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Equity Convexity and Unconventional Monetary Policy

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Equity Convexity and Unconventional Monetary Policy

Abstract

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In this paper, we intend to gain an understanding of the drivers of stock convexity, also known as gamma. First, using a bottom-up – firm-level – approach, we showcase that stock fundamentals, in particular metrics related to value (captured by the price-to-book ratio) and historical volatility, allow us to efficiently discriminate between convex and concave stocks. Building on this result, we investigate the ties between the gamma premium and traditional risk factors. Second, we adopt a top-down – macroeconomic driven – framework, to understand which economic environment is the most favorable to convexity: we highlight the importance of the short-term interest rate, the VIX, but also oil price dynamics in a univariate cointegrating vector. These variables share long-term relationships. We then evaluate the ability of different models to forecast future convexity premium dynamics. Finally, we seek to employ these signals in the design of a systematic long convexity strategy and show that it leads to significantly improved risk-adjusted returns compared to a capitalization-weighted benchmark, especially in turbulent markets. Convexity exposure appears particularly relevant in a context of monetary policy normalization.

Keywords: Convexity, co-skewness, higher-moment CAPM, time-varying moments, volatility, asset pricing, stock returns, equity strategy.

JEL classification: C50, G11, G12.

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1 Introduction

The onset of the global pandemic in 2020 led to one of the deepest recessions the world economy has seen.[1] In the US, the world's largest economy, it marked the end of a five-year period during which the Fed did its best to gradually normalize its monetary policy. The return to unconventional policy triggered by the unprecedented recession of 2020 will likely have enduring consequences on asset and risk pricing. In fact, we believe that this particular environment distorted expected equity returns through different channels, but also paved the way for an increasing need by investors to gain exposure to convexity. Concerning the link between monetary policy and stock price behavior, there is already a very broad and deep body of literature motivated by either market participant or policymaker viewpoints, or even both. In theory, in times of conventional monetary policy, central banks can affect equity prices through several channels. Three main transmission channels have been identified. The primary transmission channel is via risk-free interest rates. Monetary policy can influence the discount rate at which future cash flows are discounted by engineering either a rise or a fall in short-term risk-free interest rates. Monetary easing, i.e. a policy rate cut, will trigger a fall in risk-free interest rates, which, in turn, would increase, *ceteris paribus*, equity prices as future cash flows will be discounted at a lower rate. Conversely, any monetary policy tightening i.e. a policy rate hike would lead, *ceteris paribus*, equity prices to fall.

The second channel would generally concern the actual cash flow stream expected from stock holding. A priori, the link between earnings growth and monetary policy is more indirect compared to the first channel. It relies on a mechanism based on the asymmetry of information that exists between central banks and the public. This asymmetry was documented initially by the work of Romer and Romer (2000). Since then, several papers have highlighted the existence of what has been called an information effect. In the US, for instance, it has been established that an unexpected change in the Fed's monetary policy stance could potentially have a material effect on the unemployment rate as well as GDP growth forecasts (Campbell *et al.*, 2012; Nakamura and Steinsson, 2018; Janson and Jia, 2020). Therefore, monetary policy easing or tightening could be a strong incentive for investors to revise earnings growth expectations, as they would legitimately conclude that the central bank's economic projections have changed.

The last channel of transmission is through the equity risk premium, i.e. the excess return versus the risk-free rate investors require to hold equity. This channel comes back to the issue of the control monetary policy has over the discount rate. The information asymmetry, in this case, is critical too. A change in a central bank's monetary policy stance would, accordingly, cause market participants to reassess both expected asset returns and expected risk. This channel has been strengthened with the introduction of unconventional monetary policy. Communication, which was already broad in conventional times, has become even more important with the shift to unconventional monetary policy under the label of "forward guidance". One of the most distinguishing features of forward guidance is an explicit reference to the likely future path of the policy rate. Systemic central banks, such as those of the G5, have paid great attention to it[2], sharpening the information disclosed with tables of economic projections and surveys of the future policy rate trajectory. By doing so, forward guidance has become a monetary policy instrument designed to affect interest rate expectations.

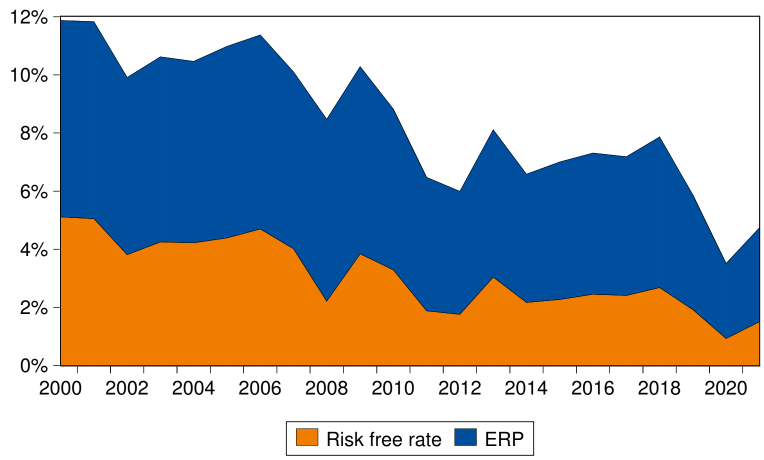
It is interesting to highlight that the forward guidance employed during the previous

[1] According to World Bank (2020), close to 93% of the world economy was in recession at the time, the highest rate ever since 1871. By comparison, this rate reached 61.2% in 2009 during the Great Financial Crisis and 83.8% in 1931 during the Great Recession.

[2] See (Yellen, 2013).

zero interest rate policy (ZIRP) experience in the US, which lasted from December 2008 to December 2016, was mostly used to communicate extensions to the anticipated period of time over which interest rates were likely to remain low (Kuttner, 2018). In the case of the Fed, Campbell *et al.* (2012) set two different goals for forward guidance. It could either be "Odyssean", that is unambiguously expansionary, by pursuing a transitory time-inconsistent policy which would let the inflation rate exceed the Fed's objective, or "Delphic" by providing information on the central bank's rule without any commitment. Whatever the true nature of forward guidance might actually be, this kind of communication has proved to be an efficient tool that could materially distort market participants' expectations about interest rates. Many studies have documented this phenomenon, such as Swanson and Williams (2014) who found a decreased sensitivity, beginning in late 2011, of medium-term interest rates to macroeconomic news. All these effects combined led to a sustained fall in expected equity returns, driven by both a lower risk-free rate and a decline in the equity risk premium (ERP), as we can see below in Figure 1 for the US market.[3]

Figure 1: Expected Equity Return



Source: Damodaran (2021)

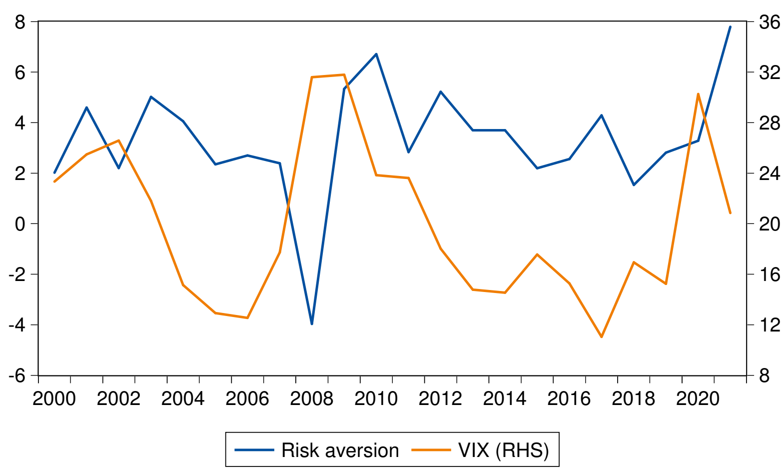
In this paper, we propose using convexity as a tool to mitigate the impact of unconventional monetary policy on the equity risk premium in the medium to long term. These policies are of heightened importance for market pricing. Bernanke and Kuttner (2005) argued, long ago, that most of the stock price variance stems from changes in the risk premium in the immediate aftermath of monetary policy decisions. This equity risk premium sensitivity has most likely grown with the shift to unconventional monetary policy. Several studies support this view. Poshakwale and Chandorkar (2016) and Fausch and Sigonius (2018) show that the impact of monetary policy on equity prices changed with the Global Financial Crisis (GFC). Moreover, Eksi and Tas (2017) went even further, pointing out that the ZIRP tends to increase the reactions of stock markets to monetary policy stance changes. Back to the focus of our paper, if risk-free rates were expected to remain low for long, this would inevitably result in lower required equity returns. Given that the level of the equity risk premium incorporates expectations about future earnings and dividends[4], a prolonged stay in unconventional territory could eventually completely distort the excess rate of return over risk-free rates investors should "normally" require from equity considering their risk

[3]We employ the most recent calculations from Damodaran's dividend discount model from https://pages.stern.nyu.edu/ adamodar/, see Damodaran (2008) for the methodology.

[4]See the seminal work on this issue from Campbell and Shiver (1988).

perception dragging down future earnings and dividends. On top of this, unconventional monetary policy impacts investors risk perception. Bekaert *et al.* (2013) established that expansionary monetary policy dampens investor risk aversion as measured by volatility expectations with an index such as the VIX. Hattori *et al.* (2016) also investigated tail risks in the equity market. They found that the cost of hedging strategies against sharp falls in stock prices for the S&P 500 index fell dramatically around major monetary policy announcements between 2008 and 2012. VIX index adjustments, by comparison, appeared more sluggish. They illustrated that the effects from both announcements and balance sheet expansions varied over time, but eventually seem to have been particularly pronounced during the latest policy phases implemented in 2012. These phases were characterized by extensive use of the forward guidance. Actually, we believe that the recent environment, marked by the use of unconventional monetary policies and the central bank's implicit put option on markets, has decreased investors' risk aversion, measured by the spread between implied and realized volatility. It is also known as the variance risk premium (Bekaert and Hoerova, 2014). Implied volatility indexes, such as the VIX, not only incorporate risk aversion but also embed market uncertainty. Typically, implied volatility is always higher than realized volatility, due to the optionality embodied in the implied measure. Still, in turbulent markets the reverse can occur, when realized volatility jumps well above historical standards. This was verified on the US market in the months of October 2008 and March 2020.

Figure 2: Risk Aversion vs. the VIX



Source: CBOE VIX Index and S&P 500 1-Month Realized Volatility Index (2021)

Actually, in Figure 2 we can see that 2008 was the only year that recorded such a drop in the variance risk premium in the US. After peaking in 2010, risk aversion was on a downward trend up to 2021, when it skyrocketed again. This corroborates the market's heightened sensitivity to new monetary policy signals, such as a change in forward guidance, as already illustrated by Eksi and Tas (2017)'s findings. Recently, realized volatility has been much lower than what is priced in by the option market, by risk adverse investors. When risk aversion increases this much, the equity risk premium should rise to compensate investors. However, we highlight how peaking risk aversion calls into question the record low expected equity returns presented in Figure 1. In this environment, we are convinced that convexity exposure should be of prime importance for an equity portfolio manager.

Our methodological bias is rooted in a familiar framework for market participants since we employ the CAPM, although in an expanded version, to account for potential non linearities. As a matter of fact, since its introduction by Sharpe (1964) and Lintner (1965), the CAPM has been extensively studied in the financial literature. In its seminal form, it implies measuring a stock's sensitivity to market returns, also known as its beta. However, such a relationship was inherently assumed to be linear. Later, academics introduced the hypothesis that in fact, stock returns may display non-linear sensitivity to market movements, which led to the development of the higher-moment CAPM. First, unconditional systematic skewness, the third moment, was introduced by Kraus and Litzenberger (1976). The four-moment CAPM was later developed, including a measure of kurtosis (Dittmar, 2002). Hung (2007) found that co-skewness and co-kurtosis bring out added value in explaining cross section returns, even when controlling for momentum and size effects.

The closest literature to our work is actually from Kraus and Litzenberger (1976), who model unconditional systematic skewness. Practically speaking, for each stock it implies estimating the gamma coefficient associated with the squared market returns. Market return squared is a measure of volatility and gamma measures the co-skewness, or the convexity. It is generally recognized that investors prefer strategies with positive skewness, meaning that they might bear frequent small losses, but from time to time will enjoy very high gains, which should compensate. In fact, this payoff profile echoes those of lotteries. Here when referring to skewness, we actually imply systematic skewness, which provides a defensive feature in case of market downturns, while idiosyncratic skewness tends to be less connected to market movements, rather translating a one-off above-market return (Langlois, 2020). This type of CAPM, integrating skewness, also exists in a conditional version and was developed by Harvey and Siddique (2000). Their proposal allows to improve the explanatory power for cross-sectional expected returns, even after controlling for size and book to market factors. Ang *et al.* (2006) also shed light on the importance of incorporating volatility into asset pricing models. They calculate stock exposure to VIX variations and conclude that the ones with the highest sensitivity to VIX variations, on average, earned lower returns.

