Valuing downside risk on international stock markets*

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Abstract

Recent and growing asset pricing literature identifies downside risk factors in an economy where the representative investor has generalized disappointment aversion (GDA) preferences. We investigate and find that global GDA factors are statistically significant sources of risk in international stock markets. Nevertheless, other sources of risk, such as skewness and cokurtosis, are still relevant in the presence of global GDA factor risks. Our results survive several robustness checks. The GDA asset pricing theory is empirically validated globally as each global GDA factor risk premium estimate has the theoretically predicted sign. Furthermore, long-short portfolio strategies based on sorting countries on financial indicators such as digital payment or financial inclusion generate significantly sizeable risk premia mainly driven by their global downstate component. It is also the case when sorting countries on economic indicators such as per capita gross domestic product, ease of doing business, or country competitiveness.

Keywords: General Disappointment Aversion, Downside risk, International Asset Pricing, Covid-19

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1 Introduction

The most recent cross-sectional asset pricing studies show a regain of interest, since Ang, Chen and Xing (2006), in demonstrating that significant portions of asset risk premia are attributable to the downside risk faced by investors (see among others, Lettau et al.; 2014 and Farago and Tédongap; 2018). In the literature, downside risk has been studied in different forms, either as an asset specific risk, or as a systematic risk with respect to a given factor. The question of what factor the systematic downside risk measure relates to has been carefully addressed by Farago and Tédongap (2012, 2018) assuming that the average investor in a consumption-based representative-agent economy has generalized disappointment aversion (GDA) preferences as in Routledge and Zin (2010), following Gul (1991).

In this article, we assume that the global representative investor has an aversion to downside risk characterized by GDA preferences. In theory, expected asset returns admit a multifactor representation in the cross-section with global GDA factors. The GDA model has two main specifications depending on whether or not volatility plays a role in the model. Our main specification assumes that the global representative investor substitutes out consumption perfectly through time, leading to a three-factor cross-sectional model where volatility plays no role, labeled GDA3. The three global factors include the market factor, the downstate factor, which is the indicator that the market factor falls below a certain threshold, and the market downside factor, which is the product of the market and the downstate factors. In the general case where intertemporal substitution of consumption is imperfect, volatility plays a role, leading to a five-factor cross-sectional model labeled GDA5. The five global factors are the market factor, the downstate factor, the market downside factor, the volatility factor, and the volatility downside factor. This latter factor corresponds to the product between the volatility and downstate factors. Unlike GDA3, the downside factor of GDA5 is determined by a combination of market and volatility factors falling below a given threshold.

Obviously, downside risk is priced globally if any of the related factors (i.e., downstate, market downside and/or volatility downside factors) appears to be a significant cross-sectional pricing factor for an international asset menu. Without confining ourselves to this simple fact, we seek to prove that the GDA theory as a whole still holds when tested on international stock market data. It involves showing that the various factors are valued and that the associated risk premiums bear the expected sign as predicted by the model. Finally, we want to verify that portfolio strategies based on sorting international assets according to country indicators make it possible to generate significant premiums and measure the contribution of downside risk factors in these premiums.

We conduct our cross-sectional asset pricing tests using the celebrated two-step regression approach of Fama and MacBeth (1973), henceforth FM. The test assets we use to examine if the GDA factors are priced globally are country and regional Morgan Stanley Capital International (MSCI) stock indexes covering both emerging and developed economies, and spanning the period from January 1972 to December 2021. We run both contemporaneous and predictive cross-sectional regressions and our results all point to the fact that the downside risk factors are significantly priced in the cross-section of country stock market indexes, and their estimated risk premia are consistent with theory. This is particularly the case for various parameterisations of the downstate. This means that, global investors ask a higher premium for investing in country stock indexes that tend to fall when the global economy is in the downstate. It is also the case for country stock indexes which returns tend to move in the same (opposite) direction as the global market (volatility) factor when the global economy is in the downstate.

We run a battery of robustness checks to confirm the validity of our empirical findings. More precisely, we consider different restrictions to the test assets menu, different lengths of the betas estimation window, different values of the downstate probability, and we check for any effect of the coronavirus (covid-19) health crisis. We also include different controls that have been used throughout the literature as measures of downside and tail risks, namely the asset specific skewness and kurtosis, and the asset coskewness and cokurtosis with the global market factor. Our results survive all these robustness checks. They suggest that the global GDA theory is validated with international stock market data. We find evidence that global GDA3 and GDA5 factor risks, whether measured by contemporaneous or predictive betas, are important drivers of risk premium heterogeneity in the cross-section of international stock indexes. However, they do not fully account for the total risk premium requested by investors globally. In fact, other sources of risk such as skewness and cokurtosis are still relevant in the presence of global GDA factor risks.

Likewise, we compare our global GDA models to nested specifications. The first nested model is the global capital asset pricing model (CAPM) examined for example by Engel and Rodrigues (1986) and Brusa et al. (2015) among others. The second nested model is the single-factor asset pricing model based on an indicator that the global market factor is less than a given threshold, similar to Delikouras and Kostakis (2019) who consider such a specification with consumption growth instead of the market return and investigate it in the context of the American instead of the international stock markets. In terms of performance, the three- and five-factor global GDA models are largely superior to all nested specifications.

Thanks to the availability of several country economic and financial indicators obtained through databases from the World Bank (WB) and the International Monetary Fund (IMF), we conduct a subsequent analysis. First, we sort countries into two groups according to a key indicator, then examine the long/short portfolio risk premium obtained by trading on the country indicator, i.e., longing stock indexes of countries with less favorable indicator value and shorting stock indexes of countries of more favorable indicator values; we assess the contributions of the different GDA factor risks to this premium. In particular, this analysis reveals which downside risk premium (downstate, market downside, and volatility downside) is more important for one group of countries relative to the other. This analysis is particularly important as economic and financial activities in a country as measured by key WB and IMF indicators may also reflect political and societal challenges characterizing the country's business and financial risks, and potentially having a significant impact on the country's stock market attractiveness by global investors.

Our findings suggest that the GDA model provides a good prediction of the risk premia obtained by sorting international stock market indexes on selected country indicators. Long/short portfolios obtained by sorting on the selected financial (economic) indicators generate a positive and statistically significant risk premium that varies from 3.21% (4.41%) when sorting on stock market index volatility (net inflow of foreign direct investment) to 7.36% (6.93%) when sorting on the financial inclusion rate (country competitiveness index). The absolute percentage error on the predicted long/short portfolio risk premium by the GDA3 model is relatively small overall. Its value is 1.81% (40.50%), 17.70% (27.85%), 4.64% (5.01%), and 10.39% (0.54%) when sorting international stock indexes on the net inflow of foreign direct investment (stock market index volatility), the gross domestic product per capita (nature of the stock market), the ease of doing business rank (use of digital payment), and the country competitiveness index (financial inclusion rate), respectively. In addition, exposure to the global downstate factor appears to be the primary determinant of the predicted long/short portfolio risk premium, irrespective of the GDA model specification. While the coronavirus pandemic may have affected the remuneration of risk-taking strategies on the international stock markets, it did not modify the risk premium composition by its different GDA components and their degree of importance.

Our paper builds on the most recent literature that examines downside risk valuation with a focus on international stock markets, as opposed to early papers where downside risk pricing is tested on American firms only. In the cross-sectional asset pricing literature, there are two main approaches of testing asset pricing factor models using international data. The first is to focus on one country or region, different than the United States (U.S.), first construct factors from the national or regional economic or financial indicators, then use national or regional individual stocks to form the test assets. In this approach, risk measures are estimated using the stock return and the index return representing the market in which the stock is listed (e.g., Alles and Murray; 2013, for downside risk tests for Asia, Alles and Murray; 2017, for Australia, Atilgan et al.; 2019, for each of 26 developed countries, and Atilgan et al.; 2018, for each of 51 countries including 24 developed and 27 emerging). These measures therefore represent the exposure of a domestically-based investor, rather than a global investor. The second approach is to design primarily worldwide or global factors from the global economic or financial indicators, then use stock market indexes across different countries as test assets. This approach estimates risk measures using a country's stock index return, the American index return representing the global market. These measures, therefore, represent the exposure of the international investor. We follow the latter approach, and the market integration advantages can mostly justify this. Indeed, investors are interested in indices that are adequate alternatives for stocks today, motivated by increased stock market integration and portfolio diversification.

As a result of Solnik (1974), it can be argued that international financial assets used in global asset pricing research are becoming more attractive to foreign investors, stimulating international diversification and increasing financial market integration. Similarly, Bekaert et al. (2009) argue that the effective growth of capital outflows and interactions between financial markets reinforce and facilitate their integration. Besides, emphasis is placed on the integration of financial markets when discussing the co-movement of key factors between different financial markets (Mobarek and Mollah; 2016). Additionally, international investing offers investors the opportunity to benefit from the results of global market segmentation, reduced currency risk, foreign diversification, and the chance to contribute to the growth and development of other economies (Bartram and Dufey; 2001). All of this opens up new challenges for investors and researchers (particularly in asset pricing) to study the global risks and rewards of stock market integration (Qiu et al.; 2022) and to test existing theories on a menu of international assets. There lie the rationale and motivation behind our study's goal to investigate global downside risk assessment using international stock indices by testing the GDA asset pricing theory at the universal level.

Our findings relate to the existing literature in several manners. We extend the work of Farago and Tédongap (2018) by showing that global downside risks, as motivated by the consumption-based general equilibrium model featuring generalized disappointment aversion, are priced across international stock market indexes. In addition we find that trading internationally on country characteristics can be mostly remunerated by exposure to global downside risks. To the contrary, we differ from Atilgan et al. (2019), and Atilgan et al. (2018), who cannot find empirical evidence that downside risk, as measured for example by the downside beta of Ang, Chen and Xing (2006), is priced internationally. We do however have different data samples and methodological approaches for testing international downside risk pricing, as highlighted earlier. In addition, as demonstrated by Farago and Tédongap (2012), the downside beta of Ang, Chen and Xing (2006), as well as many other univariate measures of downside risk considered by Atilgan et al. (2019), and Atilgan et al. (2018), are explicit linear combinations of the GDA3 risk measures.

The remaining of the paper proceeds as follows. Section 2 summarizes the theoretical foundation of the study. Section 3 introduces the data used in empirical analyses, presents summary statistics of the key variables, and describes our empirical strategy. Section 4 presents the results of our empirical investigation and evaluates their robustness. Section 5 discusses possible ways for explaining and understanding our findings. Section 6 concludes.

2 Theory

Starting from the first-order conditions derived by Hansen et al. (2007) for a dynamic consumption-based general equilibrium asset pricing model featuring generalized disappointment aversion preferences as in Routledge and Zin (2010), Farago and Tédongap (2012) exploit key model identities to substitute out consumption with the market return, assuming time-varying macroeconomic uncertainty as measured for example by the volatility of aggregate endowment. Then, they derive the implied cross-sectional representation of the GDA asset pricing model as follows:

$$E_t\left[R^e_{i,t+1}\right] = p_{W,t}\sigma_{iW,t} + p_{W\mathcal{D},t}\sigma_{iW\mathcal{D},t} + p_{\mathcal{D},t}\sigma_{i\mathcal{D},t} + p_{X,t}\sigma_{iX,t} + p_{X\mathcal{D},t}\sigma_{iX\mathcal{D},t} \tag{1}$$

where $\sigma_{iW,t} \equiv Cov_t\left(R^e_{i,t+1}, r_{W,t+1}\right)$ denotes the covariance of asset i's excess returns $R^e_{i,t+1}$ with the market return $r_{W,t+1}$, or market factor, while $\sigma_{iX,t} \equiv Cov_t\left(R^e_{i,t+1}, r_{X,t+1}\right)$ denotes the covariance of the asset excess returns with the volatility factor defined by $r_{X,t+1} = \left(\sigma_W/\sigma_\Omega\right)\Delta\sigma^2_{W,t+1}$.

The volatility factor is interpretable as a return that is perfectly correlated with changes in conditional market variance, $\Delta\sigma^2_{W,t+1}$, and has same standard deviation with the market return, and where $\sigma_W = \text{std}\left[r_{W,t+1}\right]$ and $\sigma_\Omega = \text{std}\left[\Delta\sigma^2_{W,t+1}\right]$ are the unconditional standard deviations of the market return and changes in conditional market variance, respectively.

The last quantities, $\sigma_{i\mathcal{D},t} \equiv Cov_t\left(R^e_{i,t+1}, I\left(\mathcal{D}_{t+1}\right)\right)$, $\sigma_{iW\mathcal{D},t} \equiv Cov_t\left(R^e_{i,t+1}, r_{W,t+1}I\left(\mathcal{D}_{t+1}\right)\right)$ and $\sigma_{iX\mathcal{D},t} \equiv Cov_t\left(R^e_{i,t+1}, \Delta\sigma^2_{W,t+1}I\left(\mathcal{D}_{t+1}\right)\right)$ denote covariances of asset excess returns with factors that are contingent to the disappointing event $\mathcal{D}_{t+1} \equiv \left\{r_{W,t+1} - ar_{X,t+1} < b\right\}$, and $I\left(\cdot\right)$ denotes the indicator function. The three disappointment-contingent factors are the downstate factor $I\left(\mathcal{D}_{t+1}\right)$, the market downside factor $r_{W,t+1}I\left(\mathcal{D}_{t+1}\right)$, and the volatility downside factor $r_{X,t+1}I\left(\mathcal{D}_{t+1}\right)$.

The risk prices associated with the covariance risk measures $\sigma_{iW,t}$, $\sigma_{iW\mathcal{D},t}$, $\sigma_{i\mathcal{D},t}$, $\sigma_{iX,t}$ and $\sigma_{iX\mathcal{D},t}$ i.e., the coefficients $p_{W,t}$, $p_{W\mathcal{D},t}$, $p_{\mathcal{D},t}$, $p_{X,t}$ and $p_{X\mathcal{D},t}$, respectively, as well as the volatility's disappointment-triggering coefficient a, and the disappointment threshold b, all depend on preference parameters of the representative investor. In particular, Farago and Tédongap (2012) establish that $p_{W,t} \propto \gamma$, $p_{W\mathcal{D},t} \propto \gamma\ell$, $p_{\mathcal{D},t} \propto -\ell$, $p_{X,t} \propto -\dfrac{\gamma-1}{\psi}$, and $p_{X\mathcal{D},t} \propto -\dfrac{\gamma-1}{\psi}\ell$, where $\gamma \geq 0$, $\ell \geq 0$ and $\psi > 0$ are the risk aversion, the disappointment aversion, and the elasticity of intertemporal substitution parameters, respectively. Likewise, it is also the case that $a \propto -\dfrac{1}{\psi}$. Following Farago and Tédongap (2012), we refer to the full five-factor model specification (1) as the **GDA5** model.

In the GDA5 model, the disappointing event may occur due to falling market returns or rising market volatility, or both. If the coefficient a equals one, falling market returns and rising market volatility are equally likely to provoke disappointment. As a decreases from one to zero, disappointment is more likely due to falling market returns. Otherwise, i.e., as a increases from one towards infinity, disappointment is more likely triggered by rising market volatility. If the parameter a is fixed, the parameter b matches a given disappointment probability, $\text{prob}\left(\mathcal{D}_{t+1}\right)$. In our empirical investigation of Section 4, we motivate our base case values of a and $\text{prob}\left(\mathcal{D}_{t+1}\right)$ and provide robustness of our results to departures from these benchmark values.

The GDA5 model nests one important special case which is $\psi = \infty$, corresponding to a model where the representative agent has perfect intertemporal consumption substitution. In this case, volatility disappears from the model as we have $p_{X,t} = 0$, $p_{X\mathcal{D},t} = 0$ and $a = 0$. The model reduces to a three-factor with the market factor, the market downside factor and the downstate factor. Moreover, the disappointing event $\mathcal{D}_{t+1}$ reduces to $\left\{ r_{W,t+1} < b \right\}$. We refer to this three-factor model specification as the **GDA3** model. The GDA3 model in turn nests two special cases: $\ell = 0$ where the only source of risk premium is the market factor, we call it the pure risk aversion (**PRA**) setting, and $\gamma = 0$ where the only source of risk premium is the downstate factor, we call it the pure disappointment aversion (**PDA**) setting. Also notice that the pure risk aversion setting is also equivalent to the canonical CAPM, while the pure disappointment aversion setting is equivalent to the single factor asset pricing model of Delikouras and Kostakis (2019).

