretation of the special feature of each element is presented.

4.2.1 Workplace resilience: Cross-sectional effect of COVID-19

In the specification of dividend growth (Equation 3), workplace resilience, $ln(\varphi_i)$, is introduced as the cross-sectional consequences of COVID-19 which refers to workplace firms' characteristics that determine the exposure of firms' dividend growth to this pandemic disaster. Koren and Peto (2020) show that this depends on a trade-off between the communication cost of firms and the benefits from the division of labor. They propose a measure for businesses, called "affected share", including different aspects of workplace flexibility that represent customer-facing characteristics, degree of teamwork-intensiveness, and workforce physical presence. Consequently, due to the nature of the COVID-19 pandemic that affects social interactions, this proxy reveals to what extent social distancing rules affect production costs.

$\delta ln(\varphi_i)$ captures the heterogeneous effect of workplace resilience of firm i, where φ_i is defined as workplace resilience and takes values of (100 - "affected share"), a linear transformation of the proposed "affected share" data by Koren and Peto (2020) for US firms at 3-digit NAICS sectors that practically captures heterogeneity caused by industry pandemic shock.

4.2.2 Financial resilience: Dynamic functional principal components

One of the main issues, specifically after COVID-19 emergence, is how to capture the compounding impact of different kinds of public policies, corporate policies, or even additional governmental packages e.g. PPP in the case of the US. From one side, such financial aids solve the problem of cash flow shortage in the short term by liquidity injections; While on the other side, these may change the capital structure. This is just a simple example to show the possible opposite outcomes as previous sections mentioned. Is it really possible to disentangle the single consequences of ALL these policies?

Having a huge database of cross-sectional, autocorrelated, and even lagged cross-correlated corporate financials incentivizes one to start organizing and reducing the dimension of massive data to obtain meaningful information on the financial status of firms. Corporate financials like many other phenomena can be considered as random curves, a kind of functional data which are realized over time. This time-varying intrinsic feature avoids using ordinary static data dimension reduction like Principal Component Analysis (PCA) that possibly ignores the essential information or correlation dependence in financial data. Moreover, Functional PCA (FPCA) still works in a static way and fails to capture serial dependence in random curves of corporate financials, and lots of vital information about past values of functional observations is lost. The FPCA still is not able to capture the possible lagged cross-correlations among financial ratios.

This research employs Dynamic Functional PCA (DFPCA) provided by Hormann et al. (2015) who respond to this demand with an efficient reduction technique. They propose a functional setup for a dynamic version of Karhunen-Loeve expansion and enhance the dynamic PCA originally suggested by Brillinger (2001). To obtain meaningful information on the financial status of firms as a part which is associated with an amplification of the dividend growth, this paper computes dynamic functional principal components as elements of "Financial Resilience", representing the firm's financial characteristics.

At the firm level, X_{it} is defined as a $[T \times d]$ matrix of d time series of the firm's financial ratios. The m-th dynamic functional principal component is defined as:

$$PC_{it,m} = \sum_{k \in Z} \phi'_{i,mk} X_{i,t-k}, \tag{4}$$

where $\phi'_{i,mk}$ is the corresponding filter sequence (among all Brillinger, 2001). m varies from one to a maximum value of M representing the number of principal components, which can explain the major variation originating from all financial ratios of firm i over time.

To obtain these dynamic functional principal components for each firm i, first the empirical spectral density of X_{it} is computed. The estimator $\hat{\mathcal{F}}^{X_i}(\omega)$ is the estimated spectral density evaluated at the k-th frequency[6]:

$$\hat{\mathcal{F}}^{X_i}(\omega) = \sum_{|h| \leq q} (1 - |k| / q) \hat{C}^{X_i}(h) exp(-ih\omega),$$

where $\hat{C}^{X_i}(h) = \frac{1}{T} \sum_{t=1}^{T-h} (X_{i,t+h} - \hat{\mu}^{X_i})(X_{it} - \hat{\mu}^{X_i})'$, $\hat{\mu}^{X_i} = \frac{1}{T} \sum_{t=1}^{T} X_{it}$, and the filter sequence, ϕ_i in Equation (4), is the Fourier coefficients of the dynamic eigenvector $\varphi_{il}(\omega)$ of the spectral density $\hat{\mathcal{F}}^{X_i}(\omega)$, that is:

$$\phi_{i,lk} := \frac{1}{2\pi} \int_{-\pi}^{\pi} \varphi_{il}(\omega) exp(-ik\omega) d\omega,$$

for $|k| \leq q$, $k \in Z$ and $1 \leq l \leq d$. Then, the firm's financial resilience, FR_{it} in Equation (3), is defined as a linear combination of the first M dynamic functional principal components, $PC_{it,m}$ in Equation (4):

$$FR_{it} = \sum_{m=1}^{M} \beta_m \sum_{k \in Z} \phi'_{i,mk} X_{i,t-k}. \tag{5}$$

More statistical details are beyond the scope of this paper. Methodology for L^2-curves can be directly found in Hormann et al. (2015) and its Appendices and online supplementary document. To compute m-th dynamic functional principal component Equation (4), this paper considers all monthly financial ratios of U.S. firms from 2013 - 2022, available at the WRDS database, belonging to all categories: Capitalization, efficiency, profitability, liquidity, solvency, valuation, and financial soundness. Table 9 in the appendix provides detailed definitions.

[6] To compute empirical spectral density, this paper considers Bartlett kernel (e.g. Brockwell and Davis, 1991).

4.2.3 Macro time-effect of COVID-19

An overall time-effect of exogenous COVID-19 is defined as $ln(\hat{\eta}_t^s)$, which controls common effects for the economic consequences of exogenous COVID-19 and the recession on all firms. This paper expands the methodology in Barro (2006) and considers economic contraction as a stochastic process rather than a single random variable, to obtain the estimates $\hat{\eta}_t^s$[7], based on monthly GDP data. Since the emergence of COVID-19 as a health crisis and its consequences on demand and supply side impose regime shifts in the economy, the impact of economic contraction captured by GDP evolves with a nonlinear mechanism, in a sense that the response of GDP as a proxy for macroeconomic sensitivity to COVID-19 at time t depends on the state of the economy and its duration that is not a simple linear function of previous amount, but the coefficients change by switching the state[8]. When the economy is subject to regime shifts, Markov Switching Autoregressions (MS-AR) is the dominant research strategy in empirical macroeconomics.

Accordingly, the evolution of monthly GDP, η_t, is the Markov switching process that switches among different unobservable states of the economy, S_t. Let G denote the number of feasible regimes, so that $S_t \in \{1, ..., G\}$, which indicates the regime prevailing at time t. By definition, the conditional probability density of η_t is given by:

$$Pr(\eta_t \mid H_{t-1}, s_t) = \begin{cases} f(\eta_t \mid H_{t-1}, \rho_1) & if s_t = 1 \\ \vdots & \\ f(\eta_t \mid H_{t-1}, \rho_G) & if s_t = G \end{cases}, \tag{6}$$

[7]The letter, s is to emphasize that the overall contraction depends on the state of the economy. It is eliminated for ease in the rest of this subsection.

[8]Statistical tests provided in the Appendix (Table 5) guarantee the existence of significant regime switching in the COVID-19 outbreak. Table 5 summarizes the results of the Likelihood Ratio Test (LRT) of model linearity. The null hypothesis of linearity is rejected in favor of a non-linear Markov switching model with regime shifts.

where ρ_g is the autoregressive parameter in regime $g = 1, ..., G$ and H_{t-1} are realized $\{\eta_{t-j}\}_{j=1}^{\infty}$ at time t. Thus for a given regime s_t, η_t is generated by an autoregressive process of order b, AR(b), such that the estimated fitted values, $\hat{\eta}_t$ are

$$\hat{\eta}_t = E(\eta_t \mid \eta_{t-1}, s_t) = \hat{\rho}_0 + \sum_{j=1}^{b} \hat{\rho}_j(s_t)\eta_{t-j} = \begin{cases} \hat{\rho}_0 + \sum_{j=1}^{b} \hat{\rho}_j(1)\eta_{t-j} & if s_t = 1 \\ \vdots & \\ \hat{\rho}_0 + \sum_{j=1}^{b} \hat{\rho}_j(G)\eta_{t-j} & if s_t = G \end{cases} . \tag{7}$$

Since the autoregressive process is defined based on unobservable states (Equation 6), it is necessary to complete the data-generating mechanism with the regime-generating process, which is usually assumed to be a discrete time and discrete state Markov stochastic process defined by the transition probabilities

$$p(i|i^{'}) = P(S_{t+1} = i|S_t = i^{'}) \qquad for \;\; i, i^{'} = 1, ..., G,$$

where $\sum_{i=1}^{G} p(i|i^{'}) = 1$. The provided information by the Markov chain at time t can be summarized in a vector ξ_t,

$$\xi_t = \begin{bmatrix} I(S_t = 1) & \cdots & I(S_t = G) \end{bmatrix}^{'}$$

consisting of indicator function $I(S_t = g)$ defined as

$$I(S_t = g) = \begin{cases} 1 & S_t = g \\ 0 & o.w \end{cases}$$

To estimate the parameters of autoregression (Equation 7) and the transition probabilities governing the Markov chain of the unobserved states based on observed information (monthly GDP), it is essential to calculate the desired conditional regime probabilities $Pr(\xi \mid \eta)$ given a specified observation set (observed GDP), as the following

$$Pr(\xi \mid \eta) = \frac{Pr(\eta,\xi)}{Pr(\eta)}.$$

To do this, the joint probability distribution of η and states can be obtained as

$$Pr(\eta,\xi) = Pr(\eta \mid \xi)Pr(\xi) = \prod_{t=1}^{T} Pr(\eta_t \mid \xi_t, \eta_{t-1}) \prod_{t=2}^{T} Pr(\xi_t \mid \xi_{t-1}) Pr(\xi_1),$$

where the density of the sample $\eta = \eta_T$ conditional on the states ξ is determined by

$$Pr(\eta \mid \xi) = \prod_{t=1}^{T} Pr(\eta_t \mid \xi_t, \eta_{t-1})$$

and therefore, the unconditional density of η is proposed by

$$Pr(\eta) = \int Pr(\eta,\xi) d\xi.$$

The maximization of the likelihood function of MS-AR model can be done by an EM algorithm (among all Hamilton, 1990; Krolzig, 1997; Dempster, Laird and Rubin, 1977) where at the "Expectation" step, an estimate of $Pr(\xi \mid \eta)$ of an unobserved state variable ξ, which records the history of Markov chain and S_t) is updated using the estimated MS-AR parameters obtained at the last maximization step. In the "Maximization" step, the likelihood function including these updated $Pr(\xi \mid \eta)$, is maximized and gives the updated estimates for MS-AR parameters for the next expectation step. The EM algorithm continues while the likelihood function increases at each step. For simplicity, these estimated state probabilities at time t given a specified observation set of η (realized monthly GDP) is denoted by p_t.