We investigate the drivers of unconditional systematic skewness. On top of the traditional CAPM market beta in its time-varying version, we also estimate a time-variant gamma at security level, which translates a stock's exposure to performance in the tails of the benchmark. A positive gamma therefore implies that a stock's returns are a convex function of market returns, which means that theoretically they should always outperform the benchmark (whether the latter is either in positive or negative territory). A negative gamma instead implies that such a relationship is actually concave, therefore such a stock would systematically underperform the market. The higher the gamma, the more such a stock would outperform the market, which is a particularly attractive feature, considering that periods of market stress are generally accompanied by high correlation between stock returns. This is a powerful characteristic in terms of diversification. Indeed, it could allow an investor to hedge market downturns, as a put option on asset prices in case of tumultuous markets, which is all the more important given this recent rising risk aversion combined with all-time low expected equity returns. However, moving from theory to practice, the implementation of a gamma strategy highlights the importance of gamma measurement.

In this paper, we showcase that stocks' characteristics and fundamentals can be employed to discriminate convex from concave stocks. More specifically, GICS sector, price-to-book ratio and past price volatility are particularly relevant and robust features. Analyzing the performance of the convexity premium alongside traditional risk factors such as those from the Fama-French three-factor model corroborates the negative relationship between value stocks and convexity. We also make the case for strong long-term relationships between the market's convexity, short-term interest rates, the VIX and oil prices in a top-down framework. Building on this model, we propose different models that aim to forecast the convexity premium. Based on those signals of future market convexity payoff, we propose a systematic long convexity strategy. The rationale in this approach is to time the convexity exposure. Our results demonstrate that it yields significant risk-adjusted returns enhancements compared to the benchmark. In periods of market stress, the long convexity strategy we propose allows to efficiently mitigate losses for an equity portfolio. Our study is divided as follows. Section 2 presents the analytical framework for measuring gamma, Section 3 is devoted to the analysis of convexity fundamental drivers at the stock level while Section 4 investigates its link with the macroeconomic environment. In Section 5, we propose a systematic strategy that times gamma exposure. Section 6 offers some concluding remarks.

2 Measuring convexity

The time-variant version of the standard CAPM is presented in Equation 1:

$$R_{it} = R_{ft} + \beta_{it}(Mkt_t - R_{ft}) \tag{1}$$

where R_{it} is the return on stock i at time t, R_{ft} stands for the risk-free rate at time t, Mkt_t refers to market return at time t and β_{it} is the market's sensitivity of stock i at time t. Introducing time-varing unconditional systematic co-skewness in the traditional CAPM then gives:

$$R_{it} = R_{ft} + \beta_{it}(Mkt_t - R_{ft}) + \gamma_{it}(Mkt_t - R_{ft})^2 \tag{2}$$

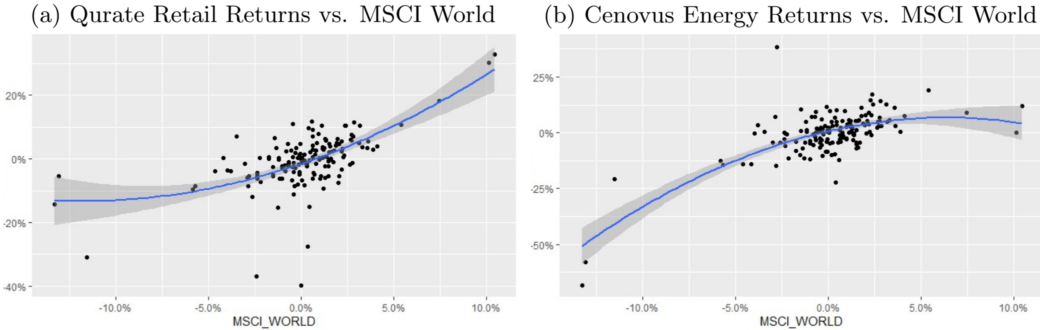
Which implies that the coefficients can be written as:

$$\beta_{it} = \frac{cov(R_{it}, Mkt_t)}{E[(Mkt_t^2)]} \quad \gamma_{it} = \frac{cov(R_t, Mkt_t^2)}{E[(Mkt_{it}^3)]} \tag{3}$$

To illustrate, based on weekly returns against the MSCI World from April 2018 to March 2021, we present below in Figure 3 two typical gamma shapes. The first is from Qurate Retail equity, which has a non-conditional γ of 8.35 for the period of analysis: we witness that it exhibits a convex shape. The second is from Cenovus Energy, with a γ of -14.92, which results in a concave shape when plotted against the MSCI World. Table 10 in Appendix shows the details of the regressions.

Figure 3: Convex vs. Concave Stocks: Gamma Representation

(a) Qurate Retail Returns vs. MSCI World (b) Cenovus Energy Returns vs. MSCI World

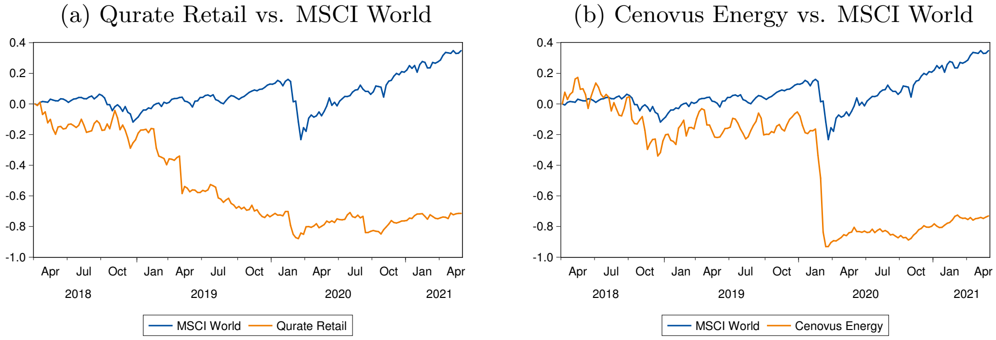


We note several severe drawdowns of the Qurate Retail equity: -37% in May 2019 followed by -39.7% in September 2020. These drawdowns seem specific to the company rather than to a market sell-off. The regression does not reflect these outliers, but they can be clearly seen on the cumulative returns, as shown in Figure 4. From Figure 3, we note that Qurate Retail gamma is positively curved because of the big negative outliers. Therefore it does not reflect a systematic outperformance of the security versus the index, highlighting the gamma must be apprehended with care. As far as Cenorus Energy is concerned, we also witness in Figure 4 two subsequent major drawdowns following the COVID-19 crisis, namely -68.2% and -58% on the second and third weeks of March 2020, well below the benchmark, which corroborates the concavity of this stock over the period of analysis.

Two points of attention must be raised. First, previous elements illustrated that gamma estimation can be artificially distorted by a few outliers, hence a stock could be falsely labeled convex or concave. In theory, convexity should always pay off, since a convex stock is supposed to outperform the benchmark independently of market conditions. Similarly, concavity should not be of interest for a long-only investor since concave stocks are supposed to consistently underperform the market. However, by definition we cannot apprehend the stock's true convexity, and have to estimate it. Estimates are the best statistics we possess to describe a true unknown underlying process. But by their own nature, these estimates can be biased: in this case a stock labeled convex can then underperform the market, and a concave one outperform. Second, the gamma of stock can change, oscillating from convexity to concavity, and vice-versa. Convex stocks can then outperform the benchmark for a given month, but underperform in the followings. A prior convexity feature does not guarantee to pay off in the future. Keeping these elements in mind, it is then possible that convexity, measured by gamma as in Equation 2, shows poor performance compared to its reference market.

Figure 4: Convex vs. Concave stocks: Weekly Cumulative Returns

(a) Qurate Retail vs. MSCI World (b) Cenovus Energy vs. MSCI World



3 Bottom-up analysis

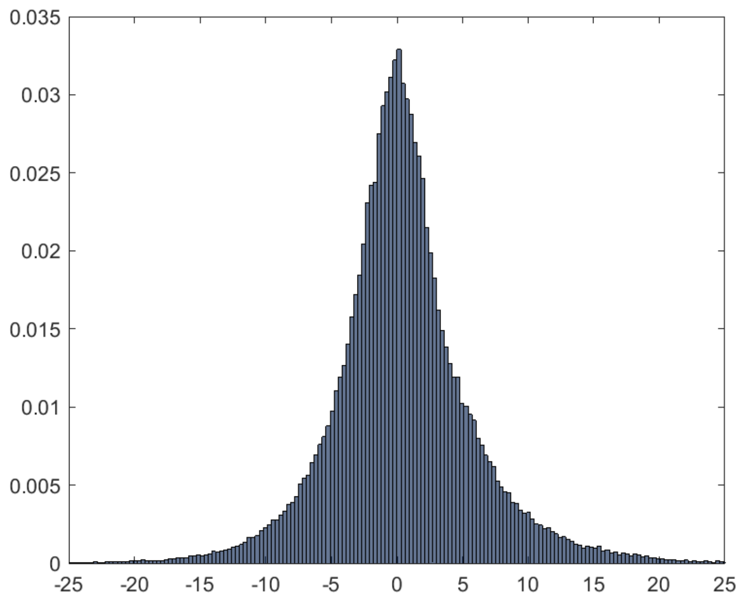
3.1 Data

We work on the MSCI World universe. For each stock, at each date the market beta and the gamma are estimated together via Ordinary Least Square (OLS), as in Equation 2, using heteroskedasticity robust standard errors, on a rolling window of 3 years, using weekly returns from February 2010 to August 2020. The probability distribution of monthly gamma is presented in Figure 5.[5] Over the full period of analysis, this distribution is positively skewed (0.007) and highly leptokurtic (9.25), implying a higher probability of extreme and

[5]Gamma monthly estimates start in March 2013. There are a few outliers outside of the thresholds from Figure 5, however in the plot we leave them out for readability purposes.

positive values of gamma. Nevertheless, it is likely that these characteristics would actually be very dependent from market environment.

Figure 5: Probability Distribution of Monthly Gamma



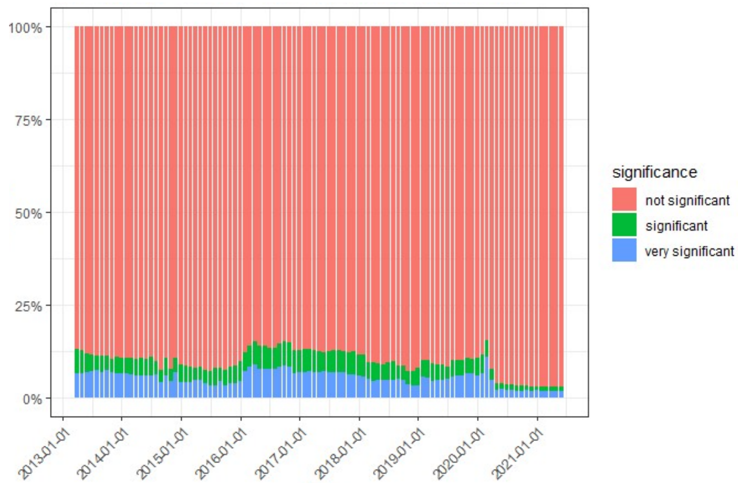
In this section, and to align with most fundamental metrics frequency, we decide to work on quarterly data. Therefore gamma is estimated at the end of the months of February, May, August and November. Actually, the beta coefficients derived from this regression are predominantly significant. However this is not the case for the gamma coefficient in general.[6] Indeed, we notice in Figure 6 that significant gammas are only observed for a small share of the MSCI World stocks over our period of analysis. In addition, the proportion of significant gammas varies over time. We refine this analysis with Figure 15 in Appendix, by examining the significance according to gamma deciles. Actually, most of the significant coefficients are identified in the lowest and highest deciles (namely decile 1 and 10). This element is important: gamma is not everywhere and only concerns a small subset of the stocks within our universe. Therefore, we build a new database, composed of the gamma that are highly significant (with a p-value below 5%) alongside corresponding stock returns data.[7] It should be stressed that, at that point, our dataset contains both positive and negative gammas, therefore both convex and concave stocks. Fundamental data is retrieved from the FactSet Fundamentals database on a quarterly basis, and data cleaning applied when necessary.[8]

[6] We consider a coefficient to be "significant" if its p-value is less than 10% and very significant with a p-value lower than 5%.