We discuss our findings using the GDA3 model specification as our benchmark throughout the article since the disappointing event is standard and corresponds to other studies in the extant literature. In addition, we discuss the GDA5 model specification as an extension and the PRA and PDA model specifications as restrictions relative to the GDA3 benchmark.

Equation (1) may ultimately be expressed as a multivariate beta pricing model:

$$E_t \left[R^e_{i,t+1} \right] = \lambda_{W,t}\beta_{iW,t} + \lambda_{W\mathcal{D},t}\beta_{iW\mathcal{D},t} + \lambda_{\mathcal{D},t}\beta_{i\mathcal{D},t} + \lambda_{X,t}\beta_{iX,t} + \lambda_{X\mathcal{D},t}\beta_{iX\mathcal{D},t} \tag{2}$$

where $\beta_{if,t}$ is the regression coefficient of asset excess returns onto the factor f, and $\lambda_{f,t}$ is the factor risk premium, respectively. The factor risk premium has the same sign as the factor risk price. In theory, we must have $\lambda_{W,t} > 0$. Thus, investors require a premium for a security with positive beta on the market factor, consistent with the CAPM theory of Sharpe (1964) and Lintner (1965). To the contrary, we must have $\lambda_{\mathcal{D},t} < 0$ so that investors require a premium for a security with negative beta on the downstate factor. Such an asset tends to move downward when the disappointing event occurs. Likewise, we must have $\lambda_{W\mathcal{D},t} > 0$, i.e., investors require a premium for a security with positive beta on the market downside factor. Such an asset tends to move downward when the market return in the disappointing state decreases further.

As pointed out by Tauchen (2011), economists generally agree that the coefficient of risk aversion exceeds unity; if so, the predicted sign of the volatility risk premium is negative, i.e., $\lambda_{X,t} < 0$. Thus, consistent with the existing theoretical and empirical literature (see for example Ang, Hodrick, Xing and Zhang; 2006; Adrian and Rosenberg; 2008), investors are willing to pay a premium for a security with positive beta the volatility factor. Similarly, we must have $\lambda_{X\mathcal{D},t} < 0$, i.e., investors pay a premium for a security with positive beta on the volatility downside factor. Such an asset tends to move upward when the market volatility in a disappointing state increases further.

Farago and Tédongap (2012, 2018) thoroughly evaluate the above GDA asset pricing theory by testing it on different United States (U.S.) stocks menus. This article examines whether tests on international stock market indices validate the model implications. Furthermore, there has been a gradual increase in global financial markets integration, which facilitates the ownership of foreign assets by domestic investors without incurring much cost. Therefore, it justifies the approach of testing existing theories on an international asset menu. Finally, since the U.S. remains a major player in this international financial markets integration, it explains the use of the U.S. stock market factors as the global factors in our upcoming empirical analysis. Pan and Singleton (2008), Longstaff et al. (2010) are other examples that emphasize the use of the U.S. financial channel as a global source of risk, albeit in the sovereign credit risk literature.

3 Data, empirical strategy and summary statistics

We want to test the above theory in the context of a worldwide representative agent who invests in international stock indexes. Thus the asset pricing factors of our cross-sectional models are constructed around a global market index, and the test assets are the country and regional stock indexes. We proxy the global market factor using the Fama-French market factor, which, together with the risk-free rate, we download daily returns directly from Kenneth French's data library. The risk-free rate corresponds to the one-month U.S. Treasury bill rate (from Ibbotson Associates) and serves to compute all excess returns in our analyses. We use daily data on 56 U.S. dollar

(UDS)-denominated stock market indexes from the Morgan Stanley Capital International (MSCI) database available on Datastream. Similar to Estrada (2007), the data cover both emerging (23) and developed (22) markets. In addition, there are 11 regional indices. As pointed out by Atanasov and Nitschka (2014), the MSCI data have the advantage that the indices are broad and calculated using the same methodology. We construct daily return series from the index values, and compute monthly return series by appropriately aggregating the daily series.

Overall, our sample runs from January 1970 to December 2021. Downside risk measures for each country are computed from the country index returns and the global factors. Notice that the volatility factor represents changes in the conditional variance of the market factor, and we use an exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model of Nelson (1991), fitted to the daily global market factor series over the whole sample period. The exact model specification and the coefficient estimates are presented in Table 1. All coefficient estimates of the volatility dynamics are statistically significant at the 99% confidence level. In particular, market volatility exhibits high persistence ($\phi = 0.9795$) and a negative leverage effect ($\theta = -0.0935$).

We will further check the sources of cross-sectional variability in the downside risk premiums across countries. From this end, we intuitively select eight indicators that are potentially associated with downside risks in the cross-section and split them into two main groups: financial and economic. Financial indicators include: (1) the percentage of the population using digital payment (**DIGP**); (2) the stock market index volatility (**SVOL**), (3) the financial inclusion appreciated by the percentage of people using a bank account (**FIIN**) and (4) the nature of the stock market (emerging or developed, **EMDV**). Economic indicators include: (5) the net inflow of foreign direct investment (**NFDI**); (6) the GDP per capita (**GDPC**); (7) the country competitiveness index (**CCOM**); and (8) the ease-of-doing-business rank (**DBUS**). These indicators, which will serve for country portfolio sorts, are annual. We obtain their 2019 (pre-Covid) and 2020 (post-Covid) values from the World Bank (WB) and the International Monetary Fund (IMF) databases.

Empirically, we follow recent literature on downside risk (Ang, Chen and Xing; 2006, Farago and Tédongap; 2012, and Lettau et al.; 2014 amongst others), and use cross-sectional regressions of Fama and MacBeth (1973) to test if global downside risk is priced on international stock markets. The downside risk measures discussed in Section 2 in the form of betas with respect to the GDA factors are computed in a first step from time series regressions of individual MSCI excess returns on the GDA factors. Formally, to compute the conditional betas in equation (2), we follow Lewellen and Nagel (2006) and instead of trying to determine the appropriate set of conditioning variables, we use short-window regressions to calculate these factor loadings.

To illustrate our approach, in the full model it means that, for every month $t \geq k$, we use k months of daily data from month $t-k+1$ to month t to run the following daily time-series regression for each MSCI index excess returns i in the first stage of the FM procedure:

$$R^e_{i,\tau} = \alpha_{i,t} + \beta_{iW,t} r_{W,\tau} + \beta_{iW\mathcal{D},t} r_{W,\tau} I(\mathcal{D}_\tau) + \beta_{i\mathcal{D},t} I(\mathcal{D}_\tau) + \beta_{iX,t} r_{X,\tau} + \beta_{iX\mathcal{D},t} r_{X,\tau} I(\mathcal{D}_\tau) + \varepsilon_{i,\tau} \quad (3)$$

where $R^e_{i,\tau}$ is the excess return on day τ and $\varepsilon_{i,\tau}$ is the error term. For our benchmark analyses throughout the article, we consider $k = 12$ and a disappointment probability of 15% for all GDA model specifications, i.e., we choose the parameter b to match $\text{prob}\,(\mathcal{D}) = 0.15$. Likewise, our base case value of the parameter a is unity, i.e., $a = 1$, in the GDA5 model.

The second stage of the FM procedure consists in estimating the following monthly cross-sectional regressions

$$R^e_{i,t} = \lambda_{0,t} + \beta_{iW,t}\lambda_{W,t} + \beta_{iW\mathcal{D},t}\lambda_{W\mathcal{D},t} + \beta_{i\mathcal{D},t}\lambda_{\mathcal{D},t} + \beta_{iX,t}\lambda_{X,t} + \beta_{iX\mathcal{D},t}\lambda_{X\mathcal{D},t} + \eta_{i,t} \quad (4)$$

where $R^e_{i,t}$ is the excess return on month t and $\eta_{i,t}$ is the error term. Factor risk premia are obtained by averaging the lambdas over the monthly sample period. As argued by Ang, Chen and Xing (2006), the use of overlapping information in estimating the conditional betas is more efficient but induces moving average effects, which can be accounted for by reporting robust standard errors that are adjusted following Newey and West (1987).

Ang, Hodrick, Xing and Zhang (2006) argue that in order to have a factor risk explanation, there should be contemporaneous patterns between factor loadings and excess returns. Several cross-sectional asset pricing studies focus on this contemporaneous relationship (e.g. Ang, Chen and Xing; 2006; Cremers et al.; 2011; Fama and MacBeth; 1973; Lewellen and Nagel; 2006; Ruenzi and Weigert; 2011; among others). We follow this common approach to derive our main results and, subsequently we also report results from cross-sectional regressions of average future excess returns on current betas, i.e., the right-hand-side of equation (4) is not the excess return on month t, but the monthly average excess return from month $t+1$ to month $t+h$, denoted by $\frac{R^e_{i,t+1:t+h}}{h}$.

Table 2 displays the summary statistics of country and regional sample averages of monthly expected excess returns together with the associated risk measures. The monthly time series for all measures are computed from rolling window estimations based on one-year of daily data, and sample averages are reported in the table. The risk measures include the standard deviation, skewness and coskewness, kurtosis and cokurtosis, as well as the GDA factor loadings computed from equation (3). Systematic risk measures corresponding to the GDA model specifications are computed assuming a base case disappointment probability of 15% and $a = 1$. We consider skewness and coskewness, kurtosis and cokurtosis, since they are used elsewhere in the literature to measure downside risk or as controls for downside risk (see for example Alles and Murray; 2017 and Alles and Murray; 2013 who use cowskewness as a measure of downside risk, and Ang, Chen and Xing; 2006 who control for coskewness and cokurtosis in their downside risk pricing model). Our coskewness and cokurtosis are measured with respect to the Fama-French market log returns used as the global market factor.

As we can see from Table 2, there is a large heterogeneity in expected excess returns across countries and regions, and well as in their associated GDA factor loadings. It is clear from the table that developed markets pay on average low average returns compared to emerging markets and there is also significant heterogeneity within either group. Overall in our sample and in annualized terms, emerging markets (EMERGING) display a 12.83% average excess returns for a 24.93% volatility, against a 8.88% average excess returns for a 20.73% volatility for developed markets (EAFE).

Table 2 also shows a significant heterogeneity in the risk measures across countries and regions. Considering risk measures from our main GDA3 (GDA5) model, the global market beta varies from -0.11 (-0.09) for Nigeria to 0.77 (0.83) for Brazil. Likewise, the global market downside beta varies from -0.09 for Brazil to 0.29 for Czech Republic in the GDA3 model, and from -0.06 for Hong Kong to 0.30 for Columbia in the GDA5 model.

Regarding the global downstate beta, its GDA3 values vary from -1.91E-3 for Brazil to 3.76E-3 for Czech Republic, while its GDA5 values vary from -2.10E-3 for Korea to 2.53E-3 for Colombia. The GDA5 volatility beta varies from -1.07 for Brazil to 0.02 for Jordan, while the downside volatility beta varies from -0.24 for India to 0.94 for Brazil. The extreme values displayed by Brazil in these systematic risk measures are notable. They are reflected in Brazil's average excess returns and standard deviation, the highest among all countries. This single example illustrates well the global downside risk compensation in international markets. Except for the Czech Republic, Jordan, and Nigeria, all MSCI country indexes display positive skewness. In addition, all the country indices exhibit negative co-skewness, positive excess kurtosis, and positive co-kurtosis.

Another striking observation that may have important implications in empirical tests relates to comparing exposures to the global factors in our three- and five-factor GDA models on the one hand and the other hand, the nested univariate specifications. We observe that exposure to the market factor does not vary much from our main GDA specification to the nested PRA specification. In contrast, while the downstate beta is negative for all indexes in the nested PDA specification, it is the case only for about 33% and 15% of the indexes with our main GDA3 and GDA5 model specifications, respectively, i.e., controlling for other factors. However, similar factor loadings are highly positively correlated overall across different model specifications, as confirmed in Table 3.

Table 3 displays the correlations between the GDA risk measures and other proxies for downside and tail risks highlighted in the literature. Interestingly, in the GDA3 (GDA5) model, the global market downside and downstate betas show moderate and tiny correlations with the global market beta, with values of -0.36 (-0.41) and 0.02 (-0.01), respectively. However, and not surprisingly, these two measures of global downside risk are highly correlated, with a positive correlation of 0.75 (0.69) in the GDA3 (GDA5) model. It is the consequence of the associated GDA factors ($r_W I(\mathcal{D})$ and $I(\mathcal{D})$) coincidence over the non-disappointing region which represents 85% of the sample period in the base case scenario.[1] Increasing the disappointment probability from 15% to higher values considerably reduces this correlation. In addition, $\beta_{i\mathcal{D}}$ and β_{iPDA} only show little correlation, 0.24 and 0.17 for the GDA3 and GDA5 models, respectively. Overall, this means that to the GDA3 and GDA5 models, the PDA specification appears as a missing variable regression where the omission of the global market downside beta may lead to severe bias and inconsistency in the estimation of the downstate risk premium due to the important correlation between $\beta_{iW\mathcal{D}}$ and $\beta_{i\mathcal{D}}$.

The volatility and the downside volatility betas have a correlation of -0.61. Both show little correlations (i.e., less than 0.15 in absolute value) with the remaining risk measures in Table 3, except for the moderate correlations of the volatility downside beta with the GDA5 market downside and downstate betas, -0.29 and -0.31, respectively. Finally, the two GDA3 measures of downside risk and their GDA5 counterparts show little correlations (i.e., less than 0.17 in absolute value) with skewness, coskewness, kurtosis, and cokurtosis, except for the moderate negative correlation of -0.47 (-0.45) between coskewness and market downside beta in the GDA3 (GDA5) model. Coskewness and cokurtosis also display a correlation of 0.25 (0.23) and 0.57 (0.58) with the market beta in the GDA3 (GDA5) model, respectively. It suggests that we should control for these other downside and tail risk measures in our GDA model specifications.

In the subsequent sections we present our main empirical findings. We first discuss the results related to the pricing of downside risks on international stock markets and second, the determinants of downside risks across countries.

[1] Estrada (2007) also finds a 90% correlation between the downside beta and the semi-deviation with MSCI indices. In contrast, Alles and Murray (2017) also have a strong positive correlation (close to 50% with 200 stocks) between downside risk measures.

4 Empirical results

4.1 Global downside risk and contemporaneous returns

We structure our discussion of the estimation results on the pricing of GDA factor risks starting with the nested single-factor specifications (PRA and PDA). We then follow with the benchmark GDA3 model and finally discuss its extension to GDA5 to assess the role of volatility in the model. When discussing the pricing of systematic risk results, we find it helpful to directly involve standard asset-specific downside and tail risk measures considered in the literature, i.e., the skewness and coskewness, and the kurtosis and cokurtosis.

Harvey and Siddique (2000) show that asset returns skewness, and their coskewness with the market factor, are important sources of risk in asset pricing. They measure how likely extreme negative returns are relative to excessive positive returns of the same magnitude. In this respect, skewness and coskewness have traditionally been treated as downside risk measures in the asset pricing literature. Likewise, asset returns kurtosis and their cokurtosis with the market factor are traditional tail risk measures, which are also crucial for asset pricing. Ang, Chen and Xing (2006) control for coskewness and cokurtosis in their cross-sectional asset pricing tests and conclude that similar to their downside beta, these risks are priced in the cross-section of American stocks. Alles and Murray (2013) and Alles and Murray (2017) use skewness and coskewness together with the downside and the upside betas of Ang, Chen and Xing (2006) in a cross-sectional asset pricing model. They conclude that, skewness and downside beta are priced risks in the cross-section of Asian stocks. In line with this literature, we directly control for individual and simultaneous effects of skewness (Skew), coskewness (Coskew), kurtosis (Kurt) and cokurtosis (Cokurt) in the different speifications of the GDA cross-sectional asset pricing models discussed in Section 2.