Subsection 6.1 and the robustness checks provided in Appendix (Figure 11 and Table 5), specifically Table 6 and the computed Bayes factors (Chib, 1998) suggest a two-state MS-AR(1) to obtain the estimated state probabilities, p_t, and the estimated economic contraction, $\hat{\eta}_t^s$[9]. Having these re-notated probabilities, p_t, allows to simplify the notation of the estimates, $\hat{\eta}_t$, in Equation 7 for the next sections and asset pricing model solution, as the following

[9]To clarify, the estimated economic contraction is the fitted values of MS-AR process, η.

$$\hat{\eta}_t^s = \begin{cases} \hat{\eta}_t^{ND} & 1 - p_t : No - Disaster.state \\ \hat{\eta}_t^{D} & p_t : Disaster.state \end{cases}$$

ΔlnD_{it} indirectly depends on the state of the economy S_t, through $\hat{\eta}_t^s$, fitted values of MS-AR process. Section 6 proposes the most appropriate regime-switching specification and estimates a two-regime MS-AR(1).

This paper uses normalized seasonally adjusted monthly GDP in US[10] from 1960 to 2022 to estimate the probability of states and to compute the fitted values, $\hat{\eta}_t^s$, as an estimation for overall economic contraction due to COVID-19.

4.2.4 Dividend growth

To sum up this section and to obtain the price of an equity claim, the dividend growth is proposed by replacing Equation 5 in Equation 3[11], as the following:

$$\Delta ln(D_{it}) = \sum_{m=1}^{M} \beta_m \sum_{k \in Z} \phi^{'}_{i,mk} X_{i,t-k} + \delta ln(\varphi_i) + \alpha ln(\hat{\eta}_t^s) + \varepsilon_{it}. \tag{8}$$

In order to estimate dividend growth and establish the resilience-heterogeneity as well as to obtain calibrated parameters in the model-based equity premium (solution of the model in the following section), this paper estimates $\beta_m, (m = 1, ..., M)$ and α as fixed coefficient effects and δ as a random coefficient effect in a mixed coefficient generalized linear model framework[12]. To mention the importance of $\delta ln(\varphi_i)$ that captures the overall impact of workplace resilience across firms, it is noteworthy to highlight that this term is actually an interaction between the statistical model[13] and the workplace resilience as a variable with heterogeneous impact on dividend growth. Empirical results, in Section 6, clarify the key

[10] Federal Reserve Bank of St. Louis, Economic Research Division.

[11] It is important to mention the impact of generated regressor on asymptotic variance.

[12] Table 8 in the appendix provides guidance on statistical model selection, especially containing the results of the Hausman test to verify the existence of the heterogeneous effect.

[13] The statistical model is Equation 8.

role of this random coefficient effect as the heterogeneous impact of workplace resilience by estimating the δ using the Restricted Maximum Likelihood method, REML. For a theoretical interpretation of mixed-effect specifications, this paper directly refers to Baayen et al. (2008), Henderson (1982), and Gelman (2005) since more statistical details are beyond the scope of the paper.

This study uses Computstat/CRSP merged for monthly fundamentals and financial ratios available at WRDS, for US firms from 2013 to 2022.

In the next section, the solution of the model and asset pricing implications for the COVID-19 disaster is presented based on estimating Equation 8 as the dividend stream.

5 Solution of the model

Given the exogenous dividend stream in Equation 8, $D_{i,t+1}$ and the assumed distribution for error term (Subsection 4.2.4), the price-to-dividend ratio is[14]:

$$log(P_{it}/D_{it}) = \theta log\beta^* + (1-\frac{\theta}{\psi})\sum_{m=1}^{M}\beta_m\sum_{k\in Z}\phi'_{i,mk}X_{i,t-k} + \frac{1}{2}(1-\frac{\theta}{\psi})^2\sigma_\varepsilon^2 + log(1-p_t)$$
$$+ log[E[(\hat{\eta}_t^{ND})^{\alpha(1-\frac{\theta}{\psi})}\varphi_i^{(1-\frac{\theta}{\psi})\delta}]] + \frac{p_t}{1-p_t}(\frac{E[(\hat{\eta}_t^{D})^{\alpha(1-\frac{\theta}{\psi})}\varphi_i^{(1-\frac{\theta}{\psi})\delta}]}{E[(\hat{\eta}_t^{ND})^{\alpha(1-\frac{\theta}{\psi})}\varphi_i^{(1-\frac{\theta}{\psi})\delta}]})$$

The expected return E_tR_{it} can be defined as $\frac{E_t(D_{i,t+1})}{P_{it}}$ and computed as:

$$logE_tR_{it} = -\theta log\beta^* + \frac{\theta}{\psi}\sum_{m=1}^{M}\beta_m\sum_{k\in Z}\phi'_{i,mk}X_{i,t-k} + \frac{1}{2}(1-(1-\frac{\theta}{\psi})^2)\sigma_\varepsilon^2$$
$$+ log[\frac{E[(\hat{\eta}_t^{ND})^{\alpha}\varphi_i^{\delta}]}{E[(\hat{\eta}_t^{ND})^{\alpha(1-\frac{\theta}{\psi})}\varphi_i^{(1-\frac{\theta}{\psi})\delta}]}] + \frac{p_t}{1-p_t}((\frac{E[(\hat{\eta}_t^{D})^{\alpha}\varphi_i^{\delta}]}{E[(\hat{\eta}_t^{ND})^{\alpha}\varphi_i^{\delta}]}) - (\frac{E[(\hat{\eta}_t^{D})^{\alpha(1-\frac{\theta}{\psi})}\varphi_i^{(1-\frac{\theta}{\psi})\delta}]}{E[(\hat{\eta}_t^{ND})^{\alpha(1-\frac{\theta}{\psi})}\varphi_i^{(1-\frac{\theta}{\psi})\delta}]}))$$

[14]Implicitly, this paper assumes asymptotic expected return where the arbitrary period length tends to zero, similar to Barro (2006). The proofs are provided in Appendix.

Moreover, the return on risk-free assets is:

$$log(R_{it}^{f}) = -\theta log\beta^{*} + \frac{\theta}{\psi}\sum_{m=1}^{M}\beta_m\sum_{k\in Z}\phi_{i,mk}^{'}X_{i,t-k} - \frac{1}{2}(\frac{\theta}{\psi})^2\sigma_{\varepsilon}^2 - log(1-p_t)$$
$$- log[E[(\hat{\eta}_t^{ND})^{-\frac{\alpha\theta}{\psi}}\varphi_i^{(-\frac{\theta}{\psi})\delta}]] - \frac{p_t}{1-p_t}(\frac{E[(\hat{\eta}_t^{D})^{-\frac{\alpha\theta}{\psi}}\varphi_i^{(-\frac{\theta}{\psi})\delta}]}{E[(\hat{\eta}_t^{ND})^{-\frac{\alpha\theta}{\psi}}\varphi_i^{(-\frac{\theta}{\psi})\delta}]})$$

Then the equity premium is given by:

$$\begin{aligned} logE_tR_{it} - log(R_{it}^{f}) = {} & \frac{\theta}{\psi}\sigma_{\varepsilon}^2 + log(1-p_t) + log[E[(\hat{\eta}_t^{ND})^{-\frac{\alpha\theta}{\psi}}\varphi_i^{(-\frac{\theta}{\psi})\delta}]] \\ & + log[\frac{E[(\hat{\eta}_t^{ND})^{\alpha}\varphi_i^{\delta}]}{E[(\hat{\eta}_t^{ND})^{\alpha(1-\frac{\theta}{\psi})}\varphi_i^{(1-\frac{\theta}{\psi})\delta}]}] + \frac{p_t}{1-p_t}[(\frac{E[(\hat{\eta}_t^{D})^{\alpha}\varphi_i^{\delta}]}{E[(\hat{\eta}_t^{ND})^{\alpha}\varphi_i^{\delta}]}) \\ & - (\frac{E[(\hat{\eta}_t^{D})^{\alpha(1-\frac{\theta}{\psi})}\varphi_i^{(1-\frac{\theta}{\psi})\delta}]}{E[(\hat{\eta}_t^{ND})^{\alpha(1-\frac{\theta}{\psi})}\varphi_i^{(1-\frac{\theta}{\psi})\delta}]}) + (\frac{E[(\hat{\eta}_t^{D})^{-\frac{\alpha\theta}{\psi}}\varphi_i^{(-\frac{\theta}{\psi})\delta}]}{E[(\hat{\eta}_t^{ND})^{-\frac{\alpha\theta}{\psi}}\varphi_i^{(-\frac{\theta}{\psi})\delta}]})] \end{aligned} \tag{9}$$

This paper considers that time discount factor β^{*} is 0.999, consistent with many papers (among all Wachter, 2013). The probability of disaster state, p_t, is monthly estimated based on the methodology provided in Subsection 4.2.3 and parameters, α, δ, $\beta_1, ..., \beta_M$ are estimated using random coefficient generalized linear model (Subsection 4.2.4). After estimating MS-AR(1) in Section 6.1 and the exogenous dividend growth over 2013 - 2022 in Section 6.2, the paper does calibration exercise for γ, ψ and σ_{ε} using price-to-dividend ratio, risk free rate and the following model-based Sharpe ratio.

$$S_{it} = \frac{\sigma_t[M_{t+1}]}{E_t[M_{t+1}]} = \frac{(exp\{ln[exp\{B\}-1] + 2\theta ln(\beta^{*}) - 2(\frac{\theta}{\psi})(A) + B\})^{1/2}}{exp\{\theta ln(\beta^{*}) - (\frac{\theta}{\psi})(A) + \frac{1}{2}B\}}$$

where, M_{t+1} is discount factor presented in Section 4.1, and

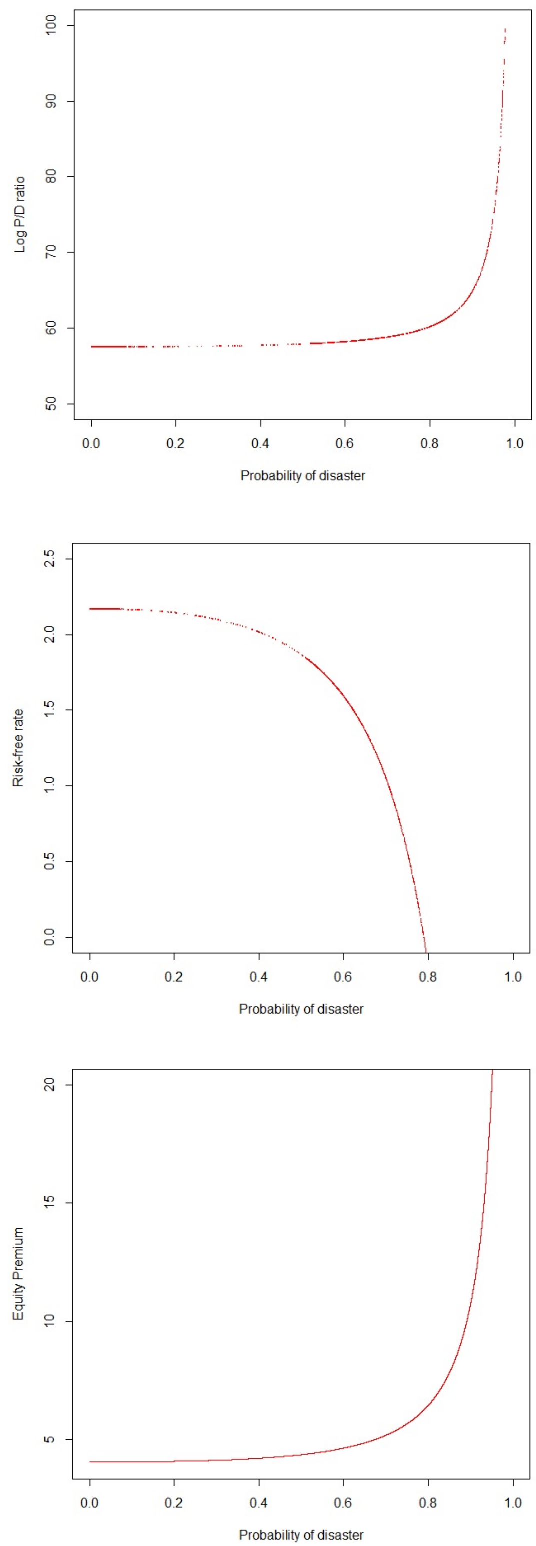

Figure 3: **Price-to-dividend ratio, risk-free rate, and equity premium:** This figure plots the log P/D ratio, log risk-free rate $logR^f_{it}$, and equity premium $logE_tR_{it} - logR^f_{it}$ as a function of probability of disaster. The log P/D ratio, log risk-free rate, and equity premium are computed based on estimated parameters α, δ, $\beta_1, ..., \beta_M$ (Section 6) and calibration exercise for γ, ψ and σ_ε. Data source: Compustat/CRSP merged and financial ratios, WRDS.

