The Global Volatility Surface and Common Predictability of International Equity Premia

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Abstract

We construct a global implied volatility surface by combining information from the index options of eighteen countries and regions. The global surface has a convex shape and the degree of convexity positively predicts equity premia around the world, in- and out-of-sample. Semi-annually, R2 are 10.7% for S&P500 and 7.9% for eighteen indexes on average. Out-of-sample R2 are 12% for S&P500 and 6.1% globally. For U.S. forecasts, global convexity subsumes other option-based predictors, including global level and slope, U.S. convexity, VIX, SVIX, variance risk premium, and left-tail volatility. The predictability of global convexity comes from its ability to forecast the global financial cycle, which captures the common component of index returns. The information revealed from the left tail of convexity relates to crash fears, and the right tail relates to market confidence. Our findings highlight the importance of global options markets for risk sharing and information aggregation.

Keywords: international return predictability, implied volatility surface, crash risk, speculation, funding conditions

1 Introduction

Option prices reflect state-price valuation of underlying risky streams (Cox and Ross, 1976),[1] implying that index options may naturally contain information about various contributors to the market risk premium. Empirical market-return predictors derived from index options include the variance-risk premium (Bollerslev, Tauchen, and Zhou, 2009; Carr and Wu, 2009), tail-risk premia (Bollerslev and Todorov, 2011; Bollerslev, Todorov, and Xu, 2015), and equity premium bounds (Martin, 2017; Chabi-Yo and Loudis, 2020). Other equity-return predictors such as short-interest (Rapach, Ringgenberg, and Zhou, 2016) relate most naturally to speculative demand, but from the logic of the law-of-one-price can also impact option prices.

International equity and option markets are further connected by global risks and cross-country risk sharing and information aggregation. Events such as the 2007-2008 financial crisis and Covid-19 pandemic have shown global events to be increasingly important. Integration of international equity markets has long been hypothesized and tested (Solnik, 1983; Harvey, 1991; Bekaert and Harvey, 1995). Recent literature documents a high degree of financial globalization and co-movement in risky asset prices as well as capital flows around the world (Bekaert and Mehl, 2019; Camanho, Hau, and Rey, 2022). This trend cultivates the development of the Global Financial Cycle literature, led by Rey (2013); Miranda-Agrippino and Rey (2020, 2022).

We contribute to these efforts by combining information from the index options of eighteen countries and regions to construct a single global implied volatility surface. Our procedure reveals a powerful and encompassing in- and out-of-sample equity-premium predictor, global-surface convexity. Implied volatilities of index options display two prominent empirical features.[2] The first, known as volatility smirk, captures that low-strike implied volatilities typically exceed high-strike implied volatilities. We measure smirk steepness with a slope factor. Controlling the slope factor, we show the global volatility surface has a convex shape–

[1] See also Debreu (1959), Arrow (1964), Breeden and Litzenberger (1978), Ross (1978), and Ross (2015).

[2] See for example Bates (1991; 2000; 2022), Bakshi, Cao, and Chen (1997), Das and Sundaram (1999), Pan (2002), and Liu, Pan, and Wang (2005).

implied volatilities of options with low and high strikes typically exceed the implied volatilities of options with medium strikes. We develop a method to measure the convexity of the volatility surface that is independent from the slope factor. In addition to slope and convexity, we also measure the level and term structure of the global volatility surface. The global level, slope, convexity, and term structure effectively summarize the time series variations in the global volatility surface. These factors measured at the individual country level have strong co-movements with their global counterparts, supporting the idea of global integration of the options market.

We test the return predictability of global option factors. The global convexity is by far the most powerful option-based return predictor. It strongly forecasts equity premia around the world, in- and out-of-sample. When the global surface is more convex, it predicts higher market returns. In the US, global convexity predicts S&P 500 index returns one-month ahead with an R^2 of 2.8%, and six-months ahead with an R^2 of 10.7%, from 1996 to 2023. Predictability does not deteriorate out-of-sample, and in fact the one- and six-month ahead out-of-sample R^2 in the U.S. are larger, 2.9% and 12% respectively.[3] Internationally, global convexity significantly predicts the semi-annual return in 17 of 18 countries and regions, with an average R^2 of 7.9%. Out-of-sample R^2 are almost all positive and average 6.1%.

Global convexity encompasses the predictability of other important option-based predictors and is highly robust to alternative specifications. For US returns, global convexity subsumes the predictive power of the global level and slope, the VIX index, SVIX, the variance risk premium, and left-tail volatility. We measure convexity using strikes of all maturities, but predictability appears to be stronger for mid-term and long-term maturities. The measure is also robust when we use OTM options only, take value-weighted averages across different countries, and directly estimate using option-level data instead of the standardized surface. Global convexity captures important fundamental information from the option surface and is not sensitive to variations in measurement.

[3]We measure OOS R^2 according to Welch and Goyal (2008). It can be higher than in-sample R^2 because it compares MSE from our predictor to a historical-mean model. The higher OOS R^2 also reflects the fact that the predictability of our predictor becomes stronger in the later sample.

Why does global convexity predict market returns so strongly? We investigate the economic source of return predictability. First, global convexity aggregates information from countries around the world. The global economy is increasingly interconnected, and shocks in one area can spread and affect other countries. A prominent example is the Covid-19 pandemic, originating from Asia and quickly spread to the entire world.[4] We find that the global convexity predicts the Global Financial Cycle factor, constructed by Miranda-Agrippino and Rey (2020). The GFC factor captures the common component of risky asset return around the world. The ability of the global convexity to forecast the GFC means that any risky asset that significantly loads on the GFC factor can be predicted by the global convexity. We verify this result in the data and show that the predictability of global convexity also extends to high-beta currencies, such as the Australian and Canadian dollar.

Global convexity also effectively combines information from both the right and left tails of the risk-neutral distribution of returns. The left tail has been widely studied in prior literature (e.g., Andersen, Fusari, and Todorov, 2015; Bollerslev, Todorov, and Xu, 2015), and is appropriately associated with fears of negative jumps or market crashes. High prices in the left tail are commonly interpreted as demand for crash insurance through out-of-the-money puts and correspondingly large risk premia. This is the conventional discount rate channel of return predictability. The right-tail contribution to convexity, while smaller, is also economically important. Controlling for the left tail, high prices in the right tail can be interpreted as market optimism. Consistent with this interpretation, the right-contribution to convexity is strongly negatively associated with funding cost measured through the TED spread and positively associated with past market returns. This market optimism positively predicts future returns through the cash flow channel by revealing future improvement in dividend growth and analyst forecast.

These contributions to global convexity from the left- and right-sides of the risk-neutral distribution have natural interpretations as the presumptive twin driving forces of financial markets – fear and greed. It is already well-known that low price in the left tail, or lack of

[4] This provides an interesting counter-example to the typical finding that the US leads the world (e.g., Rapach, Strauss, and Zhou, 2013).

fear, forecasts low future returns. New to the literature and controlling for the left tail, a low right-tail price signaling lack of speculative interest also forecasts low returns. Thus, fear and greed from the left and right tails of the risk-neutral density, while negatively correlated, are not opposites. The global convexity measure which combines both sources of information is required to optimize equity-premium predictability from the global option surface.

Our paper contributes to three strands of literature. The first is the literature on recovering the equity premium from option data. Various measures constructed based on index options have been proposed in this literature: for example, variance risk premium (Bollerslev, Tauchen, and Zhou, 2009; Carr and Wu, 2009), skew risk premium (Kozhan, Neuberger, and Schneider, 2013), left-tail volatility (Andersen, Fusari, and Todorov, 2015; Bollerslev, Todorov, and Xu, 2015), and equity premium bounds (Martin, 2017; Chabi-Yo and Loudis, 2020; Bakshi, Crosby, Gao, and Zhou, 2019; Jensen, Lando, and Pedersen, 2019; Liu, Lu, Xu, and Zhou, 2022; Back, Crotty, and Kazempour, 2022). This literature has shown that, both in theory and empirics, options data contain information about the short-to-medium-term equity premium. We contribute to this literature by discovering a new option-based predictor, namely, global convexity. This measure encompasses the return predictability of several previously documented indicators due to its strong ability to aggregate information, especially information from the international market and from the right-tail of risk neutral distribution. Convexity is also more symmetric and has smaller kurtosis than existing predictors, which contributes to its empirical success.

We contribute to the general debate on whether equity premium is predictable, especially out-of-sample. Since as early as Shiller (1981), a vast literature documents that the US equity premium is predictable, particularly at long horizons. Welch and Goyal (2008) cast doubt on whether the US equity premium is predictable out-of-sample (OOS). They show that the OOS R^2 of many predictors are negative. Campbell and Thompson (2008) show that imposing weak economic restrictions on predictors improves the OOS performance. We document a powerful short-term return predictor whose performance is robust out-of-the sample and in many countries around the world.

Lastly, we contribute to the study on the integration of the international financial market and international equity premium prediction. Henkel, Martin, and Nardari (2011) find that in the G7 countries, short-term return predictability exists only during economic contractions. Rapach, Strauss, and Zhou (2013) show that US stock return leads the stock return in other countries. Bollerslev, Marrone, Xu, and Zhou (2014) document that international variance risk premia predict stock returns in developed economies and Qiao, Xu, Zhang, and Zhou (2019) provide similar evidence for emerging markets. Miranda-Agrippino and Rey (2020) provide evidence on the co-movement in risky asset prices around the world, a phenomenon known as the Global Financial Cycle. Our measure, the global convexity significantly predicts changes in their Global Financial Cycle factor. This finding reinforces that the international options and equity market, or even other risky asset markets, are closely tied. A single measure from international options markets significantly predicts equity returns in 17 of 18 countries and regions, with similar coefficients, providing strong evidence of market integration and a common global risk premium.

2 Analysis of the global implied volatility surface

This section describes our data and analyzes the characteristics of the standardized implied volatility surface, such as its factor structure and global co-movement.

2.1 Data

Our data on index options is from the OptionMetrics Global Indices database, which provides daily prices and implied volatilities for equity index options. We select 18 index options from major developed economies around the world.[5] These index options are cash-settled European-style options. Table 1 lists their underlying indexes, primary exchanges, and data availability. The earliest in our sample is the S&P 500 index option, available since January 4, 1996. Other index options gradually appear in the database, with the latest being the OMX Stockholm 30 index option, available since May 14, 2007. Our sample period of option

[5]We select one major index option from each country or region. We require the option to have at least 15 years of available data in the database.

data is from January 1996 to December 2023.[6] This 28-year period spans several market cycles and witnesses many crises around the world, such as the Asian financial crisis, the dot-com bubble, the 9/11 attack, the subprime mortgage crisis, the European debt crisis, and, recently, the Covid-19 pandemic. During this period, the global financial market integration reaches an unprecedented level (Bekaert and Mehl, 2019; Camanho, Hau, and Rey, 2022), making it an important period to study the inter-connectedness of the global options market.

Table 1 shows that for each underlying index, there are hundreds or even thousands of different options being traded every day. To facilitate comparison across markets, OptionMetrics constructs an implied volatility surface that specifies the implied volatilities on a standardized delta-maturity grid for every index. To construct this surface, OptionMetrics applies a kernel function to compute the weighted average implied volatilities from all options each day. The kernel function puts greater weights on options that are closer to a particular grid point. Intuitively, the implied volatility on each grid point is the interpolated implied volatility of options with deltas and maturities that are close to the grid point. Appendix A provides details on the construction procedure. The standardized implied volatility surface has the same dimension in all markets, making it easy to compare across markets and aggregate information from different markets. Since most index options mature and renew on a monthly basis, our main empirical analysis is based on the monthly standardized implied volatility surface, which is the average of daily surfaces within a month.[7] When testing the return predictability of the implied volatility surface, we remove the last trading day in each month from the monthly average to avoid any potential look-ahead bias arising from the time zone mismatch across different countries.

We obtain equity index returns from FactSet. For 17 out of 18 indexes, we have available data from 1996 to 2024. The returns of the MIB index in Italy starts from 1998. In most empirical tests, we convert local-currency returns to US-dollar returns and subtract the US risk-free rate to compute excess index returns.[8] US risk-free rate is from Ken French's web-

[6]We have a longer sample period for index returns, which are available until December 2024.

[7]Most options have fixed maturity days within a month, e.g., the third Friday of each month. Due to this feature, Gao, He, and Hu (2023) show that option prices can display cyclical patterns within a month.

[8]We use local currency returns in a robustness test.

site. We obtain exchange rate data from FactSet. Table A1 provides summary statistics on excess index returns and returns of currency spot rates. In addition, we obtain factor data on the Global Financial Cycle constructed by Miranda-Agrippino and Rey (2020) from the author's website. To compare the strength of our proposed return predictor with other predictors from the literature, we also download data from various authors' websites, the CBOE website, and the FRED website.[9] Details of return predictors can be found in Appendix B.

2.2 Standardized implied volatility surface

This section discusses the characteristics of the standardized implied volatility surface. Before we proceed, we take several steps to clean the data. First, we drop all grid points with a maturity of 10 days, because the data at this maturity is missing for most indexes. We also drop all grid points with a maturity of 730 days, because many indexes do not have options with a maturity longer than two years. The implied volatility at this maturity point is largely based on the extrapolated values. The remaining set of maturities on the surface are 30, 60, 91, 122, 152, 182, 273, 365, and 547 days.

OptionMetrics constructs separate surfaces for put and call options. The available delta grid points are from 0.1 to 0.9 at 0.05 increment for call options and are from -0.1 to -0.9 at 0.05 increment for put options.[10] We re-label these grid points such that they are the same for calls and puts. Specifically, we multiply the delta of put options by -1. We multiply the delta of all call options by -1 and then add 1. After applying this one-to-one transformation, both call option surface and put option surface align with each other on the same set of delta grid points, and the new deltas also positively align with strike prices. Thus, the re-labeled deltas can be considered as option strikes, i.e., options with lower adjusted deltas correspond to options with lower strike prices. Due to put-call parity, the values on the call surface are

[9] For example, Amit Goyal's website provides a large number of return predictors published in the prior literature.

[10] For indexes in the Asian Pacific region (i.e., Australia, Japan, Taiwan, Hong Kong, and Korea), the delta grid points are slightly different from the US and European indexes. The available delta grid points for these Asian Pacific indexes are from 0.2 to 0.8 at 0.05 increment for call options and are from -0.2 to -0.8 at 0.05 increment for put options. Following OptionMetrics' methodology, we extend the implied volatility surface of indexes in the Asian Pacific region to be the same as other indexes.

almost the same as the values on the put surface at the same delta-maturity point. We take the average between put and call surfaces as a single implied volatility surface for each index. We take the average surface across all indexes as the global implied volatility surface.

Figure 1 and Table 2 present the unconditional global implied volatility surface. The implied volatilities decrease with deltas (or strikes) at all maturities. This pattern is commonly known as the volatility smirk or volatility skew. On the other hand, variations in implied volatilities across maturities are small, displaying an essentially flat term structure.

2.3 Factor structure of implied volatility surface

The implied volatility surface has 17×9 data points each period. To reduce its dimensionality and analyze its dynamics, we use a three-factor model to capture the shape of the surface. The three factors are the level, slope, and term structure of the surface.[11] We measure the level of the implied volatility surface as the average value on the surface in a given month. To measure the slope and term structure of a surface in a given month, we regress implied volatilities on the deltas and the logarithm of days to maturity. We label the coefficient on the deltas as the slope factor and the coefficient on the log of days to maturity as the term structure factor.

How effectively can level, slope, and term structure summarize the surface? Table A3 shows the R^2 of various linear regression models in summarizing monthly volatility surfaces. The model that includes delta and maturity (and a constant term to represent the level factor) produces an average R^2 of 80% across all index options (and 90% in the USA). This means a large fraction of surface variations can be summarized by these three factors. Table A3 also shows that the delta dimension is the dominant dimension. The majority of conditional variations on the surface are along the delta dimension. The model that only includes delta summarizes the surface with an average R^2 of 70% (and 81% in the USA). The term structure dimension only accounts for less than 10% of conditional variations on

[11] For example, Dumas, Fleming, and Whaley (1998) use a similar approach. Cont, Fonseca, and Durrleman (2002) use principal component analysis to summarize the surface. These methods are closely related to each other. For example, the first principal component is approximately the level of the surface.

the surface.

After controlling the level, slope, and term structure, what is the shape of the residual implied volatility surface?[12] Figure 1 and Table 2 Panel B present the residual implied volatility surface. The residual surface displays a convex shape: the implied volatilities are higher at the two tails and lower in the middle. This shape is reminiscent of the volatility smile commonly observed in individual stock options. As we show in later sections, the degree of the convexity of the surface has a strong predictability of the Global Financial Cycle, which drives equity returns around the world.

2.4 Measuring the surface convexity

We develop a simple convexity measure of the implied volatility surface. This convexity measure is the same for both the volatility surface and the residual volatility surface. Thus, it is not mechanically linked to the level, slope, or term factor. Specifically, let $V(\Delta, \tau)$ denote the implied volatility (or the residual implied volatility) with delta Δ and maturity τ. For any fixed maturity τ, we define the convexity of the implied volatility curve as

$$C(\tau) = E\left[\frac{V(\Delta_1, \tau) + V(\Delta_2, \tau)}{2} - V\left(\frac{\Delta_1 + \Delta_2}{2}, 2\right)\right] \tag{1}$$

In other words, we define the convexity of an implied volatility curve as the expected difference between the average implied volatility at two different delta points and the implied volatility at the point in the middle of the two.[13]

On the standardized implied volatility surface, we have 17 fixed delta points from 0.1 to 0.9 at 0.05 increments, which give us 64 triplets $(\Delta_i, \Delta_j, \Delta_k)$ with $\Delta_i < \Delta_k$ and $\Delta_j = (\Delta_i + \Delta_k)/2$. Numerically, the convexity at maturity τ is

$$C(\tau) = \frac{1}{64} \sum_{(i,j,k)} \frac{V(\Delta_i, \tau) + V(\Delta_k, \tau)}{2} - V(\Delta_j, \tau) \tag{2}$$

[12] In each month, we regress implied volatilities on the deltas and the log of days to maturity. We take the residuals of this regression as the residual implied volatility surface.

[13] This quantity is mathematically related to the second derivative of the implied volatility with respect to delta.

which equals to the following equation:[14]

$$
\begin{aligned}
C(\tau) = \frac{1}{64}[&4V(0.1,\tau) + 2.5V(0.15,\tau) + 2V(0.2,\tau) + 0.5V(0.25,\tau) - 1.5V(0.35,\tau) \\
&- 2V(0.4,\tau) - 3.5V(0.45,\tau) - 4V(0.5,\tau) - 3.5V(0.55,\tau) - 2V(0.6,\tau) \\
&- 1.5V(0.65,\tau) + 0.5V(0.75,\tau) + 2V(0.8,\tau) + 2.5V(0.85,\tau) + 4V(0.9,\tau)].
\end{aligned} \tag{3}
$$

The above equation shows that our proposed convexity measure is the weighted average implied volatilities at different delta points, where the weights add up to 0. The weights are positive at the tails and are negative at the center. We compute the convexity at each maturity on the standardized surface and take the simple average as the convexity of the surface. This procedure also produces the same convexity measure for the residual surface.[15]

Empirically, the convexity measure in Equation (3) is highly correlated with the regression coefficient produced from regressing implied volatilities on the squared delta. Table A3 shows that the squared-delta term in model 4 explains an additional 6% of variations on the implied volatility surface. In robustness checks, we also use alternative ways to measure convexity and find that they are similar and do not affect our main results. Figure 2 plots the level, slope, term structure, and convexity of the global and the US volatility surface from 1996 to 2023. We observe a strong co-movement between the global surface and the US surface. The correlation between the global and USA level, slope, term structure, and convexity are 96%, 79%, 93%, and 73%, respectively. This suggests the global options market is integrated.