4.1.1 Nested PRA and PDA specifications

Table 4 shows results for the PRA specification. In column (1) of the table, we find that the global market factor carries a positive risk premium in the cross-section of international stock indices. However, the premium approaches a 10% significance level while the constant-coefficient is strongly significant, suggesting that the model may be misspecified and need additional information.[2] In column (2), the market beta is unpriced when adding skewness to the PRA model, and the model's fit as measured by the cross-sectional R^2 improves from 11% to 30%. Moreover, the constant term is reduced to the fourth and becomes strongly insignificant. Results in columns (4) and (8) further confirm this observation. In contrast, controlling for coskewness or cokurtosis alone does not undermine the statistical significance of the market risk premium, and the constant-coefficient remains strongly significant with a stable magnitude. The coskewness premium is negative and statistically significant when added to the PRA model. Overall, there is no evidence of priced kurtosis effects on international stock index returns.

The main result of Table 4 is that skewness appears to be a significantly priced downside risk measure in global markets over our sample period and already embeds pricing information about the PRA market beta. However, skewness has a positive risk premium, contrary to common knowledge on the risk-return tradeoff. In theory, we shall expect assets with more negative skewness to pay higher returns on average. This finding is, however, consistent with Alles and Murray (2013) who also find that firms offering strong positive performance have positively skewed returns, whereas poorly performing firms exhibit negative skewness.

Table 5 is structured identically to Table 4 and displays results for the PDA specification. In all columns of the table, we find that the global downstate factor, as measured by the indicator that the global market factor falls below its 15% quantile, has a negative risk premium in the

[2] This finding corroborates Estrada (2007) who finds that market beta is positively linked to average excess return on MSCI indices. However, the author has monthly data, a much shorter sample period from 1988 to 2002, and deals with ordinary least squares instead of cross-sectional regressions of Fama and MacBeth (1973). In this study, we use a richer (daily) information over a much longer sample period from 1972 to 2021, and employ cross-sectional regressions of Fama and MacBeth (1973) with time-varying betas.

cross-section of international stock indices, as predicted by the theory. Moreover, the premium is statistically significant at the 99% confidence level. The skewness premium remains positive and strongly statistically significant when combined with the downstate risk. Adding skewness alone in the basic PDA model specification increases the cross-sectional R^2 from 14% to 32%. As in the PRA case, the constant-coefficient is strongly statistically significant in all PDA specifications that do not control for skewness. When controlling for skewness, the constant-coefficient loses statistical significance and reduces to about the third of its magnitude. Although skewness appears to be a significantly priced risk on international stock markets, it carries different information than the global downstate risk. In contrast to the PRA model, coskewness is not priced when added to the PDA model. Likewise, cokurtosis is negatively priced while kurtosis is not.

Our findings for the PDA model are in line with Delikouras and Kostakis (2019). They find that the downstate factor is a significantly priced downside risk factor in the cross-section of U.S. stock returns. In addition, their single-factor model performs at least as well as the Fama-French five-factor model. However, our findings controlling for cokurtosis contrast with those of Ang, Chen and Xing (2006) and Dittmar (2002) on U.S. stocks. We find that international stock indices with positive cokurtosis tend to have low returns on average.

4.1.2 Benchmark GDA3 specification and GDA5 extension to volatility

We now proceed with the empirical results of our benchmark model. In the GDA3 model, international asset risk premia are, in theory, determined by their multivariate exposures to the global market factor, the global market downside factor, and the global downstate factor. Similar to the PDA case, the disappointing event corresponds to the global market factor falling below its 15% quantile. Results of the GDA3 specification are presented in Table 6. The first striking fact is that risk premia associated with all global GDA3 factors are statistically significant at the 1% level in the cross-section of international stock indices. The first takeaway from this is that the PRA and PDA specifications are missing other GDA factors. Likewise, the skewness risk premium remains strongly significant and positive in all scenarios. It drives out the statistical significance of the constant-coefficient, confirming that stock skewness tends to summarize pricing information that is not embedded in the global GDA factor risks. Cokurtosis does the same but only residually. Adding skewness to the cross-sectional GDA3 model improves the R^2 from 28% to 36%.

In contrast, coskewness and kurtosis pricing information is already accounted for by the GDA3 factor risks. All in all, skewness and cokurtosis do not drive out any GDA3 factor risk. If anything, global downside risks drive out other risks associated with the remaining measures reflecting asymmetry and tail effects in international stock index returns, i.e., coskewness and kurtosis.

We now turn to discussing the empirical results for the five-factor GDA model. The GDA5 model has two main departures from the GDA3 model due to the presence of volatility. First, in addition to falling market returns, the disappointing event can result from rising market volatility. Our benchmark value for the volatility's disappointment-triggering coefficient is $a = 1$, and the benchmark value for the disappointment probability remains equal to 15%, similar to the baseline PRA and GDA3 specifications. Second, the model has two additional factors compared to the GDA3 specification: the volatility factor and the volatility downside factor.

Table 7 displays results of the GDA5 specification. It highlights two main conclusions. First, as shown in column (1) of Tables 7 and 6, adding the volatility and volatility downside factors increase the R^2 of the cross-sectional GDA model relative to the GDA3 specification, from 28% to 39%. Controlling for skewness in the cross-sectional GDA5 model further improves the R^2 from 39% to 49%. Second, similar to the GDA3 specification, risk premia associated with the market factor, the market downside factor, and the downstate factor are statistically significant at conventional levels. Likewise, the skewness risk premium remains positive in all scenarios and statistically significant at the 99% confidence level, driving down the magnitude of the constant-coefficient and driving out its statistical significance. Not just that, skewness also drives out the statistical significance of the volatility and volatility downside factors. This reinforces the stock skewness's ability to capture pricing information that is not accounted for by the global GDA3 factor risks.

Compared to Farago and Tédongap (2012), our findings regarding skewness and cokurtosis as controls in the cross-sectional GDA model are novel. Indeed, Farago and Tédongap (2012) do not control for skewness in their study on GDA factor pricing in the cross-section of American stocks. In contrast, they look at coskewness and find that it has a statistically significant negative risk premium, corroborating the findings of Harvey and Siddique (2000). Likewise, our results on international stock indices suggest that coskewness has a negative risk premium. However, across the different specifications as shown from Table 4 to Table 7, the statistical significance of the coskewness risk premium melts into that of the global downstate factor risk or the skewness. In the remaining analyses the cross-sectional GDA model is augmented with the skewness and cokurtosis, consistent with our findings in Tables 6 and 7.

4.2 Robustness checks

In this section, we conduct several robustness checks to confirm the validity of our empirical findings. These checks are undertaken the first relative to the benchmark GDA3 model and the results are presented in Table 8. They consist of varying the downside probability (Panel A), the beta estimation window (Panel B), and the asset menu (Panel C). Finally, we consider a subsample that stops in December 2019 (Panel D), excluding the period influenced by the covid-19 pandemic. The striking finding of Table 8 is that, across the different panels of the table, all risk premia are highly statistically significant while the constant-coefficient is largely insignificant. As found in previous analyses, all GDA factor risk premia have the theoretically expected signs. Likewise, the signs of the skewness and kurtosis risk premia remain unchanged across the different model specifications.

Starting with Panel A of Table 8, a downstate probability 5% higher or lower than the baseline value of 15% does not dramatically change the magnitude of the estimated risk premia, and the R^2 has a marginal less than 2% difference. In panel B, increasing the beta estimation window from the baseline value of $k = 12$ to $k = 30$ steadily decreases the magnitude of the estimated global market risk and downside risk premia, the skewness premium, as well as the overall fit of the model.

However, their values remain comparable to the baseline scenario.

In Panel C, we examine results obtained by removing some country groups from our baseline sample one at a time. The BRICS (Brazil, Russia, India, China, and South Africa) represent 40% of the world population and 20% of world global Gross Domestic Product (GDP). The stock markets of these countries have been prominent in the recent decade. In 2012 for example, their MSCI index returned a striking 450% compared to 350% and 98% for other emerging stock markets and developed markets, respectively (see Adu et al.; 2015). These extreme statistics point to the particularity of the BRICS, and we would like check if their exclusion from the original sample would modify the pricing of global downside risk across international stock market indices.

Removing the BRICS, the top five financial markets,[3] the emerging countries, African countries, or regional indices, one country group at a time, provides risk premia estimates and overall model fit that are close enough to the baseline scenario. Notice in the case where all emerging markets are excluded from the original sample that the magnitudes of the estimated global risk premia are the lowest compared to other sample specifications. This finding is consistent with Estrada (2007) and corroborates their conclusion that downside risk is more importantly priced in emerging compared to developed markets.

In Panel D, we estimate the cross-sectional model considering a sample period that does not include the coronavirus outbreak. Topcu and Gulal (2020) and Zhang and Mao (2022) find a negative effect of the pandemic on both national and international financial markets. Again, for the baseline downstate probability and 5% higher and lower values, our results in Panel D are sufficiently close to Panel A, which uses the whole sample period, suggesting that our main result regarding the pricing of global GDA3 factors in the cross-section of international stock indexes is unaffected by a major, rare and persistent economic event such as the pandemic.

Table 9 is organized in the same manner as Table 8 and provides robustness results for the GDA5 model specification. It confirms the strong statistical significance of the global market risk,

[3]see https://www.statista.com/statistics/710680/global-stock-markets-by-country/

downside risk and downstate risk premia, as well as the skewness premium, similar to Table 8, across the four panels of the table. In contrast, the statistical significance of the global volatility risk and downside risk premia is not sufficiently strong and stable as previously found, e.g., in Table 7. Varying the asset menu as shown in Panel C does confirm this observation. Results in Panels A and D of Table 9 tend to suggest that the global volatility risk and downside risk premia estimates are statistically significant at the 5% level when the downstate probability if sufficiently low (e.g., 10%), i.e., when downside risk is sufficiently in the tail.

Recall that in our benchmark GDA5 scenario, falling market returns and rising variance can equally cause disappointment as we assume $a = 1$. Table 10 provides results for two alternative values: $a = 0$ and $a = 2$. In the first scenario of the table, $a = 0$, similar to the GDA3 model, disappointment occurs due to falling market returns, and rising volatility may play an indirect role only through its negative correlation with the market return, the so-called leverage effect. In the second scenario, $a = 2$, rising volatility plays a more important role in causing disappointment than in the benchmark scenario. The main finding from the top panel of Table 10 is that, when volatility virtually plays no role in triggering disappointment, the volatility risk premium is not statistically different from zero at conventional levels of significance. The volatility factor is not priced, while the volatility downside factor is priced at the 5% significance level for sufficiently low downstate probability values (e.g., 15% and 10%). Therefore, there is no support for the GDA5 theory based on international stock index data. In contrast, the bottom panel of Table 10 shows results when rising volatility plays a more important role than falling market returns in triggering disappointment. In this case, both the volatility risk and downside risk premia are negative and statistically different from zero at the 5% significance level for sufficiently low values of the downstate probability. This latter finding validates the GDA5 theory based on international stock index data when downside risk sufficiently lies in the tail.

We extend the varying downstate probability analysis and run estimations of the GDA3 and GDA5 model specifications for 200 regularly spaced values of the downstate probability ranging from 5.5% to 49.5%. Then, we plot the risk premia estimates together with their 95% confidence bounds against the downstate probability. Figure 1 displays the global market risk (top graphs), downside risk (middle graphs) and downstate risk (bottom graphs) premia estimates. The first column corresponds to the GDA3 model, while the second, third and fourth columns correspond to the GDA5 model with $a = 0$, $a = 1$, and $a = 2$, respectively. The figure shows, for the three global risk premia, that zero is far from the nearest bound of the confidence interval for downstate probability values well below the median of 50%. However, it is less the case when the downstate probability is close to 50%. This finding suggests that, while global downside risks are relevant on international stock markets, they appear to be more so for lower downstate probability values, lending empirical support to generalized disappointment aversion of Routledge and Zin (2010), to the contrary of the disappointment aversion theory of Gul (1991).

For the GDA5 model, Figure 2 displays the global volatility risk (top graphs) and downside risk (bottom graphs) premia estimates. The findings in the top panel of Table 10 are confirmed in the first column of Figure 2. For all downstate probability values, the global volatility risk and downside risk premia estimates are not statistically different from zero when $a = 0$, i.e., when rising variance does not trigger disappointment. The second column shows that only for downstate probability values that are sufficiently far below the median, the statistical significance of the global volatility risk and downside risk premia estimates barely approaches the 95% confidence level when $a = 1$, i.e., when falling market returns and rising market volatility can equally cause disappointment. Likewise, the findings in the bottom panel of Table 10 are confirmed in the last column of Figure 2. Only for downstate probability values sufficiently in the tail (i.e., less than 10%) are the global volatility risk and downside risk premia estimates statistically different from zero when $a = 2$, i.e., when rising variance is more important that falling market returns in causing disappointment.

Overall, from our robustness exercise, we find sufficiently empirical solid evidence supporting the pricing of global GDA factors in the cross-section of international stock market indexes. The GDA3 model holds in the data for various levels of the downstate probability. In contrast, the

GDA5 model is supported in the data only for downstate probability values that lie sufficiently in the tail (less than 10%), provided rising volatility plays the most crucial role relative to falling market returns in triggering downside risk.

4.3 The predictive ability of global downside risk

In this subsection, we check if current multivariate betas on the global GDA factors (GDA3 and GDA5) predict high future returns over the next months, similar to the contemporaneous relationship between multivariate betas and average returns from the previous subsections. Analyzing predictive FM regressions is increasingly becoming standard in the cross-sectional asset pricing literature (see Lewellen; 2011, Ang et al.; 2009 and Farago and Tédongap; 2012, among others). Predictive FM regressions can be of practical value when building trading strategies over multiple horizons and accounting for portfolio rebalancing. We carry out the same exercise as previously, measuring the multivariate betas from equation (3), but now the left-hand side of the cross-sectional regression (4) is $\frac{R^e_{i,t+1:t+h}}{h}$ where $R^e_{i,t+1:t+h} = \sum_{j=1}^{h} R^e_{i,t+j}$, i.e. the average monthly excess returns over the next h months. We consider five different predictability horizons: one month, three months, six months, nine months and twelve months.

Results regarding the predictive ability of global downside risk in the GDA3 model are displayed in Table 11 for different values of the downstate probability. There are three main observations from the table. First, predictive betas as well as skewness and cokurtosis explain cross-sectional differences in average returns on international stock markets with the same theoretical sign as contemporaneous betas. Second, the magnitude of the risk premia (i.e., our estimates), their statistical significance (i.e., their t-statistics), and the cross-section explanatory power (i.e., the adjusted R^2) all decrease steadily with the investment horizon. These observations are true regardless of the downstate probability value. For our baseline value of 15%, the magnitude of the global market downside (resp. downstate) risk premium decreases monotonically from 0.0374 (resp. -2.5823) at the 1-month horizon to 0.0166 (resp. -1.6435) at the 12-month horizon. Likewise the magnitude of the skewness (resp. cokurtosis) risk premium decreases monotonically from 0.0037 (resp. -0.0121) at the 1-month horizon to 0.0021 (resp. -0.0057) at the 12-month horizon.

Likewise, we examine the predictive ability of global downside risk in the GDA5 model, considering the scenario $a = 2$ that favors rising volatility over falling market returns in triggering disappointment. This choice is motivated by the previous finding (see Figure 2) that a more important role for volatility in causing disappointment lends support to the GDA5 theory in the data. Results are provided in Table 12. The three main observations from Table 11 remain true in this case. In addition, for sufficiently low downstate probability, say 10%, the global volatility and downside volatility risk premia estimates are negative and statistically significant at the 95% confidence level, and their magnitudes decrease steadily with the investment horizon. For a downstate probability value of 10%, the magnitude of the global volatility downside risk premium decreases about monotonically from -0.0148 at the 1-month horizon to -0.0120 at the 12-month horizon.