[7] Using a 5% level of significance to select stocks based on their gamma values implies that we are using roughly 15% of the MSCI World observations at our disposal. Switching to a level of significance of 10% implies that we would use 22% of the initial universe.

[8] For value related metrics and dividend yield, we discard negative values, and those above 100. For ROE, values above 100 are left out from the analysis.

Figure 6: Significance of Gamma Coefficient from Equation 2



3.2 Results

In this section, we are keen to analyze, in an *ex-post* framework, what have been the fundamental drivers behind a stock's gamma. We have chosen both descriptive features (such as country and currency) and variables that are reflective of traditional risk factors. Indeed, Harvey and Siddique (2000) showed that conditional co-skewness is linked to size, value and momentum. In addition, Xu (2007) found a negative correlation between past stock returns and skewness, however the latter would be positively correlated with contemporaneous returns. Firstly, our analysis is devoted to stocks' basic non-time varying characteristics, such as their region, currency and issuer sector (GICS). Gamma being intrinsically a non-linear metric, we choose to supplement the traditional OLS framework with quantile regression estimations (for the median, but also for the second and eighth deciles, based on those with the highest gamma representativeness, as seen in Figure 15 in Appendix). We are convinced that the impact of fundamental data on convexity may vary according to gamma level and therefore are keen to adapt our estimation strategy. In more classical approaches, such as OLS, the explanatory power of independent variables is determined by its ability to explain the dependent variable mean. In the quantile regression framework, instead, the whole conditional distribution of the dependent variable is accounted for. Since gamma is by definition a non-linear relationship between stock's returns and market movements, we believe that such approach is more appropriate to identify its determinants, especially in the distribution tails. Using quantile regression analysis can allow us to quantify how the coefficient associated with a fundamental metric can change for a given gamma rank within the distribution. Actually, our focus is rather on the tails of the gamma distribution: the stocks that exhibit concave or convex returns during period of high market volatility. This approach will allow us to grasp the impact from region, currency, sector and fundamentals on gamma in its distribution tails.

We first turn toward regional analysis, examining whether gamma tends to be higher in certain areas of the globe. Regional groups have thus been formed, splitting the MSCI World constituents according to their country, between Americas, Asia-Pacific, Europe and Africa-Middle East. OLS and quantile regression results are presented in Appendix in Table 11. At first, according to OLS regression, gamma does not seem to be sensitive to regions with no significant coefficients. The quantile approach yields better results: the Asia-Pacific region is running ahead in terms of convexity, followed by Americas and Europe. In Table 12 in Appendix, we go a step further by presenting results at the country level: lower gammas appear to be driven by Greece, Canada and Germany while Israel, Norway and New-Zealand drive the bulk of higher gammas. On the currency front, Figure 13 in Appendix plots the different coefficients according to the deciles. We observe that most of the currencies display a negative sign for the lowest deciles of gamma. Plots for the full range of deciles are presented in Figure 16 in Appendix. When focusing on the highest deciles, we note that they are driven by ILS, NOK and NZD, and to a lesser extent by AUD and JPY. There results are aligned with analysis run at the country and regional levels, although it seems that countries and currencies bring out more explanatory power.

From Table 1 we can first observe how the GICS sector yields higher explanatory power compared to currency, region or country. A stock's sector is a significant driver of gamma, nonetheless such sensitivity can vary widely between the different gamma quantiles. To better apprehend these dynamics, coefficients are plotted in Figure 7.

Table 1: Stock Characteristics : GICS Sectors
Dependent Variable : Average Gamma (5% significance level)

	OLS	Q20	Q50	Q80
Constant	1.00^{**}	-5.34^{***}	2.35^{***}	7.49^{***}
Energy	-2.54^{***}	-2.87^{***}	-6.11^{***}	-4.91^{***}
Materials	4.76^{***}	0.33	1.19^{**}	8.77^{***}
Industrials	1.35^{***}	1.08^{***}	0.08	2.21^{***}
Cons. Disc	-0.64	-1.01^{*}	-0.28	-1.19^{**}
Cons. Staples	-2.80^{***}	0.46^{*}	-4.83^{***}	-5.62^{***}
Healthcare	-5.59^{***}	-3.99^{***}	-5.76^{***}	-9.07^{***}
Financials	-0.04^{***}	-0.13	-0.11	-0.38
IT	-1.24^{**}	-2.41^{***}	-0.39	-2.24^{***}
Telecoms	-0.78	-0.40	-4.37^{***}	4.83^{***}
Utilities	-2.85^{***}	1.31^{***}	-4.65^{***}	-8.89^{***}
R^2	0.06	0.01	0.08	0.08

Source: Authors' calculation based on data retrieved from FactSet.
Note: For statistical reasons we had to leave out a GICS sector (Real Estate), therefore accounted for in the constant.
For quantile regressions, R^2 actually corresponds to pseudo R^2.

For the lowest gamma deciles, we find that stocks from Healthcare, Telecoms, IT and Energy are the most likely to exhibit concave returns. For the highest deciles, we find that the Materials and Telecoms stocks, followed by Industrials and Energy tend to deliver the most convex returns. It is interesting to note that Energy, Materials and Telecoms allow to capture at the same time, some of the widest gammas (either concave and convex). However, being exposed to Healthcare should almost always imply concavity, and conversely stocks from Industrials generally exhibit convex returns in our analysis.

We now turn toward the appraisal of fundamental metrics in order to grasp their impact on gamma. We chose metrics related to traditional, well-known risk factors: namely value is accounted for by the price-to-book ratio, market value (taken in logarithm) translates size, for quality we employ the return on equity metric, leverage is approximated by the debt-to-assets ratio and growth is captured by sales growth (over one year). We also employ dividend yield, momentum (USD returns over the past three months) and volatility (calculated over the past three years). Table 2 presents the results for OLS and for quantile regressions for the second, median (fifth) and eighth deciles.

Figure 7: Quantile Process Coefficients Associated to GICS Sector

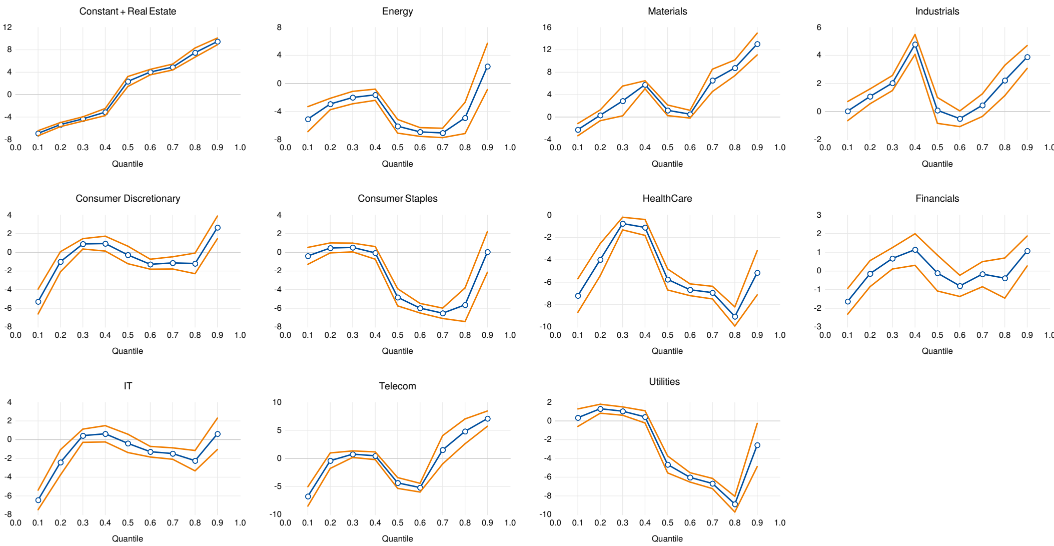


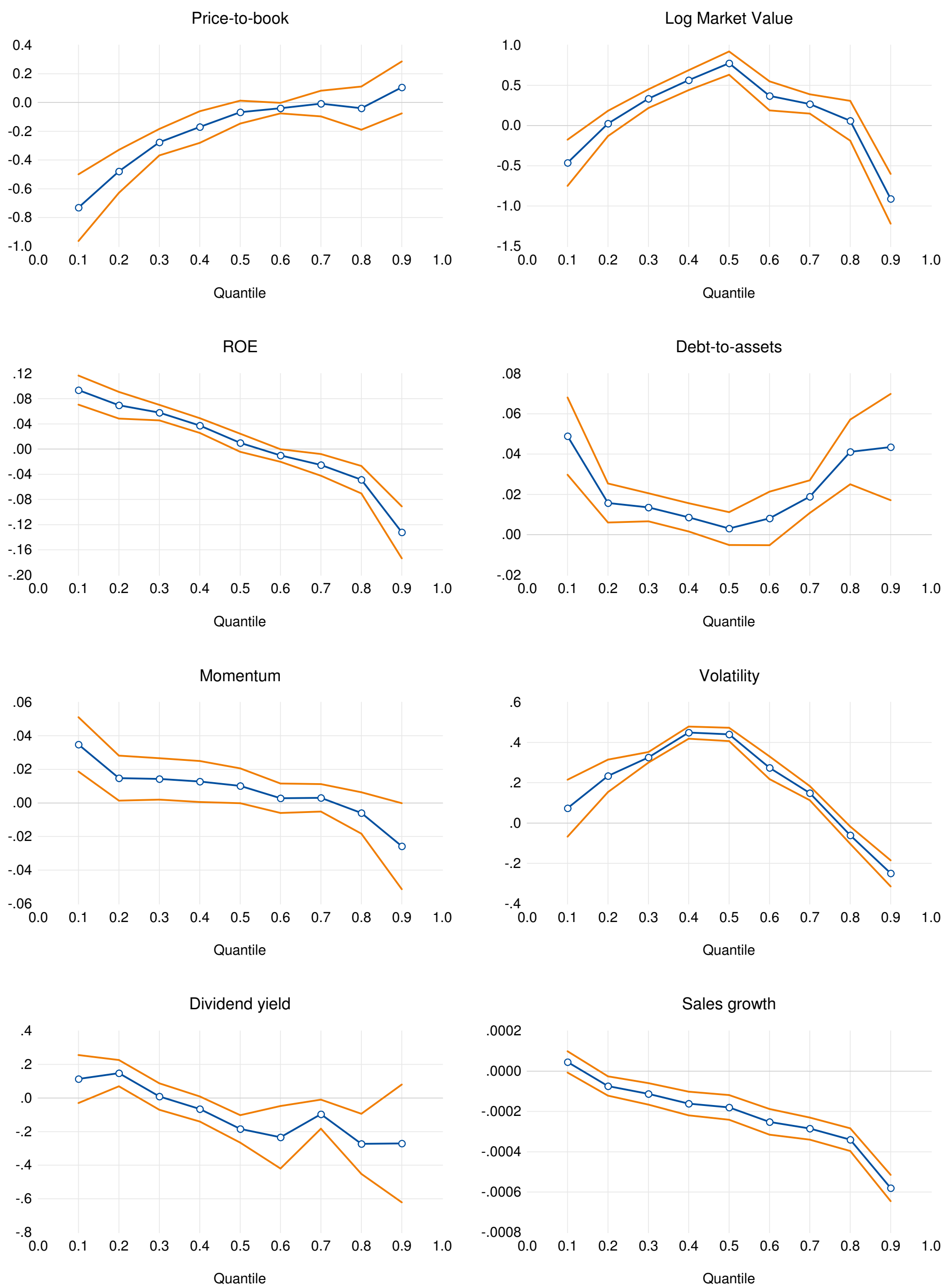
Table 2: OLS and Quantile Regressions
Dependent Variable : Average Gamma (5% significance level)

	OLS	Q20	Q50	Q80
Constant	-1.37	-7.25^{***}	-11.07^{***}	6.02^{***}
Price-to-book	-0.21^{***}	-0.48^{***}	-0.07^{*}	-0.04
log(Market Value)	-0.02	0.03	0.77^{***}	0.06
Return on Equity	-0.01	0.07^{***}	0.01	-0.05^{***}
Debt-to-Assets	0.03^{***}	0.01^{***}	0.01	0.04^{***}
Momentum	0.01^{**}	0.03^{***}	0.01^{*}	-0.01
Volatility	0.23^{***}	0.12^{***}	0.44^{***}	-0.06^{***}
Dividend yield	-0.05	0.03^{***}	-0.18^{***}	-0.27^{***}
Sales growth	-0.01	0.12^{***}	-0.01^{***}	-0.01^{***}
R^2	0.03	0.03	0.07	0.01

Source: Authors' calculation based on MSCI World stocks' fundamentals data retrieved from FactSet.
Note: For quantile regressions, R^2 actually corresponds to pseudo R^2.