[14] See Appendix C for the derivation of Equation (3)

[15] We can show that this procedure produces the same convexity measure for the residual implied volatility surface, which means that this convexity measure is not mechanically linked to the level, slope, or term structure of the surface. The reason that the convexity on the residual surface is the same is that the weights in Equation (3) add up to zero, and weights times delta also add up to zero. Since residual implied volatilities equal to

$$RV(\Delta,\tau) = V(\Delta,\tau) - b_0 - b_1\Delta - b_2 \ln\tau,$$

if we take out the effect of level, slope, and term structure by substituting this into Equation (3), the convexity measure would not change.

3 Equity premium predictability

This section documents the return predictability of several option-based variables in the US and in the international setting. In addition to the variables described in the previous section, we also collect data on the VIX index, the SVIX index introduced by Martin (2017), the left-tail volatility (LTV) index constructed by Bollerslev, Todorov, and Xu (2015), and the US variance risk premium (VRP) proposed by Bollerslev, Tauchen, and Zhou (2009).[16]

Table 3 presents the summary statistics of these option-based variables. Notably, except for the convexity indexes, option-based variables all have heavy tails with kurtosis above 4 and strong degrees of asymmetry with absolute skewness above 1. For comparison, the kurtosis and skewness of the S&P 500 monthly returns are 3.83 and -0.57, respectively. This suggests that convexity indexes behave somewhat differently from other variables. Table 3 Panel B shows the pairwise correlation among these variables. We observe strong correlations among some pairs. For example, the global level, slope, and term structure have a correlation of 93%, -80%, and, -80% with the VIX index, respectively.

3.1 Return predictability: US evidence

We test the ability of option-based measures to predict the S&P 500 index returns during our sample period of 1996 to 2023. As the theoretical literature suggests, index options contain information about near-term stock market returns (Martin, 2017). We use these variables to predict monthly or semi-annual index returns. When performing return predictability tests, we standardize all predictors by dividing their values by their full sample standard deviation. Therefore, the standard deviation of all predictors is 1 in predictive regressions. This does not affect t-statistics or R^2 but makes the regression coefficients easy to interpret.

Table 4 regresses the cumulative returns of the S&P 500 index from month $t+1$ to $t+6$

[16]We obtain the monthly average VIX index from FRED. We obtain the monthly average 30-day SVIX index from Ian Martin's website, which is available up to 2012. We replicate and extend his data to 2023. Our replication is over 99% correlated with the original SVIX data before 2012. We download LTV data from Viktor Todorov's website. His data is available until 2019. Post 2019, we use CBOE S&P 500 Left Tail Volatility Index. We download VRP data from Hao Zhou's website. All variables have a monthly frequency.

on option-based predictors in month t. Panel A of Table 4 reports the results of univariate regressions. It shows that four out of the nine predictors significantly predict the semi-annual S&P 500 returns.[17] They are global convexity, USA convexity, global slope, and LTV index. Global convexity produces the highest R^2 at 10.7%, while USA convexity produces the second highest R^2 at 8%. In terms of the economic magnitude, one standard deviation higher global convexity predicts that the S&P 500 in the next six months will have 3.66% higher return. Similarly, one standard deviation higher USA convexity predicts a 3.17% increase in return. Table 4 Panel B performs multivariate regressions to test whether the global convexity subsumes the predictability of other predictors. The global convexity is highly significant in all eight columns, whereas none of the other predictors, including the USA convexity, is significant.

Table 5 regresses S&P 500 index return in month $t+1$ on option predictors in month t. Predicting monthly market returns is more challenging because monthly returns are more noisy. Panel A shows that only two predictors, global and USA convexity, are significant. The R^2 of the two predictors are 2.8% and 1.3%, respectively. The magnitude of their coefficients are high. A one-standard-deviation increase in global convexity predicts the monthly S&P return to be 0.75% higher next month, which is more than the unconditional average return of the S&P 500. A one-standard-deviation increase in USA convexity predicts the monthly S&P 500 return to be 0.5% higher. Table 5 Panel B shows the results of multivariate regressions. Similar to Table 4, the global convexity is significant in all eight columns and none of the other predictors is significant.

Table 6 shows how convexity measures predict monthly S&P returns in each month $t+k$ with $k = 1, 2, 3, ..., 12$. This test reveals how information from a predictor in month t is realized in stock returns over time and whether there is any reversal in the future. Panel A shows that the predictability of global convexity is always significant in the first six months. The magnitude of the coefficient gradually decreases with the peak occurring in month $t+1$. The sign of the coefficients are almost all positive in the first 12 months, which means there is

[17] We use Newey-West standard errors with 6 lags of autocorrelation to calculate t-statistics when predicting semi-annual returns and 1 lag of autocorrelation to calculate t-statistics when predicting monthly returns.

no reversal. Panel B shows the predictability of the USA convexity over time. The patterns are similar to Panel A, except that the peak of the coefficient occurs in month $t+2$. Similar to global convexity, there is no reversal in the return predictability of US convexity.

This section presents strong in-sample evidence that convexity measures extracted from the global or US volatility surface predict the US equity returns. The global convexity has the best in-sample performance. It subsumes the predictability of the level, slope, or term structure factors, and some existing option-based predictors in the literature. Before we present the out-of-sample analysis, we turn our attention to the international evidence.

3.2 Return predictability: international evidence

This section evaluates the ability of the global convexity in predicting international index returns. Table 7 regresses the monthly excess return of each index in month $t+1$ on the global convexity index in month t. It shows that the global convexity significantly predicts 17 out of the 18 indexes during the past 28 years. The only insignificant case is Belgium. The R^2 of these regressions are high, all above 1%. The KOSPI 200 index in Korea is the most predictable. A one-standard-deviation increase in global convexity predicts 2.1% higher KOSPI 200 return in the next month, and the R^2 is 4.4%. The indexes in Taiwan, Australia, Sweden, and Italy are also highly predictable with the regression coefficients above 1 and the R^2 above 2%. When predicting semi-annual returns, we find similar results as shown in Table A4. The average R^2 of predicting semi-annual returns is around 8% across all indexes. The returns in this Table 7 are measured in US dollars. The ability of global convexity to predict exchange rates contributes to part of its return predictability. In the appendix, Table A6 shows that the global convexity also significantly predicts the local-currency denominated index returns.

The last column of Table 7 shows that the global convexity also significantly predicts the monthly change in the Miranda-Agrippino and Rey (2020) Global Financial Cycle (GFC) factor.[18] Miranda-Agrippino and Rey (2020) use a dynamic factor model to estimate a com-

[18] We use the newest standardized GFC factor obtained from Silvia Miranda-Agrippino's website. Its level has a mean of 0 and a standard deviation of 1. Its monthly change has a standard deviation of 0.28 in our

mon global factor from over 800 price series, covering equities, commodities, and corporate bonds around the world, and show that it explains an important fraction of the variation of risky asset prices. The fact that global convexity predicts the GFC factor suggests that it has the potential to predict a large number of other assets through the global financial cycle channel. We explore this channel further in Section 4.

3.3 Out-of-sample performance

This section tests the out-of-sample performance of convexity measures. Specifically, we use 10 years of data from 1996 to 2005 to train predictive models based on global or USA convexity and compare their performance with the naive historical-mean model from 2006 to 2023. The model parameters are updated on an expanding window basis. Following Welch and Goyal (2008), we calculated the out-of-sample R^2 based on the ratio of the mean squared errors between the predictive model and the naive model

$$R^2_{OOS} = 1 - \frac{MSE_A}{MSE_N}$$

If the mean squared error of the predictive model, MSE_A, is smaller than that of the naive model, MSE_N, then R^2_{OOS} is positive. Otherwise, it is negative.

Table 8 shows R^2_{OOS} of the global and USA convexity index in predicting 1-month and 6-month equity returns around the world. Column 1 shows that global convexity has a positive R^2_{OOS} when predicting monthly returns of all equity indexes in our sample. The average is 2.1%. The last row of Column 1 shows that global convexity also has a positive R^2_{OOS} when predicting the monthly change in the GFC factor. Column 2 shows the R^2_{OOS} of global convexity in predicting semi-annual returns. The results are similar. Global convexity has positive R^2_{OOS} in all but 2 indexes. The average R^2_{OOS} is high, at 6.1%. The R^2_{OOS} of predicting the semi-annual change in GFC factor is 10.6%. Table 8 Columns 3 and 4 show the R^2_{OOS} of USA convexity in predicting equity returns around the world. It has positive R^2_{OOS} when predicting equity returns in the US, but its R^2_{OOS} are mostly negative when

sample.

predicting the returns of other indexes.

Overall, this section documents the superiority of global convexity in predicting equity returns around the world, both in-sample and out-of-sample.

4 Return predictability via the global financial cycle

Our interpretation of the powerful return predictability of global convexity is that it contains information about the global financial cycle, which drives the returns of all risky assets around the world.

We present three sets of evidence that support this interpretation. First, we have already seen in the US that global convexity drives out the predictability of USA convexity. This finding applies to all the indexes in our sample. Global convexity has a stronger predictive power than each index's local convexity measure. Second, we find that global convexity does not predict the idiosyncratic part of index returns after controlling for the exposure to the global financial cycle. This means that the predictability of global convexity on each index must go through the global financial cycle channel. Lastly, we show that the strength of the predictability of global convexity on each asset depends on the asset's exposure to the global financial cycle. Assets that are more exposed to the global financial cycle are more predictable by the global convexity measure. The last finding applies to not only equity indexes but also other asset classes, such as currencies, fixed income, derivatives, and commodities.

4.1 Global convexity vs. local convexity

Table 9 Panel A regresses each index's monthly returns on the global convexity measure and the local convexity measure, i.e., the convexity of the index's own surface. The number of observations in each column varies depending on the availability of each index option. Similar to the US evidence, the global convexity measure dominates the local convexity measure in predicting equity returns. None of the local convexity measures is significant once we include the global convexity measure in the regression, while the global convexity is significant in predicting the returns of all but one index.[19]

Our interpretation of this finding is that each local convexity measure contains information about the index's future return, but it also contains noise that is orthogonal to stock returns. Since option prices are noisy as shown by Duarte, Jones, and Wang (2024), when used in isolation, local convexity measures have a weaker statistical power. When combined across different markets, noise from each individual market is canceled out. What remains is the information about future stock returns that is common to all markets, which is related to the global financial cycle.

4.2 Predicting common vs. idiosyncratic index returns

This section shows that the global convexity measure predicts international equity returns through the global financial cycle channel. Specifically, we regress each index return in month $t+1$ on the global convexity measure in month t and the change in the GFC factor in month $t+1$. Table 9 Panel B shows the results. There are several important results in this table. First, in all the columns, the coefficient of ΔGFC_{t+1} is positive and highly statistically significant, which means that all the equity indexes in our sample load positively on the GFC factor. Second, the R^2 from these regressions are large, ranging from 40% to 80%, which indicates that a large fraction of variation in equity index returns is explained by the variations in the GFC factor. Lastly, the coefficients on the global convexity measure become insignificant for most countries. This means that the global convexity does not predict index returns that are orthogonal to the global financial cycle for most indexes. In other words, the global convexity predicts a common component of index returns, captured by the GFC factor.

[19] In the appendix, A5 shows that each index's local convexity measure, when used alone, still possesses predictive power of local stock returns.

4.3 Return predictability and GFC beta

Given that the global convexity predicts changes in the GFC factor and the GFC factor is the dominant driver of risky asset returns around the world, we expect the global convexity to predict the return of any asset that co-moves with the GFC factor. In addition, we conjecture that the stronger an asset co-moves with the GFC factor, the greater its predicted returns are. We find supporting evidence of this conjecture and the evidence is not limited to equities.

Formally, this conjecture can be written as

$$r_{i,t+1} = a_i + \beta_i f_{t+1} + \epsilon_{i,t+1} \tag{4}$$

$$f_{t+1} = bc_t + u_{t+1} \tag{5}$$

where $r_{i,t+1}$ is the return of asset i, f_{t+1} is the change in the GFC factor, and c_t is the global convexity.[20] This implies

$$r_{i,t+1} = a_i + \gamma_i c_t + \beta_i u_{t+1} + \epsilon_{i,t+1} \tag{6}$$

where $u_{t+1} \perp c_t$, $\epsilon_{i,t+1} \perp c_t$, and,

$$\gamma_i = b\beta_i \tag{7}$$

We test Equation (7) with two-pass regressions as is common in cross-sectional asset pricing tests. We start with a group of test assets, e.g., equity indexes, currencies, or both. In the first pass, we estimate each asset's beta with respect to the GFC factor as in Equation (4). We also run predictive regressions to estimate each asset's γ_i in Equation (6). Note that γ_i can be interpreted as the expected increase in asset i's return after one unit increase in the global convexity. In the second pass, we regress γ_i on β_i to verify that b is significant and the constant term is not significantly different from zero. We compute standard errors through bootstrap.

Table 10 Panel A reports the results of this test. We have three groups of test assets: 18 equity indexes, 10 currencies, and both equities and currencies (i.e., 28 assets). The results are consistent with our conjecture. The coefficients on the GFC beta are positive and

[20] We de-mean both f_{t+1} and c_t, eliminating the need of a constant term.

statistically significant in all three groups. This means assets with higher betas on the GFC factor are expected to have a larger increase in return after one unit increase in the global convexity. The constants in these regressions are insignificant. The R^2 in these regressions are also high, suggesting that the GFC channel explains the return predictability of global convexity well. Figure 4 shows the relationship between the predicted increase in return and GFC betas for both equity indexes and currencies. We observe a strong linear relationship, consistent with the prediction of Equation (7).

As a robustness check, we repeat this two-pass exercise with 127 test assets from the He, Kelly, and Manela (2017) (HKM) dataset.[21] The HKM dataset includes test assets from several asset classes, such as equities, fixed income, options, CDS, currencies, and commodities. The results, as shown in Figure A.1 in the appendix, are consistent with Equation (7) as well. Notably, the HKM dataset contains assets with negative loadings on the GFC factor, such as US government bonds, and we observe that the global convexity negatively predicts the returns of those assets.

4.4 Conditional asset pricing model

Equation (4) is similar to the CAPM if we consider the GFC factor as the market factor. Therefore, it would be interesting to test how well it prices global risky assets in the cross-section. We use the two-pass regression procedure again to test the asset pricing implication of the GFC factor.

Table 10 Panel B reports the results. In Columns 1 to 3, we regress each asset's unconditional expected return on its GFC beta. We find that the data does not support the GFC asset pricing model within a single asset class. The coefficients on the GFC beta are insignificant and the R^2 are low in Columns 1 and 2. These results are reminiscent of the failure of the CAPM. Column 3 shows a significant coefficient on the GFC beta if both equities and currencies are included as test assets.

In Columns 4 to 6, we test the conditional asset pricing model by regressing the condi-

[21] We download the data from Asaf Manela's website. The sample period of his data ends in 2012.

tional expected return of each asset on their GFC betas. We measure each asset's expected monthly return conditional on the global convexity in the prior month being above its sample mean. In this conditional asset pricing test, we find that data supports the GFC pricing model. The coefficients on the GFC beta are positive and highly statistically significant in all three cases. The R^2's are high as well. These results show that the GFC factor successfully prices the cross-section of international assets when the global convexity is high.

5 Dissecting the predictability of global convexity

Having established the strong return predictability of the global convexity measure both in-sample and out-of-sample, this section investigates the source of its predictability. Our approach is to decompose the global convexity into two components, convexity left and convexity right, and analyze each component's information content separately.

5.1 Decompose global convexity into left and right components

Equation (3) indicates the convexity measure is the difference between the average implied volatilities at both tails and the average implied volatilities at the center of the volatility surface. A natural way to understand this measure is to examine the two tails separately. Specifically, we decompose it into two orthogonal components: the convexity left and the convexity right index. We take two steps to accomplish this. In the first step, we decompose the global convexity index into the contribution from the left-tail and the contribution from the right-tail by splitting Equation (3) into two parts: left-minus-center (LMC) and right-minus-center (RMC). The equations are the following (note that we omit subscript τ for brevity):

$$\begin{aligned} LMC = \frac{1}{64}[&4IV(0.1) + 2.5IV(0.15) + 2IV(0.2) + 0.5IV(0.25) - 0.75IV(0.35) - IV(0.4) \\ &- 1.75IV(0.45) - 2IV(0.5) - 1.75IV(0.55) - IV(0.6) - 0.75IV(0.65)] \end{aligned} \tag{8}$$

$$RMC = \frac{1}{64}[-0.75IV(0.35) - IV(0.4) - 1.75IV(0.45) - 2IV(0.5) - 1.75IV(0.55) \\ - IV(0.6) - 0.75IV(0.65) + 0.5IV(0.75) + 2IV(0.8) + 2.5IV(0.85) + 4IV(0.9)] \quad (9)$$

The sum of Equation (8) and (9) is exactly Equation (3). Empirically, the correlation between LMC and RMC is highly negative, at -88%, as shown in Table 11 Panel A. To facilitate interpretation, in the next step, we orthogonalize RMC with respect to LMC by regressing RMC on LMC:

$$RMC_t = a_0 + a_1 LMC_t + e_t \quad (10)$$

We define the convexity right index as

$$CR_t = a_0 + e_t \quad (11)$$

and the convexity left index as

$$CL_t = LMC_t(1 + a_1) \quad (12)$$

These two components are orthogonal to each other, and their sum still equals to the global convexity index. Note that the convexity left index is just a scaled version of the left-minus-center.

Table 11 Panel A reports the correlation matrix among these sub-convexity measures. Convexity left (i.e., left-minus-center) is 82% correlated with the global convexity measure, while convexity right is 58% correlated with the global convexity measure. This means approximately two-thirds of variations in the global convexity is driven by variations in convexity left, while the remaining one-third is driven by variations in convexity right.

Table 11 Panel B regresses convexity left and convexity right indexes on various option-based variables. Columns 1 to 4 show that the convexity left is highly significantly related with the global slope, VIX, SVIX, and LTV. In particular, the global slope explains 95% of variations in the convexity left. This is as expected since the convexity left is essentially the implied volatilities at the left tail minus the implied volatilities at the center, approximately the slope of the surface. The literature commonly refers to this measure as downside risk or downside jump risk, since it reflects the difference in the implied volatility between deep OTM puts and ATM options (Cao, Goyal, Wang, Zhan, and Zhang, 2024). Therefore, we interpret the convexity left as a global downside risk measure. When the left convexity is high, investors around the world seek downside protection by buying OTM puts and pushing up implied volatilities at the left tail. Figure 5 plots the time series of the convexity left index. Consistent with this interpretation, the convexity left index peaks around major crises, such as the 1998 Russian default, the 2008 sub-prime mortgage crisis, the 2010 Dow flash crash, the European debt crisis in 2010 and 2011, and the Covid-19 pandemic.[22]

Columns 5 to 8 of Table 11 Panel B show that the convexity right index is weakly related to the global slope and other option-based measures as indicated by the low R^2's. The coefficients on these variables have the opposite sign of those in Columns 1 to 4, suggesting the right tail contains different information from the left tail.

5.2 Information content in convexity right

Our interpretation of the convexity right is that it reflects short-term investor confidence. For example, when investors bet on the market to increase in the short run, they could purchase OTM call options, pushing up the implied volatilities in the right tail relative to the middle. Another possibility is that when investors want to short the market, they could buy ATM put options (Jones, Mo, and Wang, 2018; Chordia, Kurov, Muravyev, and Subrahmanyam, 2017; Muravyev, Pearson, and Pollet, 2022), driving up the implied volatilities in the middle relative to the right tail. Therefore, higher convexity right is associated with positive market sentiment, whereas lower convexity right reflects investor pessimism.