$$A = \sum_{m=1}^{M} \beta_m \sum_{k \in Z} \phi'_{i,mk} X_{i,t-k} + \alpha ln(\hat{\eta}_t^s) + ln(\varphi_i) E(\delta),$$

$$B = (\frac{\theta}{\psi})^2 ((ln(\varphi_i))^2 \sigma_\delta^2 + \sigma_\varepsilon^2).$$

This setup obtained $\gamma = 0.999$ and Elasticity of Intertemporal Substitution (EIS), $\psi = 1.013$. This calibration exercise for relative risk aversion and EIS implies that generally speaking, investors became a bit more conservative in the COVID-19 situation, in the sense that the representative investor might prefer early resolution of uncertainty since $\gamma > 1/\psi$ (Bansal et al., 2012)[15]. Moreover, the calibration suggests a reasonable value of 7.3 for σ_ε, in line with the fact that not only uncertainty but also even a very small possibility of disaster makes the dividend growth have a heavier tail distribution. This highlights the impact of a "rare" disaster in line with Weitzman (2005) and reveals the impact of COVID-19 as a rare event on the distribution of dividend growth.

Based on all estimated and calibrated parameters, Figure 3 plots the model-based asset pricing implications (the tractable formulas) as a function of disaster probability spanned on [0,1]. It shows the price-to-dividend ratio and the risk-free rate as increasing and decreasing functions of disaster probability, respectively. In periods with a higher probability of disaster, a decline in dividends happens at a higher pace than price reduction since the price is assumed to be a discounted future dividend stream including some "no-disaster" states. The first panel illustrates that when the possibility of disaster is higher than 0.85, dividends plunge to zero and the price-to-dividend ratio becomes strictly increasing at the highest pace.

In case of the possibility of disaster, there is an interest in buying more risk-free assets,

[15] In standard literature, EZ parameters, γ and ψ, are interpreted as risk aversion and elasticity of intertemporal substitution, respectively. But this interpretation may not be strictly satisfied when γ differs from the reciprocal ψ (Garcia et al.,2006 and Hansen et al., 2007). The Euler equation and the consequent calibration exercise, as expected, highlight that the model is based on a especial case of power utility with a bit of parameter relaxation (consistent with Barro, 2009).

its price goes up, and the risk-free rate decreases. The second panel shows that the model-based risk-free rate is decreasing in the probability of disaster. Clearly, in case of a very high probability of disaster state, there is no interest in the risky asset, so the equity premium increases as compensation to cover the additional risk. The third panel shows that the model-based equity premium is an increasing function of the disaster probability. Moreover, in line with Barro (2006), the equity premium is a decreasing function of risk aversion, γ. In what follows, the paper presents the estimation of exogenous dividend growth and its parameters used in the calibration exercise.

6 Results

This section presents an estimated exogenous dividend stream for model-based asset pricing implications. The first part (Subsection 6.1) clarifies that COVID-19 is a disaster and provides the estimation of the macro time-effect of COVID-19 (η_t^s) from 2013 to 2022, the period over which exogenous dividend stream is estimated. The second step (Subsection 6.2) quantifies the impact of financial resilience components. It also estimates the dividend growth (Equation 8) as well as the fixed-effects α and β_ms which are coefficients of macro economic contraction, $\hat{\eta}_t^s$ and financial resilience components, $PC_{it,m}$, respectively, and δ as the heterogeneous effect of workplace resilience, $ln(\varphi_i)$, using the Restricted Maximum Likelihood method, REML, over 2013 - 2022.

6.1 Macroeconomic sensitivity to COVID-19 disaster

In the proposed approach, the first step is to estimate the macro economic contraction due to COVID-19 to control for the aggregate time effect, as explained in Subsection 4.2.3. Figure 4 shows the fitted two-regime Markov-Switching (MS) model for the monthly GDP of the United States from 1960 to 2022 and specifies the disaster regimes. This figure provides an opportunity to empirically prove that this pandemic was a disaster with significant macroeconomic consequences and exhibits the COVID-19 pandemic period as a disaster regime. Furthermore, according to Table 1, the estimation for controlling the macro time-effect of COVID-19, $\hat{\eta}_t^s$ can be obtained from:

$$\hat{\eta}_t^s = \begin{cases} 100.69 + 0.97q_{t-1} & 1 - p_t : Non - Disaster.state \\ 100.69 + 1.03q_{t-1} & p_t : Disaster.state \end{cases}$$

with the estimated transition probabilities in Table 2. Significant switching AR(1) coefficients in Table 1 is a sign of severe economic contraction in disaster states, specifically the estimated coefficient in disaster states (1.03) shows that such macro time-effect is not mean-reverting in disasters.

The LRT statistic provided in Table 1 empirically proves the significance of nonlinear two-regime MS-AR(1). The evidence on optimally choosing the number of regimes is presented in Table 5 and Table 6 in the appendix.

Table 1: **Estimated parameters of MS-AR(1):** This table presents the maximum likelihood estimation of the two-regime Markov-Switching AR(1) and the conditional probability of disaster states. It provides the Likelihood Ratio Test to examine linear vs. nonlinear two-regime MS-AR(1). Significant codes: 0 '***', 0.001 '**'.

Nonlinear Markov-Switching	Coefficients (StDev)	t-value
Intercept: ρ_0	100.69 (0.013)	592.00***
AR-1: ρ(Disaster state)	1.03 (0.01)	65.40***
AR-1: ρ(Non-Disaster state)	0.97 (0.003)	172.00***
p(Disaster|Disaster)	0.91 (0.02)	63.20***
p(Disaster|Non-Disaster)	0.02 (0.005)	4.51***
log-likelihood statistics	431.80	
LRT statistics	1102.7**	

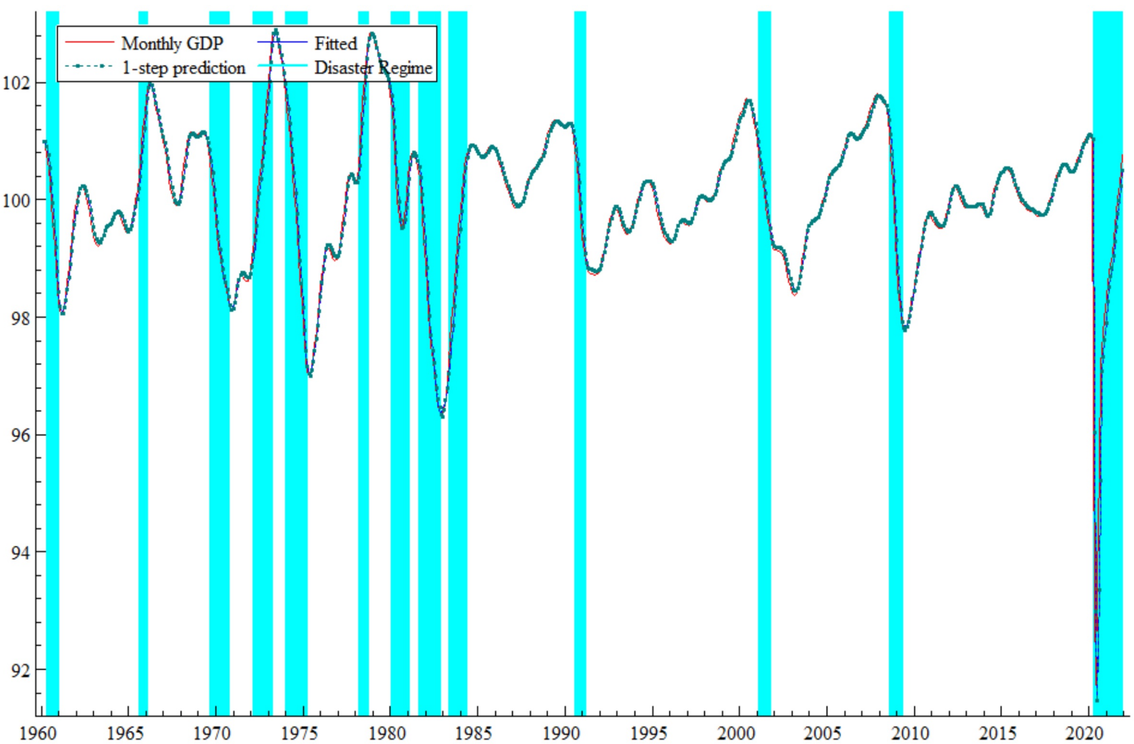

Figure 4: **Monthly GDP, fitted the two-regime MS-AR(1) and the one-step prediction from 1960 to 2022:** The blue columns show the disaster regimes (states and the duration). Data source: Normalised seasonally adjusted GDP, Federal Reserve Bank of St. Louis, Economic Research Division.

Table 2: **Estimated transition matrix:** This table shows the conditional probability of disaster states estimated by two-regime MS-AR(1).