All the fundamentals we chose are determinants of gamma, but also that as expected, the coefficients are non-linear according to the presented quantiles. Figure 8 allows to examine these relationships across the full range of deciles (with a 95% confidence interval). It is interesting to note that only price-to-book ratio, ROE, momentum, sales growth (and dividend yield, but in a lesser extent) display linear coefficients according to gamma quantiles: the coefficients associated with these variables diminish (increase for the price-to-book ratio) when gamma stands in higher quantiles. It means that for rather high values of gamma, we would find stocks with low ROE, momentum, sales growth and dividend yield, but with high a price-to-book ratio, which might be counter-intuitive at first glance. Indeed, it could mean that these stocks would be highly overvalued, considering their fairly poor fundamentals. However, we emphasize that these results hold in a non-conditional framework, meaning that we do not distinguish convexity in bull or bear markets, over the full sample period, and hence could be refined. Our findings echo the work of Zhang (2013), that highlights that glamorous stocks tend to exhibit higher skewness than value ones. The negative effect

Figure 8: Quantile Process Coefficients



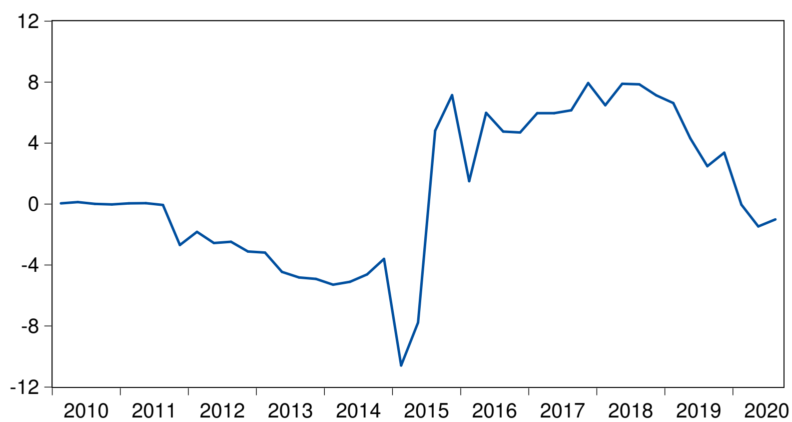
of momentum on gamma for the highest decile is very informative, in the sense that stocks with convex returns (tomorrow's winners in case of market stress) are not yesterday winners, but rather yesterday laggards, corroborating Xu (2007)'s findings.

In contrast, other fundamental metrics we focus on display strongly non-linear relationships with gamma. As a matter of fact, both market value and volatility exhibit bell-shaped functions of gamma. Extreme values of gamma (either positive - above 90th percentile - or negative, below the 10th percentile) are associated with low market value and low volatility. On the leverage side, the debt-to-assets ratio appears to be a V-shaped function of gamma: namely the more extreme the values of gamma, the higher the positive coefficient associated to debt-to-assets. We conclude that the higher the leverage, the more extreme the value of gamma can be. From this analysis, we can argue that the set of fundamental variable we chose is a significant driver of gamma. However, using only some of theses metrics does not always allow to discriminate between very high and very low gammas (namely debt-to-assets, market value, volatility). To be exposed to positive gamma, an investor should also filter stocks with low return on equity and sales growth, high price-to-book ratio and negative momentum, while for negative gamma the focus should be on stocks with high ROE, low price-to-book ratio, high momentum and high sales growth.

3.3 Robustness checks

Previous results must be taken with care: indeed our conclusions translate average effects since 2010 and are thus only valid over the whole sample. It is fairly possible that these relationships may have changed over the past decade. To assess the variability of our results and ensure their robustness, we present in Appendix results for two sub-periods: from February 2010 to February 2015 in Table 14, and from May 2015 to August 2020 in Table 15.

Figure 9: Average Quarterly Gamma (Significant at 5% level)



We have chosen this breakpoint, following a careful analysis of the average gamma value (significant at 5% level) over the sample, presented in Figure 9. Indeed, we witness that February 2015 has coincided with a true regime shift for gammas in our sample, that shifted from negative to positive territory. In fact, this date corresponds to the launch of the ECB's Asset Purchase Programme, still running at the time of writing. This hints at a connection between unconventional monetary policies and market convexity. We observe that overall, the fundamental metrics we chose remain relevant for both sub-periods (see Table 14 and

15 in Appendix). The price-to-book ratio coefficients are fairly stable: this metric allows to identify concave stocks consistently. Furthermore, we observe that some variables, less relevant before 2015, gained in significance in our subsequent estimations. For instance, debt-to-assets ratio, momentum, dividend yield and ROE were hardly significant in the first period of analysis, but much more determinant since 2015. Inversely, sales growth was a strong driver of gamma (the lower the growth the higher the gamma) but is not helpful anymore since 2015 in discriminating convex from concave stocks. Two important conclusions can be drawn from this analysis: first, the prime driver of convexity across the past 10 years has clearly been volatility. If concave stocks have inherently been characterized by a low past volatility, for convex ones it appears that the function of the volatility coefficient according to quantiles, merely flat - slightly negative - before 2015, has then actually turned into a linear, positively sloped form since 2015. This would explain the bell-shaped function over the full sample and the lower coefficients for top deciles compared to sub-periods analysis. Secondly, the relationship between gamma and market value has virtually reversed in 2015: prior to that date the higher the market value, the higher the gamma (although for upper deciles, the impact is more nuanced). For the most recent period, market value has, instead, exerted a negative effect on gamma. These results confirm the relevance of traditional risk factors for explaining gamma, but also its time-varying feature.

We conclude that the most robust metrics to differentiate concave from convex stocks are the price-to-book ratio and the past volatility: namely value stocks, with low past volatility tend to exhibit concave returns, while those with higher price-to-book ratio and more volatile past returns, are more likely to demonstrate convex returns. This idea is confirmed when comparing median values of different samples for the full period (all gammas for which we have both price-to-book ratio and volatility data, the gammas from firms with low past volatility and low price-to-book ratio and those from companies with high past volatility and high price-to-book ratio). We observe that the high volatility/ high price-to-book ratio ones exhibit higher median gamma (around 1.76) than those with low volatility/ low price-to-book ratio (-2.13). The test of equality of medians between these series confirms that these figures are statistically different.[9]

3.4 The convexity premium explained by traditional risk factors

Finally, after highlighting the impact of a firm's fundamentals on the average gamma of the MSCI World, we wonder whether traditional risk factors may be determinant of the convexity premium. Hence, we decided to employ Fama and French (1992)'s traditional framework to build an XMA factor, namely a factor that is long convex stocks and short concave ones (conveX Minus concAve). To compare the latter to other risk factors, we have to switch frequency from quarterly to monthly (namely employing data from March 2013 to May 2021). First, at each date, stocks are ranked according to their gamma: those in the lowest tercile are then defined as concave, while those in the third tercile are classified as convex.[10] We therefore discard stocks with gamma between these thresholds from our calculations. Then, using stock (capitalization-based) weight data, we split the MSCI World constituents at each date between small stocks (those with a weight below the constituents' median at a given date) and big (above the median weight) stocks. Next we are able to build four groups of stocks: the small/convex, the big/convex, the small/concave and the big/concave. We repeat this procedure each month and aggregate stocks using an equally weighted scheme to build the convex and concave return series. Equation 4 sums up the

[9] The median for the sample of gammas with both price-to-book ratio and past volatility data is -1.35.

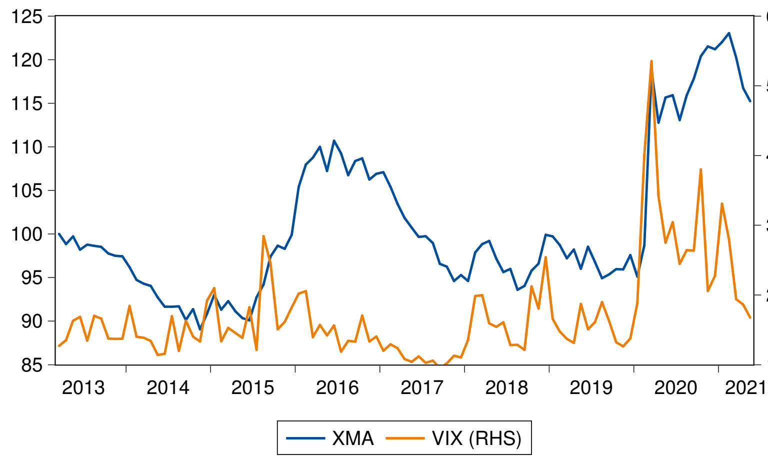
[10] The threshold of first tercile always stands in negative territory at each date, which ensures that we indeed target concave stocks.

factor construction:

$$R_{XMA} = \frac{1}{2}\left(R_{SX} + R_{BX}\right) - \frac{1}{2}\left(R_{SA} + R_{BA}\right) \tag{4}$$

where R_{XMA} refers to the return of the XMA factor at a given date, R_{SX} and R_{BX} respectively the returns of convex stocks with small and big market capitalization and R_{SA} and R_{BA} the returns of concave stocks with respectively small and big market capitalization. Running this equation from March 2013 to May 2021, we obtain the following XMA factor plotted in Figure 10.

Figure 10: XMA Performance (Long Convex Short Concave) and the VIX Index



Based on our estimates of gamma, we can observe that convex stocks outperformance, captured by the XMA factor, is strongly driven by periods of rising volatility. The three biggest spikes in the VIX (in August 2015, December 2018 and March 2020) have all been accompanied by a strong outperformance of convex stocks. This result is in line with the essence of gamma, that ensures positive payoff during market turmoils. When compared to the traditional Fama-French three-factors model for developed countries (mirroring the MSCI World) in Table 3, we note that the XMA premium loads significantly and negatively on the HML, MKT and SMB factors, which corroborates our previous conclusions: convex stocks tend to be glamorous stocks with high price-to-book ratio.[11]

Table 3: XMA Correlation with Fama-French Three-Factor Model

	HML	MKT-RF	SMB	XMA
HML	1.00			
	-			
MKT-RF	0.14	1.00		
	(0.15)	-		
SMB	0.18	0.20	1.00	
	(0.08)	(0.05)	-	
XMA	-0.21	-0.48	-0.19	1.00
	(0.03)	(0.00)	(0.05)	-

Probabilities are reported in parenthesis below correlation coefficients .

[11] We also tested the Carhart (1997)'s four-factor and Fama and French (2015)'s five-factor models: XMA does not load on MOM (momentum), RMW (profitability), CMA (investment), neither on the full sample nor on the sub-periods.

Likewise, negative loading on the market factor authenticates the put option feature of gamma that delivers strong outperformance versus concave stocks in periods of market stress. Finally, in this framework of analysis, XMA shows a negative and significant correlation coefficient with SMB, hinting at a rather large cap exposure of the XMA factor. Similarly to the previous section, we refine our analysis by splitting our sample around 2015 in Table 16 in Appendix. Results show that XMA ties to traditional risk factors over the full period of analysis are actually mostly driven by the post-2015 period: indeed, prior to that date we do not find evidence of significant correlations.