In summary, the global GDA theory is validated with international stock market data. We find evidence that global GDA3 and GDA5 factor risks, whether measured by contemporaneous or predictive betas, are important drivers of risk premium heterogeneity in the cross-section of international stock indexes. However, they do not fully account for the total risk premium requested by investors globally. In fact, other sources of risk such as skewness and cokurtosis are still relevant in the presence of global GDA factor risks. In what follows, we examine potential determinants of the global GDA factor risks.

5 Global downside risk and country characteristics

Only a few studies have examined the determinants of downside risk across investment assets. Ang, Chen and Xing (2006) argue that, although it is just an exploratory analysis, discovering that some variables are risk determinants can help develop investable strategies. At the company level and working with U.S. stock data, they study the cross-sectional determinants of downside risk and show that some company characteristics affect their relative downside beta. We carry a similar analysis at the global level, looking at the other way around; that is, this subsection aims to investigate the country characteristics that are captured by the global downside risk premium across international stock indexes. By the nature of the available data on country indicators discussed in Section 3, we cannot proceed as Ang, Chen and Xing (2006) via FM cross-sectional regressions of the betas on the assumed variables.[4] Instead, we look at the difference in the associated factor risk premium between two equal-sized groups sorted according to a given country variable for each global downside risk factor. If the spread is statistically significant, we assess by how much the related factor risk accounts for the risk premium resulting from a long/short portfolio strategy based on sorting international stock indexes on the country variable in question. The spread is computed as $\hat{E}\left[\left(\beta_{\text{grp}1,f,t} - \beta_{\text{grp}2,f,t}\right)\lambda_{f,t}\right]$ where $\beta_{\text{grp}i,f,t}$ is the time-t average of betas on factor f across countries in group i, and $\lambda_{f,t}$ is the time-t risk premium for factor f.

In all subsequent analyses, group 1 is made of less favorable countries, given a considered variable. Concerning the four assumed financial indicators presented in Section 3, group 1 shall be made of countries with emerging stock market, higher stock market index volatility, poorer use of digital payment, or lower financial inclusion rate. Likewise, for the four assumed economic indicators, group 1 shall be made of countries with higher net inflow of foreign direct investment, lower gross domestic product per capita, weaker ease of doing business rank, or lower competitiveness index. The premium for shorting stock indices of countries in group 2 and longing stock indices of countries in group 1 can be decomposed as follows:

$$\hat{E}\left[r_{\text{grp}1,t} - r_{\text{grp}2,t}\right] = \overbrace{\sum_f \hat{E}\left[\left(\beta_{\text{grp}1,f,t} - \beta_{\text{grp}2,f,t}\right)\lambda_{f,t}\right]}^{\text{predicted}} + \text{unexplained} \tag{5}$$

where $r_{\text{grp}i,t}$ is the time-t average return across group i countries. We use contemporaneous betas to analyze the determinants of global downside risk and examine the effect of the covid-19 crisis.

[4]The data are yearly, generally not available for the entire sample period and sometimes based on surveys. In addition, many variables are also qualitative.

5.1 Long/short country indicator portfolios

We start by discussing the relationship between country indicators and global downside risk based on the full sample period. In Table 13, we report estimates of the long/short risk premium for sorting international stock indexes on a given country indicator, as well as its decomposition based on equation (5). The values of country indicators corresponding to year 2019 are used. Results are provided for the GDA3 and GDA5 model specifications, distinguishing between selected country financial and economic indicators. We consider baseline values for the downstate probability and the disappointment triggering coefficient, i.e., $\text{prob}\,(\mathcal{D}) = 15\%$ and $a = 1$.

Panel A1 of Table 13 presents the GDA3 results for country financial indicators. Three key observations are highlighted. First, sorting on the selected financial variables generates a positive and statistically significant long/short portfolio risk premium at conventional levels of confidence, i.e., 90% or higher. These premia amount to 3.21%, 5.99%, 6.32% and 7.36% in annualized terms, when sorting on the stock market index volatility (SVOL), the use of digital payment (DIGP), the nature of the stock market (EMDV, i.e., emerging or developed) and the financial inclusion rate (FIIN), respectively. Second, the predicted value (absolute percentage error, APE) of the realized long/short portfolio risk premium by the GDA3 model is reasonably large (small).[5] It amounts to 1.91% (40.50%), 4.56% (27.85%), 6.29% (5.01%) and 7.32% (0.54%) when sorting international stock indexes on SVOL, EMDV, DIGP and FIIN, respectively. Third, the predicted long/short premium is mainly driven by the global downstate component which is positive, statistically significant, and large enough to compensate for the cumulative negative spread on other factors.

Panel B1 of Table 13 shows that the benchmark GDA5 model provides a better fit for the long/short SVOL and EMDV portfolio risk premia, with a predicted value (APE) of 2.71% (15.58%) and 5.41% (14.40%), respectively. While the SVOL premium is driven by the global market and

[5]The absolute percentage error (APE) is computed as

$$\left| \frac{\text{realized} - \text{predicted}}{\text{realized}} \right| \times 100.$$

volatility components, the global downstate component remains the main driver of the EMDV premium. In contrast, the GDA5 model fit is lower for the long/short DIGP and FIIN portfolio risk premia compared to the benchmark GDA3, with a predicted value (APE) of 5.31% (11.35%) and 7.90% (7.34%), respectively. The predicted value is mainly driven by the downstate and volatility downside components for the DIGP premium, and the donwstate component for the FIIN premium.

We now turn to discussing results for economic indicators. They are presented in Panel A2 of Table 13 for the GDA3 model. These results look similar to Panel A1. First, sorting on the selected economic variables generates a positive and statistically significant long/short portfolio risk premium at conventional levels of confidence. These premia are 4.41%, 5.82%, 6.90% and 6.93% in yearly values, when sorting on the net inflow of foreign direct investment (NFDI), the gross domestic product per capita (GDPC), the ease of doing business rank (DBUS) and the country competitiveness index (CCOM), respectively. Second, the predicted value (absolute percentage error) of the realized long/short portfolio risk premium by the GDA3 model is fairly large (small). Its value is 4.49% (1.81%), 6.85% (17.70%), 6.58% (4.64%) and 7.65% (10.39%) when sorting international stock indexes on NFDI, GDPC, DBUS and CCOM, respectively. Third, similar to financial indicator portfolios, the predicted long/short risk premium of economic indicator portfolios is mainly driven by the global downstate component which is positive and statistically significant, often larger than the predicted value, enough to compensate for the cumulative negative spread on other factors. In addition, the global market component co-drives the NFDI premium. It is the unique driver of the NFDI premium for the GDA5 model as shown in Panel B2 of the table. The GDA5 results for the remaining economic indicator portfolios confirm the global downstate as the main driving component of the long/short risk premia. The GDA5 model fit outperforms the GDA3 on the NFDI and GDPC premia while is contrary for the DBUS and CCOM premia.[6]

In summary, the GDA model provides a good prediction of the risk premia on international stock market investments based on selected country indicators, and exposure to the global downstate fac-

[6] Although the GDA5 model is an extension of the GDA3, the GDA3 specification is not nested unless $a = 0$.

tor is their primary determinant. Long/short portfolio strategies similar to the ones investigated in the current article may call for international financial market segmentation if a particular type of global investor is interested in specific country indicator portfolio strategies. For example, some portfolio managers may focus on trading on the nature of the stock market to exploit the investment potential of emerging markets. Other may emphasize the net inflow of foreign direct investment or the country's competitiveness. There could be a form of international financial markets segmentation if there is only a tiny overlap of these categories of global investors. We next examine how the occurrence of major financial and economic events following crisis episodes can alter these findings.

5.2 Does the covid-19 crisis matter?

The values of the country indicators used as criteria for sorting the international financial market indexes in the previous subsection are from the year 2019. Using the year 2019 values ensures that the investigated long/short strategies are not a consequence of the covid-19 pandemic and represent what we can observe in normal circumstances. The coronavirus outbreak has rattled the world mostly since the beginning of year 2020. Indeed, hundreds of millions of infections and fatalities occurred worldwide between January 2020 and December 2021. The crisis has had a major impact on almost all aspect of daily life, as well as the financial markets. According to Topcu and Gulal (2020), Alexakis et al. (2021), and Sayed and Eledum (2021), the covid-19 outbreak is having a significant impact on both national and international financial markets. In order to test this effect, we adopt two strategies. We first examine long/short portfolio strategies that still sort international stock indexes on the year 2019 country indicator values, excluding the covid-19 period returns from the sample, therefore analyzing the pre-covid subsample that ends in December 2019. The second strategy consists in sorting international stock indexes on the year 2020 country indicator values and analyzing both the full sample and the pre-covid subsample.

Table 14 displays long/short portfolio strategy results for sorting international stock indexes on the year 2019 country indicator values, excluding post-2019 returns from the original sample.

Overall, the long/short strategies are identical to Table 13 but average excess returns are higher, suggesting that group 1 international financial markets have experienced much lower returns than average during the coronavirus period relative to group 2, irrespective of the sorting indicator. Regarding financial indicator strategies, full (pre-covid) sample average excess returns of the SVOL, DIGP, EMDV and FIIN long/short portfolios are 3.21% (3.49%), 5.99% (7.76%), 6.32% (7.69%) and 7.36% (9.35%), respectively. Likewise, for economic indicator strategies, these average excess returns are 4.41% (4.64%), 5.82% (7.58%), 6.90% (8.58%) and 6.93% (8.85%) for the NFDI, GDPC, DBUS and CCOM long/short portfolios, respectively. Excluding post-2019 returns does not change the pattern of the long/short risk premium decomposition relative to Table 13. The same observations regarding the strong ability of the GDA model to predict the large share of the risk premia on international stock markets and the crucial role of the global downstate component still hold.

We finally turn to Table 15 where international stock indexes are sorted based on the 2020 country indicator values, and we provide long/short portfolio strategy results both for the full sample and the pre-covid subsample. The striking finding is that for all country indicators, but NFDI and GDPC, the long/short portfolio risk premium shrinks considerably to the point of becoming highly insignificant. In the table, we only keep results for the about or statistically significant long/short risk premia. For the rest, the configuration of the results does not change compared to the benchmark sort based on the year 2019 indicator values. We can conclude that the pandemic may have affected the remuneration of risk-taking strategies on the international stock markets without modifying its different components and their degree of importance.

6 Conclusion

There has been a growing interest in downside risk pricing over the last two decades or so. However, although several measures of downside risk are proposed in the literature, there are not properly characterized as the exposure, that is, the beta or factor loading, with respect to a precisely identified factor which is valued by risk-averse investors on financial markets. Theoretically, Farago and Tédongap (2012, 2018) clearly identify these downside risk factors in a consumption-based representative-agent economy featuring generalized disappointment aversion (GDA) preferences, and show empirically that these factors are priced in the cross-section of U.S. stocks. We extend their study by showing that these factors are also priced globally, when the asset menu is made of country and regional stock market indexes covering 23 developed and 22 emerging Morgan Stanley Capital International (MSCI) stock indices from 1972 to 2021.

Our results strongly suggest, both from statistical and economic viewpoints, that global downside risk in the cross-section of international stock market indexes is well-priced both in the three- and five-factor versions of the GDA model. The five-factor specification allows volatility to play an important role in investment decisions and downside risk is priced only when it lies sufficiently in the tail. Our results are not driven by other risk measures reflecting asymmetry and tail effects in international stock index returns, such as skewness, coskewness, kurtosis and cokurtosis. However, the GDA model does not fully account for the total risk premium requested by investors globally. In fact, other sources of risk, namely skewness and cokurtosis, are still relevant in the presence of global GDA factor risks.

We finally analyze the relationship between global downside risk and country characteristics, including selected financial and economic indicators. Our approach involves sorting international stock market indexes based on country indicator values and examining the resulting long/short portfolio risk premium and its decomposition across the different GDA components. Our findings suggest that these country indicator long/short portfolio risk premia are significant, the GDA components explain the large share cumulatively, and exposure to the global downstate factor is the primary driver of the model prediction. The coronavirus crisis did not alter the risk premium decomposition results.

Future research may extend our work by conducting a similar empirical investigation on derivative markets, on crypto-asset markets, or particularly on African stock markets which can be subject to important down movements in reaction to global phenomena.

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Table 1: Cross-sectional correlations between risk measures

	ω	ν	θ	ϕ
Coeff	-0.1894	0.1472	-0.0935	0.9795
t-stat	(-11.0890)	(17.0010)	(-17.2650)	(546.0700)

The entries of the table are coefficient estimates of the Exponential GARCH model (EGARCH) specification:

$$\begin{aligned} r_{W,t+1} &= \sigma_{W,t}\varepsilon_{t+1} \\ \ln\left(\sigma^2_{W,t+1}\right) &= \omega + \nu\left(|\varepsilon_{t+1}| - \sqrt{2/\pi}\right) + \theta\varepsilon_{t+1} + \phi\ln\left(\sigma^2_{W,t}\right) \\ \varepsilon_{t+1} &\overset{iid}{\sim} \mathcal{N}\left(0,1\right) \end{aligned}$$

using demeaned market factor daily data from January 1972 to December 2021. The t-statistics of the coefficient estimates are provided in parenthesis.