Transition probability	Disaster state at time t	Non-Disaster state at time t
Disaster state at time t+1	0.91	0.02
Non-Disaster state at time t+1	0.08	0.97

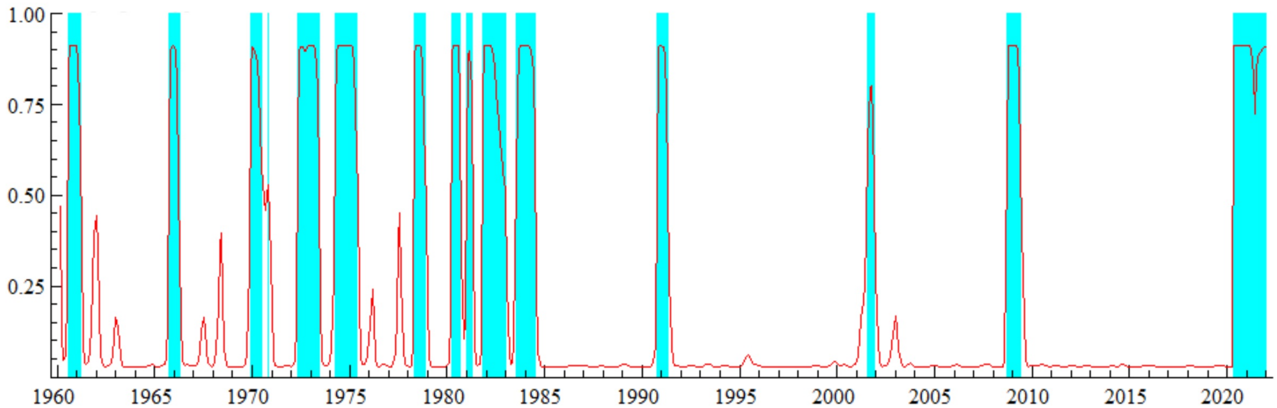

Figure 5: **Evolution of estimated probability of disaster state based on MS-AR(1), from 1960 to 2022:** The blue columns show the disaster regimes (states and the duration).

Figure 5 shows the evolution of disaster state probability, p_t. As it can be seen clearly and in line with Figure 1, the probability of a disaster state rose to around 0.9 in the fever period of COVID-19, followed by a reduction due to the impact of the good news about vaccines. Even though the probability of a disaster state at time t conditional on the non-disaster state for the previous month, is 2 percent which is in line with the calibrated static disaster probability of 1.7 percent proposed by Barro (2006), the economy will remain in disaster regime due to low transition probability of 8 percent. Table 2 shows that switching from disaster states to no-disaster ones happens with a probability of 0.08.

In addition to Figure 4, which graphically shows the goodness of fit and appropriateness of estimated economic contraction, $\hat{\eta}_t^s$, Table 7 (in the Appendix) re-verifies these results and contains not only the estimated disaster states s_t and the regimes' duration but also the evidence from Fed reports. It compares the estimated disaster regimes with the corresponding actual events. The estimation of disaster regimes accords with the historical information in Burger (1969), Supel (1978), and Hoxworth et al. (1983).

Moreover, Figure 11 (in the Appendix) shows the estimated distribution for macroeconomic sensitivity, η_t^s, and compares the bimodal distribution with the corresponding normal distribution. It provides another form of verification on the number of regime switches.

6.2 Justification for dividend stream and asset pricing moments

To interpret the impact of corporate financials and to investigate whether and to what extent the financial status of firms amplifies the consequences of COVID-19 on asset prices, this paper starts with around 70 financial ratios of 5833 U.S. firms over 2013−2022 at monthly frequency and employs Dynamic Functional Principal Component Analysis (DFPCA) to capture the impact of firm's financial status, as explained in Subsection 4.2.2.

By computing the filter sequences and dynamic functional principal components, it is possible to provide the scree plot and decide on the number of components required to include most of the variation originating from all corporate financials that possibly affected dividend growth. Figure 6 shows the portion of variance explained by each dynamic functional PC for all firms, separately, in one diagram. It suggests that the first five components explain the most variation (over 90 percent) induced by financial ratios for almost all firms.

Based on Equation 8 and the first five dynamic principal components (PCs)[16], the results of estimated dividend growth are summarized in Table 3. This table presents the quantified effect of workplace resilience and the impact of the firm's financial resilience as the elasticity of dividend growth to these two intuitions of resilience.

[16] In case of interest, the results based on the first ten principal components can be provided.

Table 3: **Dividend growth estimation:** This table provides estimation for coefficients of financial resilience components and the impact of COVID-19 including macro time-effect of COVID ($ln\hat{\eta}_t^s$) and workplace resilience (Equation 8). It presents fixed effects ($\beta_1, ..., \beta_5$) of first five cross-sectional time-varying dynamic functional PCs ($PC_1, ..., PC_5$) and the heterogeneous effect (δ) of workplace resilience $ln(\varphi_i)$, by REML estimating method. The industry sector codes from "2" to "6" belong to "Mining, Utility and Construction", "Manufacturing", "Trade, Transportation and Warehousing", "Information, Finance, Management, and Remediation Services", "Educational, Health Care and Social Assistance", respectively. Each column shows the result of estimation separately for each industry. The numbers in parentheses are standard deviations of corresponding estimated coefficients. Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'.

Dependent variable: Dividend growth

	All industries	Industry sector (NAICS code)				
		2	3	4	5	6
PC_1	0.0007** (0.0002)	0.0027 (0.0014)	0.0041*** (0.0003)	-0.0026** (0.0008)	-0.0029*** (0.0005)	0.0113*** (0.0025)
PC_2	-0.0029* (0.0004)	0.0066** (0.0021)	-0.0045*** (0.0005)	0.0052*** (0.0011)	-0.0022*** (0.0006)	-0.0082* (0.0032)
PC_3	-0.0025* (0.0005)	0.0010 (0.0028)	-0.0013 (0.0007)	0.0025 (0.0015)	-0.0050*** (0.0008)	0.0132** (0.0042)
PC_4	-0.000007*** (0.0022)	-0.0092* (0.0037)	-0.0014 (0.0008)	-0.0029 (0.0020)	0.0030** (0.0011)	0.0026 (0.0058)
PC_5	0.00001 (0.0008)	-0.0060 (0.0045)	0.0002 (0.0011)	0.0055* (0.0025)	-0.00007 (0.0013)	0.0310*** (0.0069)
$ln\hat{\eta}_t^s$	-2.3149*** (0.0889)	-0.7308 (0.4882)	-1.8041*** (0.1191)	-2.4705*** (0.2832)	-3.2298*** (0.1399)	-3.2044** (0.0085)
Average of workplace resilience (heterogeneous effect)	10.3690*** (0.4622)	2.6394*** (0.5561)	8.0623*** (0.4327)	11.2225*** (0.5193)	14.5646*** (0.3182)	14.0970*** (0.6553)
F-statistics	127.48***	4.013*	79.816***	19.303***	105.565***	11.4737***

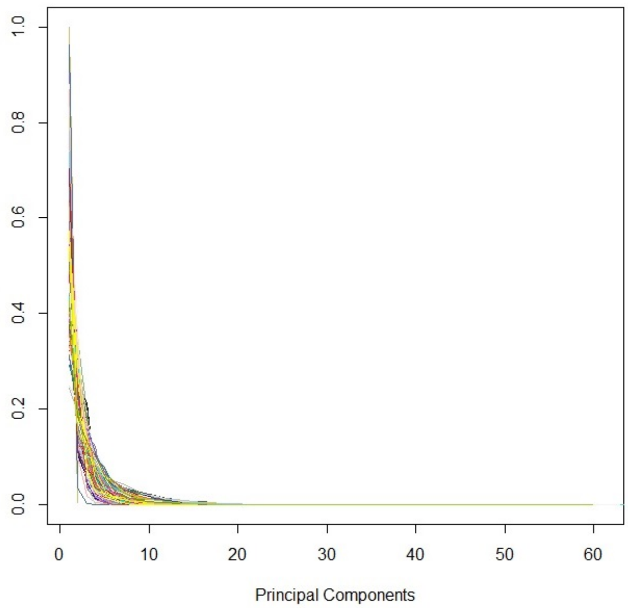

Figure 6: **Scree plot of Dynamic Functional Principal Component Analysis (DFPCA) of financial ratios:** This figure shows the portion of variance explained by each component (eigenvalues). The sample contains around 5833 US firms. Data source: Firm-level financial ratios, WRDS.

6.2.1 Interpretation of workplace resilience impact

It can be seen clearly that workplace resilience has significantly a positive average heterogeneous effect of 10.36 on dividend growth for a sample of all industries. For individual industries, the corresponding coefficient of workplace resilience in the specification of dividend growth varies on average from 2 to 14, respectively in "Mining, Utility and Construction" and "Information, Finance, Management, and Remediation Services". The key result on the averaged heterogeneous effect of workplace resilience can be seen in Figure 7. Based on workplace resilience, firms are categorized into two, three, and four groups. In each case, the first and last groups are considered as low- and high-resilience firms, respectively. This figure exhibits that the averaged heterogeneous effect of workplace resilience for low-resilience firms is higher than the one for high-resilience firms (the red line is below the blue line in Figure 7), meaning that the elasticity of dividend growth with respect to workplace resilience, $\hat{\delta}$ for firms with a very low degree of workplace resilience is much higher than the one for very high-resilience firms. On the other hand, it can be seen clearly in Figure 7 that the greater the difference in workplace resilience of firms (an increase in number of groups, equivalently), the greater the difference in the averaged heterogeneous effect or the corresponding elasticity (an increase in vertical distance between the red point and the blue one); And as a result, for the same amount of an increase in workplace resilience there is a greater change in dividend growth of low-resilience firms based on Equation 8. Daadmehr (2023) theoretically proves a similar statement for expected returns and shows an increase in COVID intensity increases the expected return of low-resilience firms much more than that of high-resilience firms.

To sum up, Figure 7 suggests that in low-resilience firms, a one percent improvement in workforce flexibility increases the dividend growth much more than in the case of high-resilience firms, since the averaged estimated heterogeneous coefficient, $\hat{\delta}$, for low-resilience firms is much higher. The summary statistics and empirical results on the heterogeneous effect of workplace resilience are provided in Table 4. This table provides statistical tests to reveal these differences in heterogeneous effect, $\hat{\delta}$, for these two groups of firms. The results in this table implicitly examine the significant differences in elasticity of dividend growth to workplace resilience between high and low workplace-flexible firms. This table empirically proves that for any number of groups (K), the heterogeneous effect of workplace resilience of high workplace-resilient firms is "significantly" different from that of the low workplace-resilient ones. Consequently, there are significant discrepancies in dividend growth of high- and low-resilience firms created by the heterogeneous effect of workplace resilience. In other words, this indicates that the dividend growth for low-resilience firms is significantly more sensitive to workplace resilience than that of high-resilience firms which technically proves the existence of significant resilience heterogeneity in expected cash flows.

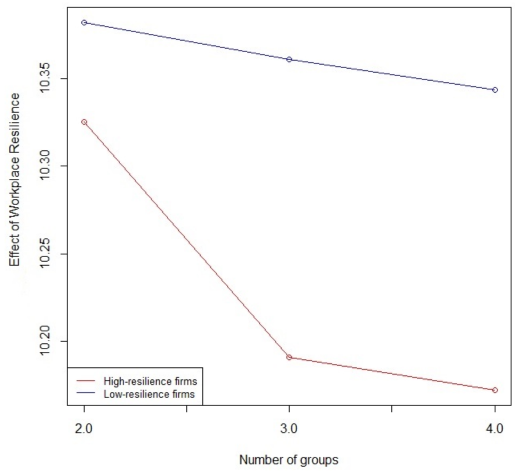

Figure 7: **The average heterogeneous effect of workplace resilience:** This figure exhibits how the difference in workplace resilience of high- and low-resilience firms changes averaged heterogeneous effect of workplace resilience, by sorting and equally splitting firms into K groups based on their workplace resilience. The first group and the last one are considered as low and high workplace-resilient firms, respectively.