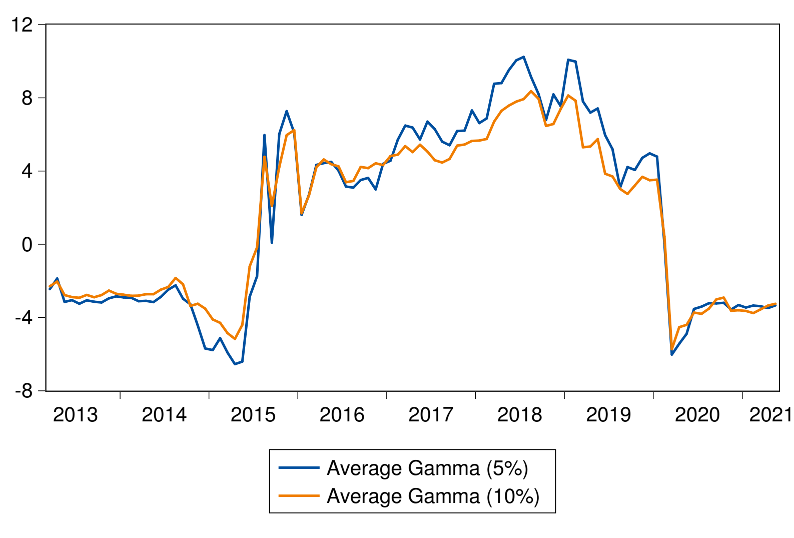
4 Macroeconomic analysis of the convexity premium

In this section, we are keen to apprehend the top-down drivers of gamma. If we saw before that firm-level characteristics, such as sector, price-to-book ratio or historical price volatility could be determinant, surely the macroeconomic environment should also be accounted for. Indeed, results from the previous section already highlighted the sensitivity of gamma to volatility regimes. The last decade has also been marked by a regime shift for average convexity around the year 2015. This section first attempts to link these empirical evidences to the macroeconomic environment, and quantify the latter's long-term relationship with convexity. Secondly, remaining in a top-down framework, we investigate the drivers of gamma's performance.

4.1 Data

A switch from micro-driven to macro-driven analysis implies that data frequency must be increased: monthly data are actually more suited than quarterly when analyzing the macroeconomic environment. Our monthly gamma dataset starts in March 2013 and ends in May 2021. For the first part of the top-down analysis, gamma will remain our dependent variable. We wonder whether the average monthly gamma from the MSCI World can be explained by macroeconomic metrics. Figure 11 illustrates the average gamma value for our sample of stocks, with a level of significance equals or below 5 and 10%. These two metrics are actually

Figure 11: Average Monthly Gamma



quite close and exhibit similar patterns: the year 2015 was characterized by a strong rise in gamma, that peaked in 2018 and turned-back negative with the COVID-19 crisis. We proceed with the average gamma significant at the 5% level in the rest of our study.

We pursue our analysis by choosing a set of macroeconomic variables that, we believe, could be determinant of gamma over the period of analysis for the MSCI World constituents. As a matter of fact, the index is predominantly composed of US companies (US represented 68% of the index in July 2021), which conducts us to principally retain US-centric data. Major stock indexes, interest rates, commodity prices, exchange rates, central banks holdings and sentiment have all been key in the recent economic environment, and thus appear as good candidates for explaining stock's convexity. We also employ the broad dollar index, that is trade weighted and measure the strength of the dollar against other world currencies. More specifically, we retrieved macroeconomic and financial monthly data, presented in Table 4.

Table 4: Macroeconomic and Financial Variables

Code	Description	Unit
GS3M	3M T-bill	%
GS1	1Y T-bill	%
GS2	2Y T-bill	%
GS10	10Y T-bill	%
VIX	Chicago Board Options Exchange Volatility Index	Index
UMCSENT	University of Michigan Consumer Sentiment	Index
WALCL	All US Federal Reserve Banks Total Assets	Millions USD
ECBAS	Central Bank Assets for Euro Area	Millions Euros
SP500	S&P 500	Index
WTI	Global price of WTI Crude	USD per Barrel
EXUSEU	USD to Euro Spot Exchange Rate	USD/Euro
YUAN	Chinese Yuan Renminbi to USD Spot Exchange Rate	Yuan/USD
RTWEXBGS	Real Broad Dollar Index	Index
DTWEXBGS	Nominal Broad U.S. Dollar Index	Index
BOGMBASE	Total Monetary Base	Millions of Dollars
CPIUS	CPI US - All items	YoY % Change
CPIG7	CPI G7 - All items	YoY % Change
SSE	Shangai Stock Exchange	Index
SLOPE	10Y-2Y	Index

Source: Inflation data is retrieved from the OECD Database, SLOPE is calculated by the authors, and SSE is obtained from FactSet. All the other variables derive from the Board of Governors of the Federal Reserve System and are retrieved from FRED, Federal Reserve Bank of St. Louis database.

4.2 Time-series properties

Before running regression analysis on gamma, time-series characteristics have to be carefully analyzed. More specifically and considering the trend of our series, stationary tests have to be undertaken. We employ Phillips and Perron (1988)'s test which has the advantage to be a non-parametric test (unlike Augmented Dickey Fuller - ADF - test for instance) thus robust to heteroskedasticity in the residuals. Additionally, it does not require lag length specification in the regression model which can be critical for auto-correlated process, a highly plausible hypothesis for our macroeconomic time series. The null hypothesis is the presence of a unit root. Spectral estimation's bandwidth selection is based on the Newey-West procedure, using Bartlett kernel. From results in Table 17 in Appendix, apart from the VIX, that is a stationary process, we conclude that all the variables are integrated of order I(1) according to our tests.

4.3 Preliminary OLS results

Table 18 in Appendix presents results of univariate regressions where the dependent variable is the average gamma of the MSCI World (for stocks with a significant gamma at 5% level). We first regress each macroeconomic or financial variable from Table 4 separately to assess if it exerts an influence on convexity. We observe that T-bill rates are all very significant, however the shortest ones (3M, 1Y and 2Y) bring the highest R^2. Other metrics stand out, such as the VIX and FED assets that have a negative impact on gamma, while the S&P500 and price of WTI seem to, instead, drive the average gamma of the sample higher. It is interesting to note that gamma therefore embodies a cyclical feature in the sense that it exhibits a close connection with stock market performance, crude oil price and interest rates. However, its negative relationships with the VIX and FED assets illustrate its sensitivity to market volatility and participants' confidence: periods of market stress are indeed associated with a decrease in the average gamma of our sample. We also witness how the trade weighted U.S. Dollar index (either in real or nominal terms) drives the gamma: both variables being highly correlated we choose to proceed with DTWEXBGS - expressed in nominal terms - in the rest of the analysis, since it brings the highest R^2.

4.4 FMOLS

With a set of macroeconomic variables that appears to be determinant of gamma, and while bearing in mind that all the variables of interest (except the VIX) are I(1), we are keen to test whether these metrics share long-term relationships with gamma, or put differently, if we can identify a cointegrating vector in a univariate framework. Fully Modified Least Squares (FMOLS hereafter) allow to achieve cointegrating regression estimates that are optimal and hence this approach is particularly suited to our exercise of modeling long-term relationships (Phillips and Hansen, 1990). This approach modifies standard OLS to account for serial autocorrelation and endogeneity that may arises within the regressors, due to their long-term connection. For rates, we retain the 1Y yield (since it has the highest explanatory power compared to other maturities). We run FMOLS on the set of the most significant variables identified previously: results are presented in Table 5.

From Model (1), (2) and (3) we are able to reject the existence of long-term links between the S&P500, FED balance-sheet and convexity (captured by the gamma). Additionally, Phillips-Ouliaris statistics suggest no cointegration within our model[12]: we can therefore discard their long-term impact on gamma. The constant is significant across all models, which supports our choice of trend specification for the cointegrating equation. Model (4) confirms the strong relationships between short-term interest rates, oil price, volatility and gamma. More particularly, the cointegrating vector illustrates that rising oil price and VIX appear to hinder convexity, while 1Y interest rate drives it upward. It is interesting to note that the VIX, an apparently I(0) time series according to Phillips-Perron test, does belong to this cointegrating vector. ADF test, using MAIC information criterion for lag

[12] Phillips-Ouliaris test is a residuals-based test that assesses the presence of a unit root. It is composed of a variance ratio and multivariate trace statistic: the latter is often preferred since it is not sensitive to normalization. Hence it would yield the same result independently of the dependent variable chosen among the series in the model. The null hypothesis of the test is that series are not cointegrated, implying that the residuals from the model are not stationary.

Table 5: FMOLS
Dependent Variable : Average Gamma (5% significance level)

	(1)	(2)	(3)	(4)	(5)	(6)
GS1	5.21***	4.17***	4.54***	4.30***	4.16***	3.67***
VIX	-0.21***	-0.20***	-0.19***	-0.23***	-0.24***	-0.26***
WTI	-0.07***	-0.08***	-0.07***	-0.07***	-0.06	
SP500	-0.01		-0.01			
WALCL	0.01	-0.01				
DTWEXBGS					0.04	0.20
Constant	6.83***	8.36***	8.11***	6.06***	1.28	-18.44***
R^2	0.81	0.80	0.81	0.80	0.79	0.78
Phillips-Ouliaris tau-statistic	-4.25	-4.10	-4.13	-4.15	-4.14	-4.02
prob	0.18	0.13	0.13	0.06	0.12	0.08
Phillips-Ouliaris z-statistic	-30.91	-28.71	-29.26	-29.46	-29.30	-27.93
prob	0.16	0.12	0.11	0.05	0.11	0.07

Source: Authors' calculation based on data retrieved from FRED, Federal Reserve Bank of St. Louis database. Average gamma is calculated on the MSCI World over our sample period, retaining only stocks with gamma that are significant at the 5% level).
Note: The constant enters the cointegrating equation as a deterministic variable.

specification (6^{th} lag being selected) on the VIX actually shows that it possesses a unit root and would thus be I(1). This ambiguous result on the stationarity of the VIX, not settled in the literature, does not alter our modeling framework, as showed by the significant Phillips-Ouliaris statistics for Model (4) and does not undermine the use of FMOLS that remain suited for multiple cointegration orders (Chang and Phillips, 1995; Phillips, 1995). In Model (5) and (6) we propose an alternative definition of the model, by replacing WTI by DTWEXBGS, these two variables being highly correlated. Still, we observe that Model (6) is less powerful than Model (4), DTWEXBGS loosing in significance. We conclude that a regime with rising interest rates, decreasing oil price and VIX tends to drive higher the average gamma of our sample. This result is insightful, and topical at the dawn of US monetary policy normalization: such environment could foster a rise in the convexity of the MSCI World stocks.

4.5 Forecasting XMA performance

After appraising where average market convexity should stand based on macroeconomic variables, this section is now devoted to the identification of market environments that trigger gamma performance and subsequently, our ability to forecast this premium. Gamma performance remains defined as in the model previously presented in Equation 4, between March 2013 and May 2021. We recall that the XMA factor is long convex stocks and short concave ones. Actually, XMA is also stationary. Building only on the long-term relationships identified between gamma and macroeconomic variables in Table 5, we propose a similar framework of analysis for XMA performance. Indeed, having proven the long-run, close ties between gamma, market volatility, oil price and interest rates, we are confident to use these metrics to explain XMA performance - the convexity premium - and formulate forecasts. A straightforward modeling framework is proposed in Table 6, that is only based on lagged macroeconomic variables to explain XMA performance. More specifically, we are particularly interested in the sign of XMA - not its magnitude - that will be then used as a signal in the next section. We propose two kinds of models: the first ones (models from 1 to 4) are estimated via OLS and use XMA returns as the dependent variable. On the other hand, other models (those from 5 to 8) instead employ a binary dependent variable, that takes the value of 1 when XMA returns are positive (0 when negative): these are Logit models. We estimate these different models on 80% of the sample, data from November 2019 onward being exploited for out-of-sample performance. For robustness checks we also estimate these eight models in-sample, but with only 66% of the data: we will elaborate on these results in the next section.

Table 6: In-Sample Estimates from March 2013 to October 2019

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) Logit	(6) Logit	(7) Logit	(8) Logit
Constant	-0.20	-0.17	-0.21	-0.29	-0.53*	-0.50*	-0.55**	-0.64**
ΔGS1(-1)	5.61**	5.27**	5.52**	5.12**	10.5**	10.11**	10.45**	8.18**
ΔGS1(-2)	0.08	0.12	0.02		-2.52	-2.34	-2.45	
ΔVIX(-1)	0.10*	0.13**	0.11*	0.06	0.19**	0.21**	0.19*	0.12
ΔVIX(-2)	0.07	0.09*	0.08		0.18**	0.20**	0.19**	
ΔVIX(-1)^2				0.01*				0.02
ΔWTI(-1)	-0.06				-0.05			
ΔWTI(-2)	-0.02				-0.01			
VIX(-1)≥20			0.46				0.55	
R^2	0.20	0.17	0.17	0.16	0.17	0.16	0.16	0.11

Source: Authors' calculation based on data retrieved from FRED, Federal Reserve Bank of St. Louis database.
Note: For logit regressions, R^2 actually corresponds to McFadden pseudo - R^2.