We present two sets of evidence that support this interpretation. In the first exercise, we identify extreme realizations of convexity right from Figure 5 and ask ChatGPT what happened in the financial market during those periods. The headline response from ChatGPT

[22] We identify seven peaks of the global convexity left visually and ask ChatGPT 4o "What happened in the financial market" during each peak. Table A7 reports the headline response from ChatGPT 4o, which is consistent with the view that global convexity left peaks during crisis time.

4o is listed in Table A7. Consistent with the confidence interpretation, at the peak of the convexity right, the response typically mentions "rebound" or "optimism." At the bottom of the convexity right, the response often contains negative words, such as "bear market" and "uncertainty."

To further understand what explains the convexity right, we collect data on many macroeconomic variables, including equity premium predictors from the literature and other state variables relevant to asset pricing. Details of these variables are in Appendix B. We use LASSO to select the most informative variables for the convexity right.[23] By adjusting the tuning parameter in LASSO, we select k most informative variables with $k = 1, 2, ..., 5$. Table 12 presents the selected variables in the order of their importance. They are TED spread, 6-month S&P 500 cumulative return, output gap of industrial production, term structure of the global volatility surface, and aggregate short interest in the US.[24]

Table 12 Panel A presents the correlation matrix among these variables. The correlation between convexity right and TED spread is -56%, strongest among all variables. TED spread measures the funding cost of institutional investors around the world. A higher TED spread means traders face higher funding costs relative to the T-bill rate, which is a bad sign for the market. Convexity right is positively correlated with S&P 500 returns and the term structure of implied volatilities with correlations at 41% and 39%, respectively. These two variables reflect positive news in the market. Convexity right is also negatively associated with the output gap and aggregate short interest in the US, both suggest negative economic conditions. Panel B of Table 12 regresses the convexity right on these variables and shows that collectively, the five variables explain about half of the variations in the convexity right. The signs of the regression coefficients are consistent with the view that the convexity right reflects market confidence.

[23]LASSO has been used in the recent asset pricing literature to select the most important variables to explain the anomaly zoo, e.g., Freyberger, Neuhierl, and Weber (2020) and DeMiguel, Martin-Utrera, Nogales, and Uppal (2020)

[24]Cooper and Priestley (2009) show that industrial production output gap predicts equity returns in the US and G7 countries. Rapach, Ringgenberg, and Zhou (2016) show that the aggregate short interest in the US predicts stock market returns.

5.3 Predicting cash flow and discount rate news

Given that the convexity left and convexity right reflect different information, we expect their return predictability to come from different channels. We use a modified Campbell-Shiller decomposition to decompose the monthly S&P 500 excess returns into discount rate news and cash flow news. We find that the convexity left significantly predicts the discount rate news, but not the cash flow news, whereas the convexity right mainly predicts the cash flow news, but not discount rate news.

To decompose market returns, we first construct a proxy of the discount rate by regressing market returns on the dividend price ratio, earnings price ratio, T-bill yield, SVIX, and LTV. The predicted market return from these conditioning variables is our discount rate proxy $\hat{E}[R_{t+1}]$. We then regress the market return on the changes in the discount rate proxy to extract discount rate news and cash flow news component as in the following equation

$$R_{t+1} = a + \underbrace{b \times \Delta\hat{E}[R_{t+1}]}_{\text{DR news}} + \underbrace{\epsilon_{t+1}}_{\text{CF news}} .$$

Table 13 presents the results of regressing discount rate and cash flow news on various convexity measures. Panel A shows that two-thirds of global convexity's return predictability comes from predicting the discount rate news (i.e., 0.5% of the 0.75%), and the remaining one-third comes from predicting the cash flow news (i.e., 0.25% of the 0.75%). Panel B shows that the convexity left only predicts the discount rate news, while Panel C shows that the convexity right mainly predicts the cash flow news.

To further verify the cash flow predictability, we regress the dividend growth rate of S&P 500 companies and changes in the analyst forecast of long-term earnings on the lagged convexity left and convexity right. Panel D shows that convexity left does not predict dividend growth or analyst forecast, while convexity right significantly predicts both measures. This shows that the convexity right, reflecting market confidence, positively predicts future cash flow. Overall, this section shows that the global convexity contains information about the discount rate news through the left-tail and cash flow news through the right-tail. Both the convexity left and convexity right contribute to the predictability of the global convexity.

6 Additional analysis and robustness checks

This section conducts additional analysis and robustness checks.

6.1 Alternative methodologies to measure convexity

We consider five different alternative ways to measure global convexity and show that these alternative convexity measures all significantly predict the monthly and semi-annual S&P 500 returns. The five measures are the following.

OTM Convexity In this specification, we combine the out-of-the-money (OTM) section of the call and put surface as the global surface. We define the OTM call surface as the part of the call surface with the adjusted delta greater or equal to 0.5 and the OTM put surface as the part of the put surface with the adjusted delta less or equal to 0.5. When delta equals 0.5, we take the average between the calls and puts. With this OTM surface, we apply Equation (3) to compute the global convexity.

Value weighted In this specification, we take the value-weight average of local convexity measures from each country or region as the global convexity measure. The value weights are based on the total size of each country or region's stock market capitalization, which we obtain from the World Bank.

Coefficient on delta-squared Instead of calculating convexity using Equation (3), we use a regression approach by regressing implied volatilities of a given surface on the delta, the log days to maturity, and the delta-squared terms. We use the estimated coefficient on the delta-squared term as the convexity measure.

Individual option In this approach, we directly measure convexity from individual option data without using the volatility surface data. To measure convexity using option-level data, we first clean the data. We remove options with a maturity shorter than 5 days. We also set a maximum implied volatility to be 200%. We use only OTM options (i.e., put options with adjusted delta less than or equal to 0.5 and call options with adjusted delta greater than or equal to 0.5). We then classify options into three bins based on their adjusted delta.[25] Those with an adjusted delta less than 1/3 (i.e., low-strike options) are grouped in the left-tail bin. Those with an adjusted delta greater than 2/3 (i.e., high-strike options) are in the right-tail bin. The remaining are in the middle bin. We then take the simple average of the implied volatility of options in each bin on each day. We average these implied volatilities within each month. The convexity measure of each index is then the average of left-tail and right-tail implied volatility minus the middle implied volatility. We take the average across all indexes as the global convexity.

Annual change We measure the change of our baseline convexity measure from its value 12 months ago and use this change as the predictor to predict equity returns.

Table 14 Panel A shows the correlation of these alternative measures of convexity with our baseline measure. In general, the correlations are high. For example, using the regression approach to compute convexity produces a near-identical measure. Panel B tests these alternative measures' predictability on semi-annual S&P 500 returns. These measures are all highly significant with similar R^2 at around 10%. Panel C tests the monthly return predictability of alternative convexity measures. Similarly, all measures are statistically significant at the 5% or 1% level and the predictive R^2 are high, ranging from 1.4% to 3.4%.

6.2 Top ten equity premium predictors

This section ranks the predictability of 70 equity premium predictors. The details of these variables are in Appendix B. We start the process from the dataset compiled by Welch and Goyal (2008) and Goyal, Welch, and Zafirov (2024), which collectively contain 45 predictors. We then add 14 option-related variables, mainly the ones constructed from our dataset. In addition, we add 13 important macroeconomic state variables, such as past market returns, proxies of funding cost and liquidity, intermediary leverage, sentiment, etc.

In total, we have 70 variables with a complete history from January 1996 or earlier to

[25] See Section 2.2 for delta adjustment.

December 2023. Table 15 Panel A lists the top 10 predictors in terms of their in-sample and out-of-sample R^2 when predicting monthly S&P 500 returns.[26] Notably, the global convexity ranks at the top both in-sample and out-of-sample. Moreover, other sub-convexity indexes, such as the convexity left and USA convexity, also rank among the top 10 list. Table 15 Panel B shows which variables have strong predictive power of the global financial cycle. The global convexity also ranks at the top, both in-sample and out-of-the-sample. The global convexity is the only variable in the in-sample top 10 list of both panels.

Table 15 Panel B suggests that predicting the GFC is more difficult than predicting the S&P 500. The average in-sample R^2 of the top 10 GFC predictors is 1.29%, compared to the 1.95% average R^2 from the top 10 S&P 500 predictors. The average OOS R^2 when predicting the GFC is 0.81% and for the US is 1.21%. Given the importance of the GFC factor in driving the returns of risky assets around the world, understanding the drivers of the GFC factor is an interesting area of future research.

6.3 Predicting local-currency equity premium and exchange rates

In our main specifications, we find that the global convexity predicts equity index returns denominated in the US dollar. This section tests whether the global convexity measure can predict each index's local currency return. We find that when we measure index returns in the local currency, the global convexity continue to significantly predict the returns of almost all the indexes in our sample.

The difference between the US dollar return and the local currency return is the currency surprise, so we also test the global convexity's ability to predict exchange rates. Table A6 in the appendix reports the results. Panel A shows that global convexity positively and significantly predicts the returns of the Australian dollar, Canadian dollar, and New Taiwan dollar at monthly frequency.[27] Panel B shows that at semi-annual frequency, the global

[26] We use all available data as far back as possible to conduct the out-of-sample test for each variable. The S&P 500 return data in this test is from CRSP, available since 1926. In Panel B, the GFC factor data is available since 1980.

[27] We measure exchange return as the percentage change in a currency's value against the dollar. A positive coefficient indicates the currency is appreciating against the US dollar.

convexity also positively and significantly predicts the return of Korean Won. The global convexity significantly and negatively predicts the return of the Hong Kong dollar.

6.4 Term structure of convexity measures

In our baseline measure, we take the average convexity value across different maturities. Table A8 Panel A shows the summary statistics of the convexity measure at each maturity. In general, the global convexity is positive at all maturities. Convexity declines with maturity. The 30-day implied volatility curve has the highest convexity on average. The standard deviation, skewness, and kurtosis all tend to decline with maturity, suggesting that the convexity of short-term options are more volatility and more likely to take extremely large values over time.

Does the predictability of the convexity change with maturity? We classify maturity into three groups and take the average convexity measure within each group. We classify 30-, 60, and 91-day options as short-term, 122-, 152-, and 182-day options as mid-term, and the remaining as long-term. As shown in Panel B, short-term convexity tends to have worse predictability than mid-term and long-term convexity measures. For example, the R^2 of short-term convexity in predicting the 1-month and 6-month S&P 500 return is only 0.5% and 7.5%, respectively. The mid-term convexity performs the best in predicting monthly returns, and the long-term convexity performs the best in predicting semi-annual returns. The result is similar if we only focus on the USA convexity, short-term US convexity measure performs worse than mid-term and long-term US convexity measures. One potential explanation is that the short-term convexity is more noisy, making its predictability less reliable. Averaging convexity across maturities generates better return predictability by reducing noise.

7 Conclusion

We document that the convexity measured from the global implied volatility surface robustly predicts the stock market index return in the US and many other countries around the world.

Our convexity index measures the degree of curvature of the implied-volatility curve. The convexity index is higher if the implied volatilities of options with both high and low strike prices are greater than the implied volatilities of options with medium strike prices. When this happens, the expected stock market return is higher. Empirically, the global convexity predicts the monthly S&P 500 returns with an in-sample and OOS R2 of 2.8% and 2.9%, respectively. The average R^2 of using this index to predict all 18 index returns in our sample is 2.2% in-sample and 2.1% out-of-sample. The global convexity subsumes the predictability of several existing option-based predictors, including the VIX index, SVIX index, variance risk premium, and left-tail volatility. Through various alternative specifications, we find the predictability of global convexity to be extremely robust.

The global convexity index's predictability is not limited to equities. Because the global convexity index predicts the global financial cycle (GFC), it can also predict any asset that co-moves with the GFC factor. For example, the global convexity index can predict the return of currencies, such as the Australian dollar, Canadian dollar, Korean won, and New Taiwan dollar. The strength of the global convexity's predictability on an asset increases when the asset co-moves more strongly with the GFC.

The predictive power of the global convexity index comes from its ability to aggregate information from across the globe and combine information from both the left and right tail of the risk-neutral return distribution. Information contained in the left tail reveals investors' fear of a market crash, while information contained in the right tail reveals investor confidence.

Lastly, the fact that the global level, slope, and convexity index co-move strongly with their country-level counterparts indicates that the global options markets are closely connected. It is plausible that the same group of marginal investors operate in all these markets. The fact that the information extracted from the global options market predicts stock returns around world also indicates that the marginal investors in the options market play a significant role in the pricing of the equity around the world. Understanding how information or preference is revealed and transmitted across different markets through these marginal investors is an interesting future research question.

References

Andersen, Torben G, Nicola Fusari, and Viktor Todorov, 2015, The risk premia embedded in index options, *Journal of Financial Economics* 117, 558–584.

Arrow, Kenneth J, 1964, The role of securities in the optimal allocation of risk-bearing, *The Review of Economic Studies* 31, 91–96.

Atanasov, Victoria, Stig V Møller, and Richard Priestley, 2020, Consumption fluctuations and expected returns, *The Journal of Finance* 75, 1677–1713.

Back, Kerry, Kevin Crotty, and Seyed Mohammad Kazempour, 2022, Validity, tightness, and forecasting power of risk premium bounds, *Journal of Financial Economics* 144, 732–760.

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *The Journal of Finance* 61, 1645–1680.

Bakshi, Gurdip, Charles Cao, and Zhiwu Chen, 1997, Empirical performance of alternative option pricing models, *The Journal of Finance* 52, 2003–2049.

Bakshi, Gurdip, John Crosby, Xiaohui Gao, and Wei Zhou, 2019, A new formula for the expected excess return of the market, *Fox School of Business Research Paper*.

Bates, David S, 1991, The crash of '87: was it expected? the evidence from options markets, *The Journal of Finance* 46, 1009–1044.

———, 2000, Post-'87 crash fears in the s&p 500 futures option market, *Journal of Econometrics* 94, 181–238.

———, 2022, Empirical option pricing models, *Annual Review of Financial Economics* 14, 369–389.

Bekaert, Geert, and Campbell R Harvey, 1995, Time-varying world market integration, *the Journal of Finance* 50, 403–444.

Bekaert, Geert, and Arnaud Mehl, 2019, On the global financial market integration "swoosh" and the trilemma, *Journal of International Money and Finance* 94, 227–245.

Belo, Frederico, and Jianfeng Yu, 2013, Government investment and the stock market, *Journal of Monetary Economics* 60, 325–339.

Bollerslev, Tim, James Marrone, Lai Xu, and Hao Zhou, 2014, Stock return predictability and variance risk premia: Statistical inference and international evidence, *Journal of Financial and Quantitative Analysis* 49, 633–661.

Bollerslev, Tim, George Tauchen, and Hao Zhou, 2009, Expected stock returns and variance risk premia, *The Review of Financial Studies* 22, 4463–4492.

Bollerslev, Tim, and Viktor Todorov, 2011, Tails, fears, and risk premia, *The Journal of Finance* 66, 2165–2211.

———, and Lai Xu, 2015, Tail risk premia and return predictability, *Journal of Financial Economics* 118, 113–134.

Breeden, Douglas T, and Robert H Litzenberger, 1978, Prices of state-contingent claims implicit in option prices, *Journal of Business* pp. 621–651.

Camanho, Nelson, Harald Hau, and Hélene Rey, 2022, Global portfolio rebalancing and exchange rates, *The Review of Financial Studies* 35, 5228–5274.

Campbell, John Y, and Samuel B Thompson, 2008, Predicting excess stock returns out of sample: Can anything beat the historical average?, *The Review of Financial Studies* 21, 1509–1531.

Cao, Jie, Amit Goyal, Yajing Stalla Wang, Xintong Zhan, and Weiming Elaine Zhang, 2024, Opioid crisis and firm downside tail risks: Evidence from the option market, *Working paper*.

Carr, Peter, and Liuren Wu, 2009, Variance risk premiums, *The Review of Financial Studies* 22, 1311–1341.

Chabi-Yo, Fousseni, and Johnathan Loudis, 2020, The conditional expected market return, *Journal of Financial Economics* 137, 752–786.

Chava, Sudheer, Michael Gallmeyer, and Heungju Park, 2015, Credit conditions and stock return predictability, *Journal of Monetary Economics* 74, 117–132.

Chen, Yong, Gregory W Eaton, and Bradley S Paye, 2018, Micro (structure) before macro? the predictive power of aggregate illiquidity for stock returns and economic activity, *Journal of Financial Economics* 130, 48–73.

Chordia, Tarun, Alexander Kurov, Dmitriy Muravyev, and Avanidhar Subrahmanyam, 2017, The informational role of index option trading, Discussion paper Working paper, University of California at Los Angeles.

Cont, Rama, Jose da Fonseca, and Valdo Durrleman, 2002, Stochastic models of implied volatility surfaces, *Economic Notes* 31, 361–377.

Cooper, Ilan, and Richard Priestley, 2009, Time-varying risk premiums and the output gap, *The Review of Financial Studies* 22, 2801–2833.

Cox, John C, and Stephen A Ross, 1976, The valuation of options for alternative stochastic processes, *Journal of Financial Economics* 3, 145–166.

Das, Sanjiv Ranjan, and Rangarajan K Sundaram, 1999, Of smiles and smirks: A term structure perspective, *Journal of Financial and Quantitative Analysis* 34, 211–239.

Debreu, Gerard, 1959, *Theory of value: An axiomatic analysis of economic equilibrium* . , vol. 17 (Yale University Press).

DeMiguel, Victor, Alberto Martin-Utrera, Francisco J Nogales, and Raman Uppal, 2020, A transaction-cost perspective on the multitude of firm characteristics, *The Review of Financial Studies* 33, 2180–2222.

Driesprong, Gerben, Ben Jacobsen, and Benjamin Maat, 2008, Striking oil: another puzzle?, *Journal of Financial Economics* 89, 307–327.

Duarte, Jefferson, Christopher S Jones, and Junbo L Wang, 2024, Very noisy option prices and inference regarding the volatility risk premium, *The Journal of Finance* 79, 3581–3621.

Dumas, Bernard, Jeff Fleming, and Robert E Whaley, 1998, Implied volatility functions: Empirical tests, *The Journal of Finance* 53, 2059–2106.

Freyberger, Joachim, Andreas Neuhierl, and Michael Weber, 2020, Dissecting characteristics nonparametrically, *The Review of Financial Studies* 33, 2326–2377.

Gao, Chao, Jia He, and Grace Xing Hu, 2023, The monthly cycle of option prices, *PBCSF-NIFR Research Paper*.

Goyal, Amit, Ivo Welch, and Athanasse Zafirov, 2024, A comprehensive 2022 look at the empirical performance of equity premium prediction, *The Review of Financial Studies* 37, 3490–3557.

Harvey, Campbell R, 1991, The world price of covariance risk, *The Journal of Finance* 46, 111–157.

He, Zhiguo, Bryan Kelly, and Asaf Manela, 2017, Intermediary asset pricing: New evidence from many asset classes, *Journal of Financial Economics* 126, 1–35.

Henkel, Sam James, J Spencer Martin, and Federico Nardari, 2011, Time-varying short-horizon predictability, *Journal of Financial Economics* 99, 560–580.

Hirshleifer, David, Kewei Hou, and Siew Hong Teoh, 2009, Accruals, cash flows, and aggregate stock returns, *Journal of Financial Economics* 91, 389–406.