Table 4: **Summary statistics of heterogeneous effect of workplace resilience:** This table provides the summary statistics on the heterogeneous effect of workplace resilience for high-resilience and low-resilience firms, including the results of group comparisons. Based on workplace resilience, firms are sorted and splitted into K groups. The first group and the last one are considered as low and high workplace-resilient firms, respectively. It compares the heterogeneous effect of two groups of firms using the nonparametric Wilcoxon test. The heterogeneous effect of high-resilience firms is significantly different from the low-resilience ones. Significant codes: 0 '***', 0.001 '**'.

K	Workplace Resilience	Minimum	1^{st} Qu.	Median	Mean	3^{rd} Qu.	Maximum	Group Comparison test P-Values
2	High	9.88	10.21	10.29	10.33	10.52	10.52	0.00***
	Low	9.35	9.16	10.41	10.38	10.69	10.51	
3	High	10.05	10.05	10.22	10.19	10.22	10.33	0.00***
	Low	9.35	10.15	10.41	10.36	10.72	11.41	
4	High	10.05	10.05	10.21	10.17	10.22	10.29	0.00***
	Low	9.35	10.16	10.44	10.34	10.72	11.41	

6.2.2 Interpretation of macro time-effect of COVID-19

Table 3 emphasizes the importance of the macroeconomic COVID-sensitivity that implies a significant reduction in dividend growth not only at the level of "All industries" but also within each industry, except "Mining, Utility and Construction". The estimated coefficient of $ln(\hat{\eta}_t^s)$ is statistically significant, showing that all sectors are significantly sensitive to the recession caused by COVID-19, except "Mining, Utility and Construction".

Does the low amount of estimated workplace resilience, $\hat{\delta}$, imply such insignificant effect of macro economics contraction due to COVID-19? In this sector, the reason for the lack of statistical significance of $\hat{\alpha}$ is related to the low amount of estimated averaged heterogeneous effect of workplace resilience of 2.6. Firms in this sector have much lower averaged heterogeneous effect of workplace resilience with respect to its average amount plotted in Figure 7 (the red line is below the blue line in Figure 7 and the average amount of 2.6 for this industry is much smaller than the average in the case of "all industry", in Figure 7). Accordingly, this suggests that firms in this industry are more workplace-resilient, on average. Hence in this industry, social distancing restrictions are not disturbing as much as it is in other sectors so it is not surprising to see such insignificant impact of macro time-effect of COVID-19.

6.2.3 Interpretation of financial resilience

Table 3 also shows the results of elements of financial resilience. The significance of dynamic functional principal components of financial ratios not only suggests the significant effect of firms' financial status on dividend growth but also proves the significant amplification of workplace resilience by corporate financials[17], $G_{it} = f(FR_{it})g_{it}$, in Section 4. This table reveals that financial resilience, especially the first two principal components, containing most

[17] In line with the intuition of financial-based resilience and its role in composite-financial resilience index in Daadmehr (2024).

variations originating from financial ratios, directly affects dividend growth and makes its resilience more heterogeneous. These small estimated effects, $\beta_1, ..., \beta_M$, is not catastrophic in such pandemic crisis but is significant enough. Then, overall resilience heterogeneity is not just from the workforce resilience perspective but also based on what firms financially experienced before and during the COVID-19 outbreak. Next section introduces the major elements with more contribution in firms' financial resilience.

On top of all these, since the averaged heterogeneous effect of workplace resilience is greater than the estimated coefficients of financial resilience elements (PCs), dividend growth is more elastic and responsive to workplace resilience. Equivalently, the role of workplace flexibility is more prominent in explaining the resilience heterogeneity in dividend growth.

Moreover, the empirical results in this section show "to what extent" cash flows can be resilience heterogeneous and the solution of the proposed model in Section 5, sheds light on "how" such significant resilience-heterogeneity, specifically the heterogeneous effect of workplace resilience and the amplification effect by financial resilience, can be transferred to the expected returns as well as all asset pricing implications. The calibrated exercise compares model-based asset pricing moments with the corresponding values from historical data. The model-based equity premium (5.269) is close to the average equity premium from data (5.147). The result holds for the risk-free rate (1.137 vs. 1.006 from historical data). The model-based standard deviation of the log risk-free rate (2.531) is in line with the corresponding amount presented by Ghaderi et al. (2022) using historical data from 1950 to 2019[18].

7 Major elements of financial resilience

Section 6 explained the significant role of the financial resilience of assets in the amplification of the dominant heterogeneous effect of workplace resilience in exogenous dividend growth

[18]All values are reported in percentage terms.

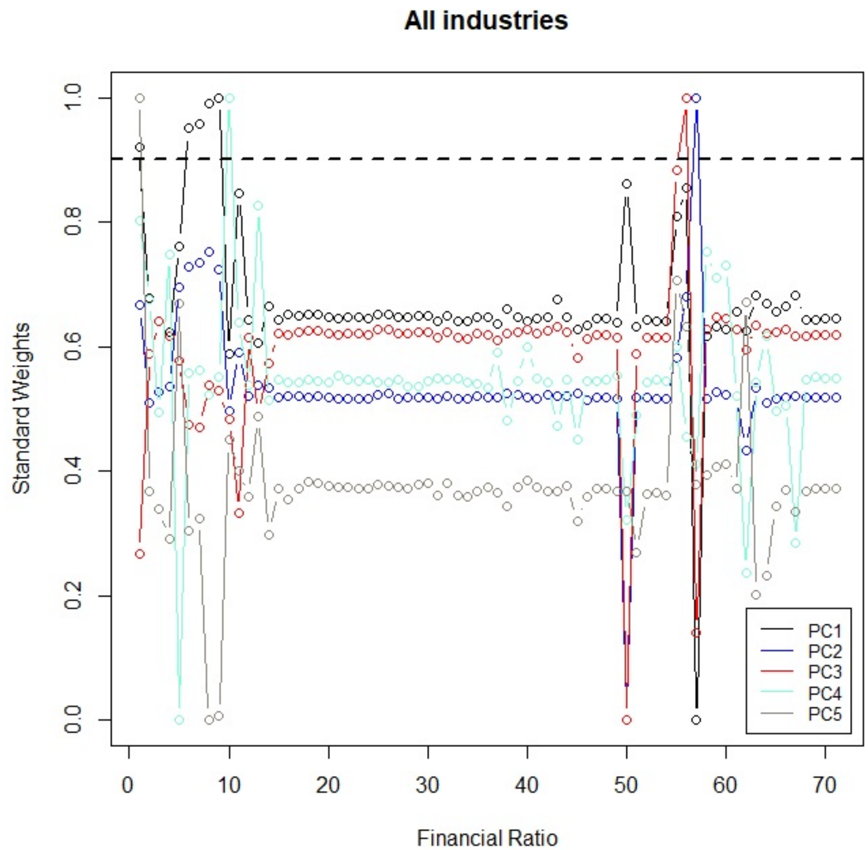

Figure 8: **Overall weights of financial ratios (average of filter sequences, ϕ, for the first five PCs):** This figure shows the standardized weights of all financial ratios obtained by DFPCA. The sample contains 5833 firms in all industries. The black dash line is the threshold of 90 percent for weights. Data source: Firm-level financial ratios, WRDS.

as well as asset pricing implications (Section 5). The key application of Dynamic Functional Principal Component Analysis (DFPCA) determined the first five major PCs as components of financial resilience, FR_{it}, at the firm level over time, including the COVID-19 era. This section clarifies which financial ratios mostly drive fluctuations in these firms' financial resilience components.

Figure 8 exhibits weights of financial ratios for each of $PC_1, ..., PC_5$. It provides the opportunity to compare the relative importance of financial ratios in determining the firm's resilience. This figure reveals major ratios with over 90 percent average weight (above the black dash line) in the specification of at least one of the first five principal components,

$PC_{it,m} = \sum_{k \in Z} \phi'_{i,mk} X_{i,t-k}$, for $m = 1, ..., 5$. It determines Shillers Cyclically Adjusted P/E Ratio, Price/Operating Earnings (Basic), Price/Operating Earnings (Diluted), P/E (Diluted, Excl. EI), P/E (Diluted, Incl. EI) and Price/Sales (valuation ratios); Cash Conversion Cycle (liquidity ratio); and Interest Coverage Ratio (solvency ratio) as main elements of dynamic functional PCs and the financial resilience as well.

Daadmehr (2024) explains to what extent valuation and liquidity ratios are significantly correlated with the proposed financial-based resilience index and emphasizes the necessity of workplace flexibility to define a novel "Composite-Financial Resilience Index". The machine-based (DFPCA) choice of valuation ratios is in line with Glossner et al. (2022) who emphasize the important amplification role of institutional investors in valuation and the severe price decline in COVID-19. Furthermore, having liquidity ratio as one of the important ratios determined by DFPCA is consistent with Pagano and Zechner (2022) who mention the significant change in liquidity levels of listed U.S. firms, from before the emergence of the pandemic to after the onset.

The choice of Interest Coverage Ratio is in line with Palomino et al. (2019) who interpret the countercyclicality and its negative relation with economic activity. In what follows, there is an interpretation of the relation between these ratios, workplace resilience, and firms' vulnerability and riskiness.

7.1 Valuation Ratios

By definition, valuation ratios are appropriate to measure the relationship between market value and some stream of fundamentals. Figure 9 shows time-variation in different kinds of valuation ratios with higher than 90 percent weight (averaged ϕ in Equation 4) in elements of firms' financial resilience ($PC_1, ..., PC_5$) after the onset of COVID pandemic, diagnosed by Dynamic Functional PCA (DFPCA). The first panel shows that the time trend for almost all of these ratios is the same, especially different kinds of price-to-earning ratios that are commonly used as good financial metrics to get a better understanding of the overall picture, and accessible to a wide range of investors. In this paper, DFPCA technically proved its significant role on resilience heterogeneous dividend growth through the firm's financial resilience (Subsection 6.2).

This figure compares the descriptive behavior of these valuation ratios, also separately for high- and low-resilience firms (the second and third panels), in the sense of workplace resilience. It can be seen clearly from the second panel that these ratios have a more homogeneous trend for high-resilience firms. This homogeneity is less clear in the case of low-resilience firms. To make a better comparison between the valuation ratios of high- and low-resilience firms, one of these ratios is selected as a representative. The dynamic functional PCA determines "Shillers Cyclically Adjusted P/E Ratio" as an effective main element of either PC_1 or PC_5 with a weight of more than 90 percent (Figure 8). In particular, DFPCA implicitly mentions the inflated P/E due to low or even negative earnings during economic downturns like COVID-19 and refers to the cyclicality of earnings over these periods. It highlights the importance of cyclically adjusting of P/E and selects "Shillers Cyclically Adjusted P/E Ratio" as the most promising valuation ratio among different definitions of P/E ratio. The first panel of Figure 10 shows that the adjusted P/E ratio for low-resilience firms is higher than that of the high-resilience ones during the COVID-19 outbreak, except for a short time at almost the end of the fever period in the first wave of this pandemic. The flip point in the fever period is consistent with Pagano et al. (2023).