First, we witness that oil price significance is not compelling at standard levels of confidence, neither in Model (1) nor (5). However, these models are those with the highest R^2, which corroborates previous conclusions drawn from the co-integration framework, where oil price, VIX and short-term rate shared long-term relationships. Besides, past values of VIX and GS1 - the one-year T-bill rate - are substantial drivers of convex stocks outperformance over concave ones. More precisely, if we saw previously that rising short-term rates and falling market volatility tend to increase the convexity of MSCI World stocks, it appears that an increase in both of these metrics rewards convexity exposure over concave one. This hints at the relevance of convexity exposure in the current macroeconomic context, characterized by rising interest rates and market uncertainty. In Model (3), we built a dummy variable that takes the value of 1 if the VIX value in the previous period was above 20: the idea is to embed the volatility regime, not only its direction, that is a strong determinant of gamma has already shown in Figure 10. However, this dummy is not statistically significant. In Model (5), previous lag value of the VIX squared is also introduced to capture the non-linearity of gamma: it is determinant in Model (4) and significant at a level of confidence at 15% for Model (8). Overall, we observe that all models seem relevant to explain XMA performance, although some of them may turn out to be more accurate or better at predicting the sign of the convexity premium. In order to retain the best models, we present in Table 7 the in-sample statistics, alongside the hit ratio, which we defined here as the proportion of the forecast data points with the correct sign compared to realized XMA performance. We recall that we are interested in the sign of our XMA prediction, not its value *per-se*, therefore we pay a particular attention to the hit ratio.

In-sample statistics are informative and hint at some models dominance. However to draw conclusions over the full dataset they need to be complemented by out-of-sample statistics (see Table 8) from the models estimated between March 2013 and October 2019, forecast on the latest period of analysis.

Table 7: In-Sample Statistics from March 2013 to October 2019

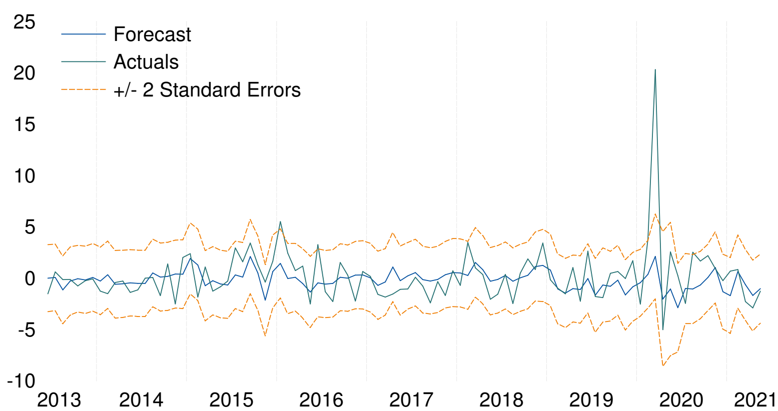
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) Logit	(6) Logit	(7) Logit	(8) Logit
RMSE	1.52	1.68	1.68	1.68	0.46	0.46	0.44	0.46
MAE	1.21	1.33	1.33	1.33	0.43	0.43	0.39	0.44
MAPE	166.22	165.92	178.51	185.72				
Theil inequality	0.62	0.60	0.58	0.56	0.39	0.39	0.38	0.40
Hit ratio (%)	74.03	68.83	71.43	66.67	68.83	72.73	72.73	67.95

Table 8: Out-Sample Statistics from November 2019 to May 2021

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) Logit	(6) Logit	(7) Logit	(8) Logit
RMSE	4.72	4.74	4.66	4.00	0.51	0.53	0.51	0.49
MAE	2.84	2.98	2.84	2.52	0.38	0.40	0.39	0.36
MAPE	389.29	422.96	390.07	308.24				
Theil inequality	0.73	0.71	0.72	0.59	0.42	0.43	0.40	0.36
Hit ratio (%)	68.42	68.42	57.89	57.89	73.68	57.89	63.16	57.89

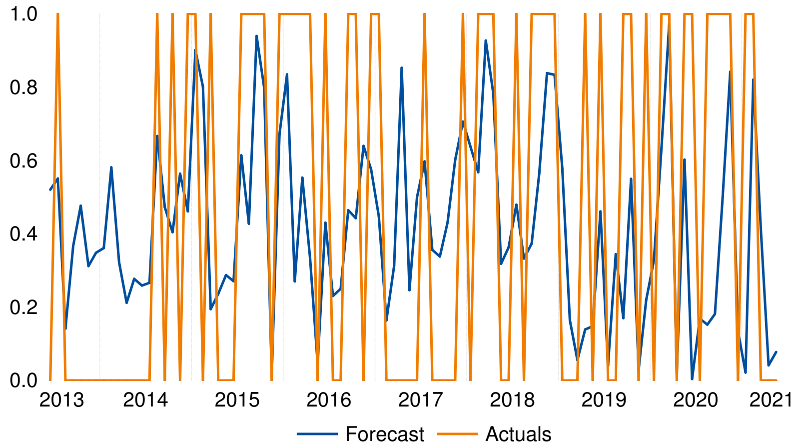
Based on both in-sample and out-sample statistics, within the OLS framework we choose to proceed with Model (1) that has the best RMSE, MAE and hit ratio in-sample, but also fairly goods out-of sample metrics, especially on the hit ratio. For comparative purposes, we also pursue the analysis with a logistic model, and choose Model (5) that scores reasonably well both in and out-sample, notably on the hit ratio. Both in-sample and out-sample forecasts (from November 2019 onward) from Model (1) and Model (5) are presented in Figure 12 and Figure 13, respectively.

Figure 12: XMA Forecast - Model (1)



Overall, both models allow to predict fairly well XMA move in positive or negative territory, however the ability to predict the magnitude of the largest jumps is weaker. As a matter of fact, Model (4) and (8), that include lagged VIX squared value, yield better results on that front. However, our aim being to forecast the sign of the convexity premium, signals from Model (1) and (5) will be exploited in the next section to build strategies that time the exposure to convexity.

Figure 13: XMA Forecast - Model (5)



5 Gamma-based strategies

5.1 Designing the strategies

We propose to embed our XMA forecast in the design of a systematic strategy. We purposely choose to present a simple, intuitive framework and introduce a long convexity strategy. If in practice, we could make the most of all the data points at our disposal to estimate our model and forecast next period XMA move, we take a more conservative approach here and present the strategy in an out-of-sample exercise. We recall that the forecast is only a function of lagged macroeconomic data and that analyzing performance exclusively out-of-sample ensures that our model, estimated as of October 2019 is not over-fitted. In this systematic long convexity strategy, the aim is to time the convexity exposure. The idea is the following: each month t in the out-of-sample period, we use the sign of the $t+1$ forecasts from Model (1) or Model (5) to decide whether we should invest in convex stocks (if XMA forecast is above 0 for Model (1) or above 0.5 for Model (5)), or hold the MSCI World, our benchmark. To keep this strategy fairly implementable, we only hold the top gamma decile when choosing to expose to convexity, which means that when holding this decile, on average we would roughly have 161 stocks at each date between November 2019 and May 2021.[13] Depending on the model, our signal x can hence translate as follows at each date:

Using Model (1):

$$x = \begin{cases} 1, & \text{if } X\hat{M}A \geq 0 \\ 0, & \text{if } X\hat{M}A < 0 \end{cases}$$

Using Model (5)

$$x = \begin{cases} 1, & \text{if } X\hat{M}A \geq 0.5 \\ 0, & \text{if } X\hat{M}A < 0.5 \end{cases}$$

Then at each date, we proceed as follows:

$$\textit{Long Convexity} = \begin{cases} \textit{Convex exp.}, & \text{if } x = 1 \\ \textit{Benchmark exp.}, & \text{if } x = 0 \end{cases}$$

where *Convex exp.*= *MSCI World Gamma* 10^{th} *Decile*
where *Benchmark exp.*= *MSCI World*

[13] We choose to only hold a decile to contain turnover, and compare in Figure 18 the performance of the most convex and concave deciles to the XMA factor components, that is instead based on terciles (see Equation 4). Series present analogous patterns, however they differ in magnitude, deciles being more concentrated.

In terms of signals, Model (1) and (5) actually yield very similar results: over the 19 forecast periods, there is only one month (May 2020) where their direction diverges.

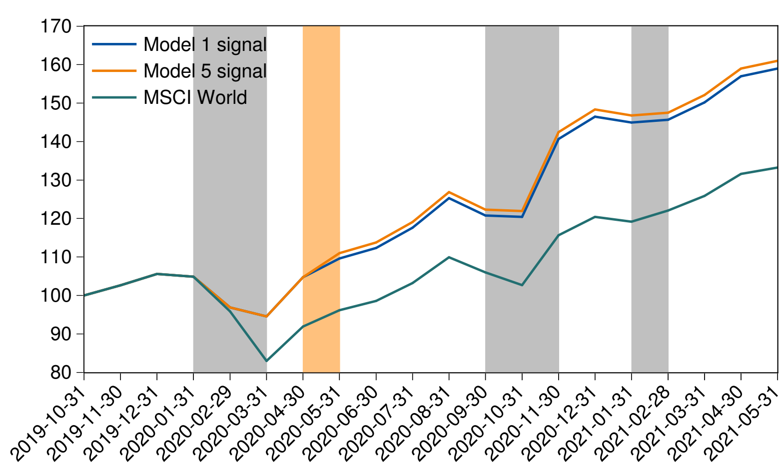
Table 9: Out-of-Sample Performance of Different Gamma Strategies
November 2019 - May 2021

	MSCI World	Signal from Model (1) Long Convexity	Signal from Model (5) Long Convexity
Total returns(%)	33.23	37.09	37.88
Ann. returns(%)	19.91	34.09	35.17
Volatility	20.48	17.89	18.01
Sharpe ratio	0.97	1.91	1.95
Beta	1.00	0.78	0.78
Tracking error		9.31	9.29

Source: Strategies based on signal forecasts from Models (1) and (5) are estimated on the sample from March 2013 to October 2019. Forecast thus starts from November 2019 onward.

The two strategies presented deliver strong risk-adjusted returns versus the benchmark during the out-of-sample period of analysis, as illustrated in Table 9. It is interesting to note that this time frame encompasses the COVID-19 outbreak, an ideal example of market stress, where in theory an investor should typically be exposed to convexity. Actually, both signals from Model (1) and (5) were positive in March 2020 - which implies the strategies were exposed to convexity - cushioning the sharp market decline in global markets, such as the MSCI World. Actually, both models already turned positive in February 2020, when first market contractions occurred. Graphically, and in accordance with the long convexity strategy construction, we observe in Figure 14 that outperformance is driven by a few market phases (namely between February and March 2020 as well as between October and November 2020), dates at which our models' signals were positive. In Figure 14, the grey shaded areas correspond to the months when both strategies were long convexity, the orange shaded area corresponds the month when only the strategy based on Model (5) was long convexity.

Figure 14: Performance of Long Convexity Strategies



The strategies we propose, that aim at timing convexity exposure in a systematic way, deliver strong risk-adjusted returns compared to their benchmark, with a Sharpe ratio close to 2 for our period of analysis. Furthermore, long convexity strategies, by exposing to convexity during period of market stress, efficiently manage to reduce portfolio volatility. This authenticates the relevance of such strategy for mitigating equity portfolio losses in turbulent markets, in a defensive manner. Moreover, as witnessed during the month of November 2020, unconditional positive gamma exposure can amplify market rallies.

5.2 Robustness checks

For robustness checks, we run the same steps on a longer out-of-sample window in Appendix: namely we estimate all the models on data from March 2013 to September 2018 (2/3 of our total sample). Results and in-sample fit statistics are presented in Appendix in Table 19. In terms of overall goodness-of-fit and judging by the R^2, the models are very close to those previously estimated (on 80% of the dataset, hence ending about a year later, in October 2019). Model (1) and (5), again rank fairly well on that front. Table 20 in Appendix depicts a mixed picture: for both OLS and Logit models, those with the highest hit ratio do not score as well on RMSE, MAE or MAPE criteria in-sample. Still, in the spirit of timing the convexity premium sign, models should be selected according to the hit ratio. Out-sample statistics have to be employed to assess the models' reliability over time. Forecasts are produced from October 2018 onward: the synthesis of their accuracy in presented in Table 21 in Appendix. Among OLS models, Model (4) has superior statistics both in and out-sample compared to Model (1), but both models have very close hit ratios. Similarly, among the logits, Model (7) has stronger fit statistics than Model (5) but a similar hit ratio. Finally, their risk-adjusted returns can be directly compared in a long convexity framework in Table 22, while their performances are presented in Figure 17, both in Appendix. All the models outpace the benchmark significantly, although Model (8) is somewhat lagging in terms of Sharpe ratio. It is interesting to note that on this forecasting sample (33% of our data), Model (1) and (5), presented previously on the other sample, yield exactly the same statistics, owing to their identical XMA's sign forecasts. These robustness tests support the relevance of employing macroeconomic variables that share a long-term connection with gamma to forecast the convexity premium. A strategy timing long convexity exposure delivers substantial improvements compared to the benchmark, by lowering volatility and enhancing returns, independently of the samples we tested.