Table 2: Summary statistics

Country Name	Mean (%)	Std (%)	Skew	CoSkew	Kurt	CoKurt	β_{iW3}	$\beta_{iW\mathcal{D}3}$	$\beta_{i\mathcal{D}3}$	β_{iW5}	$\beta_{iW\mathcal{D}5}$	$\beta_{i\mathcal{D}5}$	β_{X}	$\beta_{X\mathcal{D}}$	β_{iPRA}	β_{iPDA}
AC WORLD	9.53	18.44	0.68	-0.24	22.51	3.12	0.45	0.06	3.79E-4	0.46	0.02	4.79E-5	-0.27	0.04	0.47	-9.13E-3
AUSTRALIA	10.43	28.37	0.47	-0.11	23.01	0.75	0.09	0.17	1.63E-3	0.10	0.09	1.06E-4	-0.36	-0.06	0.12	-2.37E-3
AUSTRIA	9.54	29.78	0.68	-0.14	19.31	0.87	0.20	0.10	5.71E-4	0.23	0.16	9.37E-4	-0.43	0.18	0.25	-5.03E-3
BELGIUM	10.84	26.11	0.86	-0.13	21.46	0.96	0.21	0.10	6.04E-4	0.22	0.07	8.18E-5	-0.33	0.11	0.24	-4.87E-3
BRAZIL	41.45	82.86	1.44	-0.17	22.92	1.98	0.77	-0.09	-1.91E-3	0.83	-0.02	-5.37E-4	-1.07	0.94	0.80	-1.54E-2
BRIC	11.33	29.71	0.02	-0.21	15.75	2.23	0.43	0.17	2.04E-3	0.46	0.12	1.52E-3	-0.66	-0.01	0.46	-8.55E-3
CANADA	8.73	23.80	1.19	-0.17	31.06	1.71	0.31	0.16	1.19E-3	0.32	0.10	5.76E-4	-0.09	-0.13	0.35	-6.81E-3
CHILE	14.83	30.00	0.94	-0.16	18.47	1.86	0.36	0.12	2.02E-3	0.38	0.03	7.34E-4	-0.39	0.10	0.38	-6.85E-3
COLOMBIA	14.99	35.18	0.69	-0.23	17.90	1.74	0.32	0.27	2.35E-3	0.35	0.30	2.53E-3	-0.34	-0.07	0.40	-7.57E-3
CZECH REPUBLIC	13.99	31.98	-0.06	-0.20	13.70	1.62	0.21	0.29	3.76E-3	0.23	0.22	2.38E-3	-0.49	-0.07	0.27	-5.10E-3
DENMARK	15.12	25.34	0.72	-0.09	19.83	0.80	0.19	0.08	9.52E-4	0.19	0.04	6.38E-5	-0.31	0.20	0.20	-3.71E-3
EAFE	8.88	20.73	1.12	-0.14	35.80	1.26	0.17	0.06	6.97E-5	0.19	0.02	-3.04E-4	-0.33	0.02	0.20	-4.17E-3
EGYPT	14.12	33.57	0.20	-0.18	24.47	0.69	-0.02	0.32	3.22E-3	-0.01	0.18	7.38E-4	-0.43	0.09	0.05	-1.08E-3
EMERGING	12.83	24.93	0.24	-0.20	26.09	1.75	0.25	0.13	8.03E-4	0.27	0.07	-8.24E-5	-0.56	0.01	0.30	-5.94E-3
EMERGING EUROPE	12.26	35.68	0.85	-0.16	33.09	1.56	0.39	0.13	2.08E-3	0.41	0.04	8.18E-4	-0.57	-0.02	0.40	-7.44E-3
EUROPE	10.18	22.63	1.06	-0.13	37.74	1.35	0.24	0.05	1.13E-4	0.27	0.02	5.09E-5	-0.29	0.06	0.27	-5.39E-3
FINLAND	13.90	36.88	0.53	-0.11	18.41	1.64	0.47	0.03	1.03E-3	0.49	-0.02	4.18E-4	-0.75	0.31	0.46	-8.38E-3
FRANCE	11.94	28.79	0.85	-0.11	22.49	1.19	0.28	0.09	8.09E-4	0.30	0.07	3.41E-4	-0.36	0.14	0.30	-5.87E-3
G7	10.46	18.65	1.30	-0.19	31.99	2.49	0.37	0.04	8.09E-5	0.38	0.02	-9.64E-6	-0.11	-0.03	0.39	-7.71E-3
GERMANY	10.95	27.35	0.51	-0.11	20.37	1.21	0.29	0.06	4.59E-4	0.31	0.04	1.67E-4	-0.33	0.15	0.31	-6.14E-3
HONG KONG	17.17	38.59	1.53	-0.07	36.49	0.53	0.09	0.01	-4.16E-4	0.10	-0.06	-1.85E-3	-0.14	-0.21	0.12	-2.28E-3
HUNGARY	19.74	42.91	0.72	-0.19	21.55	1.73	0.41	0.26	3.72E-3	0.44	0.14	1.10E-3	-0.46	-0.09	0.46	-8.72E-3
INDIA	12.38	31.65	0.26	-0.13	15.69	1.16	0.20	0.20	2.34E-3	0.21	0.18	1.88E-3	-0.48	-0.24	0.22	-4.21E-3
INDONESIA	19.31	52.30	1.13	-0.11	27.09	0.66	0.05	0.14	-6.68E-4	0.11	0.15	3.79E-4	-0.60	-0.19	0.16	-4.08E-3
IRELAND	8.65	30.63	0.54	-0.16	15.93	1.56	0.35	0.11	1.03E-3	0.36	0.06	6.63E-5	-0.48	0.06	0.38	-7.46E-3
ISRAEL	6.85	27.11	0.29	-0.18	16.28	1.79	0.33	0.09	1.06E-3	0.34	-0.02	-6.18E-4	-0.38	0.05	0.35	-6.78E-3
ITALY	8.35	32.23	1.27	-0.11	28.84	1.13	0.27	0.12	6.85E-4	0.29	0.11	6.16E-4	-0.22	0.19	0.31	-6.02E-3
JAPAN	8.70	25.61	0.82	-0.09	22.19	0.22	-0.01	0.12	3.23E-4	-0.01	0.05	-6.62E-4	-0.44	0.00	0.04	-1.03E-3
JORDAN	-1.27	21.40	-0.45	-0.08	38.56	0.38	0.01	0.08	1.15E-3	0.00	0.03	1.98E-4	0.02	-0.18	0.02	-1.42E-4
KOREA	13.36	41.07	0.69	-0.11	20.18	0.70	0.05	0.15	-5.79E-4	0.08	0.06	-2.10E-3	-0.60	-0.09	0.15	-4.03E-3
MALAYSIA (EM)	8.37	29.67	0.63	-0.14	21.03	0.75	0.04	0.09	6.82E-5	0.06	0.03	-4.10E-4	-0.34	-0.05	0.10	-2.08E-3
MEXICO	20.00	36.76	0.92	-0.16	17.56	2.18	0.53	0.08	-2.17E-4	0.58	0.04	3.35E-4	-0.51	0.17	0.58	-1.15E-2
MOROCO	10.73	19.35	0.55	-0.07	12.30	0.37	-0.01	0.03	-5.40E-5	0.01	0.02	-2.81E-5	-0.11	0.08	0.02	-7.82E-4
NETHERLANDS	14.52	25.80	0.86	-0.12	21.83	1.14	0.24	0.12	8.93E-4	0.26	0.09	4.93E-4	-0.30	0.05	0.27	-5.46E-3
NEW ZEALAND	9.09	26.39	0.56	-0.16	17.13	0.77	0.04	0.24	1.70E-3	0.06	0.18	7.67E-4	-0.40	-0.02	0.10	-2.39E-3
NIGERIA	9.87	27.88	-0.30	-0.12	11.25	0.16	-0.11	0.09	-4.93E-4	-0.09	0.04	-1.69E-3	-0.06	-0.09	-0.02	-4.70E-4
NORDIC	13.95	26.39	1.32	-0.11	32.32	1.25	0.29	0.05	9.02E-4	0.31	-0.01	8.57E-5	-0.41	0.14	0.29	-5.44E-3
NORWAY	12.22	33.65	0.71	-0.13	26.86	0.98	0.23	0.19	2.04E-3	0.23	0.16	9.80E-4	-0.33	0.04	0.27	-5.14E-3
PACIFIC	8.99	24.60	1.37	-0.11	34.86	0.52	0.03	0.08	-6.25E-5	0.05	0.02	-7.25E-4	-0.40	-0.04	0.08	-1.79E-3
PAKISTAN	6.38	35.76	0.34	-0.09	20.60	0.26	0.00	0.05	7.94E-4	0.02	0.02	4.51E-4	-0.07	-0.02	0.01	-2.20E-5
PERU	20.33	36.20	0.19	-0.21	21.47	2.16	0.53	0.12	6.72E-4	0.55	0.07	-1.29E-4	-0.39	0.27	0.58	-1.13E-2
PHILIPPINES	11.59	34.38	0.59	-0.12	21.13	0.62	0.02	0.12	4.96E-4	0.05	0.09	5.17E-5	-0.65	0.02	0.08	-1.63E-3
POLAND	13.70	43.84	0.68	-0.19	19.56	1.67	0.46	0.19	3.21E-3	0.48	0.07	9.81E-4	-0.62	-0.21	0.48	-8.37E-3
PORTUGAL	3.27	27.63	0.85	-0.13	21.09	1.36	0.28	0.09	8.72E-4	0.30	0.02	9.12E-6	-0.38	0.22	0.30	-5.72E-3
SINGAPORE	11.57	31.92	0.71	-0.10	32.63	0.79	0.09	0.11	5.90E-4	0.11	0.04	-3.56E-4	-0.38	0.04	0.14	-2.73E-3
SOUTH AFRICA	12.20	33.15	0.33	-0.20	17.93	1.79	0.41	0.19	1.54E-3	0.46	0.12	8.91E-4	-0.79	0.24	0.47	-9.08E-3
SPAIN	8.70	29.82	0.74	-0.11	27.01	1.13	0.26	0.12	8.41E-4	0.27	0.07	2.43E-4	-0.26	0.07	0.29	-5.73E-3
SWEDEN	15.69	31.43	1.25	-0.11	25.48	1.14	0.31	0.07	9.48E-4	0.33	-0.01	-2.07E-4	-0.44	0.24	0.32	-6.10E-3
SWITZERLAND	12.37	23.66	0.40	-0.11	18.36	0.99	0.13	0.13	1.00E-3	0.14	0.09	4.18E-4	-0.25	0.12	0.17	-3.43E-3
TAIWAN	14.41	37.73	0.95	-0.15	26.80	0.76	0.07	0.13	2.24E-4	0.09	0.09	-5.05E-4	-0.51	-0.06	0.13	-2.94E-3
THAILAND	13.12	40.21	0.65	-0.11	23.93	0.88	0.07	0.08	-5.34E-4	0.09	0.02	-1.20E-3	-0.45	0.21	0.14	-3.51E-3
TURKEY	22.92	64.81	1.93	-0.13	29.92	1.27	0.37	0.28	3.05E-3	0.39	0.19	1.83E-3	-0.76	0.26	0.41	-7.80E-3
UK	9.96	27.50	0.88	-0.11	24.57	1.16	0.23	0.06	1.86E-4	0.25	0.03	5.97E-6	-0.22	-0.06	0.26	-5.18E-3
USA	10.76	20.84	1.47	-0.17	36.33	2.37	0.43	0.04	2.14E-4	0.43	0.03	1.13E-4	0.06	-0.09	0.44	-8.55E-3
WORLD	9.36	18.44	1.30	-0.18	37.14	2.17	0.32	0.05	1.63E-4	0.33	0.02	-8.59E-5	-0.12	-0.04	0.34	-6.66E-3
WORLD excl. USA	8.98	20.58	1.14	-0.15	36.25	1.33	0.18	0.07	1.72E-4	0.20	0.02	-2.42E-4	-0.31	0.00	0.21	-4.35E-3

The table shows the summary statistics of country and regional sample averages of monthly expected excess returns, standard deviation, skewness and coskewness, kurtosis and cokurtosis, as well as multivariate (GDA3 and GDA5) and univariate (PRA and PDA) factor loadings. The monthly time series for all measures are computed from rolling-window estimations based on one-year of daily data, and sample averages are reported in the table. Average monthly expected excess returns and standard deviations are annualized. The reported figures correspond to our baseline scenario where the disappointment probability is 15% and $a = 1$. The sample period is from January 1972 to December 2021.

Table 3: Cross-sectional correlations between risk measures

	β_{iW3}	$\beta_{iW\mathcal{D}3}$	$\beta_{i\mathcal{D}3}$	β_{iW5}	$\beta_{iW\mathcal{D}5}$	$\beta_{i\mathcal{D}5}$	β_X	$\beta_{X\mathcal{D}}$	Skew	Coskew	Kurt	Cokurt	β_{iPRA}
β_{iW3}													
$\beta_{iW\mathcal{D}3}$	−0.36												
$\beta_{i\mathcal{D}3}$	0.02	0.75											
β_{iW5}	0.96	−0.39	−0.06										
$\beta_{iW\mathcal{D}5}$	−0.42	0.82	0.53	−0.41									
$\beta_{i\mathcal{D}5}$	−0.07	0.45	0.56	−0.01	0.69								
β_X	−0.04	−0.04	−0.06	−0.05	0.01	−0.03							
$\beta_{X\mathcal{D}}$	0.06	−0.15	−0.13	0.06	−0.29	−0.31	−0.61						
Skew	0.08	−0.10	−0.09	0.07	−0.13	−0.13	0.03	0.05					
Coskew	0.25	−0.49	−0.17	0.23	−0.45	−0.10	0.01	0.04	0.06				
Kurt	−0.02	0.05	0.03	−0.01	0.04	0.03	0.08	−0.11	0.16	0.01			
Cokurt	0.57	0.09	0.17	0.58	0.04	0.10	0.01	−0.03	0.02	−0.12	0.00		
β_{iPRA}	0.87	−0.18	−0.01	0.87	−0.22	−0.08	−0.04	0.02	0.09	−0.02	0.00	0.71	
β_{iPDA}	−0.44	0.04	0.24	−0.50	0.01	0.17	0.03	−0.05	−0.13	0.29	0.01	−0.59	−0.75

The table displays the correlations between the main risk measures (global market regular risk, β_{iW}, global market downside risk, $\beta_{iW\mathcal{D}}$, global downstate risk, $\beta_{i\mathcal{D}}$, volatility risk, β_X, and volatility downside risk, $\beta_{X\mathcal{D}}$), together with skewness (Skew), coskewness (Coskew), kurtosis (Kurt), cokurtosis (Cokurt), and the univariate factor loadings, β_{iPRA} and β_{iPDA}. The model under consideration is indicated by the indexing "i" in the variable names. As a result, the codes "3" and "5" denote that the variable is calculated in the GDA3 and GDA5 models, respectively. The entries are monthly time series averages of the cross-sectional correlations computed from rolling window estimations based on one-year of daily data. The information are for the benchmark situation where the disappointment probability is 15% and parameter $a = 1$. The sample period is from January 1972 to December 2021.

Table 4: Contemporaneous Fama-Macbeth regressions: PRA and controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cons	0.0084***	0.0020	0.0079***	0.0012	0.0037	0.0082***	0.0048*	0.0025
	(3.2778)	(0.7908)	(3.0317)	(0.4638)	(1.3331)	(3.1151)	1.6085	(0.8867)
λ_W	0.0160	0.0030	0.0183*	0.0031	0.0139	0.0242**	0.0168	0.0151
	(1.5816)	(0.3822)	(1.7308)	(0.3541)	(1.3349)	(2.0315)	(1.3293)	(1.3821)
Skew		0.0041***		0.0042***				0.0058***
		(6.2228)		(6.1075)				(6.7233)
Coskew			−0.0437***	−0.0198**				−0.0219*
			(−3.6162)	(−2.4985)				(−1.8104)
Kurt					0.0001		0.0000	−0.0001
					(1.1034)		(0.2750)	(−1.0530)
Cokurt						−0.0062*	−0.0055	−0.0103***
						(−1.6794)	(−1.5693)	(−2.7571)
Adj.Rsq.	0.1072	0.3032	0.1902	0.3603	0.1687	0.1739	0.2366	0.4560
RMSE	0.0005	0.0004	0.0005	0.0004	0.0005	0.0005	0.0005	0.0003

The table presents results of the Fama and MacBeth (1973) cross-sectional regression tests of the nested PRA model specification, for the benchmark downstate probability value of 15%, a rolling window of 12 months in measuring the betas, and the full test asset menu. For each month $t \geq 12$ the betas are calculated using daily data over the previous 12 months (months $t-11$ to t). The dependent variable in the cross-sectional regression for each month t is the average monthly excess return from month $t-11$ to t. The t-statistics (in parenthesis) are corrected for 12 Newey and West (1987) lags. Adjusted R^2 and RMSE of the model are also reported. The sample period is from January 1972 to December 2021.

Table 5: Contemporaneous Fama-Macbeth regressions: PDA and controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cons	0.0084***	0.0032	0.0088***	0.0027	0.0044	0.0087***	0.0061**	0.0038
	(3.2394)	(1.3103)	(3.2934)	(1.0369)	(1.5797)	(3.2714)	(1.9865)	(1.4103)
$\lambda_{\mathcal{D}}$	−2.5270***	−1.6782***	−2.5452***	−1.5642***	−2.5640***	−2.9309***	−2.8934***	−1.9819***
	(−4.1576)	(−3.3329)	(−4.1874)	(−2.9327)	(−4.2313)	(−4.3986)	(−4.2884)	(−3.1397)
Skew		0.0038***		0.0040***				0.0057***
		(5.7358)		(5.7390)				(6.6435)
Coskew			−0.0075	−0.0011				0.0035
			(−0.7347)	(−0.1286)				(0.2670)
Kurt					0.0001		0.0000	−0.0001
					(1.0420)		(0.2962)	(−1.0000)
Cokurt						−0.0069*	−0.0071**	−0.0099**
						(−1.8952)	(−1.9729)	(−2.5015)
Adj.Rsq.	0.1371	0.3192	0.2018	0.3710	0.1998	0.2045	0.2636	0.4607
RMSE	0.0005	0.0004	0.0005	0.0004	0.0005	0.0005	0.0005	0.0003

The table presents results of the Fama and MacBeth (1973) cross-sectional regression tests of the nested PDA model specification, for the benchmark downstate probability value of 15%, a rolling window of 12 months in measuring the betas, and the full test asset menu. For each month $t \geq 12$ the betas are calculated using daily data over the previous 12 months (months $t-11$ to t). The dependent variable in the cross-sectional regression for each month t is the average monthly excess return from month $t-11$ to t. The t-statistics (in parenthesis) are corrected for 12 Newey and West (1987) lags. Adjusted R^2 and RMSE of the model are also reported. The sample period is from January 1972 to December 2021.