Generally speaking, when a firm has a high P/E ratio, it implies that investors are willing to pay a premium for its stock relative to its current earnings. While high P/E ratios signal growth expectations, they also introduce risk. Investors should take into account these risks carefully in their investment decisions. Simply, a firm with a high P/E ratio can be seen as risky for several reasons: i) Uncertainty: The stock price may suffer if the company fails to meet those expectations. ii) Market Sentiment: Any negative news can lead to a sharp decline in the price of stock with higher expectations. Then, investor sentiment plays an

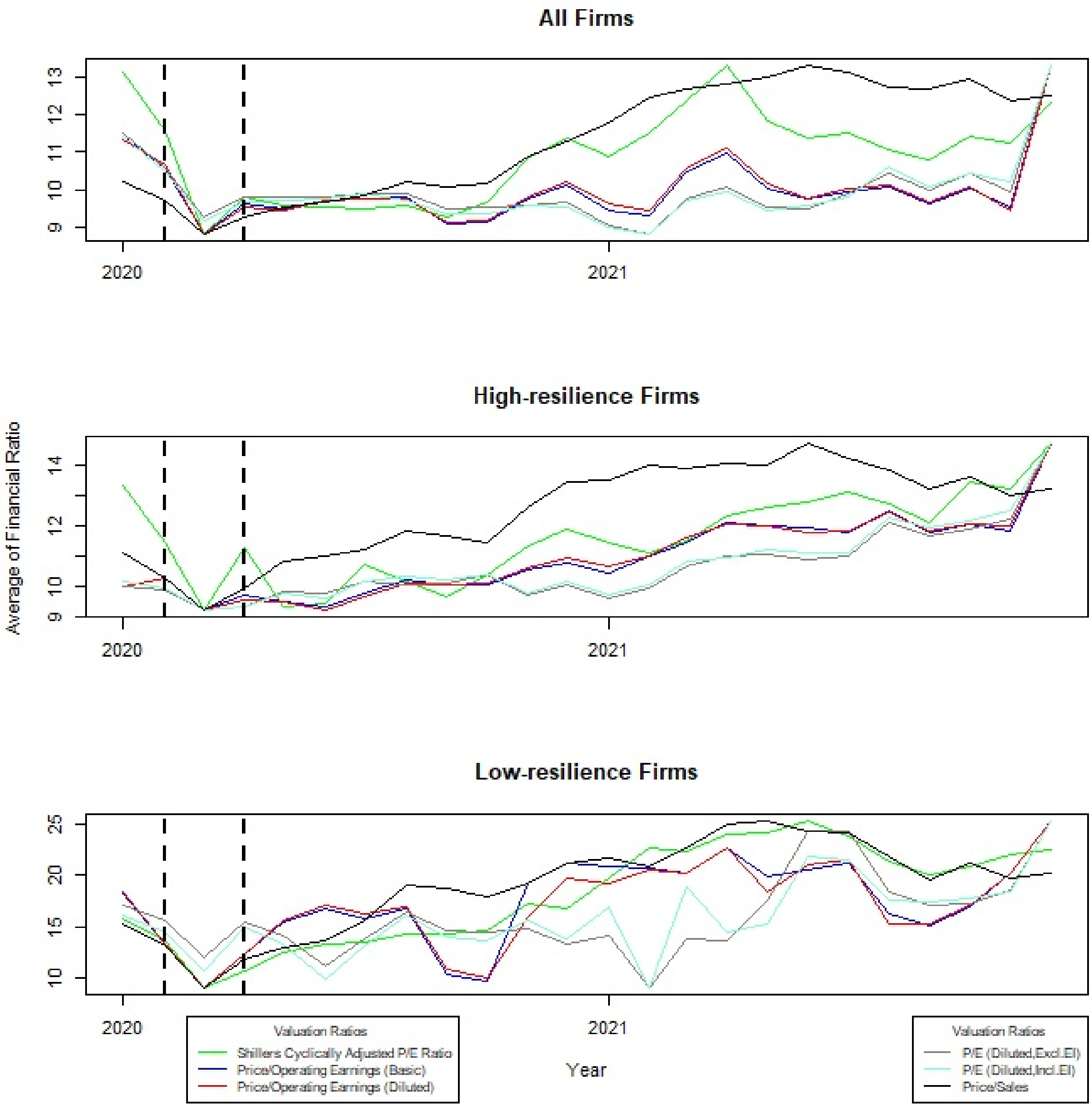

Figure 9: **Valuation ratios:** This figure shows the time series of major valuation ratios determined by Dynamic Functional Principal Component Analysis. The categorization of firms into high- and low-resilience groups, in the sense of workplace flexibility, follows Koren and Peto (2020) and Daadmehr (2024). Firms with an 'affected share' of less than 40 are assigned to the high-resilience group and ones with greater than 65 are assigned to the low-resilience. Vertical black dash lines refer to the fever period of the COVID-19 pandemic, from February to April 2020. Data source: Firm-level financial ratios, WRDS.

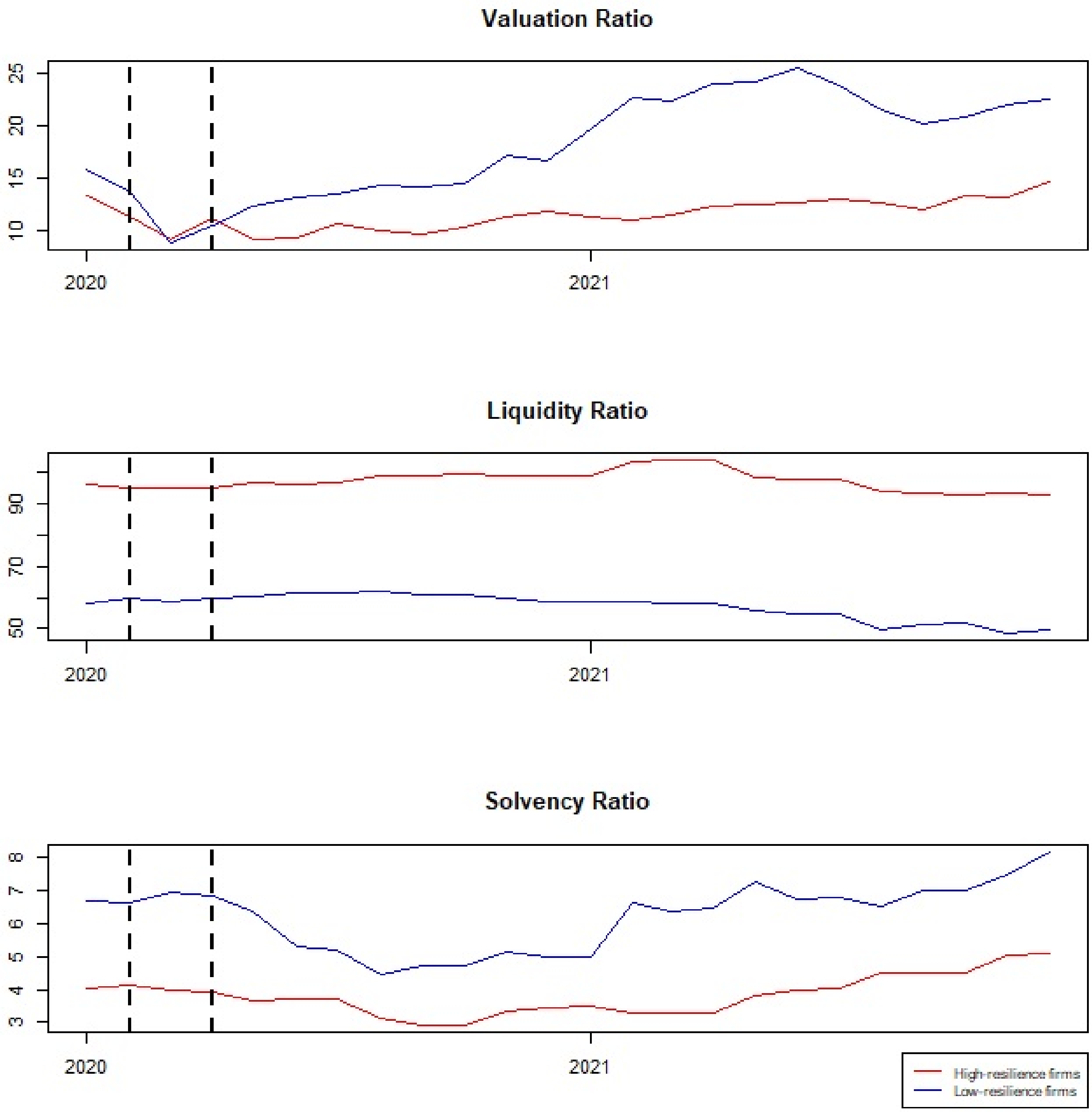

Figure 10: **Representative financial ratios:** This figure shows the time series of Shillers Cyclically Adjusted P/E (valuation ratio), Cash Conversion Cycle (liquidity ratio), and Interest Coverage Ratio (solvency ratio) as major elements determined by DFPCA. The categorization of firms into high- and low-resilience groups, in the sense of workplace flexibility, follows Koren and Peto (2020) and Daadmehr (2024). Firms with 'affected share' less than 40 are assigned to the high-resilience group and ones with greater than 65 are assigned to the low-resilience. Vertical black dash lines refer to the fever period of the COVID-19 pandemic, from February to April 2020. Data source: Firm-level financial ratios, WRDS.

important role. iii) Volatility: The price of stocks with high P/E ratios reacts more strongly to market events. iv) Missed Expectations: It is disappointing for investors if the firm loses its growth targets, leading to a potential sell-off.

Firms with higher P/E ratios can be possibly considered riskier since they have higher growth expectations[19], making them more vulnerable as explained. So, stocks with lower P/E ratios may be perceived as less risky, but this is not sufficient enough to assess the overall firm's financial status and health. Figure 10 (first panel) explains that these firms with higher adjusted P/E ratios are low-resilience in their workforce, in line with Daadmehr (2024) who empirically proves that low-resilience firms are riskier and naturally investors expect more returns on these stocks.

Firms can control the level of P/E ratio through different kinds of policies. Many papers investigate the impact of dividend policy on the price-to-earnings ratio. Among all, Jitmaneeroj (2017) discusses how these policies and the P/E ratio have a negative and positive association depending on the firm's profitability. Despite the sticky preferences for dividend policy, many papers explain the existence of determinants that affect firms' decisions on this kind of policy. One growing strand of the literature suggests that dividend policy can be influenced by ownership structure and affect firms' performance. Lopes and Narciso (2020) examine the ability of earnings management practices to predict the dividend policy and suggest ownership concentration as a main driver of this relationship. Furthermore, the association between insider ownership and financial performance affects the firm's P/E ratio. Houmes and Chira (2015) explain that high insider ownership makes the board ineffective and perpetuates weak performance with lower P/E, showing that managers are not capable enough to create value and firms are riskier in this sense and investors require higher returns.