Hu, Grace Xing, Jun Pan, and Jiang Wang, 2013, Noise as information for illiquidity, *The Journal of Finance* 68, 2341–2382.

Huang, Dashan, Fuwei Jiang, Jun Tu, and Guofu Zhou, 2015, Investor sentiment aligned: A powerful predictor of stock returns, *The review of Financial studies* 28, 791–837.

Jensen, Christian Skov, David Lando, and Lasse Heje Pedersen, 2019, Generalized recovery, *Journal of Financial Economics* 133, 154–174.

Jondeau, Eric, Qunzi Zhang, and Xiaoneng Zhu, 2019, Average skewness matters, *Journal of Financial Economics* 134, 29–47.

Jones, Christopher S, Haitao Mo, and Tong Wang, 2018, Do option prices forecast aggregate stock returns?, *Available at SSRN 3009490*.

Jones, Christopher S, and Selale Tuzel, 2013, New orders and asset prices, *The Review of Financial Studies* 26, 115–157.

Kelly, Bryan, and Hao Jiang, 2014, Tail risk and asset prices, *The Review of Financial Studies* 27, 2841–2871.

Kelly, Bryan, and Seth Pruitt, 2013, Market expectations in the cross-section of present values, *The Journal of Finance* 68, 1721–1756.

Kozhan, Roman, Anthony Neuberger, and Paul Schneider, 2013, The skew risk premium in the equity index market, *The Review of Financial Studies* 26, 2174–2203.

Li, Jun, and Jianfeng Yu, 2012, Investor attention, psychological anchors, and stock return predictability, *Journal of Financial Economics* 104, 401–419.

Liu, Hong, Yueliang Jacques Lu, Weike Xu, and Guofu Zhou, 2022, Market risk premium expectation: Combining option theory with traditional predictors, *Available at SSRN*.

Liu, Jun, Jun Pan, and Tan Wang, 2005, An equilibrium model of rare-event premia and its implication for option smirks, *The Review of Financial Studies* 18, 131–164.

Maio, Paulo, 2013, The "fed model" and the predictability of stock returns, *Review of Finance* 17, 1489–1533.

———, 2016, Cross-sectional return dispersion and the equity premium, *Journal of Financial Markets* 29, 87–109.

Martin, Ian, 2017, What is the expected return on the market?, *The Quarterly Journal of Economics* 132, 367–433.

Miranda-Agrippino, Silvia, and Hélene Rey, 2020, Us monetary policy and the global financial cycle, *The Review of Economic Studies* 87, 2754–2776.

Miranda-Agrippino, Silvia, and Hélène Rey, 2022, The global financial cycle, in *Handbook of International Economics*, vol. 6 . pp. 1–43 (Elsevier).

Møller, Stig V, and Jesper Rangvid, 2015, End-of-the-year economic growth and time-varying expected returns, *Journal of Financial Economics* 115, 136–154.

Muravyev, Dmitriy, Neil D Pearson, and Joshua M Pollet, 2022, Is there a risk premium in the stock lending market? evidence from equity options, *The Journal of Finance* 77, 1787–1828.

Neely, Christopher J, David E Rapach, Jun Tu, and Guofu Zhou, 2014, Forecasting the equity risk premium: the role of technical indicators, *Management science* 60, 1772–1791.

Pan, Jun, 2002, The jump-risk premia implicit in options: Evidence from an integrated time-series study, *Journal of Financial Economics* 63, 3–50.

Piazzesi, Monika, Martin Schneider, and Selale Tuzel, 2007, Housing, consumption and asset pricing, *Journal of Financial Economics* 83, 531–569.

Pollet, Joshua M, and Mungo Wilson, 2010, Average correlation and stock market returns, *Journal of Financial Economics* 96, 364–380.

Qiao, Fang, Lai Xu, Xiaoyan Zhang, and Hao Zhou, 2019, Variance risk premiums in emerging markets, *Available at SSRN 3199522.*

Rapach, David E, Matthew C Ringgenberg, and Guofu Zhou, 2016, Short interest and aggregate stock returns, *Journal of Financial Economics* 121, 46–65.

Rapach, David E, Jack K Strauss, and Guofu Zhou, 2013, International stock return predictability: what is the role of the united states?, *The Journal of Finance* 68, 1633–1662.

Rey, Hélène, 2013, Dilemma not trilemma: the global financial cycle and monetary policy independence, Discussion paper Proceedings - Economic Policy Symposium - Jackson Hole.

Ross, Steve, 2015, The recovery theorem, *The Journal of Finance* 70, 615–648.

Ross, Stephen A, 1978, A simple approach to the valuation of risky streams, *Journal of Business* pp. 453–475.

Solnik, Bruno, 1983, International arbitrage pricing theory, *The Journal of Finance* 38, 449–457.

Welch, Ivo, and Amit Goyal, 2008, A comprehensive look at the empirical performance of equity premium prediction, *The Review of Financial Studies* 21, 1455–1508.

Yu, Jialin, 2011, Disagreement and return predictability of stock portfolios, *Journal of Financial Economics* 99, 162–183.

Appendix A Construction of volatility surface

This section details how OptionMetrics constructs the standardized implied volatility surface. OptionMetrics first computes Black-Scholes implied volatility for options with available data. For European-style options, the Black-Scholes model:

$$C = Se^{-qT}N(d_1) - Ke^{-rT}N(d_2)$$

$$P = Ke^{-rT}N(-d_2) - Se^{-qT}N(-d_1)$$

where

$$d_1 = \frac{1}{\sigma\sqrt{T}}\left(\ln\left(\frac{S}{K}\right) + \left(r - q + \frac{1}{2}\sigma^2\right)T\right)$$

$$d_2 = d_1 - \sigma\sqrt{T}$$

C or P is the midpoint of the best closing bid price and best closing offer price for the call (put) option, S is the current underlying security price, K is the strike price, T is the time in years remaining to option maturity, r is the continuously compounded interest rate, q is the continuously compounded dividend yield, and σ is the implied volatility.

Then, OptionMetrics organizes the data by the log of days to maturity and by "call-equivalend delta" (i.e., delta for a call option, one plus delta for a put option). Then, at each grid point j on the volatility surface, the standardized implied volatility $\hat{\sigma}_j$ is calculated as a weighted sum of option implied volatilities:

$$\hat{\sigma}_j = \frac{\sum_i V_i \sigma_i \Phi(x_{ij}, y_{ij}, z_{ij})}{\sum_i V_i \Phi(x_{ij}, y_{ij}, z_{ij})}$$

where i is indexed over all available options on each day, V_i is the vega of the option, σ_i is the implied volatility, and $\Phi(\cdot)$ is the kernel function:

$$\Phi(x, y, z) = \frac{1}{\sqrt{2\pi}} e^{-\left(\frac{x^2}{2h_1} + \frac{y^2}{2h_2} + \frac{z^2}{2h_3}\right)}$$

The inputs to the kernel function measures the "distance" between an actual option i and the grid point j:

$$x_{ij} = \ln(T_i/T_j)$$

$$y_{ij} = \Delta_i - \Delta_j$$

$$z_{ij} = I_{\{CP_i = CP_j\}}$$

where T_i and T_j are measured in days; Δ_i and Δ_j are call-equivalent deltas; and z_{ij} is an indicator function, which equals one if both the option and the surface have the same call or put type. The kernel bandwidth parameters are set at $h_1 = 0.05$, $h_2 = 0.005$, and $h_3 = 0.001$.

Appendix B Definition of variables

B.1 Variables from implied volatility surface

Variable name	Short name	Availability	Definition
Global level	level	1996m1-2023m12	Average implied volatilities on the global volatility surface
Global slope	slope	1996m1-2023m12	Coefficient on delta when regressing implied volatilities of the global volatility surface on delta and log. days to maturity
Global term structure	term	1996m1-2023m12	Coefficient on log days to maturity when regressing implied volatilities of the global volatility surface on delta and log. days to maturity
Global convexity	convex	1996m1-2023m12	Convexity measure of the global volatility surface according to Equation (3), averaged across all maturities
Convexity left	convex_left	1996m1-2023m12	Convexity left of the global volatility surface according to Equation (8), averaged across all maturities
Convexity right	convex_right	1996m1-2023m12	Convexity left of the global volatility surface according to Equation (9), averaged across all maturities
USA level	usa_level	1996m1-2023m12	Average implied volatilities on the USA volatility surface
USA slope	usa_slope	1996m1-2023m12	Coefficient on delta when regressing implied volatilities of the USA volatility surface on delta and log. days to maturity
USA term structure	usa_term	1996m1-2023m12	Coefficient on log days to maturity when regressing implied volatilities of the USA volatility surface on delta and log. days to maturity
USA convexity	usa_convex	1996m1-2023m12	Convexity measure of the USA volatility surface according to Equation (3), averaged across all maturities

B.2 Equity premium predictors from the literature

Variable name	Short name	Availability	Definition
SVIX index	svix	1996m1-2023m12	Monthly equity premium lower bound proposed by Martin (2017)
Variance risk premium	vrp	1990m1-2023m12	Model free implied variance minus the variance of the market from Bollerslev, Tauchen, and Zhou (2009)
Left tail volatility	ltv	1996m1-2023m12	Left tail volatility estimated from short-term put options from Bollerslev, Todorov, and Xu (2015)
Dividend price ratio	div_prc	1871m1-2023m12	Dividend to price ratio of S&P 500 firms
Dividend yield	div_yield	1872m1-2023m12	Dividend yield of S&P 500 firms
Earnings price ratio	earn_prc	1871m1-2023m12	Earnings to price ratio of S&P 500 firms
Dividend payout ratio	div_pay	1871m1-2023m12	Dividend to earnings ratio
S&P 500 Var	svar	1885m2-2023m12	Sum of squared daily returns on the S&P 500
DJIA Book-to-market	bm	1921m3-2023m12	Book-to-market of Dow Jones Industrial Average stocks
Equity issuance	ntis	1926m12-2023m12	Ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization
T-bill yield	tbill	1986m1-2023m12	Treasury bill yield
Long-term gov. yield	lty	1919m1-2023m12	Yield of long-term government bond
Long-term bond return	ltr	1926m1-2023m12	Return of long-term government bond
Treasury term spread	tms	1920m1-2023m12	Difference in yield between long-term and short-term government bond
AAA bond yield	AAA	1919m1-2023m12	Yield of AAA corporate bond
BAA bond yield	BAA	1919m1-2023m12	Yield of BAA corporate bond
BAA-AAA yield	dfy	1919m1-2023m12	Difference in yield between BAA and AAA corporate bond
BAA-AAA return	dfr	1926m1-2023m12	Difference in return between BAA and AAA corporate bond
Corporate bond return	corpr	1926m1-2023m12	Return of corporate bond
Inflation	infl	1913m2-2023m12	CPI Inflation rate
Average correlation	avgcor	1926m3-2023m12	Average correlation of daily stock returns proposed by Pollet and Wilson (2010)
Disagreement	disag	1981m12-2023m12	Analyst forecast disagreements from Yu (2011)
Dow 52-week high	dtoy	1926m1-2023m12	Nearness to Dow 52-week high from Li and Yu (2012)
Dow historical high	dtoat	1926m1-2023m12	Nearness to the Dow historical high from Li and Yu (2012)
B/M factor	fbm	1926m6-2023m12	Kelly and Pruitt (2013) extracts a factor from the cross-section of B/M ratios
Illiquidity	lzrt	1926m1-2023m12	An illiquidity factor from Chen, Eaton, and Paye (2018)
Durable goods	ndrbl	1958m2-2023m12	New orders to shipments of durable goods from Jones and Tuzel (2013)
Output gap	output_gap	1926m1-2023m12	Estimated industrial production output gap from Cooper and Priestley (2009)
Return dispersion	rdsp	1926m7-2023m12	Cross-sectional dispersion of stock returns from Maio (2016)
Stock skewness	skvw	1926m7-2023m12	Average stock skewness proposed by Jondeau, Zhang, and Zhu (2019)
Optimal sentiment	hjtz_sentiment	1965m7-2023m12	Investor sentiment index optimized for return prediction by Huang, Jiang, Tu, and Zhou (2015)
Optimal sentiment	hjtz_sent_orth	1965m7-2023m12	Huang, Jiang, Tu, and Zhou (2015) sentiment orthogonalized to macro variables
Short-interest	short_int_is	1973m1-2023m12	In-sample detrended aggregate short interest from Rapach, Ringgenberg, and Zhou (2016)
Short-interest	short_int_oos	1978m1-2023m12	Out-of-sample detrended aggregate short interest from Rapach, Ringgenberg, and Zhou (2016)
Cross-section tail risk	tail	1926m7-2023m12	Tail risk estimated from the cross-section of firm-level price crashes by Kelly and Jiang (2014)
Technical indicators	tchi	1951m1-2023m12	A combination of technical indicators from Neely, Rapach, Tu, and Zhou (2014)
Oil price changes	wtexas	1926m1-2023m12	Changes in oil price from Driesprong, Jacobsen, and Maat (2008)
Stock-bond yield gap	ygap	1953m4-2023m12	Stock-bond yield gap from Maio (2013)
Public investment	govik	1947m4-2023m12	Public sector investment proposed by Belo and Yu (2013)
Consumption	consumption	1954m1-2023m12	Cyclical component of aggregate consumption proposed by Atanasov, Møller, and Priestley (2020)
Credit standards	crdstd	1990m7-2023m12	Loan officer credit standards from Chava, Gallmeyer, and Park (2015)
Housing consumption	house	1930m1-2023m12	Share of housing in consumption from Piazzesi, Schneider, and Tuzel (2007)
Year-end growth PCE	gpce	1948m1-2023m12	Personal consumption growth near year-end from Møller and Rangvid (2015)
Year-end growth IP	gip	1927m1-2023m12	Industrial production growth near year-end from Møller and Rangvid (2015)
Aggregate accruals	accrul	1966m1-2023m12	Aggregate accruals from Hirshleifer, Hou, and Teoh (2009)
Aggregate cash flow	cfacc	1966m1-2023m12	Aggregate cash flows from Hirshleifer, Hou, and Teoh (2009)
Past return 1 month	usa_1mon_ret	1927m6:2023m12	1-month S&P 500 return from Rapach, Strauss, and Zhou (2013)

B.3 Additional macroeconomic state variables

Variable name	Short name	Availability	Definition
S&P500 Vol	sp500_sd	1990m1:2023m12	Volatility of daily returns of S&P 500 index
VIX index	vix	1990m1:2023m12	CBOE VIX index
TED spread	tedrate	1986m1:2023m12	TED spread: 3 month Libor minus T-bill rate
Libor	libor	1986m1:2023m12	3 month LIBOR rate
Past return 6 month	usa_6mon_ret	1926m12:2023m12	6-month S&P 500 return
Past return 12 month	usa_12mon_ret	1927m6:2023m12	12-month S&P 500 return
Treasury noise	noise	1987m1:2023m12	Residual errors from fitted Treasury yield curve, proposed by Hu, Pan, and Wang (2013)
Sentiment	bw_sentiment	1965m7:2023m12	Baker and Wurgler (2006) sentiment index
Orthogonal sentiment	bw_sentiment_orth	1965m7:2023m12	Baker and Wurgler (2006) sentiment index orthogonalized to macro variables
Capital ratio	capital_ratio	1970m1:2023m12	Capital ratio of financial intermediaries constructed by He, Kelly, and Manela (2017)
Capital factor	capital_factor	1970m1:2023m12	Capital ratio factor of financial intermediaries constructed by He, Kelly, and Manela (2017)
CBOE Skew	cboe_skew	1990m1:2023m12	CBOE SKEW Index, estimates the skewness of S&P 500 returns
Financial stress	sl_fin_stress	1993m12:2023m12	St. Louis Fed Financial Stress Index

Appendix C Derivation of the convexity equation

This section derives Equation (3).

The delta grid points on the surface are from 0.1 to 0.9 at 0.05 increments. This means there are 64 triplets of $(\Delta_i, \Delta_j, \Delta_k)$ with $\Delta_i < \Delta_k$ and $\Delta_j = (\Delta_i + \Delta_k)/2$. The 64 triplets are:

$\Delta_i = .10, (\Delta_j, \Delta_k) = (.15, .2), (.2, .3), (.25, .4), (.3, .5), (.35, .6), (.4, .7), (.45, .8), (.5, .9)$

$\Delta_i = .15, (\Delta_j, \Delta_k) = (.2, .25), (.25, .35), (.3, .45), (.35, .55), (.4, .65), (.45, .75), (.5, .85)$

$\Delta_i = .20, (\Delta_j, \Delta_k) = (.25, .3), (.3, .4), (.35, .5), (.4, .6), (.45, .7), (.5, .8), (.55, .9)$

$\Delta_i = .25, (\Delta_j, \Delta_k) = (.3, .35), (.35, .45), (.4, .55), (.45, .65), (.5, .75), (.55, .85)$

$\Delta_i = .30, (\Delta_j, \Delta_k) = (.35, .4), (.4, .5), (.45, .6), (.5, .7), (.55, .8), (.6, .9)$

$\Delta_i = .35, (\Delta_j, \Delta_k) = (.4, .45), (.45, .55), (.5, .65), (.55, .75), (.6, .85)$

$\Delta_i = .40, (\Delta_j, \Delta_k) = (.45, .5), (.5, .6), (.55, .7), (.6, .8), (.65, .9)$

$\Delta_i = .45, (\Delta_j, \Delta_k) = (.5, .55), (.55, .65), (.6, .75), (.65, .85)$

$\Delta_i = .50, (\Delta_j, \Delta_k) = (.55, .6), (.6, .7), (.65, .8), (.7, .9)$

$\Delta_i = .55, (\Delta_j, \Delta_k) = (.6, .65), (.65, .75), (.7, .85)$

$\Delta_i = .60, (\Delta_j, \Delta_k) = (.65, .7), (.7, .8), (.75, .9)$

$\Delta_i = .65, (\Delta_j, \Delta_k) = (.7, .75), (.75, .85)$

$\Delta_i = .70, (\Delta_j, \Delta_k) = (.75, .8), (.8, .9)$

$\Delta_i = .75, (\Delta_j, \Delta_k) = (.8, .85)$

$\Delta_i = .80, (\Delta_j, \Delta_k) = (.85, .9)$

We count how many times each delta point appears as Δ_i, Δ_j, or Δ_k from the above equation.