Table 6: Contemporaneous Fama-Macbeth regressions: GDA3 and controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cons	0.0066***	0.0017	0.0058**	0.0010	0.0032	0.0062**	0.0046	0.0042
	(2.6713)	(0.6726)	(2.2520)	(0.3773)	(1.1149)	(2.4341)	(1.4587)	(1.5727)
λ_W	0.0480***	0.0300***	0.0473***	0.0301***	0.0461***	0.0775***	0.0717***	0.0550***
	(3.5332)	(2.9462)	(3.0319)	(2.3910)	(3.4992)	(3.9154)	(3.6424)	(2.9497)
$\lambda_{W\mathcal{D}}$	0.0388***	0.0273***	0.0336***	0.0243***	0.0387***	0.0572***	0.0555***	0.0432***
	(3.6111)	(3.3009)	(2.4203)	(2.0961)	(3.7418)	(3.6706)	(3.6622)	(2.6843)
$\lambda_{\mathcal{D}}$	−3.4262***	−2.2442***	−3.0512***	−2.1526***	−3.3949***	−4.2744***	−4.1116***	−2.7822***
	(−4.6616)	(−3.8736)	(−3.8653)	(−3.2165)	(−4.7318)	(−5.2309)	(−5.1226)	(−3.5628)
Skew		0.0036***		0.0037***				0.0052***
		(5.2809)		(5.8037)				(6.5211)
Coskew			−0.0203	−0.0039				0.0115
			(−1.2704)	(−0.3489)				(0.7509)
Kurt					0.0001		0.0000	−0.0001
					(0.8597)		(−0.2208)	(−1.0327)
Cokurt						−0.0195***	−0.0178***	−0.0137***
						(−3.9088)	(−3.7395)	(−2.7768)
Adj.Rsq.	0.2766	0.3644	0.2813	0.4117	0.2724	0.2852	0.3379	0.4920
RMSE	0.0004	0.0003	0.0004	0.0003	0.0004	0.0004	0.0004	0.0003

The table presents results of the Fama and MacBeth (1973) cross-sectional estimation for GDA3 model alternative specification, for the benchmark downstate probability value of 15%, a rolling window of 12 months in measuring the betas, and the full test asset menu. For each month $t \geq 12$ the betas are calculated using daily data over the previous 12 months (months $t-11$ to t). The dependent variable in the cross-sectional regression for each month t is the average monthly excess return from month $t-11$ to t. The t-statistics (in parenthesis) are corrected for 12 Newey and West (1987) lags. Adjusted R^2 and RMSE of the model are reported. Information are from January 1972 to December 2021

Table 7: Contemporaneous Fama-Macbeth regressions: GDA5 and controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cons	0.0059^{***}	0.0012	0.0053^{**}	0.0008	0.0040	0.0056^{**}	0.0041	0.0026
	(2.7552)	(0.5449)	(2.3498)	(0.3362)	(1.5450)	(2.3746)	(1.4341)	(1.0407)
λ_W	0.0476^{***}	0.0325^{***}	0.0418^{***}	0.0276^{***}	0.0472^{***}	0.0746^{***}	0.0736^{***}	0.0615^{***}
	(3.9330)	(3.4186)	(3.3870)	(2.6466)	(3.8181)	(4.1409)	(3.9412)	(3.9241)
$\lambda_{W\mathcal{D}}$	0.0375^{***}	0.0290^{***}	0.0269^{**}	0.0222^{**}	0.0394^{***}	0.0538^{***}	0.0562^{***}	0.0445^{***}
	(3.9651)	(3.9560)	(2.4893)	(2.4845)	(4.2023)	(3.9284)	(4.0858)	(3.4809)
$\lambda_{\mathcal{D}}$	-3.6155^{***}	-2.5670^{***}	-3.1031^{***}	-2.3462^{***}	-3.6839^{***}	-4.4327^{***}	-4.4547^{***}	-3.1784^{***}
	(-5.5005)	(-4.9656)	(-4.5365)	(-4.0773)	(-5.5651)	(-5.8751)	(-5.8922)	(-4.6143)
λ_X	-0.0142^{*}	-0.0028	-0.0143	-0.0070	-0.0069	-0.0238^{**}	-0.0187^{**}	-0.0105
	(-1.7835)	(-0.6893)	(-1.4660)	(-1.0144)	(-1.4479)	(-1.9920)	(-2.1247)	(-1.4273)
$\lambda_{X\mathcal{D}}$	-0.0144^{*}	-0.0028	-0.0136	-0.0056	-0.0074	-0.0228^{**}	-0.0177^{**}	-0.0098
	(-1.8145)	(-0.6605)	(-1.4765)	(-0.8740)	(-1.4434)	(-2.0721)	(-2.1501)	(-1.4519)
Skew		0.0031^{***}		0.0034^{***}				0.0044^{***}
		(4.9444)		(5.7670)				(6.1655)
Coskew			-0.0301^{**}	-0.0148				-0.0078
			(-2.1826)	(-1.3732)				(-0.4617)
Kurt					0.0000		-0.0001	-0.0001
					(0.1432)		(-0.5735)	(-1.3046)
Cokurt						-0.0154^{***}	-0.0158^{***}	-0.0168^{***}
						(-3.4090)	(-3.2025)	(-3.5472)
Adj.Rsq.	0.3938	0.4912	0.4402	0.5237	0.4362	0.4440	0.4836	0.5883
RMSE	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003	0.0002

The table presents results of the Fama and MacBeth (1973) cross-sectional estimation of the GDA5 model alternative specification, for the benchmark downstate probability value of 15%, a rolling window of 12 months in measuring the betas, and the full test asset menu. For each month $t \geq 12$ the betas are calculated using daily data over the previous 12 months (months $t-11$ to t). The dependent variable in the cross-sectional regression for each month t is the average monthly excess return from month $t-11$ to t. The t-statistics (in parenthesis) are corrected for 12 Newey and West (1987) lags. Adjusted R^2 and RMSE of the model are reported. The sample period is from January 1972 to December 2021.

Table 8: GDA3 Contemporaneous Fama-Macbeth estimations results

Down Prob	Cons.	λ_W	$\lambda_{W\mathcal{D}}$	$\lambda_{\mathcal{D}}$	Skew	Cokurt	Adj.Rsq.	RMSE
A. Downside probability								
15%	0.0014	0.0500***	0.0398***	−2.7731***	0.0039***	−0.0132***	0.4196	0.0003
	(0.5393)	(3.2192)	(3.1879)	(−4.2827)	(6.2092)	(−3.4448)		
10%	0.0011	0.0635***	0.0494***	−2.7591***	0.0040***	−0.0200***	0.4060	0.0003
	(0.4211)	(3.8629)	(3.7481)	(−4.7213)	(6.5141)	(−4.2198)		
20%	0.0016	0.0502***	0.0396***	−3.1683***	0.0037***	−0.0104***	0.4330	0.0003
	(0.6616)	(3.7160)	(3.4967)	(−4.2153)	(5.8071)	(−2.7981)		
B. Beta estimation window								
$K = 18$	0.0014	0.0448***	0.0316***	−2.2298***	0.0032***	−0.0136***	0.3515	0.0003
	(0.5107)	(3.1372)	(3.2266)	(−3.3288)	(4.9086)	(−3.2023)		
$K = 24$	0.0019	0.0439***	0.0278***	−2.2012***	0.0026***	−0.0122***	0.3040	0.0004
	(0.7212)	(2.7134)	(2.7119)	(−3.0346)	(3.9674)	(−2.7813)		
$K = 30$	0.0029	0.0399**	0.0240**	−2.3501***	0.0025***	−0.0096**	0.2866	0.0004
	(1.0456)	(2.1927)	(1.9571)	(−2.6543)	(4.0217)	(−2.3618)		
C. Asset menu								
Without_BRICS	0.0011	0.0511***	0.0401***	−2.8921***	0.004***	−0.0138***	0.4120	0.0003
	(0.4186)	(3.1853)	(3.2780)	(−4.2136)	(6.1277)	(−3.4264)		
Without_TOP5	0.0012	0.0512***	0.0391***	−2.9581***	0.0040***	−0.0153***	0.4281	0.0003
	(0.4490)	(3.0856)	(2.7941)	(−4.3894)	(6.0656)	(−3.5947)		
Without_Emerging	0.0004	0.0424***	0.0325***	−2.5313***	0.0034***	−0.0116***	0.3862	0.0002
	(0.1590)	(2.9633)	(3.1624)	(−4.2304)	(4.7109)	(−3.0379)		
Without_Africa	0.0014	0.0489***	0.0389***	−2.7749***	0.0033***	−0.0125***	0.4214	0.0003
	(0.5403)	(3.1638)	(3.1384)	(−4.3233)	(4.7541)	(−3.3273)		
Without_Regional_I	0.0007	0.0503***	0.0394***	−2.6821***	0.0045***	−0.0141***	0.4161	0.0004
	(0.2495)	(3.1104)	(3.0984)	(−4.2065)	(6.9899)	(−3.2948)		
D. Excluding COVID 19 crisis period								
15%	0.0008	0.0533***	0.0434***	−2.9288***	0.0039***	−0.0139***	0.4244	0.0003
	(0.3066)	(3.3284)	(3.4053)	(−4.3998)	(6.0302)	(−3.5347)		
10%	0.0005	0.0674***	0.0533***	−2.9085***	0.0040***	−0.0211***	0.4101	0.0003
	(0.1934)	(3.9866)	(3.9635)	(−4.8546)	(6.3409)	(−4.3162)		
20%	0.0011	0.0534***	0.0430***	−3.3337***	0.0036***	−0.0111***	0.4373	0.0003
	(0.4439)	(3.8493)	(3.7287)	(−4.3056)	(5.6018)	(−2.8690)		

The table presents the GDA3 main results of the Fama and MacBeth (1973) cross-sectional regressions, for different values of the downstate probability (Panel A), for different lengths of the rolling window in measuring the betas (Panel B),for different test asset menus (Panel C), and when removing COVID 19 period from original data sample (Panel D). For each month $t \geq 12$ the betas are calculated using daily data over the previous 12 months (months $t-11$ to t). The dependent variable in the cross-sectional regression, for each month t, is the average monthly excess return from month $t-11$ to t. The t-statistics (in parenthesis) are corrected for 12 Newey and West (1987) lags. Adjusted R^2 and RMSE of the model are also reported. The sample period is from January 1972 to December 2021.

Table 9: Contemporaneous Fama-Macbeth estimations results of the GDA5 model

Down Prob	Cons.	λ_W	$\lambda_{W\mathcal{D}}$	$\lambda_{\mathcal{D}}$	λ_X	$\lambda_{X\mathcal{D}}$	Skew	Cokurt	Adj.Rsq.	RMSE
A. Downside probability										
15%	0.0007	0.0567***	0.0435***	−3.2575***	−0.0137*	−0.0123*	0.0032***	−0.0124***	0.5290	0.0003
	(0.2990)	(3.8752)	(3.8063)	(−5.3840)	(−1.8757)	(−1.8230)	(5.6564)	(−3.3412)		
10%	0.0004	0.0602***	0.0423***	−2.9016***	−0.0144**	−0.0119**	0.0036***	−0.0126***	0.5200	0.0003
	(0.1561)	(3.5805)	(3.5196)	(−5.3587)	(−2.3776)	(−2.0484)	(6.1766)	(−3.1476)		
20%	0.0005	0.0487***	0.0371***	−2.9863***	−0.0124	−0.0122*	0.0034***	−0.0090**	0.5280	0.0003
	(0.1995)	(3.5312)	(3.4232)	(−4.744)	(−1.5659)	(−1.6783)	(5.9540)	(−2.4708)		
B. Beta estimation window										
$K = 18$	0.0004	0.0467***	0.0342***	−2.677***	−0.0136*	−0.0133	0.0023***	−0.0080**	0.5051	0.0002
	(0.2010)	(3.6879)	(3.5951)	(−4.7006)	(−1.6503)	(−1.5174)	(4.1114)	(−2.3114)		
$K = 24$	0.0007	0.0354***	0.0263***	−2.2364***	−0.0158*	−0.0178*	0.0017***	−0.0038	0.4845	0.0001
	(0.3400)	(3.1401)	(3.1022)	(−3.6409)	(−1.8269)	(−1.7368)	(3.2173)	(−1.2289)		
$K = 30$	0.0004	0.0307***	0.0236***	−1.9090***	−0.0180**	−0.0220*	0.0014***	−0.0032	0.4658	0.0001
	(0.1945)	(2.9966)	(3.0537)	(−3.2430)	(−2.0307)	(−1.9230)	(2.5757)	(−1.2993)		
C. Asset menu										
Without_BRICS	0.0007	0.0600***	0.0459***	−3.4158***	−0.0140*	−0.0123*	0.0033***	−0.0137***	0.5292	0.0003
	(0.2996)	(3.9136)	(3.9519)	(−5.3492)	(−1.9240)	(−1.8215)	(5.5548)	(−3.5796)		
Without_TOP5	0.0000	0.0661***	0.0484***	−3.7013***	−0.0071	−0.0068	0.0032***	−0.0145***	0.5465	0.0003
	(−0.0030)	(4.0710)	(3.7793)	(−5.4161)	(−1.1829)	(−1.2475)	(5.3842)	(−3.6023)		
Without_Emerging	0.0002	0.0573***	0.0394***	−3.0695***	−0.0134*	−0.0125*	0.0033***	−0.0128***	0.5574	0.0001
	(0.0903)	(3.7983)	(3.9308)	(−4.8983)	(−1.7877)	(−1.8609)	(4.4692)	(−3.4285)		
Without_Africa	0.0002	0.0561***	0.0425***	−3.1934***	−0.0134*	−0.0126*	0.0028***	−0.0118***	0.5438	0.0002
	(0.0909)	(3.8548)	(3.7507)	(−5.2879)	(−1.8595)	(−1.8822)	(4.2635)	(−3.2280)		
Without_Regional_I	−0.0002	0.0578***	0.0431***	−3.2444***	−0.0142**	−0.0123*	0.0037***	−0.0128***	0.5321	0.0003
	(−0.0889)	(3.8662)	(3.7965)	(−5.3432)	(−2.0655)	(−1.8715)	(6.4518)	(−3.2413)		
D. Excluding COVID 19 crisis period										
15%	0.0005	0.0601***	0.0469***	−3.3878***	−0.0139*	−0.0120*	0.0032***	−0.0131***	0.5341	0.0003
	(0.1867)	(4.0023)	(4.0193)	(−5.4305)	(−1.8261)	(−1.7076)	(5.5379)	(−3.4352)		
10%	0.0001	0.0638***	0.0456***	−3.0250***	−0.0149**	−0.0120**	0.0036***	−0.0133***	0.5247	0.0003
	(0.0317)	(3.6853)	(3.7077)	(−5.4272)	(−2.3685)	(−1.9835)	(6.0565)	(−3.2317)		
20%	0.0001	0.0518***	0.0403***	−3.0927***	−0.0126	−0.0121	0.0034***	−0.0096**	0.5331	0.0003
	(0.0581)	(3.6582)	(3.6423)	(−4.7495)	(−1.5306)	(−1.5893)	(5.8251)	(−2.5474)		

The table presents the GDA5 main results of the Fama and MacBeth (1973) cross-sectional regressions, for different values of the downstate probability (Panel A), for different lengths of the rolling window in measuring the betas (Panel B), for different test asset menus (Panel C), and when considering COVID 19 effect (Panel D). For each month $t \geq 12$ the betas are calculated using daily data over the previous 12 months (months $t - 11$ to t). The dependent variable in the cross-sectional regression for each month t is the average monthly excess return from month $t - 11$ to t. The t-statistics (in parenthesis) are corrected for 12 Newey and West (1987) lags. Adjusted R^2 and RMSE of the model are also reported. The sample period is from January 1972 to December 2021.