On another front, accounting and investment policies can jointly affect the P/E ratio. Staehle and Lampenius (2013) compare firms with different accounting and investment

[19] The P/E ratio can present insights into investors' expectations for a firm's future growth prospects. A high P/E ratio implies that investors anticipate strong earnings growth in the future, which increases the risk of possible missed expectations.

policies and combine a model with overlapping capacity investments (among all, Rogerson, 2008).

However, this ratio itself cannot be representative of corporate financials such as the level of the firm's debt or cash flow. This emphasizes the necessity of quantifying the financial resilience, FR_{it}, as an overall indicator of corporate financials and refers to its important role in not only exogenous dividend growth but also in asset pricing implications. This directly highlights the novel application of dynamic functional PCA as a new definition of financial resilience.

7.2 Liquidity Ratio

Another important element with over 90 percent weight in dynamic functional PCs (PC_2 according to Figure 8) is the "Cash Conversion Cycle (CCC)" which can be an indicator of liquidity risk, operational efficiency, and overall financial status. This indicator represents the number of days needed to convert resources to cash. The fewer days it takes, the better it is for the business. The second panel of Figure 10 exhibits that not surprisingly, there is almost no fluctuation in this kind of liquidity ratio in the case of either high-resilience or low-resilience firms in the sense of workplace flexibility. However, this panel reveals a huge cross-sectional difference between these two groups of firms in the number of days it takes to convert the cash spending on inventory back into cash by selling its product. This refers to the novel application of dynamic functional PCA that can simultaneously capture not only time variation but also cross-sectional heterogeneity in corporate financials.

Holding physical inventories is not a big issue for high workplace-resilient firms who are capable enough to run distance-working plans and consequently, no matter to what extent conversion takes time. As it is expected, for high workplace-resilient firms the period of conversion is longer since the cash cycle is not a significant consideration for such firms (second panel of Figure 10). On the other hand, low workplace-resilient firms are riskier in the presence of COVID-related lockdown periods (Daadmehr, 2024) and they face more workplace disruption since it is not possible to conduct different tasks in hybrid mode. Therefore, low workplace-resilient firms need more liquidity and so put more effort into cash cycle reduction by improving performance in Days Payable Outstanding (DPO), Days Sales Outstanding (DSO), and Days Inventory Outstanding (DIO)[20].

Since the Cash Conversion Cycle depends on industry type, management, and many other factors, it is not an appropriate representative measure of firms' performance and should be considered with other performance criteria. This is exactly what this paper cares about. The financial resilience, FR_{it}, part of exogenous dividend growth provides a hybrid quantification of firms' financial status.

7.3 Solvency Ratio

A firm's dividend policy can be also affected by solvency ratios due to debt covenants and related restrictions from the lenders' side (DeAngelo and DeAngelo, 1990; Ali et al., 2017). This financial ratio helps to determine the short-term financial health of a firm and it is used by investors and lenders to determine the riskiness of lending money to the firm[21]. Another major element with over 90 percent impact on firms' financial resilience components is the "Interest Coverage Ratio (ICR)" which plays a main role in cross-sectional and time variation in the third dynamic functional PC (Figure 8). The third panel of Figure 10 reveals a decrease in ICR level starting from April 2020. A declining ICR represents that firms may not be capable enough to meet their debt obligations in the future and become riskier.

In COVID-time, low-resilience firms are riskier since they are not workplace flexible enough under new social distancing rules. These industries saw business disruptions and became even more financially vulnerable in the COVID era (Koren and Peto, 2020; Pagano et al., 2023; Daadmehr, 2024). After April 2020, the ICR decline for low workplace-resilient firms is steeper with respect to the one for high workplace-resilient ones, showing that low

[20] The standard definition of cash conversion cycle = DIO + DSO - DPO. Increasing DPO, decreasing DSO, or decreasing DIO results in quicker conversion.

[21] The ideal target ratio may vary by industry.

workplace-resilient firms had more difficulties to meet their debt obligations.

Palomino et al. (2019) use DealScan information and a predictive regression of the relevant ICR threshold at the firm level and show that there is a large cross-industry variation in ICR in different industries. They propose a vulnerability index based on ICR which signals a deterioration of corporate financial conditions, and any increase in the index is associated with a decrease in future economic activity. This index displays a very strong countercyclical pattern since the 1970s, with particularly high levels in the late 1980s and during the Great Recession.

As it is explained, the low workplace-resilient firms are riskier (Daadmehr, 2024) due to the impact of the exogenous COVID-19 pandemic. Risky industries with limited access to external debt financing (e.g. Computer Equipment or Chemicals) require even higher ICRs to be considered creditworthy and financially stable. The third panel of Figure 10 exhibits the persistent higher ICR for low workplace-resilient firms which are riskier during all periods of the COVID-19 outbreak (Daadmehr, 2024) and suggests that such workplace riskiness can be amplified by the impact of ICR. The results in Section 6 empirically prove such significant amplifications in exogenous dividend growth. The novel asset pricing model and the solution in Section 5, reveal how such significant amplification affects expected returns.

The vital role of all these three kinds of financial ratios strictly emphasizes the necessity of a setup showing how the financial status of firms interacts with workplace resilience and plays an asset pricing role in the time of COVID-19. The novel application of dynamic functional principal component analysis highlights the major and significant role of these valuation, liquidity, and solvency ratios (among all others) in the snapshot of firms' financial status as well as asset pricing implications (Sections 5 and 6.2).

8 Conclusion

In this paper, the key aspect of the empirical results is twofold. First, results on the heterogeneous effect of workplace resilience assert that not only this kind of resilience has a direct positive relation with dividend growth but also the dividend growth for high-resilience firms has less sensitivity to workplace resilience as opposed to low-resilience firms. More importantly, the low amount of averaged heterogeneous effect in some industries can be a sign of a high degree of workplace resilience as well as insensitivity to aggregate time-varying economic contraction of the COVID-19 disaster.

This study answers the ambiguity of the amplification effect of financial resilience on asset prices mentioned by Daadmehr (2024), by quantifying this kind of resilience and taking into account the firm's financial status in an appropriate mechanism for asset pricing models. The methodology in this part clearly reveals how the amplification effect of corporate financials has a significant impact on the dividend stream. In order to understand to what extent such amplification affects the asset pricing implications, the paper estimates dividend growth and calibrates preference parameters based on a novel extension of Barro (2006) including the workplace resilience (Koren and Peto, 2020) and financial resilience components. The estimated dividend growth highlights that the effect of workplace resilience is dominant although the impact of firms' financial resilience is statistically significant.

The novel application of dynamic functional principal component analysis decomposes the impact of financial resilience and reveals the major and significant role of the valuation, liquidity, and solvency ratios in not only the amplification of the COVID effect, especially the impact of workplace resilience but also exogenous dividend growth as well as equity premium in a tractable formula. The results emphasize the necessity of financial resilience components (dynamic functional PCs) as a novel definition that could capture time-varying and cross-sectional variation in all corporate financials.

Second, this paper prepares an opportunity to assert and prove that COVID-19 not only is a health crisis but also can be considered as a disaster with significant macroeconomic consequences. Findings from the Markov-Switching approach establish the significant economic contraction during COVID-19. The most prominent result on this part is related to estimating the probability of disaster that has a direct impact on model-based equity premium (Equation 9). The estimated macroeconomic sensitivity to the COVID-19 disaster shows a negative impact on dividend growth. By controlling the overall economic contraction due to COVID-19, this paper presents the asset pricing implications of the COVID-19 disaster. The tractable formulas reveal how equity premium can be characterized by different cross-sectional and time-varying sources of variation, specifically, the model shows that the equity premium is an increasing function of disaster probability. The exercise on calibration, especially on the standard deviation of dividend growth explained the impact of COVID-19 as a disaster on the distribution of dividend growth that accords with Weitzman (2005) who emphasizes the impact of rare events to have a heavier tail distribution.

The asset pricing model developed in this paper can be applicable in any pandemic-like disaster when workplace sustainability drives investors' beliefs and plays a key role in pricing mechanisms. This evidence sheds light on future research ideas to propose an asset pricing model with rare events including not only the COVID-19 disaster but also previous crises from WW1 to the Russia-Ukraine war. This agenda needs a longer discussion on how different kinds of disasters with different economic consequences can be considered under the broader setup of the asset pricing model. This paper leaves this for future work.

9 Appendix

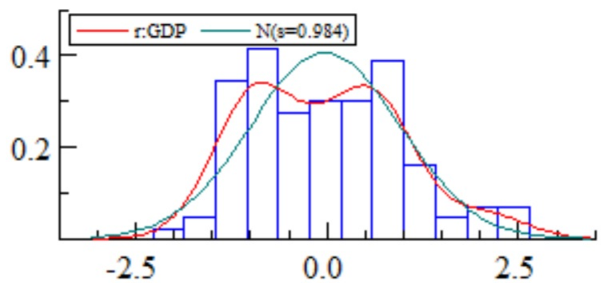

Figure 11: **Estimated distribution of macroeconomic contraction η_t^s:** This figure compares the empirical distribution of macro time-effect of COVID-19 with the corresponding normal distribution.

Table 5: **Tests of Markov-Switching non-linearity:** This table compares the linear model with the Markov-Switching model with the different number of regimes, using the Likelihood Ratio Test. In all cases, the null hypothesis (linear model) is rejected at the level of 0.001.

Model comparison	Lin vs. MS(2)	Lin vs. MS(3)	Lin vs. MS(4)	Lin vs. MS(5)	Lin vs. MS(6)
LR-Test	1102.7	1413.4	1710.0	1790.3	1813.5

Table 6: **Test for number of regimes in Markov-Switching:** This table compares the non-linear Markov-Switching model with different numbers of regimes with the base model of two-regime Markov-Switching, using the Likelihood Ratio Test and Bayes factor (Chib, 1998).

Number of regimes (i)	i=2	i=3	i=4	i=5	i=6
Bayes factor (B_{2i})	1	1.28	1.55	1.63	1.64

Table 7: **Verification of disaster regimes:** This table compares the estimated disaster regimes by MS-AR(1) with the real events. The first two columns are obtained based on the estimated Markov-Switching process and the information in the last column is obtained from Burger (1969), Supel (1978), and Hoxworth et al. (1983).

Estimated disaster regimes	Estimated duration	Reported by NBER/Fed or related publications
1960-05 to 1961-01	9	GDP was -2.1% in Q2 in 1960, rose by 2.0% in Q3, was down by 5.0% in Q4.
1965-08 to 1966-02	7	August 1965, the month of the so-called Credit Crunch in the financial markets, corporations and Federal Government agencies.
1969-09 to 1970-10	14	Economy contracted by 1.9% in Q4, and by 0.6% in Q1 1970, rose by 0.6% in Q2 and 3.7% in Q3, fell by 4.2% in Q4.
1972-03 to 1973-04	14	OPEC oil embargo leads to quadrupling oil prices: instituting wage-price controls.
1974-01 to 1975-04	16	OPEC oil embargo leads to quadrupling oil prices: Stagflation started in 1973 Q4, continued to 1975 Q1.
1978-03 to 1978-10	8	Due to unemployment trended down slightly by the end of the decade, inflation continued to rise, reaching 11 percent in June 1979 (Federal Reserve Bank of St. Louis).
1980-02 to 1981-02	13	Double whammy of two recession: Oil shock of 1978-79 (Iranian oil embargo).
1981-09 to 1982-11	15	Raising interest rates to combat inflation by Fed.
1983-05 to 1984-05	13	Large federal budget deficit put upward pressure on interest rates.
1990-08 to 1991-03	8	Saving and loan crisis, higher interest rates and Iraq's invasion of Kuwait, July 1990 to March 1991.
2001-02 to 2001-10	9	Boom and subsequent bust in dot-com businesses, March to November 2001.
2008-08 to 2009-05	10	The great recession (subprime mortgage crisis, a global bank credit crisis), lasted in 2009.
2020-04 to 2021-12	21	COVID-19 pandemic crisis, the skyrocketing of unemployment rate.