5.3 Practical implementation

We are aware that the strategies we propose, in their current forms, may lead to a certain amount of turnover for most portfolio managers. Buying and selling the whole MSCI World several times a year is obviously not sustainable: future contracts might be considered instead. Alternatively, a basket of the most convex stocks could be considered, or selecting those that belong to convex sectors and/or based on the fundamentals identified in the bottom-up part of our analysis. This would allow to mitigate the turnover issue. Still, our results highlight the importance of the timing the convexity exposure. The models we presented could be easily transformed into a convexity tilt, that would complement the main strategy of a manager that is keen to take a defensive stance in case of turbulent markets. Alternatively the signal could be employed for option overlay strategies, allowing to choose the time when upside capture strategies or downside protection strategies are implemented. Having an exposure signal enables to limit the cost due to the passing of time (theta) for the option overlay structure.

6 Conclusion

A decade of unconventional monetary policy has led to reflect upon its consequences on asset pricing. Indeed, the fall in the risk-free rate was accompanied by a sustained drop in the equity risk premium, dampening expected returns on the asset class. In the meantime, risk aversion and market uncertainty diminished. However, at the dawn of the normalization of monetary policy, a decoupling between peaking risk aversion and realized volatility, which remained fairly contained, was observed in 2021. These effects combined make the case for convexity exposure more topical than ever. From an investor's viewpoint, holding the most convex stocks in a few critical market phases can mitigate portfolio losses. In this spirit, we first resolved to investigate gamma drivers in an empirical framework. From a bottom-up viewpoint, we showed that over the last 10 years, stocks with convex returns have been mostly found in the Asia-Pacific region and in sectors such as Materials, Telecoms, Industrials and Energy. Despite varying gamma regimes over the period, we demonstrate that past volatility and the price-to-book ratio have been the most efficient discriminant features of concavity and convexity. Namely, stocks with volatile past returns, from companies that are rather classified as glamorous (as opposed to value) tend to have higher gammas. Analyzing the correlations between traditional Fama-French factors and the XMA factor (long convexity, short concavity) corroborates this idea. In a top-down approach, we investigate the macroeconomic drivers of gamma. Applying a cointegrating vector framework, we find that it exhibits long-term relationships with the VIX, as expected from gamma's essence, but also with short-term interest rates, and oil prices. Building on those results, we attempt to forecast the XMA premium. Increasing short-term interest rates and market volatility are conducive to the outperformance of the convexity premium in the subsequent period. We use this signal to propose a systematic long convexity strategy. Back-testing this proposal from the end of 2019 yields significantly higher risk-adjusted returns than our benchmark, supporting the relevance of gamma exposure in the way we modeled it. This result is robust to a varying sample. In particular, it cushions the correction in periods of market stress, as illustrated during the COVID-19 pandemic. In an environment characterized by monetary policy normalization, rising volatility and risk aversion, combined with low expected returns on equity, we are convinced of the value added of a long convexity exposure to preserve portfolio value. The framework we propose for this strategy, relying solely on a couple of past macroeconomic and financial metrics, could easily be translated from a monthly to a daily signal as well. In fact, our gamma estimates are based on past stock returns but a forecast of gamma's turning points at the stock level could also be considered. Besides, modeling conditional gamma based on bull and bear markets may suit portfolio managers with different convictions or investing styles.

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Appendix

Table 10: Convex vs. Concave Stocks: Gamma Estimates
Apr. 2018- Mar. 2021

	Qurate Retail	Cenovus Energy
Constant	-0.01***	0.01
MSCI World	1.98***	1.89***
MSCI World^2	8.35***	-14.92***
R^2	0.39	0.53

Figure 15: Significance of Gamma Coefficients from Equation 1 by Gamma Deciles
with Dates on the x-axis

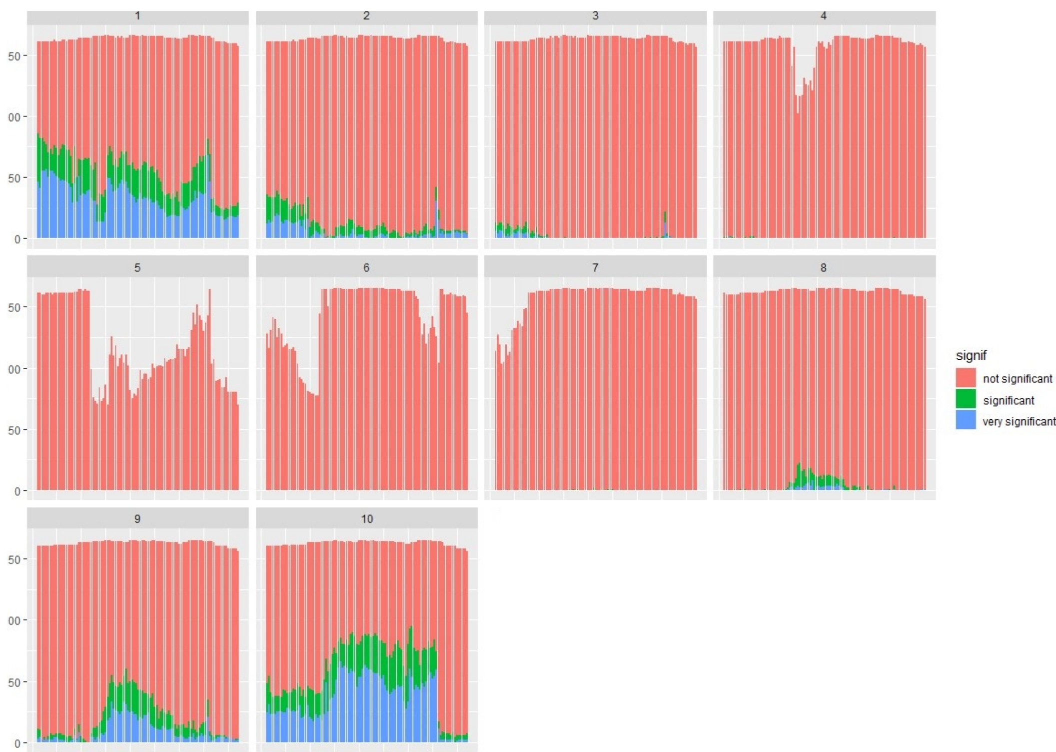


Table 11: Stock Characteristics : Regions

	OLS	Q20	Q50	Q80
Constant	-1.26	-3.95^{***}	-3.42^{***}	-1.72
Americas	1.97	-1.28^{**}	5.28^{***}	7.19^{***}
Asia-Pacific	3.46	0.01	1.40^{*}	12.53^{***}
Europe	0.60	-2.40^{***}	1.05	7.31^{***}
R^2	0.01	0.01	0.02	0.03

Source: Authors' calculation based on MSCI World universe.
Note: For statistical reasons we had to leave out a region (Africa-Middle-East), therefore accounted for in the constant.

Figure 16: Quantile Process Coefficients Associated to Currency

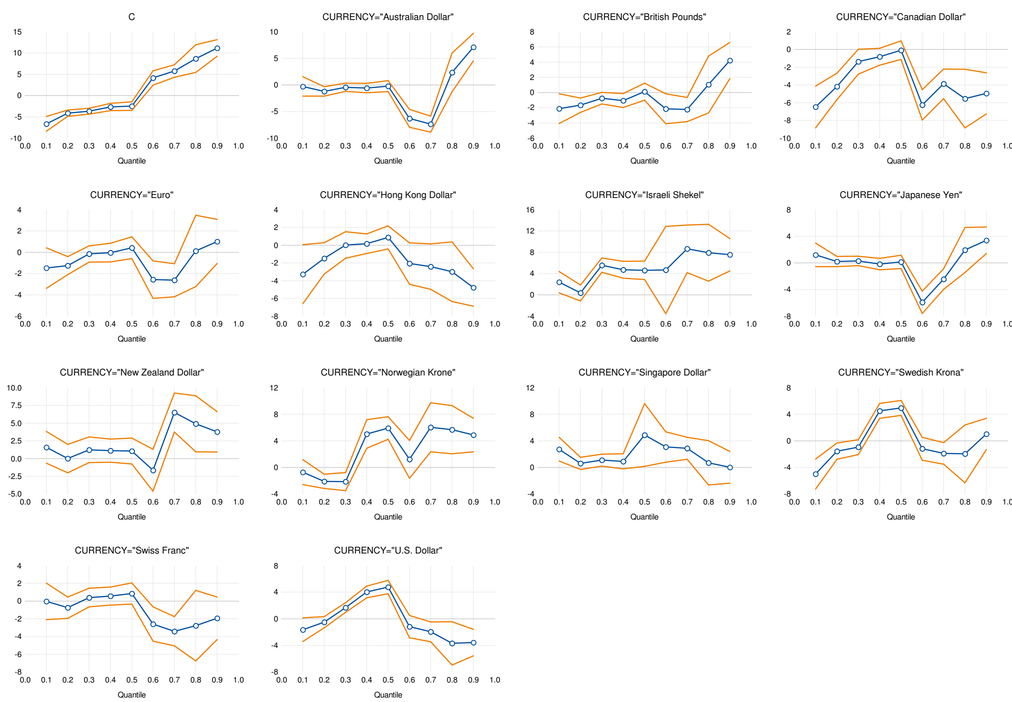


Table 12: Stock Characteristics : Country

	OLS	Q20	Q50	Q80
Constant	-3.07^{***}	-6.01^{***}	-4.16^{***}	-1.94^{***}
AU	4.15^{***}	0.48	1.35^{***}	13.40^{***}
BE	5.24^{***}	0.57	2.79^{***}	13.92^{***}
CA	-0.56	-4.45^{***}	0.76^{**}	4.77^{***}
CH	2.11	0.32	2.24^{***}	7.22^{***}
DE	0.83	-4.41^{***}	1.61^{***}	9.47^{***}
DK	3.48^{**}	1.70^{***}	2.30^{**}	10.62^{***}
ES	4.31^{***}	3.36^{***}	2.43^{***}	10.70^{***}
FI	3.16^{**}	-1.20^{*}	1.57^{**}	8.68^{**}
FR	5.86^{***}	0.89	6.14^{***}	12.13^{***}
GB	4.82^{***}	-0.05	2.26^{***}	13.59^{***}
GR	-12.90^{***}	-32.31^{***}	-1.27	5.22^{***}
HK	2.36^{*}	0.38	2.56^{***}	7.86^{***}
IE	1.26	0.31	0.93	4.50^{***}
IL	9.64^{***}	1.14	6.31^{***}	21.67^{***}
IT	1.04	0.60	1.91^{***}	5.07^{***}
JP	4.28^{***}	2.01^{***}	1.83^{***}	12.39^{***}
NL	4.71^{***}	2.69^{***}	1.99^{***}	12.31^{***}
NO	7.71^{***}	-0.35	7.51^{***}	15.90^{***}
NZ	5.90^{***}	0.96	2.60^{***}	14.73^{***}
PT	-0.21	0.45	1.11	12.79^{***}
SE	4.10^{***}	0.44	6.70^{***}	8.99^{***}
SG	6.70^{***}	2.47^{***}	8.13^{***}	12.67^{***}
US	3.59^{***}	-0.28	6.36^{***}	7.36^{***}
R^2	0.03	0.03	0.05	0.05

Source: Authors' calculation based on MSCI World universe, fundamental data retrieved from FactSet.
Note: For statistical reasons we had to leave out a country (Austria), therefore accounted for in the constant.