	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9
Δ_i	8	7	7	6	6	5	5	4	4	3	3	2	2	1	1	0	0
Δ_j	0	1	2	3	4	5	6	7	8	7	6	5	4	3	2	1	0
Δ_k	0	0	1	1	2	2	3	3	4	4	5	5	6	6	7	7	8

Since our definition of convexity is

$$C(\tau) = \frac{1}{64} \sum_{(i,j,k)} \frac{V(\Delta_i, \tau) + V(\Delta_k, \tau)}{2} - V(\Delta_j, \tau)$$

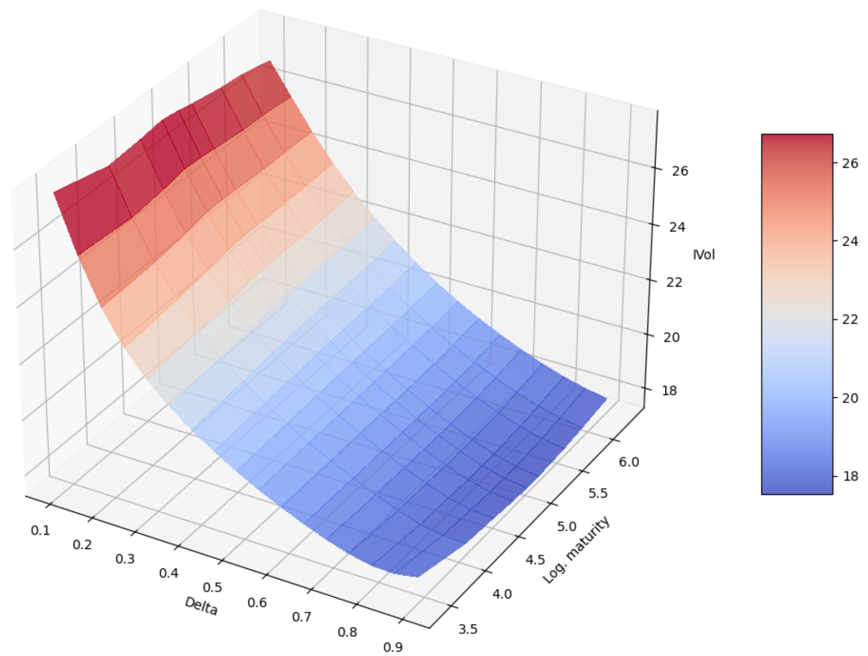
For every $(\Delta_i, \Delta_j, \Delta_k)$, the coefficient of Δ_i and Δ_k is 1/2 divided by 64 and the coefficient of Δ_j is 1 divided by 64. Adding up these coefficients, we have

$$\begin{aligned} C(\tau) = \frac{1}{64}[&4V(0.1,\tau) + 2.5V(0.15,\tau) + 2V(0.2,\tau) + 0.5V(0.25,\tau) - 1.5V(0.35,\tau) \\ &- 2V(0.4,\tau) - 3.5V(0.45,\tau) - 4V(0.5,\tau) - 3.5V(0.55,\tau) - 2V(0.6,\tau) \\ &- 1.5V(0.65,\tau) + 0.5V(0.75,\tau) + 2V(0.8,\tau) + 2.5V(0.85,\tau) + 4V(0.9,\tau)]. \end{aligned}$$

Figure 1: Global implied volatility surface

The figure plots the unconditional global implied volatility surface and residual global implied volatility surface. The residual surface plots the residuals from regressing implied volatilities on the deltas and the log. of days to maturity.

Panel A: Global implied volatility surface



Panel B: Residual global implied volatility surface

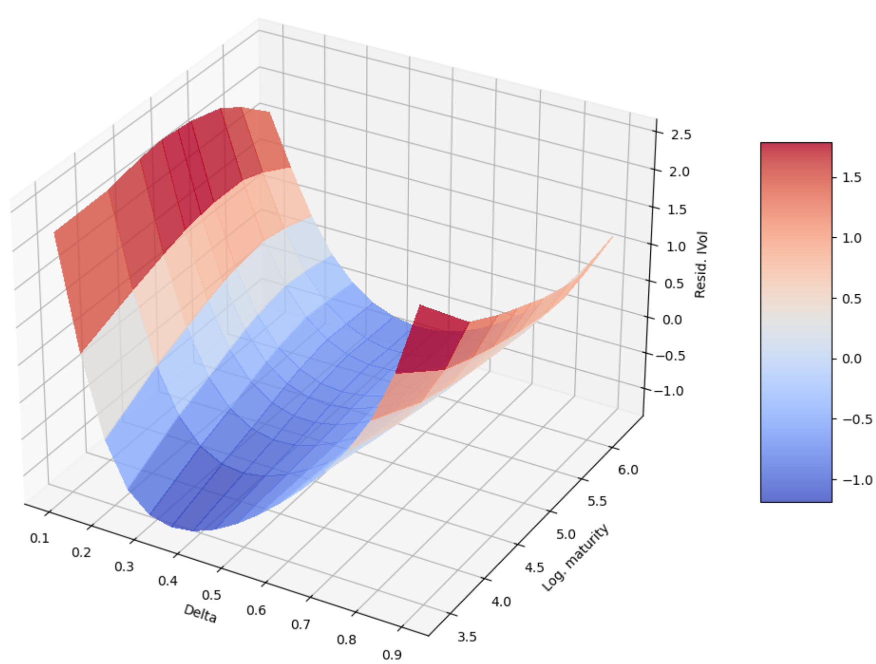


Figure 2: Level, slope, term and convexity of the implied volatility surface

The figure plots the level, slope, term structure, and convexity of global and US implied volatility surface.

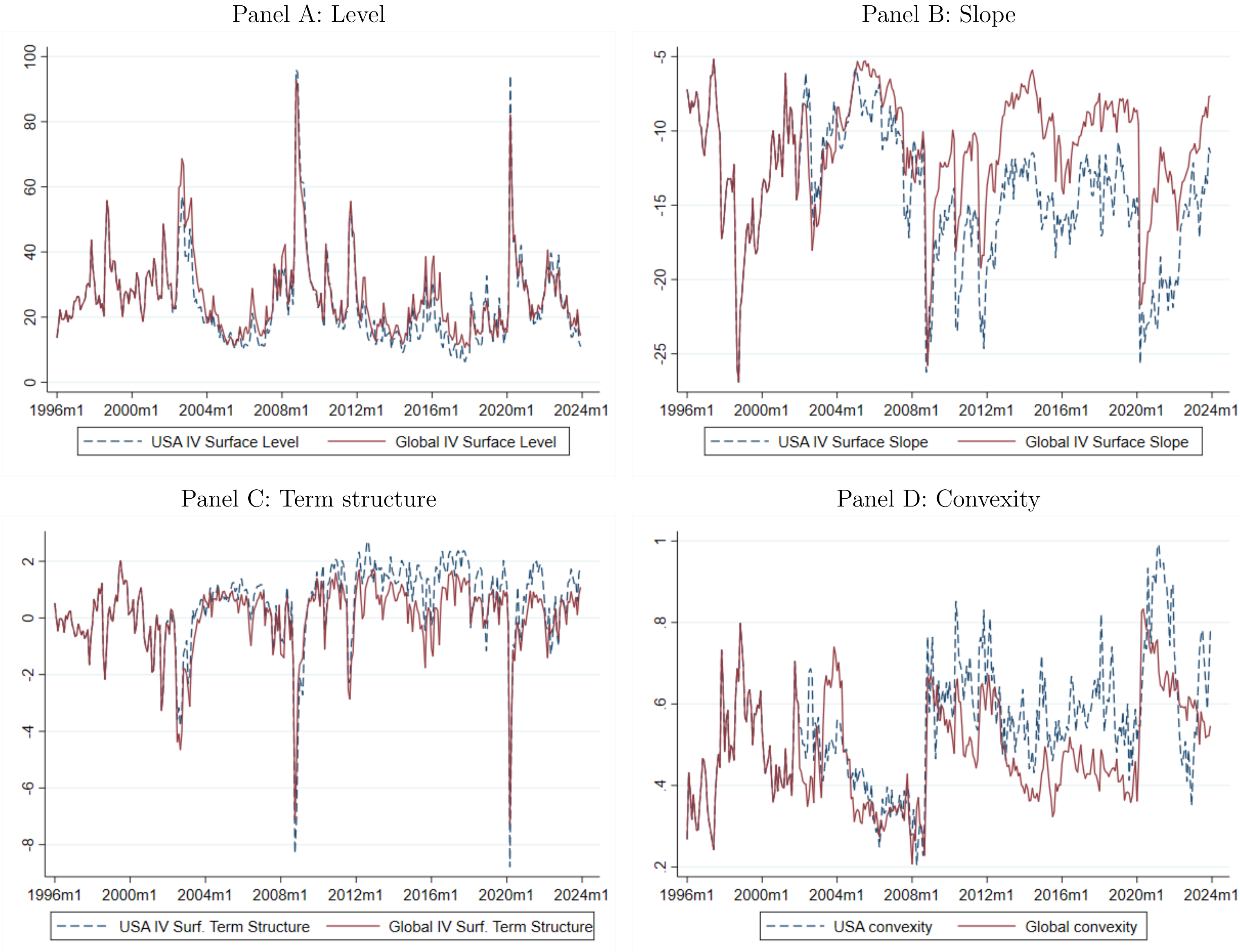


Figure 3: Predicting USA equity return

The figure plots the forward-looking semi-annual S&P 500 returns from month $t + 1$ to $t + 6$ against their predicted values based on the global convexity in month t.

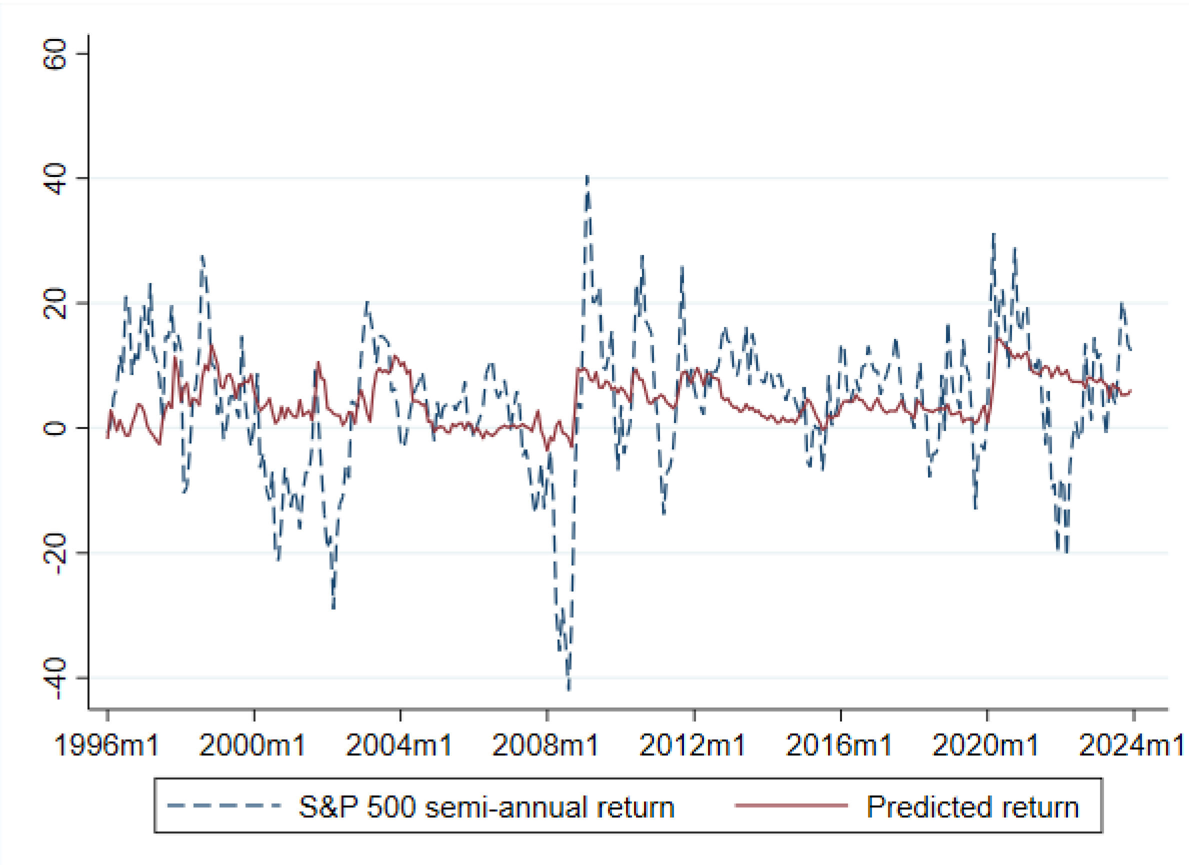


Figure 4: Predicted increase in return and Global Financial Cycle beta

The figure plots the percentage increase in each asset's return in month $t+1$ for 1 standard deviation increase in global convexity in month t. The x-axis is the beta of the asset with respect to the Miranda-Agrippino and Rey (2020) Global Financial Cycle factor. The sample period is from 1996 to 2023. The triangles indicate the 18 equity indexes. The diamonds indicate the spot rate returns of 10 currencies (against the US dollar). The line fitted through all test assets has a slope of 5.67 (t-statistic: 3.10), a constant of -0.03 (t-statistic: -0.33), and an R^2 of 76%.

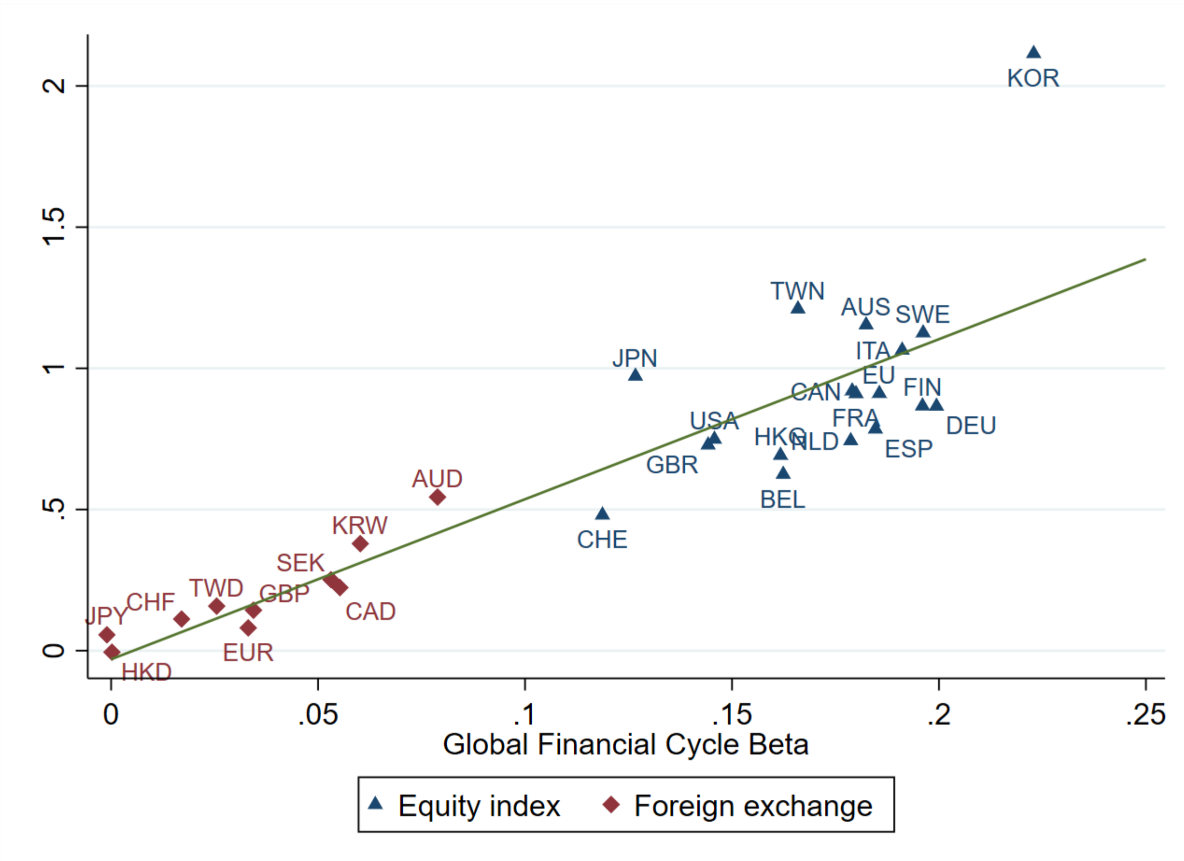


Figure 5: Global convexity left and global convexity right indexes

This figure plots global convexity left index and global convexity right index. The convexity right index is orthogonalized to the convexity left index. The sum of the two indexes is the global convexity index.

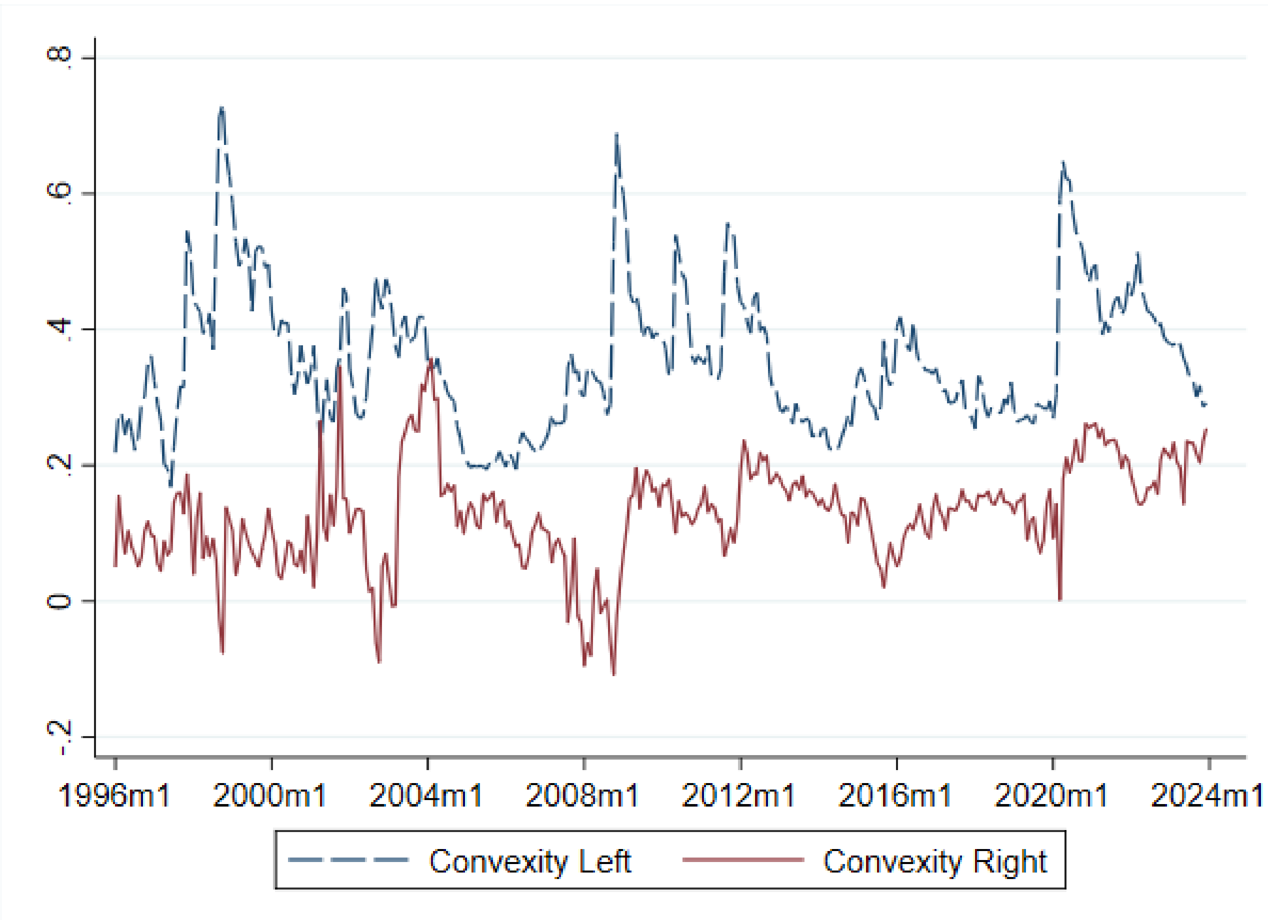


Table 1: list of index options in our sample

This table lists the availability of index options from each country or region in our sample. This table also lists the underlying market index in each region and the major exchanges from which option prices are obtained. The last column shows the average number of available options in each region per day.