Table 8: **Some model checking for panel analysis:** The industry sector codes from "2" to "6" belong to "Mining, Utility and Construction", "Manufacturing", "Trade, Transportation and Warehousing", "Information, Finance, Management, and Remediation Services", "Educational, Health Care and Social Assistance", respectively.

Sector NAICS code	Sectors	Panel effect	Cross-sectional dependence	heterogeneous effect	Serrial correlation
2	Mining, Utility and Construction	+	+	+	+
3	Manufacturing	+	+	+	+
4	Trade, Transportation and Warehousing	+	+	+	+
5	Information, Finance, Insurance, Real State Rental, Scientific Services, Management and Remediation Services	+	+	+	+
6	Educational, Health Care and Social Assistance	+	+	+	+

Table 9: **Financial ratios and categorization:** Data source: Financial ratios, WRDS database (To be continued).

Financial Ratio	Variable Name	Category	Formula
Capitalization Ratio	capital_ratio	Capitalization	Total Long-term Debt as a fraction of the sum of Total Long-term Debt, Common/Ordinary Equity and Preferred Stock
Common Equity/Invested Capital	equity_invcap	Capitalization	Common Equity as a fraction of Invested Capital
Long-term Debt/Invested Capital	debt_invcap	Capitalization	Long-term Debt as a fraction of Invested Capital
Total Debt/Invested Capital	totdebt_invcap	Capitalization	Total Debt (Long-term and Current) as a fraction of Invested Capital
Asset Turnover	at_turn	Efficiency	Sales as a fraction of the average Total Assets based on the most recent two periods
Inventory Turnover	inv_turn	Efficiency	COGS as a fraction of the average Inventories based on the most recent two periods
Payables Turnover	pay_turn	Efficiency	COGS and change in Inventories as a fraction of the average of Accounts Payable based on the most recent two periods
Receivables Turnover	rect_turn	Efficiency	Sales as a fraction of the average of Accounts Receivables based on the most recent two periods
Sales/Stockholders Equity	sale_equity	Efficiency	Sales per dollar of total Stockholders' Equity
Sales/Invested Capital	sale_invcap	Efficiency	Sales per dollar of Invested Capital
Sales/Working Capital	sale_nwc	Efficiency	Sales per dollar of Working Capital, defined as difference between Current Assets and Current Liabilities
Inventory/Current Assets	invt_act	Financial Soundness	Inventories as a fraction of Current Assets
Receivables/Current Assets	rect_act	Financial Soundness	Accounts Receivables as a fraction of Current Assets
Free Cash Flow/Operating Cash Flow	fcf_ocf	Financial Soundness	Free Cash Flow as a fraction of Operating Cash Flow, where Free Cash Flow is defined as the difference between Operating Cash Flow and Capital Expenditures
Operating CF/Current Liabilities	ocf_lct	Financial Soundness	Operating Cash Flow as a fraction of Current Liabilities
Cash Flow/Total Debt	cash_debt	Financial Soundness	Operating Cash Flow as a fraction of Total Debt
Cash Balance/Total Liabilities	cash_lt	Financial Soundness	Cash Balance as a fraction of Total Liabilities
Cash Flow Margin	cfm	Financial Soundness	Income before Extraordinary Items and Depreciation as a fraction of Sales
Short-Term Debt/Total Debt	short_debt	Financial Soundness	Short-term Debt as a fraction of Total Debt
Profit Before Depreciation/Current Liabilities	profit_lct	Financial Soundness	Operating Income before D&A as a fraction of Current Liabilities
Current Liabilities/Total Liabilities	curr_debt	Financial Soundness	Current Liabilities as a fraction of Total Liabilities
Total Debt/EBITDA	debt_ebitda	Financial Soundness	Gross Debt as a fraction of EBITDA
Long-term Debt/Book Equity	dltt_be	Financial Soundness	Long-term Debt to Book Equity
Interest/Average Long-term Debt	int_debt	Financial Soundness	Interest as a fraction of average Long-term debt based on most recent two periods
Interest/Average Total Debt	int_totdebt	Financial Soundness	Interest as a fraction of average Total Debt based on most recent two periods
Long-term Debt/Total Liabilities	lt_debt	Financial Soundness	Long-term Debt as a fraction of Total Liabilities
Total Liabilities/Total Tangible Assets	lt_ppent	Financial Soundness	Total Liabilities to Total Tangible Assets
Cash Conversion Cycle (Days)	cash_conversion	Liquidity	Inventories per daily COGS plus Account Receivables per daily Sales minus Account Payables per daily COGS
Cash Ratio	cash_ratio	Liquidity	Cash and Short-term Investments as a fraction of Current Liabilities
Current Ratio	curr_ratio	Liquidity	Current Assets as a fraction of Current Liabilities
Quick Ratio (Acid Test)	quick_ratio	Liquidity	Quick Ratio: Current Assets net of Inventories as a fraction of Current Liabilities
Accruals/Average Assets	Accrual	Other	Accruals as a fraction of average Total Assets based on most recent two periods
Research and Development/Sales	RD_SALE	Other	R&D expenses as a fraction of Sales
Avertising Expenses/Sales	adv_sale	Other	Advertising Expenses as a fraction of Sales
Labor Expenses/Sales	staff_sale	Other	Labor Expenses as a fraction of Sales
Effective Tax Rate	efftax	Profitability	Income Tax as a fraction of Pretax Income
Gross Profit/Total Assets	GProf	Profitability	Gross Profitability as a fraction of Total Assets
After-tax Return on Average Common Equity	aftret_eq	Profitability	Net Income as a fraction of average of Common Equity based on most recent two periods
After-tax Return on Total Stockholders' Equity	aftret_equity	Profitability	Net Income as a fraction of average of Total Shareholders' Equity based on most recent two periods

Table 9: **Financial ratios and categorization:** Data source: Financial ratios, WRDS database.

Financial Ratio	Variable Name	Category	Formula
After-tax Return on Invested Capital	aftret_invcapx	Profitability	Net Income plus Interest Expenses as a fraction of Invested Capital
Gross Profit Margin	gpm	Profitability	Gross Profit as a fraction of Sales
Net Profit Margin	npm	Profitability	Net Income as a fraction of Sales
Operating Profit Margin After Depreciation	opmad	Profitability	Operating Income After Depreciation as a fraction of Sales
Operating Profit Margin Before Depreciation	opmbd	Profitability	Operating Income Before Depreciation as a fraction of Sales
Pre-tax Return on Total Earning Assets	pretret_earnat	Profitability	Operating Income After Depreciation as a fraction of average Total Earnings Assets (TEA) based on most recent two periods, where TEA is defined as the sum of Property Plant and Equipment and Current Assets
Pre-tax return on Net Operating Assets	pretret_noa	Profitability	Operating Income After Depreciation as a fraction of average Net Operating Assets (NOA) based on most recent two periods, where NOA is defined as the sum of Property Plant and Equipment and Current Assets minus Current Liabilities
Pre-tax Profit Margin	ptpm	Profitability	Pretax Income as a fraction of Sales
Return on Assets	roa	Profitability	Operating Income Before Depreciation as a fraction of average Total Assets based on most recent two periods
Return on Capital Employed	roce	Profitability	Earnings Before Interest and Taxes as a fraction of average Capital Employed based on most recent two periods, where Capital Employed is the sum of Debt in Long-term and Current Liabilities and Common/Ordinary Equity
Return on Equity	roe	Profitability	Net Income as a fraction of average Book Equity based on most recent two periods, where Book Equity is defined as the sum of Total Parent Stockholders' Equity and Deferred Taxes and Investment Tax Credit
Total Debt/Equity	de_ratio	Solvency	Total Liabilities to Shareholders' Equity (common and preferred)
Total Debt/Total Assets	debt_assets	Solvency	Total Debt as a fraction of Total Assets
Total Debt/Total Assets	debt_at	Solvency	Total Liabilities as a fraction of Total Assets
Total Debt/Capital	debt_capital	Solvency	Total Debt as a fraction of Total Capital, where Total Debt is defined as the sum of Accounts Payable and Total Debt in Current and Long-term Liabilities, and Total Capital is defined as the sum of Total Debt and Total Equity (common and preferred)
After-tax Interest Coverage	intcov	Solvency	Multiple of After-tax Income to Interest and Related Expenses
Interest Coverage Ratio	intcov_ratio	Solvency	Multiple of Earnings Before Interest and Taxes to Interest and Related Expenses
Dividend Payout Ratio	dpr	Valuation	Dividends as a fraction of Income Before Extra. Items
Forward P/E to 1-year Growth (PEG) ratio	PEG_1yrforward	Valuation	Price-to-Earnings, excl. Extraordinary Items (diluted) to 1-Year EPS Growth rate
Forward P/E to Long-term Growth (PEG) ratio	PEG_ltgforward	Valuation	Price-to-Earnings, excl. Extraordinary Items (diluted) to Long-term EPS Growth rate
Trailing P/E to Growth (PEG) ratio	PEG_trailing	Valuation	Price-to-Earnings, excl. Extraordinary Items (diluted) to 3-Year past EPS Growth
Book/Market	bm	Valuation	Book Value of Equity as a fraction of Market Value of Equity
Shillers Cyclically Adjusted P/E Ratio	capei	Valuation	Multiple of Market Value of Equity to 5-year moving average of Net Income
Dividend Yield	divyield	Valuation	Indicated Dividend Rate as a fraction of Price
Enterprise Value Multiple	evm	Valuation	Multiple of Enterprise Value to EBITDA
Price/Cash flow	pcf	Valuation	Multiple of Market Value of Equity to Net Cash Flow from Operating Activities
P/E (Diluted, Excl. EI)	pe_exi	Valuation	Price-to-Earnings, excl. Extraordinary Items (diluted)
P/E (Diluted, Incl. EI)	pe_inc	Valuation	Price-to-Earnings, incl. Extraordinary Items (diluted)
Price/Operating Earnings (Basic, Excl. EI)	pe_op_basic	Valuation	Price to Operating EPS, excl. Extraordinary Items (Basic)
Price/Operating Earnings (Diluted, Excl. EI)	pe_op_dil	Valuation	Price to Operating EPS, excl. Extraordinary Items (Diluted)
Price/Sales	ps	Valuation	Multiple of Market Value of Equity to Sales
Price/Book	ptb	Valuation	Multiple of Market Value of Equity to Book Value of Equity

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