Table 13: Stock Characteristics : Currencies

	OLS	Q20	Q50	Q80
Constant	0.75	-4.14^{***}	-2.43^{***}	8.68^{***}
Australian Dollar	0.33	-1.21^{***}	-0.27	2.36
British Pounds	0.57	-1.67^{***}	0.07	1.05
Canadian Dollar	-2.90^{***}	-4.17^{***}	-0.13	-5.54^{***}
Euro	-0.63	-1.26^{***}	0.38	0.12
Hong-Kong Dollar	-2.03	-1.49	0.82	-2.99^{*}
Israeli Shekel	5.65^{***}	0.36	4.58^{***}	7.91^{***}
Japanese Yen	0.46	0.21	0.09	1.94
New-Zealand Dollar	3.81^{*}	0.01	4.71^{***}	4.91^{***}
Norwegian Krone	4.77^{***}	-2.10^{***}	5.87^{***}	5.68^{***}
Singapore Dollar	2.40^{*}	0.61^{**}	4.93^{**}	0.69^{**}
Swedish Krona	0.03	-1.55^{**}	4.92^{***}	-1.95
Swiss Franc	-0.90	-0.73	0.80	-2.78
U.S. Dollar	0.32	-0.51	4.71^{***}	-3.69^{**}
R^2	0.01	0.01	0.05	0.04

Source: Authors' calculation based on MSCI World universe, fundamental data retrieved from FactSet.
Note: For statistical reasons we had to leave out a currency (Danish Krone), therefore accounted for in the constant.

Table 14: OLS and Quantile Regressions for the 2010-2015 Period

	OLS	Q20	Q50	Q80
Constant	-9.92^{***}	-9.94^{***}	-13.00^{***}	-6.58^{***}
Price-to-book	-0.06^{**}	-0.13^{**}	0.03	0.11^{**}
Log(Market Value)	0.71^{***}	0.45^{***}	0.91^{***}	0.63^{***}
Return on Equity	0.02^{***}	0.04^{***}	0.01	-0.01^{*}
Debt-to-assets	-0.01	-0.01	-0.01	0.01
Momentum	-0.01	-0.01^{*}	0.01	0.01
Volatility	0.29^{***}	0.21^{***}	0.47^{***}	0.36^{***}
Dividend Yield	-0.06	-0.01	-0.19^{***}	0.01
Sales growth	-0.01	-0.01^{***}	-0.01^{***}	-0.01^{***}
R^2	0.10	0.03	0.16	0.11

Source: Authors' calculation based on fundamentals data retrieved from FactSet between February 2010 and February 2015.
Note: For quantiles regression, R^2 actually corresponds to pseudo R^2.

Table 15: OLS and Quantile Regressions for the 2015-2020 Period

	OLS	Q20	Q50	Q80
Constant	12.02^{***}	-0.56	19.73^{***}	15.89^{***}
Price-to-book	-0.50^{***}	-0.66^{***}	-0.70^{***}	0.01
Log(Market Value)	-1.67^{***}	-0.78^{**}	-2.45^{***}	-1.37^{***}
Return on Equity	0.05^{**}	0.04	0.11^{***}	-0.04^{*}
Debt-to-assets	0.10^{***}	0.13^{***}	0.12^{***}	0.03^{***}
Momentum	0.08^{***}	0.08^{***}	0.10^{**}	0.02
Volatility	0.67^{***}	-0.42^{**}	0.84^{***}	1.24^{***}
Dividend Yield	-0.05	0.35^{*}	-0.07	0.22
Sales growth	0.01	0.01	0.01	0.01
R^2	0.12	0.04	0.07	0.16

Source: Authors' calculation based on fundamentals data retrieved from FactSet between May 2015 and August 2020.
Note: For quantiles regression, R^2 actually corresponds to pseudo R^2.

Table 16: XMA Correlation with Fama-French 3 Factors: Sub-periods Analysis

	HML	MKT	SMB	XMA
HML	1.00			
	-			
MKT	0.18	1.00		
	(0.38)	-		
SMB	-0.03	-0.07	1.00	
	(0.90)	(0.71)	-	
XMA	-0.16	-0.24	0.25	1.00
	(0.45)	(0.23)	(0.21)	-

(a) March 2013 to April 2015

	HML	MKT	SMB	XMA
HML	1.00			
	-			
MKT	0.14	1.00		
	(0.24)	-		
SMB	0.22	0.26	1.00	
	(0.07)	(0.03)	-	
XMA	-0.21	-0.51	-0.27	1.00
	(0.07)	(0.00)	(0.02)	-

(b) May 2015 to May 2021

Note: Probabilities are reported below correlation coefficients in parenthesis.

Table 17: Phillips-Perron Test: Probability

	None	Constant	Constant & Trend		None	Constant	Constant & Trend
Gamma 5%	0.12	0.50	0.88	ΔGamma 5%	0	0	0
EXUSEU	0.52	0.44	0.88	ΔEXUSEU	0	0	0
GS2	0.39	0.69	0.98	ΔGS2	0	0	0
GS10	0.45	0.46	0.52	ΔGS10	0	0	0
GS1	0.37	0.72	0.99	ΔGS1	0	0	0
GS3M	0.35	0.73	0.98	ΔGS3M	0	0	0
CPIUS	0.75	0.74	0.81	ΔCPIUS	0	0	0
CPIG7	0.65	0.48	0.69	ΔCPIG7	0	0	0
VIX	0.29	0	0	ΔVIX	0	0	0
UMCSENT	0.67	0.10	0.37	ΔUMCSENT	0	0	0
WALCL	0.98	0.98	0.98	ΔWALCL	0	0	0
SP500	1	1	0.93	ΔSP500	0	0	0
ECBAS	1	1	0.89	ΔECBAS	0	0	0
WTI	0.26	0.42	0.89	ΔWTI	0	0	0
SLOPE	0.38	0.68	0.99	ΔSLOPE	0	0	0
SSE	0.77	0.25	0.41	ΔSSE	0	0	0
YUAN	0.73	0.46	0.81	ΔYUAN	0	0	0
RTWEXBGS	0.90	0.36	0.86	ΔRTWEXBGS	0	0	0
DTWEXBGS	0.90	0.29	0.89	ΔDTWEXBGS	0	0	0
BOGMBASE	1	0.98	0.99	ΔBOGMBASE1	0	0	0

Note: Gamma 5% refers to the average gamma from MSCI World's constituents that are significant at the 5% level.

Table 18: Single Regression Analysis
Dependent Variable: ΔGamma 5%

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	-0.01	0.00	0.00	0.00	-0.01	-0.03	-0.02	1.01**	-0.01	0.06
ΔEXUSEU	3.32									
ΔGS2		4.69***								
ΔGS10			2.30**							
ΔGS1				5.17***						
ΔGS3M					4.57***					
ΔCPIUS						0.46				
ΔCPIG7							0.65			
VIX								-0.06**		
ΔUMCSENT									0.06	
ΔWALCL										-0.01*
R^2	0.00	0.14	0.05	0.17	0.15	0.01	0.01	0.06	0.02	0.03

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
Constant	-0.14	0.02	0.01	-0.01	-0.01	0.00	0.05	0.04	0.03
ΔSP500	0.01***								
ΔECBAS		0.01							
ΔWTI			0.06*						
ΔSLOPE				-1.74					
ΔSSE					0.00				
ΔYUAN						-2.35			
ΔRTWEXBGS							-0.35**		
ΔDTWEXBGSE								-0.27***	
ΔBOGMBASE									-0.01
R^2	0.09	0.00	0.03	0.01	0.00	0.01	0.06	0.07	0.00

Table 19: In-Sample Estimates from March 2013 to September 2018

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) Logit	(6) Logit	(7) Logit	(8) Logit
Constant	-0.36	-0.31	-0.49	-0.44*	-0.93**	-0.82**	-1.03***	-1.07***
ΔGS1(-1)	6.52**	6.42**	7.93**	6.29**	14.63***	13.35**	15.24***	10.98**
ΔGS1(-2)	0.47	-0.02	0.14		-1.37	-1.66	-1.71	
ΔVIX(-1)	0.10	0.12*	0.07	0.06	0.17	0.18*	0.13	0.18
ΔVIX(-2)	0.02	0.05	0.00		0.14	0.18*	0.10	
$\Delta VIX(-1)^2$				0.01*				0.04**
ΔWTI(-1)	-0.02				-0.05			
ΔWTI(-2)	-0.06				-0.10			
VIX(-1)≥20			1.55*				2.29	
R^2	0.19	0.15	0.19	0.18	0.20	0.16	0.19	0.16

Table 20: In-Sample Statistics from March 2013 to September 2018

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) Logit	(6) Logit	(7) Logit	(8) Logit
RMSE	1.52	1.56	1.53	1.52	0.43	0.44	0.43	0.45
MAE	1.2	1.26	1.17	1.18	0.37	0.39	0.37	0.39
MAPE	167.16	160.83	159.26	145.27				
Theil inequality	0.63	0.67	0.63	0.64	0.38	0.39	0.38	0.39
Hit ratio (%)	67.19	68.75	73.44	67.69	71.88	73.44	70.31	67.69

Table 21: Out-Sample Statistics from October 2018 to May 2021

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) Logit	(6) Logit	(7) Logit	(8) Logit
RMSE	3..90	3.88	3.9	3.25	0.54	0.53	0.51	0.53
MAE	2.19	2.25	2.27	2.07	0.41	0.41	0.39	0.42
MAPE	305.42	305.14	299.05	268.97				
Theil inequality	0.70	0.69	0.66	0.57	0.47	0.46	0.40	0.41
Hit ratio (%)	59.38	62.50	65.63	59.38	59.38	65.63	59.38	56.25

Table 22: Out-Sample Performance of Long Convexity Strategies from October 2018 to May 2021

	MSCI World	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) Logit	(6) Logit	(7) Logit	(8) Logit
Total returns(%)	36.25	63.38	65.06	61.00	62.85	63.38	61.66	64.72	49.02
Ann. returns(%)	11.90	19.54	19.99	18.91	19.40	19.54	19.09	19.90	15.61
Volatility	19.04	18.24	18.04	18.41	18.52	18.24	17.71	18.06	18.58
Sharpe ratio	0.63	1.07	1.11	1.03	1.05	1.07	1.08	1.10	0.84
Beta	1.00	0.88	0.87	0.87	0.90	0.88	0.86	0.85	0.87
Tracking error		7.40	7.40	8.38	7.34	7.40	7.33	8.42	8.81

Figure 17: Performance of Long Convexity Strategies

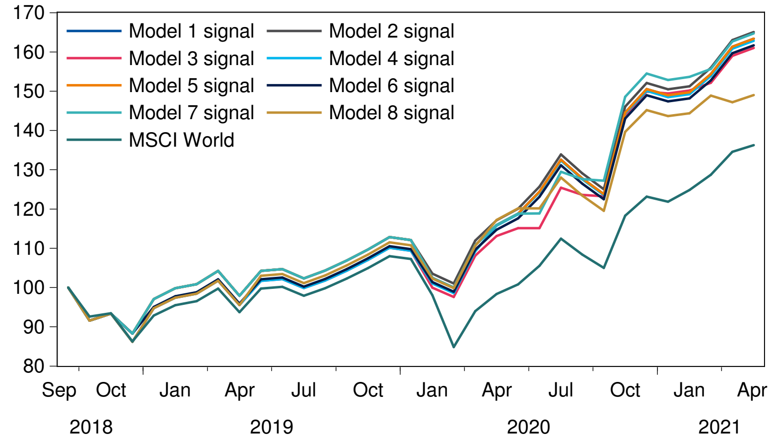
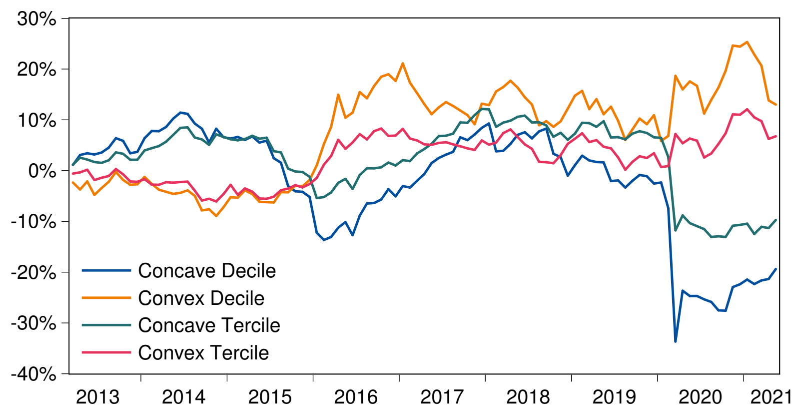


Figure 18: Cumulative Excess Returns vs. MSCI World



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