Country / Region	Short Name	Market Index	Main Exchange	Start	Finish	Num. Obs./Day
Australia	AUS	S&P/ASX 200	Australia Futures and Options	1/2/2004	12/29/2023	1110
Belgium	BEL	BEL 20	Euronext Brussels	1/2/2002	12/29/2023	177
Canada	CAN	S&P/TSX 60	Montreal Exchange	3/26/2007	12/29/2023	343
Switzerland	CHE	SMI	EUREX Frankfurt	1/2/2002	12/29/2023	1178
Germany	DEU	DAX	EUREX Frankfurt	1/2/2002	12/29/2023	1716
Spain	ESP	IBEX 35	Mercado Espanol de Futuros	10/11/2006	12/29/2023	1575
Europe	EUR	STOXX 50	EUREX Frankfurt	1/2/2002	12/29/2023	2501
Finland	FIN	HELSINKI 25	EUREX Frankfurt	1/2/2002	12/29/2023	303
France	FRA	CAC 40	Euronext Paris	4/14/2003	12/29/2023	812
United Kingdom	GBR	FTSE 100	Euronext London	1/2/2002	12/29/2023	1754
Hong Kong	HKG	HANG SENG	Hong Kong Futures Exchange	1/3/2006	12/29/2023	1346
Italy	ITA	MIB	Mercato Derivati Milano	10/10/2006	12/29/2023	770
Japan	JPN	NIKKEI 225	Osaka Day Session	5/6/2004	12/29/2023	1808
Korea	KOR	KOSPI 200	Korea Futures Market	5/3/2004	12/28/2023	475
Netherlands	NLD	AEX	Euronext Amsterdam	1/2/2002	12/29/2023	582
Sweden	SWE	OMXS30	Stockholmborsen Options Market	5/14/2007	12/29/2023	647
Taiwan	TWN	TAIEX	Taiwan Futures Exchange	1/2/2004	12/29/2023	310
United States	USA	S&P 500	National Best BidOffer	1/4/1996	12/29/2023	4858

Table 2: Global implied volatility surface

This table reports the average implied volatility in Panel A and the average residual implied volatility in Panel B at each delta-maturity grid point on the global implied volatility surface. In Panel A, we first take the average implied volatility at each grid point across all available countries and regions in a given month and then take the average across time. In Panel B, we first estimate the residuals of a linear regression model by regressing the implied volatilities on the adjusted delta and the logarithm of days until maturity within a country or region in each month. We then take the average residual implied volatilities across available countries and regions at each grid point in a given month. Lastly, we take the average across time. The sample period is from 1996m1 to 2023m12.

Panel A: Unconditional surface										
	Maturity (days)									
Delta	30	60	91	122	152	182	273	365	547	Avg.
0.10	27.8	27.3	27.4	27.5	27.4	27.3	27.1	27.0	26.8	27.3
0.15	25.9	25.7	25.9	26.0	26.0	25.9	25.8	25.8	25.7	25.8
0.20	24.3	24.4	24.5	24.7	24.7	24.7	24.6	24.6	24.6	24.6
0.25	23.1	23.3	23.4	23.6	23.6	23.6	23.6	23.6	23.6	23.5
0.30	22.2	22.4	22.6	22.7	22.7	22.7	22.7	22.8	22.8	22.6
0.35	21.5	21.7	21.8	21.9	22.0	22.0	22.0	22.0	22.1	21.9
0.40	20.9	21.1	21.2	21.2	21.3	21.3	21.3	21.4	21.4	21.2
0.45	20.4	20.5	20.6	20.7	20.7	20.7	20.7	20.8	20.8	20.7
0.50	20.0	20.0	20.1	20.1	20.1	20.2	20.2	20.2	20.3	20.1
0.55	19.5	19.6	19.6	19.6	19.6	19.7	19.7	19.7	19.8	19.7
0.60	19.2	19.2	19.2	19.2	19.2	19.2	19.3	19.3	19.4	19.2
0.65	18.8	18.8	18.8	18.8	18.8	18.8	18.8	18.9	19.0	18.8
0.70	18.5	18.5	18.4	18.4	18.4	18.4	18.5	18.6	18.7	18.5
0.75	18.3	18.1	18.1	18.1	18.1	18.1	18.2	18.2	18.4	18.2
0.80	18.1	17.9	17.8	17.8	17.8	17.8	17.9	18.0	18.2	17.9
0.85	18.1	17.7	17.7	17.6	17.6	17.6	17.7	17.8	18.0	17.7
0.90	18.2	17.7	17.6	17.5	17.5	17.5	17.5	17.6	17.8	17.7
Avg.	20.9	20.8	20.9	20.9	20.9	20.9	20.9	21.0	21.0	

Panel B: Residual surface										
	Maturity (days)									
Delta	30	60	91	122	152	182	273	365	547	Avg.
0.10	2.4	1.9	2.0	2.1	2.0	1.8	1.6	1.5	1.3	1.8
0.15	1.1	0.9	1.0	1.1	1.1	1.0	0.9	0.9	0.7	1.0
0.20	0.1	0.1	0.3	0.4	0.4	0.4	0.3	0.3	0.2	0.3
0.25	-0.5	-0.4	-0.3	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.2
0.30	-0.9	-0.7	-0.6	-0.5	-0.5	-0.4	-0.5	-0.5	-0.4	-0.5
0.35	-1.0	-0.9	-0.8	-0.7	-0.7	-0.6	-0.7	-0.6	-0.6	-0.7
0.40	-1.0	-0.9	-0.9	-0.8	-0.8	-0.8	-0.8	-0.7	-0.7	-0.8
0.45	-1.0	-0.9	-0.9	-0.8	-0.8	-0.8	-0.8	-0.8	-0.7	-0.8
0.50	-0.9	-0.8	-0.8	-0.8	-0.8	-0.8	-0.8	-0.7	-0.7	-0.8
0.55	-0.7	-0.7	-0.7	-0.7	-0.7	-0.7	-0.7	-0.7	-0.6	-0.7
0.60	-0.5	-0.6	-0.6	-0.6	-0.6	-0.6	-0.6	-0.5	-0.4	-0.5
0.65	-0.3	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.2	-0.4
0.70	0.0	-0.1	-0.2	-0.2	-0.2	-0.2	-0.2	-0.1	0.0	-0.2
0.75	0.3	0.1	0.1	0.0	0.0	0.0	0.0	0.1	0.3	0.1
0.80	0.7	0.4	0.3	0.3	0.3	0.3	0.3	0.4	0.6	0.4
0.85	1.2	0.8	0.7	0.7	0.6	0.6	0.7	0.8	0.9	0.8
0.90	1.9	1.4	1.2	1.1	1.1	1.1	1.1	1.2	1.4	1.3
Avg.	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

Table 3: Summary statistics of option based predictors

This table shows the summary statistics of various option-based measures in Panel A and their pairwise correlation in Panel B. The sample period is from 1996m1 to 2023m12. Appendix and the main text contain detailed description of each variable.

Panel A: summary statistics

	count	mean	median	sd	min	max	skewness	kurtosis
Global convexity	336	0.48	0.46	0.13	0.21	0.83	0.41	2.45
US convexity	336	0.54	0.53	0.15	0.20	0.99	0.42	3.13
Global level	336	20.91	20.07	5.74	12.29	49.89	1.57	6.89
Global slope	336	-0.11	-0.11	0.04	-0.27	-0.05	-1.07	4.43
Global term structure	336	0.05	0.34	1.24	-7.30	2.04	-2.33	11.60
VIX index	336	20.36	19.14	7.86	10.13	62.67	1.91	9.11
SVIX index	336	4.23	3.31	3.90	0.92	32.65	3.92	24.52
Variance risk premium (VRP)	336	14.61	12.77	31.60	-403.40	115.85	-7.78	101.49
Left-tail volatility (LTV)	336	8.08	7.37	3.20	2.39	25.65	1.69	7.21

Panel B: correlation matrix

	G. convex	US convex	Level	Slope	Term	VIX	SVIX	VRP	LTV
Global convexity	100%	73%	43%	-67%	-9%	42%	34%	16%	63%
US convexity	73%	100%	23%	-46%	0%	23%	19%	11%	65%
Global level	43%	23%	100%	-82%	-71%	93%	88%	-2%	62%
Global slope	-67%	-46%	-82%	100%	50%	-80%	-72%	-5%	-70%
Global term structure	-9%	0%	-71%	50%	100%	-80%	-81%	29%	-49%
VIX index	42%	23%	93%	-80%	-80%	100%	96%	-12%	73%
SVIX index	34%	19%	88%	-72%	-81%	96%	100%	-27%	72%
Variance risk premium (VRP)	16%	11%	-2%	-5%	29%	-12%	-27%	100%	-13%
Left-tail volatility (LTV)	63%	65%	62%	-70%	-49%	73%	72%	-13%	100%

Table 4: Predicting semi-annual USA equity premium

This table shows predictive regressions. The y-variables are 6-month cumulative excess returns of the S&P500 index in percentage points from month $t+1$ to $t+6$. The x-variables are standardized option-based predictors in month t. The sample period of predictors is from 1996m1 to 2023m12. To save space, we only report the coefficients of predictors. Standard errors are Newey-West standard errors with 6 lags of autocorrelations. The t-statistics are reported in parentheses. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: univariate regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Global convex	US convex	G. Level	G. Slope	G. Term	VIX	SVIX	VRP	LTV
Predictor Coef.	3.66***	3.17**	1.36	-2.06**	-0.66	1.56	1.73	0.97	2.69**
	(2.96)	(2.25)	(1.18)	(-2.30)	(-0.63)	(1.39)	(1.50)	(0.58)	(2.28)
Obs.	336	336	336	336	336	336	336	336	336
R^2	0.107	0.080	0.015	0.034	0.003	0.019	0.024	0.007	0.057

Panel B: multivariate regressions

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Global convex	2.88***	3.78**	4.13**	3.63***	3.65**	3.47**	3.59***	3.26**
	(2.70)	(2.44)	(2.25)	(2.87)	(2.43)	(2.44)	(2.86)	(2.43)
US convex	1.06							
	(0.76)							
Global Level		-0.28						
		(-0.20)						
Global Slope			0.70					
			(0.48)					
Global Term				-0.33				
				(-0.35)				
VIX					0.02			
					(0.02)			
SVIX						0.55		
						(0.47)		
VRP							0.40	
							(0.32)	
LTV								0.62
								(0.50)
Obs.	336	336	336	336	336	336	336	336
R^2	0.111	0.107	0.109	0.107	0.107	0.109	0.108	0.108

Table 5: Predicting monthly USA equity premium

This table shows predictive regressions. The y-variables are 1-month excess returns of the S&P500 index in percentage points in month $t+1$. The x-variables are standardized option-based predictors in month t. The sample period of predictors is from 1996m1 to 2023m12. To save space, we only report the coefficients of predictors. Standard errors are Newey-West standard errors with 1 lag of autocorrelations. The t-statistics are reported in parentheses. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: univariate regressions

VARIABLES	(1) Global convex	(2) US convex	(3) Level	(4) Slope	(5) Term	(6) VIX	(7) SVIX	(8) VRP	(9) LTV
Predictor Coef.	0.75***	0.50**	0.20	-0.43	-0.24	0.31	0.28	0.14	0.30
	(2.88)	(2.08)	(0.53)	(-1.46)	(-0.63)	(0.79)	(0.61)	(0.22)	(0.84)
Obs.	336	336	336	336	336	336	336	336	336
R^2	0.028	0.013	0.002	0.009	0.003	0.005	0.004	0.001	0.005

Panel B: multivariate regressions

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Global convex	0.82**	0.82**	0.84**	0.73***	0.75**	0.74**	0.74***	0.93**
	(2.38)	(2.51)	(2.13)	(2.77)	(2.32)	(2.44)	(2.64)	(2.54)
US convex	-0.09							
	(-0.30)							
Global Level		-0.16						
		(-0.37)						
Global Slope			0.13					
			(0.30)					
Global Term				-0.17				
				(-0.46)				
VIX					-0.00			
					(-0.01)			
SVIX						0.03		
						(0.06)		
VRP							0.02	
							(0.04)	
LTV								-0.28
								(-0.63)
Obs.	336	336	336	336	336	336	336	336
R^2	0.028	0.029	0.028	0.029	0.028	0.028	0.028	0.030

Table 6: Predicting k-period ahead monthly US equity premium

This table shows predictive regressions. The y-variables are 1-month excess returns of the S&P500 index in percentage points in month $t+k$ with $k = 1, 2, 3, ..., 12$. The x-variables are standardized global and USA convexity in month t. The sample period of predictors is from 1996m1 to 2023m12. Standard errors are Newey-West standard errors with 1 lag of autocorrelations. The t-statistics are reported in parentheses. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: global convexity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	monthly S&P 500 excess return in month t+k											
VARIABLES	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12
Global convex$_t$	0.75***	0.67***	0.61**	0.67***	0.50**	0.45*	0.40	0.14	-0.05	0.31	0.31	0.15
	(2.88)	(2.63)	(2.46)	(2.82)	(2.11)	(1.89)	(1.53)	(0.51)	(-0.17)	(1.19)	(1.26)	(0.64)
Obs.	336	336	336	336	336	336	336	336	336	336	336	336
R^2	0.028	0.022	0.019	0.022	0.012	0.010	0.008	0.001	0.000	0.005	0.005	0.001

Panel B: USA convexity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	monthly S&P 500 excess return in month t+k											
VARIABLES	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+11	t+12
USA convex$_t$	0.50**	0.61**	0.52**	0.53**	0.58**	0.51*	0.38	0.10	0.06	0.31	0.19	0.05
	(2.08)	(2.33)	(2.05)	(2.25)	(2.21)	(1.87)	(1.45)	(0.36)	(0.20)	(1.05)	(0.70)	(0.19)
Obs.	336	336	336	336	336	336	336	336	336	336	336	336
R^2	0.013	0.019	0.013	0.014	0.017	0.013	0.007	0.000	0.000	0.005	0.002	0.000

Table 7: Predicting monthly equity premium around the world

This table shows predictive regressions. The y-variables in columns 1 to 17 are 1-month excess returns of various indexes in percentage points in month $t+1$. The y-variable in column 18 is the monthly change in the level of Miranda-Agrippino and Rey (2020) Global Financial Cycle factor in month $t+1$. The x-variables are standardized global convexity in month t. The sample period of predictors is from 1996m1 to 2023m12. Standard errors are Newey-West standard errors with 1 lag of autocorrelations. The t-statistics are reported in parentheses. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	AUS	BEL	CAN	CHE	DEU	ESP	EUR	FIN	FRA
Global convex$_t$	1.15***	0.62	0.92***	0.48*	0.87**	0.78**	0.91**	0.87**	0.91***
	(3.20)	(1.62)	(2.77)	(1.77)	(2.19)	(2.00)	(2.49)	(2.14)	(2.59)
Obs.	336	336	336	336	336	336	336	336	336
R^2	0.035	0.011	0.025	0.010	0.017	0.013	0.021	0.016	0.022

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
VARIABLES	GBR	HKG	ITA	JPN	KOR	NLD	SWE	TWN	Global Fin. Cycle
Global convex$_t$	0.73**	0.69*	1.06**	0.97***	2.11***	0.74*	1.13***	1.21***	0.05***
	(2.56)	(1.70)	(2.59)	(3.08)	(3.68)	(1.91)	(2.88)	(2.81)	(2.73)
Obs.	336	336	312	336	336	336	336	336	336
R^2	0.024	0.010	0.021	0.032	0.044	0.015	0.028	0.028	0.028

Table 8: Out-of-sample predictive R^2

This table reports the OOS R2 of predicting monthly and semi-annual stock returns in different countris and regions. The last row reports the OOS R2 of predicting the monthly and semi-annual change in Miranda-Agrippino and Rey (2020) Global Financial Cycle factor. The predictor is the global convexity index in columns 1 and 2 and USA convexity index in columns 3 and 4. The OOS R2 is computed as

$$R^2_{OOS} = 1 - \frac{MSE_A}{MSE_N}$$

where MSE_A is the mean squared error of the predictive model based on a given predictor and MSE_N is the mean squared error of the historical mean model. The testing period is from 2006m1 to 2023m12. Predictions in the first month of the testing period are based on the training data from 1996m1 to 2005m12. Predictions in each subsequent month are based on the training data from 1996m1 to the month prior to testing (i.e., the training data is updated on an expanding window basis).

	(1)	(2)	(3)	(4)
	Global Convexity		USA Convexity	
Country	1-month return	6-month return	1-month return	6-month return
USA	2.9%	12.0%	1.0%	6.8%
AUS	3.6%	7.6%	-0.1%	-2.8%
BEL	0.9%	2.8%	-2.4%	-9.9%
CAN	2.5%	8.2%	-0.7%	-0.6%
CHE	1.2%	4.2%	-1.2%	-6.0%
DEU	1.9%	3.8%	-1.0%	-7.2%
ESP	1.1%	-0.1%	-0.8%	-7.9%
EUR	2.2%	6.5%	-0.5%	-4.6%
FIN	1.3%	3.3%	-0.8%	-5.6%
FRA	2.3%	9.4%	-0.4%	-2.6%
GBR	2.6%	9.4%	-0.3%	-3.1%
HKG	0.4%	-3.4%	-0.8%	-10.1%
ITA	10.6%	6.7%	8.8%	-2.8%
JPN	2.8%	9.5%	1.0%	-0.9%
KOR	2.8%	6.3%	-5.3%	-23.1%
NLD	1.7%	4.7%	-1.1%	-7.2%
SWE	3.3%	9.6%	0.2%	-3.3%
TWN	2.7%	9.1%	1.0%	1.4%
Average	2.1%	6.1%	-0.7%	-5.0%
Global Financial Cycle	2.8%	10.6%	-0.2%	-0.8%

Table 9: Global convexity vs. local convexity and global financial cycle

This table shows predictive regressions. The y-variables are 1-month excess returns of various indexes in percentage points in month $t+1$. In Panel A, the x-variables standardized global convexity index and own-country convexity index in month t. In Panel B, the x-variables standardized global convexity index in month t and change in the Miranda-Agrippino and Rey (2020) Global Financial Cycle factor in month $t+1$. The sample period varies depending on the index option availability with the longest sample period being 1996m1 to 2023m12. To save space, we only report the coefficients of predictors. Standard errors are Newey-West standard errors with 1 lag of autocorrelations. The t-statistics are reported in parentheses. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: controlling own country convexity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
VARIABLES	USA	AUS	BEL	CAN	CHE	DEU	ESP	EU	FIN	FRA	GBR	HKG	ITA	JPN	KOR	NLD	SWE	TWN
Global convex$_t$	0.82**	1.12***	0.64	1.15*	1.07***	1.86**	1.43**	1.52**	0.73	0.88*	0.81*	0.73	1.45	0.64	1.88***	1.31*	2.23***	0.85*
	(2.38)	(2.77)	(1.15)	(1.75)	(2.65)	(2.31)	(2.26)	(2.46)	(1.52)	(1.70)	(1.88)	(1.43)	(1.11)	(1.37)	(2.81)	(1.84)	(3.15)	(1.81)
Local convex$_t$	-0.09	0.26	0.42	0.81	-0.60	-1.07	-0.39	-0.75	0.11	0.19	0.13	-0.28	-0.06	0.08	-1.00	-0.21	-0.80	0.21
	(-0.30)	(0.44)	(0.93)	(1.56)	(-1.28)	(-1.35)	(-0.64)	(-1.13)	(0.27)	(0.52)	(0.34)	(-0.42)	(-0.05)	(0.21)	(-1.58)	(-0.30)	(-1.31)	(0.44)
Obs.	336	240	254	191	264	264	207	264	264	249	264	216	207	236	236	246	200	240
R^2	0.028	0.036	0.023	0.045	0.030	0.032	0.033	0.031	0.015	0.030	0.034	0.012	0.033	0.021	0.037	0.034	0.074	0.024