Table 10: Fama-Macbeth GDA5 estimations results: varying the disappointing event definition

Down Prob	Cons.	λ_W	$\lambda_{W\mathcal{D}}$	$\lambda_{\mathcal{D}}$	λ_X	$\lambda_{X\mathcal{D}}$	Skew	Cokurt	Adj.Rsq.	RMSE
				A. $a = 0$						
15%	0.0008	0.0601***	0.0477***	−3.3307***	−0.0066	−0.0060**	0.0038***	−0.0120***	0.5270	0.0003
	(0.3429)	(3.7256)	(3.8150)	(−5.1250)	(−0.9545)	(−2.0443)	(6.9121)	(−2.7823)		
10%	0.0008	0.0672***	0.0508***	−3.0996***	−0.0064	−0.0045**	0.0036***	−0.0179***	0.5175	0.0003
	(0.3096)	(4.1165)	(4.0931)	(−5.5589)	(−0.9544)	(−2.1282)	(6.7262)	(−4.0012)		
20%	0.0012	0.0553***	0.0425***	−3.5468***	−0.0065	−0.0048*	0.0036***	−0.0094***	0.5343	0.0003
	(0.5172)	(4.0345)	(4.0509)	(−4.4996)	(−0.9174)	(−1.6774)	(6.6473)	(−2.4854)		
				B. $a = 2$						
15%	0.0008	0.0492***	0.0382***	−3.3821***	−0.0145**	−0.0141**	0.0032***	−0.0094***	0.5305	0.0003
	(0.3507)	(3.6985)	(3.4749)	(−5.0532)	(−1.9993)	(−2.0535)	(5.6498)	(−2.9864)		
10%	0.0002	0.0456***	0.0348***	−2.6300***	−0.0148**	−0.0149**	0.0035***	−0.0099***	0.5222	0.0003
	(0.0651)	(3.2928)	(2.8427)	(−4.5290)	(−2.2377)	(−2.3165)	(5.9268)	(−2.8977)		
20%	0.0008	0.0388***	0.0303***	−2.5834***	−0.0108	−0.0108	0.0033***	−0.0094**	0.5245	0.0003
	(0.3259)	(3.0537)	(3.1632)	(−4.4771)	(−1.4160)	(−1.5287)	(5.9884)	(−2.9672)		

The table presents the GDA5 results of the Fama and MacBeth (1973) cross-sectional regressions, when higher weight is given to the disappointment event than volatility effect ($a = 0$), and vice versa ($a = 2$). For each month $t \geq 12$ the betas are calculated using daily data over the previous 12 months (months $t-11$ to t). The dependent variable in the cross-sectional regression for each month t is the average monthly excess return from month $t-11$ to t. The t-statistics (in parenthesis) are corrected for 12 Newey and West (1987) lags. The two last columns report the Adjusted R^2 and RMSE for each disappointment event. The sample period is from January 1972 to December 2021.

Table 11: Predictive Fama-Macbeth regressions results in GDA3 model

	Investment horizon														
	$h=1$			$h=3$			$h=6$			$h=9$			$h=12$		
Down Prob	(15%)	(10%)	(20%)	(15%)	(10%)	(20%)	(15%)	(10%)	(20%)	(15%)	(10%)	(20%)	(15%)	(10%)	(20%)
Cons	0.0016	0.0013	0.0017	0.0020	0.0018	0.0020	0.0021	0.0020	0.0020	0.0024	0.0023	0.0021	0.0027	0.0027	0.0024
	(0.6173)	(0.5295)	(0.7076)	(0.8260)	(0.7250)	(0.8339)	(0.8825)	(0.8296)	(0.8529)	(1.0532)	(1.0192)	(0.9753)	(1.2528)	(1.2594)	(1.1512)
λ_W	0.0474***	0.0585***	0.0486***	0.0416***	0.0501***	0.0415***	0.0371***	0.038,00***	0.035,00***	0.0289**	0.0297**	0.0264**	0.0226*	0.0236*	0.0192
	(3.2200)	(3.7223)	(3.6973)	(2.9954)	(3.6075)	(3.2589)	(3.0433)	(2.9560)	(2.8709)	(2.4499)	(2.2989)	(2.1354)	(1.9459)	(1.7261)	(1.5678)
$\lambda_{W\mathcal{D}}$	0.0374***	0.0451***	0.0381***	0.0323***	0.0376***	0.0332***	0.0271***	0.0250***	0.0272***	0.0211***	0.0180**	0.0215**	0.0166**	0.0143*	0.0166**
	(3.2061)	(3.6332)	(3.4660)	(3.0952)	(3.6482)	(3.2033)	(3.1822)	(2.8400)	(2.9283)	(2.7445)	(2.1060)	(2.4739)	(2.1828)	(1.6187)	(1.9772)
$\lambda_{\mathcal{D}}$	-2.5823^{***}	-2.5735^{***}	-3.0219^{***}	-2.2808^{***}	-2.2457^{***}	-2.7587^{***}	-2.1169^{***}	-1.8625^{***}	-2.5358^{***}	-1.8619^{***}	-1.6139^{***}	-2.2968^{***}	-1.6435^{***}	-1.3937^{***}	-1.9972^{***}
	(-4.0443)	(-4.5413)	(-4.0204)	(-3.6732)	(-4.1257)	(-3.6458)	(-3.5859)	(-3.7599)	(-3.4356)	(-3.2315)	(-3.1795)	(-3.0816)	(-2.8526)	(-2.6816)	(-2.7359)
Skew	0.0037***	0.0038***	0.0035***	0.0033***	0.0035***	0.0032***	0.0027***	0.0029***	0.0026***	0.0023***	0.0026***	0.0023***	0.0021***	0.0023***	0.0020***
	(5.9351)	(6.1997)	(5.5658)	(5.4727)	(5.6855)	(5.3027)	(4.4764)	(4.8123)	(4.6353)	(3.9915)	(4.4327)	(4.1494)	(3.5679)	(3.9141)	(3.6423)
Cokurt	-0.0121^{***}	-0.0184^{***}	-0.0104^{***}	-0.0109^{***}	-0.0160^{***}	-0.0087^{**}	-0.0103^{***}	-0.0136^{***}	-0.0074^{**}	-0.0080^{**}	-0.0109^{***}	-0.0052	-0.0057	-0.0082^{*}	-0.0033
	(-3.3109)	(-4.0501)	(-2.8582)	(-2.8317)	(-3.7028)	(-2.4912)	(-2.8881)	(-3.3604)	(-2.2147)	(-2.1261)	(-2.6762)	(-1.4951)	(-1.5611)	(-1.9333)	(-0.9620)
Adj.Rsq.	0.4146	0.4024	0.4281	0.4065	0.3941	0.4168	0.4010	0.3813	0.4059	0.3939	0.3714	0.3991	0.3878	0.3652	0.3949
RMSE	0.0003	0.0003	0.0003	0.0002	0.0003	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002

The table presents results of the Fama and MacBeth (1973) cross-sectional regression tests of the main GDA3 model specification, for the downstate probability values of 15%, 10% and 20%, a rolling window of 12 months in measuring the betas, and the full test asset menu. For each month $t \geq 12$ the betas are calculated using daily data over the previous 12 months (months $t-11$ to t). The dependent variable in the cross-sectional regression for each month t is the average monthly excess return from month $t+1$ to $t+h$, and the table presents results for $h=1$, $h=3$, $h=6$, $h=9$ and $h=12$. The t-statistics (in parenthesis) are corrected for 12 Newey and West (1987) lags. Adjusted R^2 and RMSE of the model are also reported. The sample period is from January 1972 to December 2021.

Table 12: Predictive Fama-Macbeth regressions results of GDA5 model ($a = 2$)

	Investment horizon														
	$h=1$			$h=3$			$h=6$			$h=9$			$h=12$		
Down Prob	(15%)	(10%)	(20%)	(15%)	(10%)	(20%)	(15%)	(10%)	(20%)	(15%)	(10%)	(20%)	(15%)	(10%)	(20%)
Cons	0.0010	0.0003	0.0009	0.0012	0.0007	0.0012	0.0013	0.0010	0.0014	0.0013	0.0010	0.0014	0.0015	0.0013	0.0016
	(0.4131)	(0.1112)	(0.3695)	(0.5012)	(0.2733)	(0.4874)	(0.5809)	(0.4349)	(0.5996)	(0.5713)	(0.4162)	(0.5879)	(0.6525)	(0.5834)	(0.6981)
λ_W	0.0454***	0.0432***	0.0344***	0.0379***	0.0352***	0.0274***	0.0335***	0.0292***	0.0231***	0.0316***	0.0274***	0.0217***	0.0281***	0.0244***	0.0199***
	(3.9089)	(3.5471)	(3.0784)	(4.0505)	(3.5566)	(2.9879)	(4.1375)	(3.5114)	(2.9829)	(4.2184)	(3.7019)	(3.0498)	(4.1570)	(3.6043)	(3.0510)
$\lambda_{W\mathcal{D}}$	0.0347***	0.0326***	0.0260***	0.0272***	0.0253***	0.0189***	0.0237***	0.0199***	0.0161***	0.0223***	0.0183***	0.0155***	0.0197***	0.0155***	0.0148***
	(3.6231)	(2.9306)	(3.1623)	(3.6140)	(2.7369)	(2.9356)	(3.8310)	(2.5714)	(3.0702)	(4.0965)	(2.7187)	(3.4107)	(4.2449)	(2.5732)	(3.5447)
$\lambda_{\mathcal{D}}$	−3.1632***	−2.5021***	−2.3270***	−2.7266***	−2.1055***	−2.0251***	−2.4311***	−1.6922***	−1.8196***	−2.2033***	−1.4740***	−1.6776***	−1.9429***	−1.2466***	−1.5661***
	(−4.9565)	(−4.4919)	(−4.3487)	(−4.6132)	(−3.9957)	(−4.1256)	(−4.5143)	(−3.5338)	(−4.1980)	(−4.4525)	(−3.5532)	(−4.4016)	(−4.4243)	(−3.3453)	(−4.5604)
λ_X	−0.0138**	−0.0142**	−0.0101	−0.0132*	−0.0139**	−0.0105	−0.0116*	−0.0126**	−0.0092	−0.0104**	−0.0107**	−0.0082	−0.0113**	−0.0107**	−0.0095*
	(−1.9876)	(−2.2310)	(−1.3986)	(−1.8770)	(−2.1058)	(−1.4732)	(−1.8412)	(−2.0403)	(−1.4690)	(−1.9853)	(−2.0917)	(−1.5487)	(−2.1023)	(−2.0591)	(−1.7076)
$\lambda_{X\mathcal{D}}$	−0.0139**	−0.0148**	−0.0108	−0.0137*	−0.0144**	−0.0115*	−0.0130*	−0.0136**	−0.0111*	−0.0119**	−0.0118**	−0.0101*	−0.0126**	−0.0120**	−0.0111*
	(−2.0596)	(−2.3313)	(−1.5655)	(−1.9420)	(−2.1535)	(−1.6515)	(−1.9166)	(−2.0162)	(−1.6667)	(−2.0600)	(−2.0590)	(−1.7688)	(−2.1383)	(−2.0502)	(−1.8730)
Skew	0.0031***	0.0033***	0.0031***	0.0028***	0.0031***	0.0028***	0.0023***	0.0026***	0.0023***	0.0020***	0.0023***	0.0020***	0.0017***	0.0020***	0.0017***
	(5.3507)	(5.6159)	(5.6740)	(5.1524)	(5.3434)	(5.4185)	(4.3416)	(4.5629)	(4.4168)	(3.9261)	(4.0676)	(4.0017)	(3.5997)	(3.6763)	(3.5853)
Cokurt	−0.0085	−0.0093***	−0.0079**	−0.0062**	−0.0064**	−0.0055**	−0.0051*	−0.0048**	−0.0047**	−0.0039**	−0.0033	−0.0030	−0.0030*	−0.0024	−0.0022
	(−2.7608)	(−3.0051)	(−2.4965)	(−2.1174)	(−2.2374)	(−1.8865)	(−1.9192)	(−1.7215)	(−1.9204)	(−1.7889)	(−1.4213)	(−1.4809)	(−1.6720)	(−1.2468)	(−1.1859)
Adj.Rsq.	0.5245	0.5170	0.5177	0.5141	0.5040	0.5078	0.5000	0.4901	0.4914	0.4896	0.4777	0.4805	0.4765	0.4650	0.4700
RMSE	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002

The table presents results of the Fama and MacBeth (1973) cross-sectional regression tests of the main GDA5 model specification, for the downstate probability values of 15%, 10% and 20%, a rolling window of 12 months in measuring the betas, and the full test asset menu. For each month $t \geq 12$ the betas are calculated using daily data over the previous 12 months (months $t-11$ to t). The dependent variable in the cross-sectional regression for each month t is the average monthly excess return from month $t+1$ to $t+h$, and the table presents results for $h=1$, $h=3$, $h=6$, $h=9$ and $h=12$. The t-statistics (in parenthesis) are corrected for 12 Newey and West (1987) lags. Adjusted R^2 and RMSE of the model are also reported. The sample period is from January 1972 to December 2021.In this case $a=2$

Table 13: Sorting on 2019 country indicators: long/short premium decomposition, full sample

	TotalPrem	r_W	$r_W I(\mathcal{D})$	$I(\mathcal{D})$	Pred.	Unexpl.	r_W	$r_W I(\mathcal{D})$	$I(\mathcal{D})$	r_X	$r_X I(\mathcal{D})$	Pred.	Unexpl.
	A1. GDA3: financial indicators						B1. GDA5: financial indicators						
EMDV	6.32** (2.00)	12.31 (1.51)	−14.02* (−1.69)	6.27** (2.49)	4.56	1.75	10.20 (1.34)	−10.76 (−1.53)	4.38* (1.82)	−0.63 (−0.45)	2.23 (1.30)	5.41	0.91
SVOL	3.21*** (2.97)	3.17 (1.34)	−4.09 (−1.49)	2.83*** (2.59)	1.91	1.30	3.63* (1.62)	−1.67 (−0.66)	−0.61 (−0.34)	2.15** (2.76)	−0.80 (−0.65)	2.71	0.50
DIGP	5.99* (1.63)	13.98 (1.49)	−17.99* (−1.74)	10.30** (2.55)	6.29	−0.30	11.71 (1.33)	−14.14 (−1.51)	6.29* (1.94)	−2.24 (−1.39)	3.70* (1.89)	5.31	0.67
FIIN	7.36** (2.03)	17.28 (1.46)	−19.63 (−1.57)	9.66** (2.31)	7.32	0.04	14.52 (1.33)	−15.32 (−1.46)	6.76** (2.17)	−1.18 (−0.61)	3.12 (1.34)	7.90	−0.54
	A2. GDA3: economic indicators						B2. GDA5: economic indicators						
NFDI	4.41* (1.64)	10.25** (2.26)	−9.43** (−2.13)	3.68** (2.31)	4.49	−0.08	7.90** (2.11)	−6.31 (−1.22)	2.29 (0.87)	−1.52 (−0.69)	2.09 (0.76)	4.44	−0.03
GDPC	5.82* (1.60)	12.90 (1.38)	−15.25 (−1.53)	9.20** (2.18)	6.85	−1.02	11.40 (1.25)	−10.84 (−1.37)	4.23* (1.61)	−1.35 (−0.79)	2.99 (1.46)	6.43	−0.61
DBUS	6.90** (2.04)	13.61 (1.33)	−17.16 (−1.55)	10.13** (2.45)	6.58	0.32	11.97 (1.26)	−14.46 (−1.47)	6.80** (2.37)	−1.77 (−0.94)	3.70 (1.56)	6.23	0.66
CCOM	6.93* (1.82)	15.92 (1.34)	−17.68 (−1.41)	9.42** (2.07)	7.65	−0.72	14.24 (1.27)	−12.84 (−1.30)	5.21* (1.81)	−0.16 (−0.08)	2.08 (0.92)	8.54	−1.61

The table reports, at 15% downside probability, on the one hand the average excess returns (TotalPrem) as well as the part that is predicted (Pred.) and unexplained (Unexpl.). On the other hand the table shows the annualized spread, computed as $\hat{E}\left[\left(\beta_{\text{grp1},f,t} - \beta_{\text{grp2},f,t}\right)\lambda_{f,t}\right]$, where $\beta_{\text{grpi},f,t}$ is the time-t average of betas on the risk factors ($f \in \left\{r_W, r_W I(\mathcal{D}), I(\mathcal{D}), r_X, r_X(\mathcal{D})\right\}$) across countries in group i, and $\lambda_{f,t}$ is the time-t risk premium for factor f. Countries are sorted in two equal-sized groups according to a given country variable, and group 1 is made by countries with less favorable value on both these financial and economic variables in 2019. For each month $t \geq 12$ the betas are calculated using daily data over the previous 12 months (months $t-11$ to t). The lambdas are computed from cross-sectional regressions where the dependent variable for each month t is the average monthly excess return from month $t-11$ to t. Description of these variables are given in 3. The t-statistics of the spreads (in parenthesis) are corrected for 12 Newey and West (1987) lags. The sample runs from January 1972 to December 2021.