Panel B: controlling for global financial cycle

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
VARIABLES	USA	AUS	BEL	CAN	CHE	DEU	ESP	EU	FIN	FRA	GBR	HKG	ITA	JPN	KOR	NLD	SWE	TWN
Global convex$_t$	0.07	0.31*	-0.14	0.09	-0.07	-0.07	-0.08	0.05	-0.05	0.07	0.06	-0.07	-0.06	0.39*	1.10**	-0.09	0.21	0.45
	(0.66)	(1.72)	(-0.69)	(0.59)	(-0.40)	(-0.31)	(-0.34)	(0.26)	(-0.25)	(0.42)	(0.42)	(-0.25)	(-0.30)	(1.72)	(2.40)	(-0.51)	(1.08)	(1.35)
ΔGFC_{t+1}	0.15***	0.18***	0.16***	0.18***	0.12***	0.20***	0.18***	0.19***	0.20***	0.18***	0.14***	0.16***	0.19***	0.12***	0.22***	0.18***	0.20***	0.16***
	(26.88)	(26.81)	(17.66)	(28.90)	(13.68)	(20.35)	(20.24)	(22.05)	(20.13)	(21.41)	(24.88)	(12.11)	(20.90)	(15.79)	(13.86)	(17.30)	(18.58)	(15.70)
Obs.	336	336	336	336	336	336	336	336	336	336	336	336	312	336	336	336	336	336
R^2	0.695	0.585	0.744	0.488	0.683	0.552	0.688	0.637	0.672	0.733	0.432	0.579	0.428	0.392	0.663	0.664	0.411	0.820

Table 10: Cross-sectional asset pricing test with global financial cycle

This table performs several cross-sectional asset pricing tests. In Panel A, we regress the predicted increase in an asset's return on its GFC beta. The predicted increase and GFC beta are both estimated for each individual asset in the first-pass regression. The three groups of tests assets are the 18 equity indexes (column 1), 10 currencies (column 2), and both equities and currencies (column 3). In Panel B, we regress each asset's expected return on its GFC beta. The y-variable in Columns 1 to 3 is the full sample expected return. The y-variables in Columns 4 to 6 is the expected return when the global convexity in the prior month is above its full sample mean. The sample period is from 1996m1 to 2023m12. Standard errors are bootstrapped standard errors from 1,000 random samples of the data with replacement. The t-statistics are reported in parentheses. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Predicted change in return vs. GFC beta

	(1)	(2)	(3)
VARIABLES	Equity	Currency	Both
GFC beta	8.22***	5.73**	5.67***
	(2.86)	(2.13)	(3.10)
Constant	-0.49	-0.01	-0.03
	(-1.15)	(-0.11)	(-0.33)
Observations	18	10	28
R^2	0.391	0.839	0.764

Panel B: Expected return vs. the global financial cycle beta

	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample $E[R]$			High global convexity period		
VARIABLES	Equity	Currency	Both	Equity	Currency	Both
GFC beta	2.53	-0.31	3.90**	14.57***	7.96**	11.06***
	(0.98)	(-0.15)	(2.36)	(3.23)	(2.30)	(4.42)
Constant	0.14	0.01	-0.11	-0.84	-0.10	-0.23
	(0.42)	(0.09)	(-1.27)	(-1.31)	(-0.75)	(-1.63)
Observations	18	10	28	18	10	28
R^2	0.176	0.016	0.796	0.625	0.740	0.901

Table 11: Decompose global convexity into left and right components

We decompose the global convexity index into the left and right components. The details of the decomposition are in the text. We regress the right component on the left component and extract the residuals as the orthogonalized right convexity. Panel A reports the correlation of these measures. Panel B regresses the standardized left convexity and orthogonalized right convexity on standardized global slope, VIX, SVIX, and LTV. Standard errors are Newey-West standard errors with 1 lag of autocorrelations. The t-statistics are reported in parentheses. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Correlation matrix

	Global convexity	LMM	RMM	Convex Right
Global convexity	100%	82%	-45%	58%
Left-minus-center	82%	100%	-88%	0%
Right-minus-center	-45%	-88%	100%	47%
Convexity right	58%	0%	47%	100%

Panel B: Explain the left and right components

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES		Convexity left				Convexity Right		
Global slope	-0.97***				0.22***			
	(-55.90)				(3.13)			
VIX		0.73***				-0.30***		
		(10.94)				(-4.37)		
SVIX			0.64***				-0.32***	
			(6.02)				(-5.55)	
LTV				0.71***				0.10
				(15.22)				(1.01)
Constant	0.55***	1.50***	2.72***	1.50***	2.37***	2.51***	2.07***	1.47***
	(11.53)	(9.48)	(25.08)	(12.03)	(12.19)	(14.79)	(25.59)	(5.66)
Obs.	336	336	336	336	336	336	336	336
R^2	0.950	0.533	0.407	0.507	0.047	0.091	0.105	0.010

Table 12: Dissecting the information in convexity right index

This table reports the contemporaneous relationship between the orthogonalized right convexity and other state variables, which include the TED spread, short-interest, past 6-month S&P 500 return, global term structure, and output gap. These state variables are selected from LASSO regressions. Details of this procedure are in the text. We winsorize and standardize these state variables. Panel A reports the correlation matrix. Panel B reports the results of regression analysis. To save space, we omit the reporting of constants. Standard errors are Newey-West standard errors with 1 lag of autocorrelations. The t-statistics are reported in parentheses. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Correlation matrix

	Convex right	TED	Past Ret	O-gap	Term	Short
Convex right	100%	-56%	41%	-41%	39%	-40%
TED spread	-56%	100%	-33%	37%	-29%	35%
Past 6 month return	41%	-33%	100%	-11%	58%	-16%
Output gap	-41%	37%	-11%	100%	-8%	60%
Global term	39%	-29%	58%	-8%	100%	-15%
Short interest	-40%	35%	-16%	60%	-15%	100%

Panel B: Explain the orthogonalized right convexity

	(1)	(2)	(3)	(4)	(5)
VARIABLES			Convexity right		
TED spread	-0.56***	-0.47***	-0.38***	-0.36***	-0.35***
	(-10.72)	(-8.11)	(-6.03)	(-5.64)	(-5.25)
Past 6 month return		0.25***	0.25***	0.16**	0.15**
		(3.11)	(3.52)	(2.44)	(2.37)
Output gap			-0.24***	-0.25***	-0.19***
			(-4.10)	(-4.16)	(-3.00)
Global term				0.18**	0.17**
				(2.29)	(2.23)
Short interest					-0.11**
					(-1.97)
Obs.	336	336	336	336	336
R^2	0.308	0.365	0.417	0.437	0.445

Table 13: Predicting cash flow and discount rate news

We decompose the monthly S&P 500 returns into various components and test their predictability. We first estimate a proxy of the discount rate, $\hat{E}[R]$, by regressing monthly returns in month $t+1$ on a set of conditioning variables in month t, which include dividend price ratio, earnings price ratio, T-bill yield, SVIX, and LTV. We use the fitted values from this regression as a proxy of discount rate $\hat{E}[R]$. We then regress monthly returns on changes in $\hat{E}[R]$ to extract the discount rate (DR) news and cash flow (CF) news component of returns. The decomposition is specified in the following equation:

$$R_{t+1} = a + \underbrace{b \times \Delta\hat{E}[R_{t+1}]}_{\text{DR news}} + \underbrace{\epsilon_{t+1}}_{\text{CF news}}$$

Panels A, B, and C regress the monthly return in month $t+1$, the discount rate in month t, the discount rate news and cash flow news in month $t+1$ on the standardized month t global convexity, left convexity, and orthogonalized right convexity, respectively. Panel D regresses quarterly S&P 500 dividend growth rate in quarter $t+1$ and the quarterly changes in the average analyst forecast of long-term earnings growth rate on left and orthogonalized right convexity in quarter t. Dividend data is from Robert Shiller's website. We measure the average analyst forecast of US companies and non-US companies in the I/B/E/S dataset, separately. To save space, we omit the reporting of constants. Standard errors are Newey-West standard errors with 1 lag of autocorrelations. The t-statistics are reported in parentheses. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Global convexity

	(1)	(2)	(3)
VARIABLES	R_{t+1}	DR News	CF News
Global convex	0.75***	0.50***	0.25
	(2.88)	(3.44)	(1.22)
Obs.	336	335	335
R^2	0.028	0.034	0.005

Panel B: Global convexity left

VARIABLES	(1) R_{t+1}	(2) DR News	(3) CF News
Convex left	0.55**	0.57***	-0.02
	(1.99)	(4.31)	(-0.09)
Obs.	336	335	335
R^2	0.015	0.045	0.000

Panel C: Global convexity right

VARIABLES	(1) R_{t+1}	(2) DR News	(3) CF News
Convex right	0.52*	0.05	0.47**
	(1.69)	(0.35)	(2.12)
Obs.	336	335	335
R^2	0.013	0.000	0.017

Panel D: Predicting dividend and analysis forecast

	(1)	(2)	(3)
	S&P 500	Analyst forecast	
VARIABLES	Dividend growth	USA stocks	Non-USA stocks
Convex left	-0.13	0.03	-0.01
	(-1.36)	(0.37)	(-0.08)
Convex right	0.24***	0.14**	0.26***
	(2.64)	(2.09)	(2.75)
Lag. value	0.88***	0.72***	0.61***
	(10.01)	(6.43)	(6.02)
Obs.	112	112	112
R^2	0.831	0.575	0.487

Table 14: Robustness to alternative methodologies

This table reports the correlation of alternative measures of global convexity with the baseline measure and the return predictability of alternative measures of global convexity. We construct five different measures of global convexity. "OTM surface" means we measure convexity from OTM option surface. "Value weighted" means we take the value-weighted average of convexity measures from each country. "Δ^2 Coef." means that we regress implied volatilities on the squared delta term and use the regression coefficient as the convexity measure. "Individual option" means we measure convexity directly from individual options data without constructing the volatility surface. "ΔConvex" measures the annual change in the baseline convexity measure. The details of these alternative measures are in the text. To save space, we only report the coefficient of predictors. All predictors are standardized. Standard errors are Newey-West standard errors with 1 lag of autocorrelation in Panel B and 6 lags in Panel C. The t-statistics are reported in parentheses. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: correlation with baseline global convexity

	(1)	(2)	(3)	(4)	(5)
	OTM surface	Value weighted	Regression	Individual option	ΔConvex
Baseline	91.18%	87.39%	99.95%	74.23%	58.80%

Panel B: Predict semi-annual S&P 500 excess return

	(1)	(2)	(3)	(4)	(5)
VARIABLES	OTM surface	Value weighted	Regression	Individual option	ΔConvex
Predictor Coef.	3.78***	3.56***	3.69***	3.26**	3.51***
	(2.85)	(2.76)	(2.96)	(2.35)	(3.68)
Obs.	336	336	336	336	324
R^2	0.114	0.101	0.109	0.085	0.097

Panel C: Predict monthly S&P 500 excess return

	(1)	(2)	(3)	(4)	(5)
VARIABLES	OTM surface	Value weighted	Regression	Individual option	ΔConvex
Predictor Coef.	0.83***	0.62**	0.76***	0.80***	0.54**
	(3.03)	(2.41)	(2.93)	(3.27)	(1.98)
Obs.	336	336	336	336	324
R^2	0.034	0.019	0.029	0.032	0.014

Table 15: Top ten predictors

This table reports top 10 US equity premium and GFC predictors based on in-sample R^2 or out-of-sample R^2 from a list of 70 predictors. The complete list of predictors is in Appendix B. We compute in-sample R^2 based on the data from Jan 1996 to Dec 2023. We compute out-of-sample R^2 according to the formula

$$R^2_{OOS} = 1 - MSE_A/MSE_N$$

where MSE_A is the mean squared error of the predictive model based on a predictor and MSE_N is the mean squared error of the historical mean model. The testing period for OOS R^2 is from Jan 2006 to Dec 2023. We use all available data from as early as 1926 until the testing month to train both the historical mean and the predictive models (e.g., the training data is updated on an expanding window basis). The data for all predictors are available from 1996m1 or earlier to 2023m12. Panels A predicts monthly S&P 500 excess returns, and Panel B predicts monthly changes in the Miranda-Agrippino and Rey (2020) GFC factor.

Panel A: top 10 predictors of monthly S&P 500 return

Rank	In-sample R^2: 1996-2023		Rank	Out-of-sample R^2: 2006-2023	
1	**convex**	**2.79%**	1	**convex**	**2.80%**
2	div_yield	2.35%	2	short_int_oos	1.99%
3	hjtz_sent_orth	2.35%	3	consumption	1.79%
4	short_int_oos	1.86%	4	convex_right	1.48%
5	div_prc	1.82%	5	output_gap	0.92%
6	output_gap	1.81%	6	usa_convex	0.85%
7	consumption	1.69%	7	lty	0.72%
8	hjtz_sentiment	1.63%	8	corpr	0.51%
9	usa_slope	1.57%	9	AAA	0.51%
10	accrul	1.56%	10	convex_left	0.51%

Panel B: top 10 predictors of monthly Global Financial Cycle

Rank	In-sample R^2: 1996-2023		Rank	Out-of-sample R^2: 2006-2023	
1	**convex**	**2.80%**	1	**convex**	**2.66%**
2	tedrate	2.19%	2	convex_right	2.00%
3	convex_right	2.14%	3	output_gap	0.97%
4	cfacc	1.12%	4	corpr	0.71%
5	convex_left	1.02%	5	convex_left	0.58%
6	dtoat	0.97%	6	cfacc	0.42%
7	usa_1mon_ret	0.72%	7	div_prc	0.25%
8	bm	0.70%	8	gip	0.21%
9	ntis	0.65%	9	tedrate	0.16%
10	corpr	0.62%	10	bm	0.13%

Table A1: Summary statistics of index returns and currency spot returns

This table lists the data coverage and summary statistics of monthly index excess returns and currency spot rate returns for our in-sample tests. Index returns, reported in percentage points per month, include dividends and are calculated on a USD basis. Currency returns are reported in percentage points per month against the USD, with positive value meaning appreciation against the USD.

Panel A: index excess returns (percentage per month)

Country / Region	Market Index	Start	Finish	Mean	SD	Skewness	Kurtosis
AUS	S&P/ASX 200	1996m1	2024m12	0.68	6.07	-0.59	5.01
BEL	BEL 20	1996m1	2024m12	0.53	5.88	-0.55	5.54
CAN	S&P/TSX 60	1996m1	2024m12	0.70	5.74	-0.67	5.49
CHE	SMI	1996m1	2024m12	0.59	4.72	-0.35	3.62
DEU	DAX	1996m1	2024m12	0.63	6.65	-0.35	4.26
ESP	IBEX 35	1996m1	2024m12	0.67	6.85	-0.10	4.49
EUR	STOXX 50	1996m1	2024m12	0.55	6.17	-0.29	3.80
FIN	HELSINKI 25	1996m1	2024m12	0.81	6.81	0.09	4.99
FRA	CAC 40	1996m1	2024m12	0.62	6.07	-0.28	3.83
GBR	FTSE 100	1996m1	2024m12	0.39	4.66	-0.36	4.37
HKG	HANG SENG	1996m1	2024m12	0.54	6.92	0.12	5.36
ITA	MIB	1998m1	2024m12	0.44	7.10	-0.10	3.98
JPN	NIKKEI 225	1996m1	2024m12	0.15	5.36	-0.21	3.39
KOR	KOSPI 200	1996m1	2024m12	0.47	9.98	0.99	9.92
NLD	AEX	1996m1	2024m12	0.62	6.05	-0.62	4.97
SWE	OMXS30	1996m1	2024m12	0.68	6.66	-0.15	4.23
TWN	TAIEX	1996m1	2024m12	0.68	7.19	0.09	4.09
USA	S&P 500	1996m1	2024m12	0.72	4.45	-0.57	3.83

Panel B: currency spot rate returns against USD (percentage per month)

Symbol	Name	start	finish	mean	sd	skewness	kurtosis
AUD	Australian dollar	1996m1	2024m12	0.01	3.40	-0.27	4.40
CAD	Canadian dollar	1996m1	2024m12	0.01	2.34	-0.36	5.79
CHF	Swiss franc	1996m1	2024m12	0.11	2.85	0.33	4.77
EUR	Euro	1996m1	2024m12	0.00	2.54	0.00	4.51
GBP	British pound	1996m1	2024m12	-0.03	2.43	-0.25	3.95
HKD	Hong Kong dollar	1996m1	2024m12	0.00	0.14	0.78	8.38
JPY	Japanese yen	1996m1	2024m12	-0.08	2.98	0.63	5.87
KRW	Korean won	1996m1	2024m12	-0.11	3.79	-1.34	18.97
SEK	Swedish krona	1996m1	2024m12	-0.10	3.07	0.12	3.34
TWD	New Taiwan dollar	1996m1	2024m12	-0.04	1.53	0.02	5.97

Table A2: USA implied volatility surface

This table reports the average implied volatility in Panel A and the average residual implied volatility in Panel B at each delta-maturity grid point on the USA implied volatility surface, averaged across time. The sample period is from 1996m1 to 2023m12.

Panel A: Unconditional surface

	Maturity (days)								
Adj. delta	30	60	91	122	152	182	273	365	547	Avg.
0.10	26.7	27.0	27.3	27.5	27.6	27.6	27.7	27.6	27.5	27.4
0.15	24.5	25.1	25.5	25.7	25.8	25.9	26.1	26.1	26.1	25.6
0.20	22.7	23.5	23.8	24.1	24.3	24.4	24.7	24.7	24.8	24.1
0.25	21.5	22.2	22.5	22.8	23.0	23.1	23.4	23.5	23.6	22.8
0.30	20.5	21.1	21.5	21.7	21.9	22.1	22.3	22.4	22.6	21.8
0.35	19.7	20.3	20.6	20.8	21.0	21.1	21.4	21.5	21.7	20.9
0.40	19.0	19.5	19.8	20.0	20.2	20.3	20.6	20.7	20.8	20.1
0.45	18.5	18.9	19.1	19.3	19.5	19.6	19.8	19.9	20.1	19.4
0.50	17.9	18.3	18.5	18.7	18.8	18.9	19.1	19.2	19.4	18.8
0.55	17.4	17.7	17.9	18.1	18.2	18.3	18.5	18.6	18.8	18.2
0.60	17.0	17.2	17.4	17.5	17.6	17.7	17.9	18.0	18.2	17.6
0.65	16.6	16.8	16.9	17.0	17.1	17.2	17.3	17.4	17.7	17.1
0.70	16.2	16.3	16.4	16.5	16.6	16.7	16.8	16.9	17.2	16.6
0.75	15.9	15.9	16.0	16.1	16.2	16.2	16.3	16.4	16.7	16.2
0.80	15.6	15.6	15.6	15.7	15.8	15.8	15.9	16.0	16.3	15.8
0.85	15.6	15.4	15.4	15.4	15.5	15.5	15.6	15.7	16.0	15.6
0.90	15.8	15.4	15.3	15.3	15.3	15.3	15.3	15.4	15.7	15.4
Avg.	18.9	19.2	19.4	19.5	19.7	19.8	19.9	20.0	20.2	

Panel B: Residual surface

	Maturity (days)								
Adj. delta	30	60	91	122	152	182	273	365	547	Avg.
0.10	2.2	2.2	2.3	2.3	2.3	2.3	2.2	2.0	1.6	2.1
0.15	0.7	1.0	1.1	1.2	1.2	1.3	1.3	1.2	0.9	1.1
0.20	-0.4	0.0	0.2	0.3	0.4	0.5	0.5	0.5	0.3	0.3
0.25	-1.0	-0.6	-0.4	-0.3	-0.2	-0.1	0.0	-0.1	-0.1	-0.3
0.30	-1.2	-0.9	-0.8	-0.6	-0.5	-0.5	-0.4	-0.4	-0.5	-0.6
0.35	-1.3	-1.1	-0.9	-0.8	-0.7	-0.7	-0.6	-0.6	-0.7	-0.8
0.40	-1.3	-1.1	-1.0	-0.9	-0.9	-0.8	-0.7	-0.8	-0.8	-0.9
0.45	-1.1	-1.0	-1.0	-0.9	-0.9	-0.8	-0.8	-0.8	-0.8	-0.9
0.50	-1.0	-0.9	-0.9	-0.9	-0.8	-0.8	-0.8	-0.8	-0.8	-0.9
0.55	-0.8	-0.8	-0.8	-0.8	-0.7	-0.7	-0.7	-0.8	-0.7	-0.7
0.60	-0.5	-0.6	-0.6	-0.6	-0.6	-0.6	-0.6	-0.6	-0.6	-0.6
0.65	-0.2	-0.3	-0.4	-0.4	-0.4	-0.4	-0.5	-0.5	-0.4	-0.4
0.70	0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.3	-0.3	-0.2	-0.2
0.75	0.5	0.2	0.1	0.1	0.0	0.0	0.0	-0.1	0.0	0.1
0.80	1.0	0.6	0.5	0.4	0.3	0.3	0.2	0.2	0.3	0.4
0.85	1.6	1.1	0.9	0.8	0.8	0.7	0.6	0.6	0.7	0.9
0.90	2.6	1.8	1.6	1.4	1.3	1.2	1.1	1.0	1.2	1.5
Avg.	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

Table A3: Summarizing implied volatility surface with linear models

This table reports the average R^2 of various linear models used to summarize the implied volatility surface in each country or region. Specifically, we estimate linear models in each country-month by regressing implied volatilities on a combination of deltas and maturities and report the average R^2 of these monthly regressions over time. The models are

$$\text{Model 1: } IVOL_{ij} = b_0 + b_1\Delta_i + \epsilon_{ij}$$
$$\text{Model 2: } IVOL_{ij} = b_0 + b_2\tau_j + \epsilon_{ij}$$
$$\text{Model 3: } IVOL_{ij} = b_0 + b_1\Delta_i + b_2\tau_j + \epsilon_{ij}$$
$$\text{Model 4: } IVOL_{ij} = b_0 + b_1\Delta_i + b_2\tau_j + b_3\Delta_i^2 + \epsilon_{ij}$$
$$\text{Model 5: } IVOL_{ij} = b_0 + b_1\Delta_i + b_2\tau_j + b_3\Delta_i^2 + b_4\tau_j^2 + \epsilon_{ij}$$
$$\text{Model 6: } IVOL_{ij} = b_0 + b_1\Delta_i + b_2\tau_j + b_3\Delta_i^2 + b_4\tau_j^2 + b_5\Delta_i\tau_j + \epsilon_{ij}$$

where b's are coefficients to be estimated in each time period, Δ_i is the adjusted delta, and τ_j is the log of days to maturity.

Country / Region	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
USA	81%	9%	90%	96%	96%	96%
AUS	60%	9%	69%	77%	79%	81%
BEL	65%	13%	78%	83%	85%	87%
CAN	57%	13%	70%	73%	76%	78%
CHE	78%	10%	88%	95%	95%	95%
DEU	78%	9%	87%	93%	94%	94%
ESP	82%	8%	89%	93%	94%	95%
EUR	77%	9%	86%	94%	95%	95%
FIN	69%	9%	78%	86%	87%	88%
FRA	78%	9%	87%	94%	94%	95%
GBR	77%	12%	88%	95%	95%	96%
HKG	55%	13%	69%	80%	82%	83%
ITA	81%	8%	89%	95%	96%	97%
JPN	58%	10%	67%	82%	83%	85%
KOR	63%	5%	68%	75%	77%	79%
NLD	74%	10%	84%	92%	93%	94%
SWE	81%	9%	90%	93%	94%	94%
TWN	47%	6%	53%	58%	59%	60%
Average	70%	9%	80%	86%	87%	89%

Table A4: Predicting semi-annual equity premium around the world

This table shows predictive regressions. The y-variables in columns 1 to 17 are 6-month excess returns of various indexes in percentage points in month $t+1$. The y-variable in column 18 is the semi-annual change in the level of Miranda-Agrippino and Rey (2020) Global Financial Cycle factor in month $t+1$. The x-variables are standardized global convexity in month t. The sample period of predictors is from 1996m1 to 2023m12. Standard errors are Newey-West standard errors with 6 lag of autocorrelations. The t-statistics are reported in parentheses. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	AUS	BEL	CAN	CHE	DEU	ESP	EU	FIN	FRA
Global convex	5.09***	3.49*	4.25**	2.64*	3.65*	2.92	4.31**	4.28**	4.78***
	(2.73)	(1.75)	(2.53)	(1.95)	(1.97)	(1.47)	(2.52)	(2.08)	(2.94)
Obs.	336	336	336	336	336	336	336	336	336
R^2	0.108	0.047	0.080	0.048	0.045	0.026	0.074	0.050	0.095

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
VARIABLES	GBR	HKG	ITA	JPN	KOR	NLD	SWE	TWN	Global Fin. Cycle
Global convex	3.98***	3.48*	5.41***	5.35***	9.32***	3.83**	5.98***	5.53***	0.26***
	(2.65)	(1.75)	(2.76)	(3.57)	(3.01)	(2.03)	(2.91)	(2.75)	(2.76)
Obs.	336	336	312	336	336	336	336	336	336
R^2	0.098	0.043	0.091	0.133	0.122	0.058	0.105	0.084	0.119

Table A5: Predictability of local convexity measures

This table presents the result of predicting each index's monthly and semi-annual returns with the index's own convexity measure. We omit the reporting of the constant for brevity. The sample period is based on the availability of each index option. Standard errors are Newey-West standard errors with 1 lag in Panel A and 6 lags in Panel B. The t-statistics are reported in parentheses. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: predicting monthly returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
VARIABLES	USA	AUS	BEL	CAN	CHE	DEU	ESP	EU	FIN	FRA	GBR	HKG	ITA	JPN	KOR	NLD	SWE	TWN
Local convex	0.50**	0.59	0.77*	0.78	0.16	0.44	0.03	0.33	0.43	0.75***	0.69**	-0.02	1.14**	0.43	0.22	0.73	0.42	0.52
	(2.08)	(0.91)	(1.96)	(1.45)	(0.48)	(0.98)	(0.05)	(0.71)	(1.04)	(2.60)	(2.23)	(-0.03)	(2.09)	(1.57)	(0.43)	(1.45)	(0.79)	(1.12)
Obs.	336	240	254	191	264	264	207	264	264	249	264	216	207	236	236	246	200	240
R^2	0.013	0.009	0.016	0.018	0.001	0.004	0.000	0.003	0.005	0.016	0.020	0.000	0.023	0.009	0.001	0.014	0.004	0.007

Panel B: predicting semi-annual returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
VARIABLES	USA	AUS	BEL	CAN	CHE	DEU	ESP	EU	FIN	FRA	GBR	HKG	ITA	JPN	KOR	NLD	SWE	TWN
Local convex	3.17***	2.33	3.92***	1.99	2.00**	3.48**	0.30	2.73*	2.50**	4.03***	4.47***	-0.43	5.56***	1.73*	0.12	4.85***	1.14	0.13
	(3.43)	(1.46)	(2.84)	(1.55)	(1.98)	(2.54)	(0.15)	(1.90)	(2.15)	(3.93)	(4.11)	(-0.35)	(2.91)	(1.76)	(0.07)	(3.81)	(0.42)	(0.09)
Obs.	336	240	254	191	264	264	207	264	264	249	264	216	207	236	236	246	200	240
R^2	0.080	0.019	0.057	0.018	0.029	0.042	0.000	0.029	0.021	0.069	0.116	0.001	0.081	0.021	0.000	0.087	0.004	0.000

Table A6: Predicting currency return and local-currency equity premium

This table shows predictive regressions of various currency returns and local-currency equity premium. In Panel A, the y-variables are currency returns in month $t+1$, measured as the rate of return (in percentage points) of the USD value of a currency. A positive currency return means that the currency is appreciating against the USD. In Panel B, the y-variables are semi-annual cumulative currency returns from month $t+1$ to $t+6$. In Panel C, the y-variables are the excess returns of equity indexes in local currencies in month $t+1$. We remove local risk-free rate when measuring the excess return. All x-variables are standardized global convexity in month t. To save space, we only report the coefficient on the predictor. The sample period is from 1996m12 to 2023m12. Standard errors are Newey-West standard errors with 1 lag of autocorrelations in Panels A and C and 6 lags in Panel B. The t-statistics are reported in parentheses. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Predict monthly currency return

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	AUD	CAD	CHF	EUR	GBP	HKD	JPY	KRW	SEK	TWD
Global convex	0.54**	0.22*	0.11	0.08	0.14	-0.01	0.06	0.38	0.25	0.16*
	(2.56)	(1.75)	(0.71)	(0.52)	(0.98)	(-0.72)	(0.32)	(1.59)	(1.31)	(1.78)
Obs.	336	336	336	336	336	336	336	336	336	336
R^2	0.025	0.009	0.002	0.001	0.003	0.002	0.000	0.010	0.007	0.011

Panel B: Predict semi-annual currency return

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	AUD	CAD	CHF	EUR	GBP	HKD	JPY	KRW	SEK	TWD
Global convex	2.06**	1.29**	0.42	0.01	0.97	-0.06**	-0.13	2.52***	1.28	0.95**
	(2.06)	(2.04)	(0.64)	(0.01)	(1.19)	(-2.19)	(-0.19)	(2.81)	(1.38)	(2.26)
Obs.	336	336	336	336	336	336	336	336	336	336
R^2	0.058	0.053	0.004	0.000	0.024	0.046	0.000	0.085	0.026	0.054

Panel C: Predict local-currency monthly equity return

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	AUS	BEL	CAN	CHE	DEU	ESP	EU	FIN	FRA
Global convex	0.62***	0.53*	0.69***	0.33	0.76**	0.68**	0.81***	0.78**	0.81***
	(2.91)	(1.72)	(2.76)	(1.36)	(2.32)	(2.08)	(2.67)	(2.27)	(2.78)
Obs.	336	336	336	336	336	336	336	336	336
R^2	0.026	0.011	0.026	0.006	0.016	0.013	0.022	0.016	0.023
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
VARIABLES	GBR	HKG	ITA	JPN	KOR	NLD	SWE	TWN	USA
Global convex	0.59***	0.70*	0.96***	0.85***	1.68***	0.66**	0.86***	1.01**	0.75***
	(2.67)	(1.72)	(2.85)	(2.67)	(3.72)	(1.98)	(2.82)	(2.58)	(2.88)
Obs.	336	336	312	336	336	336	336	336	336
R^2	0.022	0.010	0.023	0.024	0.046	0.015	0.024	0.025	0.028

Table A7: Description of events during extreme period of convexity left and right measures

We identify extreme realizations of the convexity left and convexity right indexes visually. We then ask ChatGPT 4o "what happened in the financial market during" a specific period surrounding an extreme realization. The table reports the headline responses.

Panel A: Peaks of global convexity left index

Date	Headline response from ChatGPT 4o
1997m11-1997m12	November & December 1997: Escalation of the Asian Financial Crisis and Market Volatility
1998m9-1998m10	September & October 1998: The LTCM Crisis & Market Turmoil
2008m10-2008m11	October & November 2008: The Heart of the Global Financial Crisis
2010m5-2010m6	May & June 2010: Flash Crash & Eurozone Debt Crisis Intensify
2011m9-2011m11	September to November 2011: Market Volatility Amidst Eurozone Debt Crisis and U.S. Recession Fears
2020m3-2020m4	March & April 2020: COVID-19 Market Crash & Initial Recovery
2022m3	March 2022: Market Turmoil Amidst War, Inflation, and Fed Rate Hikes

Panel B: Peaks of global convexity right index

Date	Headline response from ChatGPT 4o
2001m4	April 2001: Market Rebound Amidst the Dot-Com Crash & Fed Rate Cuts
2001m10	October 2001: Market Recovery After the 9/11 Selloff
2004m1-2004m2	January & February 2004: Market Optimism Amid Economic Recovery
2009m5	May 2009: Stock Market Rebound Amid Economic Recovery Hopes
2012m2	February 2012: Market Optimism Amid Eurozone Stabilization & Economic Growth
2020m11-2021m2	November 2020 – February 2021: Vaccine Rally, Stimulus, and Market Mania

Panel C: Troughs of global convexity right index

Date	Headline response from ChatGPT 4o
1998m9-1998m10	September & October 1998: The LTCM Crisis & Market Turmoil
2002m9-2002m10	September & October 2002: Bear Market Lows Amid Economic Uncertainty
2008m1	January 2008: Markets Enter Bear Territory Amid Recession Fears
2008m10	October 2008: The Height of the Global Financial Crisis
2011m8	August 2011: Market Chaos Amid U.S. Credit Downgrade & Eurozone Crisis
2015m9	September 2015: Market Volatility Amid China Fears & Fed Uncertainty
2019m9	September 2019: Market Volatility Amid Repo Market Crisis & Trade War Uncertainty

Figure A.1: Predicted increase in return and Global Financial Cycle beta

The figure plots the percentage increase in each asset's return in month $t+1$ for 1 standard deviation increase in global convexity in month t. Each point represents a single asset. The x-axis is the beta of the asset against the monthly change in the Miranda-Agrippino and Rey (2020) Global Financial Cycle factor. The data spans several asset classes, and the sample period is from 1996 to 2012. The line fitted through all test assets has a slope of 6.21 (t-statistic: 2.73), a constant of -0.05 (t-statistic: -0.83), and an R^2 of 65%.

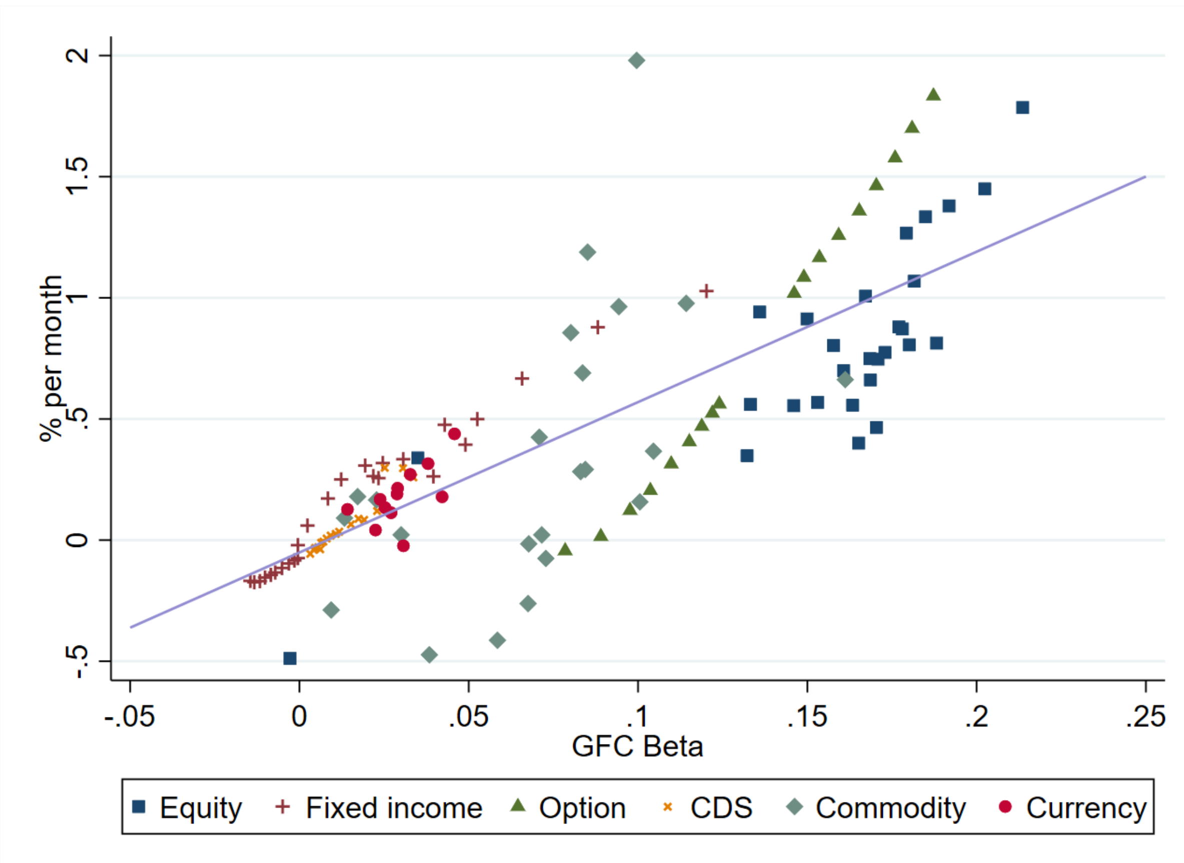


Table A8: Convexity from different maturity horizons

This table reports the summary statistics (Panel A) and predictability (Panel B and C) of convexity indexes measured from options with different maturity horizons. Short-term convexity is constructed from 30-, 60-, and 91-day implied volatilities. Mid-term convexity is constructed from 122-, 152-, and 182-day implied volatilities. Long-term convexity is constructed from 273-, 365-, and 547-day implied volatilities. Standard errors are Newey-West standard errors with 1 lag of autocorrelations in Panel B and 6 lags in Panel C. The t-statistics are reported in parentheses. Superscripts ***, **, * correspond to statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: summary statistics of global convexity from different horizons

horizon (days)	mean	p50	sd	min	max	skewness	kurtosis
30	0.61	0.58	0.17	0.17	1.26	0.93	4.41
60	0.50	0.48	0.15	-0.01	1.09	0.68	4.19
91	0.49	0.46	0.15	0.18	0.92	0.54	2.85
122	0.49	0.45	0.15	0.20	0.90	0.54	2.51
152	0.48	0.45	0.15	0.20	0.87	0.52	2.41
182	0.46	0.43	0.14	0.18	0.83	0.47	2.36
273	0.45	0.43	0.14	0.17	0.76	0.29	2.12
365	0.44	0.43	0.14	0.17	0.76	0.11	1.94
547	0.42	0.41	0.14	0.11	0.79	0.10	2.33

Panel B: Predict monthly S&P 500 return

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Global convexity				USA convexity		
VARIABLES	Baseline	Short-term	Mid-term	Long-term	Baseline	Short-term	Mid-term	Long-term
Global convex	0.75***	0.65**	0.72***	0.71***	0.50**	0.34	0.51**	0.54**
	(2.88)	(2.38)	(2.85)	(2.84)	(2.08)	(1.36)	(2.05)	(2.25)
Obs.	336	336	335	335	336	336	336	336
R^2	0.028	0.005	0.034	0.005	0.013	0.006	0.013	0.015

Panel C: Predict semi-annual S&P 500 return

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Global convexity				USA convexity		
VARIABLES	Baseline	Short-term	Mid-term	Long-term	Baseline	Short-term	Mid-term	Long-term
Global convex	3.66***	3.08**	3.43***	3.65***	3.17**	2.34*	3.10**	3.28**
	(2.96)	(2.38)	(2.87)	(2.95)	(2.25)	(1.67)	(2.16)	(2.54)
Observations	336	336	336	336	336	336	336	336
R-squared	0.107	0.075	0.094	0.106	0.080	0.044	0.077	0.086