Table 14: Sorting on 2019 country indicators: long/short premium decomposition, excluding covid-19 returns

	TotalPrem	r_W	$r_W I(\mathcal{D})$	$I(\mathcal{D})$	Pred.	Unexpl.	r_W	$r_W I(\mathcal{D})$	$I(\mathcal{D})$	r_X	$r_X I(\mathcal{D})$	Pred.	Unexpl.
	A1. GDA3: financial indicators						B1. GDA5: financial indicators						
EMDV	7.65^{**}	13.08	-14.48^{*}	6.70^{**}	5.30	2.35	10.88	-11.09	4.90^{*}	-0.58	2.39	6.50	1.16
	(2.32)	(1.51)	(−1.64)	(2.52)			(1.35)	(−1.48)	(1.94)	(−0.39)	(1.31)		
SVOL	3.49^{***}	3.30	-4.28	2.95^{***}	1.97	1.52	3.78^{*}	-1.73	-0.64	2.26^{***}	-0.84	2.82	0.66
	(3.12)	(1.34)	(−1.50)	(2.60)			(1.62)	(−0.66)	(−0.35)	(2.80)	(−0.66)		
DIGP	7.76^{**}	14.86	-18.57^{*}	10.99^{***}	7.27	0.49	12.49	-14.59	6.98^{**}	-2.27	3.96^{*}	6.57	1.19
	(2.03)	(1.49)	(−1.69)	(2.57)			(1.34)	(−1.47)	(2.04)	(−1.33)	(1.91)		
FIIN	9.35^{**}	18.38	-20.34	10.31^{**}	8.34	1.01	15.48	-15.91	7.54^{**}	-1.12	3.32	9.31	0.04
	(2.47)	(1.46)	(−1.53)	(2.33)			(1.34)	(−1.43)	(2.31)	(−0.54)	(1.34)		
	A2. GDA3: economic indicators						B2. GDA5: economic indicators						
NFDI	4.64^{*}	10.70^{**}	-9.71^{**}	3.82^{**}	4.81	-0.17	8.22^{**}	-6.51	2.39	-1.58	2.15	4.66	-0.01
	(1.66)	(2.27)	(−2.11)	(2.31)			(2.10)	(−1.21)	(0.87)	(−0.69)	(0.75)		
GDPC	7.58^{**}	13.73	-15.74	9.81^{**}	7.81	-0.22	12.15	-11.11	4.83^{*}	-1.26	3.18	7.79	-0.21
	(1.99)	(1.38)	(−1.48)	(2.19)			(1.25)	(−1.32)	(1.75)	(−0.69)	(1.46)		
DBUS	8.58^{**}	14.46	-17.68	10.79^{**}	7.58	1.00	12.73	-14.92	7.59^{**}	-1.74	3.87	7.53	1.05
	(2.44)	(1.33)	(−1.50)	(2.47)			(1.26)	(−1.43)	(2.53)	(−0.86)	(1.53)		
CCOM	8.85^{**}	16.92	-18.14	10.02^{**}	8.80	0.06	15.17	-13.18	5.95^{**}	-0.04	2.16	10.06	-1.20
	(2.24)	(1.34)	(−1.36)	(2.08)			(1.27)	(−1.25)	(1.98)	(−0.02)	(0.89)		

The table reports on the one hand the average excess returns (TotalPrem)as well as the part that is predicted (Pred.) and unexplained (Unexpl.). On the other hand the table shows the annualized spread,computed as $\hat{E}\left[\left(\beta_{\text{grp1},f,t} - \beta_{\text{grp2},f,t}\right)\lambda_{f,t}\right]$, where $\beta_{\text{grpi},f,t}$ is the time-t average of betas on the GDA5 downside risk factor ($f \in \left\{r_W, r_W I(\mathcal{D}), I(\mathcal{D}), r_X, r_X(\mathcal{D})\right\}$) across countries in group i, and $\lambda_{f,t}$ is the time-t risk premium for factor f. Countries are sorted into two equal-sized groups according to a given country's variable, and group 1 is made by countries with less favorable value on these economic and financial variables in 2019. For each month $t \geq 12$ the betas are calculated using daily data over the previous 12 months (months $t-11$ to t). The lambdas are computed from cross-sectional regressions where the dependent variable for each month t is the average monthly excess return from month $t-11$ to t. Description of these variables are given in 3. The t-statistics of the spreads (in parenthesis) are corrected for 12 Newey and West (1987) lags. The sample runs from January 1972 to December 2019.

Table 15: Sorting on 2020 country indicators: long/short premium decomposition

	TotalPrem	r_W	$r_W I(\mathcal{D})$	$I(\mathcal{D})$	Pred.	Unexpl.	r_W	$r_W I(\mathcal{D})$	$I(\mathcal{D})$	r_X	$r_X I(\mathcal{D})$	Pred.	Unexpl.
		GDA3					GDA5						
A. Full sample													
NFDI	3.79	8.04**	−11.24***	6.54***	3.34	0.45	6.29*	−11.19**	7.79*	−0.44	−0.19	2.27	1.52
	(1.58)	(2.04)	(−2.71)	(2.81)			(1.82)	(−2.14)	(1.86)	(−0.32)	(−0.08)		
GDPC	6.31*	13.49	−15.67	8.94**	6.77	−0.45	11.70	−11.20	4.19	−1.46	3.26*	6.49	−0.18
	(1.70)	(1.38)	(−1.54)	(2.23)			(1.24)	(−1.36)	(1.58)	(−0.87)	(1.66)		
B. Excluding covid-19 returns													
NFDI	3.98*	8.40**	−11.70***	6.81***	3.51	0.47	6.54*	−11.71**	8.14*	0.48	0.16	2.33	1.66
	(1.61)	(2.05)	(−2.71)	(2.81)			(1.82)	(−2.15)	(1.86)	(−0.34)	(−0.06)		
GDPC	8.04**	14.36	−16.20	9.55**	7.71	0.33	12.48	−11.49	4.77	−1.39	3.47	7.84	0.20
	(2.07)	(1.38)	(−1.50)	(2.25)			(1.24)	(−1.32)	(1.71)	(−0.78)	(1.66)		

The table reports on the one hand the average excess returns (TotalPrem)as well as the part that is predicted (Pred.) and unexplained (Unexpl.). On the other hand the table shows the annualized spread,computed as $\hat{E}\left[\left(\beta_{\text{grp1},f,t}-\beta_{\text{grp2},f,t}\right)\lambda_{f,t}\right]$, where $\beta_{\text{grpi},f,t}$ is the time-t average of betas on the risk factors $\left(f \in \left\{r_W, r_W I(\mathcal{D}), I(\mathcal{D}), r_X, r_X(\mathcal{D})\right\}\right)$ across countries in group i, and $\lambda_{f,t}$ is the time-t risk premium for factor f. Countries are sorted into two equal-sized groups according to a given country's variables, and group 1 is made by countries with less favorable value on these economic variables in 2020. For each month $t \geq 12$ the betas are calculated using daily data over the previous 12 months (months $t-11$ to t). The lambdas are computed from cross-sectional regressions where the dependent variable for each month t is the average monthly excess return from month $t-11$ to t. Description of these variables are given in 3. The t-statistics of the spreads (in parenthesis) are corrected for 12 Newey and West (1987) lags. The returns are calculated on a data sample from January 1972 to December 2021 in Panel A and from January 1972 to December 2019 in Panel B .

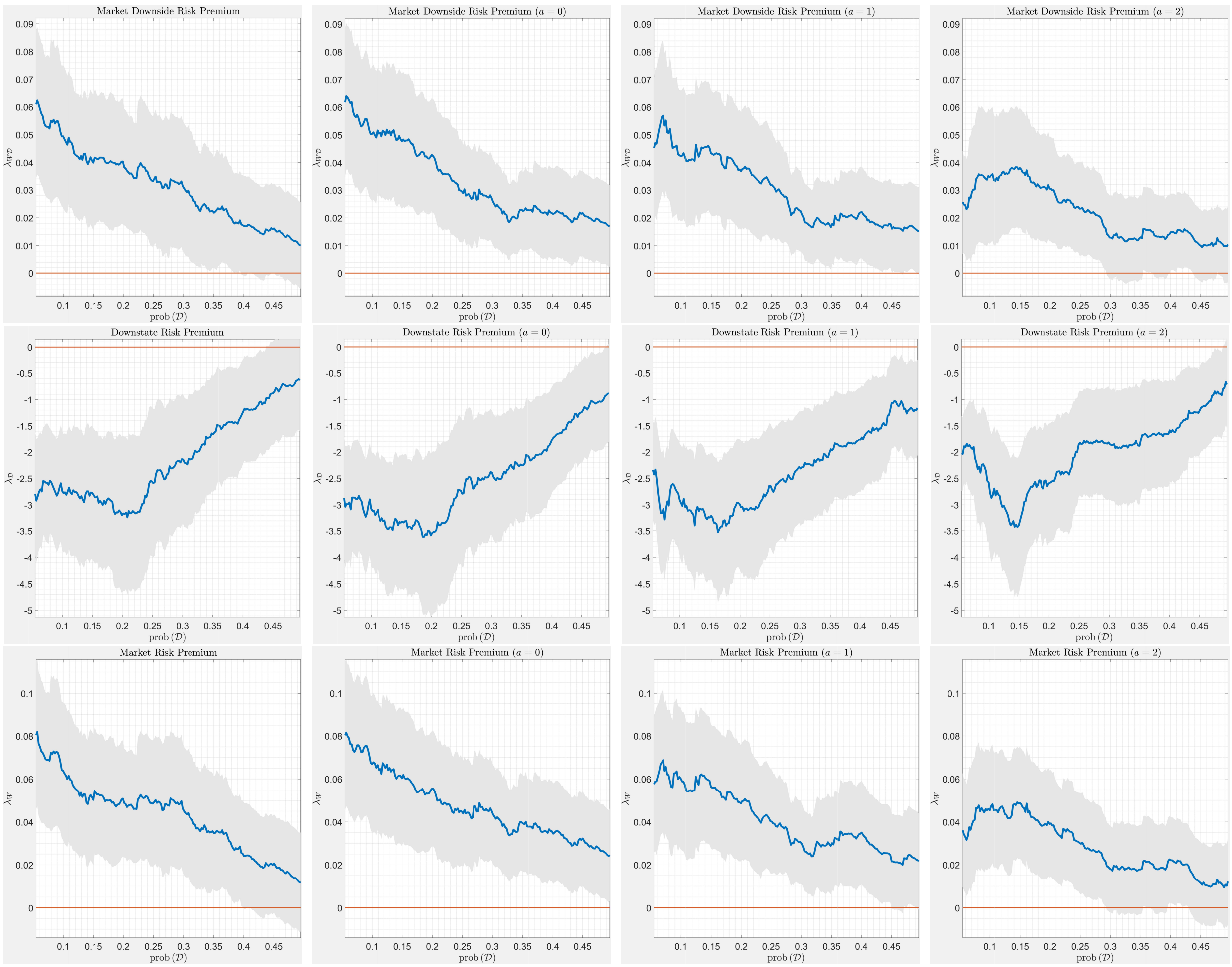

Figure 1:
The figure displays estimates of the market risk premium (top graphs), the market downside risk premium (medium graphs), and the downstate risk premium (bottom graphs), for the GDA3 model (first column) and the GDA5 models (second to fourth columns), as functions of the downside probability. The shaded region highlights the 95% confidence bounds.

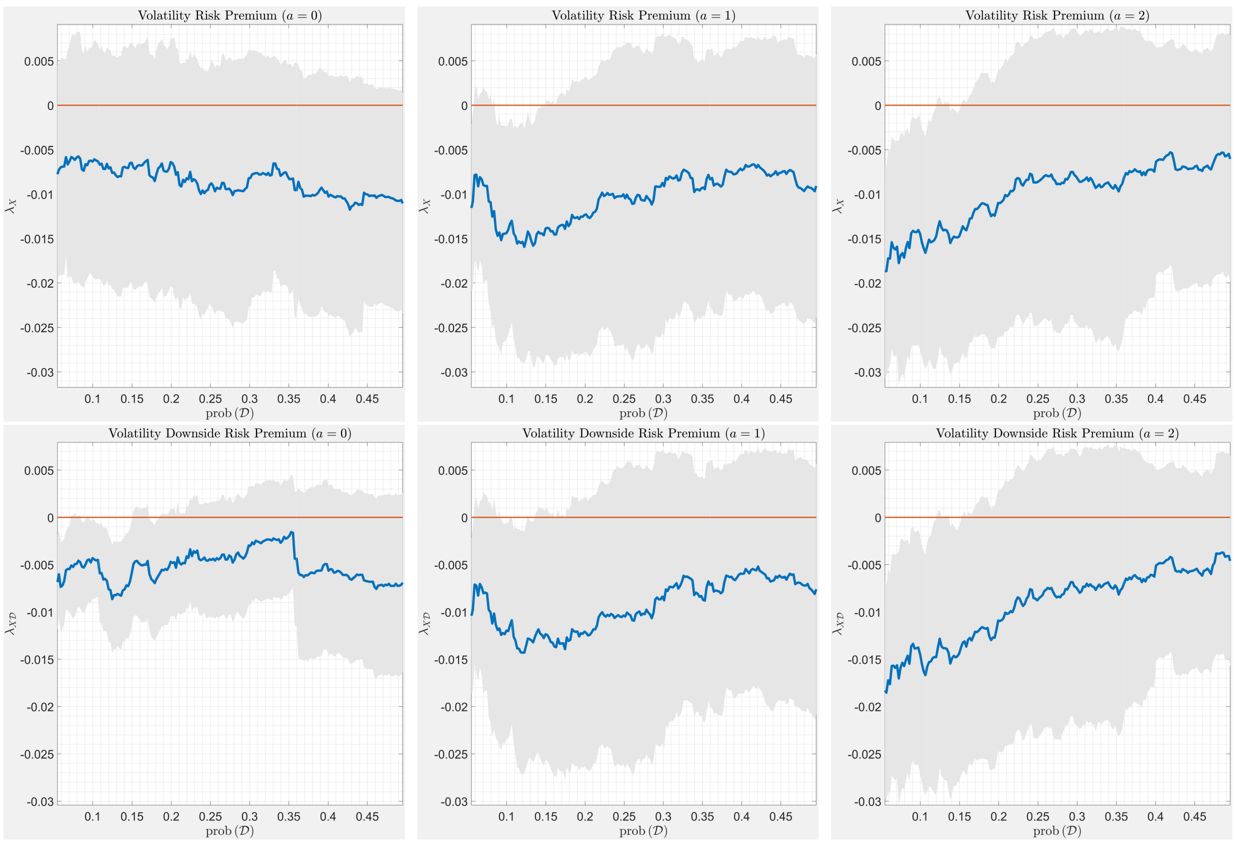

Figure 2:
The figure displays estimates of the volatility risk premium (top graphs) and the volatility downside risk premium (bottom graphs) as functions of the downside probability. The shaded region highlights the 95% confidence bounds.