Interest rate risk, inflation, and the cross section of stock returns

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Abstract

We posit that the pricing mechanism of interest rate risk is contingent upon the prevailing inflation levels; in times of high (low) inflation, a positive (negative) shock to interest rates is indicative of a negative economic state. In line with this proposition, we introduce a conditional interest rate factor, defined as the shock to interest rates multiplied by the standardized inflation level. The proposed *single* factor effectively indicates the states of both raising interest rates to combat inflation and lowering interest rates to counteract a recession. We find supporting evidence that interest rate risk is not unconditionally priced, but rather contingent upon inflation. Specifically, the sensitivity of stock returns to interest rate innovation cannot account for the cross-section of stock returns, but when interacted with standardized inflation, it produces significant cross-sectional return differences, even after controlling for standard risk factors. Moreover, when examining standard equity portfolios as test assets, our conditional interest rate factor outperforms its unconditional counterpart in terms of pricing performance, as measured by R^2 and absolute pricing error, and is comparable to the Fama-French three-factor model. Finally, we provide further validation for our proposed factor by demonstrating its ability to predict future consumption growth and achieving a Sharpe ratio comparable to the tangency portfolio.

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1 Introduction

"The most important single factor driving the economy is the level of interest rates"

Alan Greenspan, *The Age of Turbulence: Adventures in a New World*, 2008

Is the interest rate a priced risk factor? From the view of the inter-temporal asset pricing model (ICAPM) framework, the interest rate is supposedly an asset pricing factor in that it influences a wide range of other economic variables from borrowing costs to the present values of future payoffs. In other words, an interest rate is an essential macroeconomic variable closely related to changes in the investment opportunity set. However, there has been surprisingly little research that uses the (innovation on) interest rates as a risk factor in the asset pricing literature. One recent exception is Maio and Santa-Clara (2017), who show that the innovation on a short-term interest rate helps explaining seven capital asset pricing model (CAPM) anomalies. Can this result be generalized? We expand the test assets from the seven specific anomaly portfolios to the entire stock universe, and find that the interest rate beta loses its explanatory power for the cross section of stock returns.

Why is not the interest rate risk robustly priced? According to Cochrane (2009), a pricing factor is a variable that indicates a bad economic state in which investors are especially concerned about their portfolios' performance. Maio and Santa-Clara (2017) implicitly assume that an unanticipated increase in the interest rate indicates a bad state. This assumption could hold for some portfolios or in specific periods, but it may not be always true. In this research, we posit that the mechanism through which the interest rate risk is priced depends on prevailing inflation. Under this argument, a positive shock to interest rates can be both good and bad news depending on the situation. This could be why the interest rate risk fails to be unconditionally priced, so that it has not been widely controlled for in the asset pricing literature.

Specifically, we argue that under the high inflation regime, a positive innovation in the interest rate reflects a bad state. This notion is intuitive and consistent with the observations in 2022; under the prolonged high inflation, the Federal Reserve continuously and rapidly raises the interest rate, which is clearly bad news for the overall stock market. In contrast, during 2010's when the inflation rate had stayed low, interest rate cuts tend to indicate a gloomy future economic situation. The increase in the interest rate had been regarded as the normalization and the stock market indeed performed well during the period of the interest rate normalization.

This argument is in line with the reporting tone of various business new media. For example, on November 1, 2022, when the prevailing inflation level was high, CNBC reported the news under the heading: *Dow closes 500 points lower, Nasdaq sheds 3% as Fed Chair Powell signals intent to continue hiking rates.*[1] Three weeks later, Barron's also reported an article with the same implication, but in the opposite direction, under the headline: *Stocks end strong. Hope of a more dovish Fed fueled the pop.*[2] These news articles commonly suggest that a positive (negative) innovation in interest rates indicates a bad (good) state. However, from the late 2000's until the end of 2010's, news tone had been in a stark contrast. On December 17, 2008, at the height of the global financial crisis, New York Times reported, "The Fed, in a statement accompanying its rate decision, acknowledged that the recession was more severe than officials had thought at their last meeting in October" with the title *Fed Cuts Key Rate to a Record Low.*[3] When the Fed raised the rate for the second time in a decade in 2016, CNBC viewed it positively with the comment, "U.S. economy soon could shed its long period

[1] https://www.cnbc.com/2022/11/01/stock-market-futures-open-to-close-news.html
[2] https://www.barrons.com/livecoverage/stock-market-today-112222/card/stock-futures-fall-on-concerns-of-more-china-lockdowns-d79BdFdVWqAHo7C42bkM
[3] https://www.nytimes.com/2008/12/17/business/economy/17fed.html

of stagnation".[4] The latter two articles imply that a negative (positive) innovation in interest rate indicates a bad (good) state. Since the interest rate, the inflation rate and the stock returns are convoluted in this way, an analysis that considers the *unconditional* relationship between interest rates and stock returns could fail to robustly explain the reality.

Guided by this argument, this research proposes a *conditional* interest rate factor, defined as the shock to the interest rate multiplied by the standardized level of inflation. Note that this proposed factor would increase both when raising interest rates to curb high inflation and when cutting interest rates to fight against a recession and consequently low inflation, and vice versa. In other words, this *single* factor can effectively indicate a bad state regardless of the direction of interest rates, whereas the shock to the interest rate cannot. We find strong empirical support for this argument. Specifically, the portfolios sorted by the return sensitivity to the innovation in interest rates (unconditional interest rate factor) do not exhibit the cross-sectional return difference; the long-short excess return is insignificant and has a sign opposite to the model prediction. However, when the portfolios are formed by the sensitivity to the conditional interest rate factor, the long-short excess return is highly significant even after controlling for standard risk factors. For example, the risk-adjusted long-short excess return is as high as 0.637% per month, amounting to 7.644% per annum, when the Fama-French five factors and the Carhart momentum factor are controlled for. We also examine the asset pricing performance of the conditional interest rate factor in the classical Fama-MacBeth framework using several anomaly portfolios as test assets, and find that our conditional interest rate factor outperforms its unconditional counterpart in terms of pricing performance, as measured by R^2 and absolute pricing error, and is

[4] `https://www.cnbc.com/2016/12/14/fed-raises-rates-for-the-second-time-in-a-decade.html`

comparable to the Fama-French three-factor model. When the 25 portfolios sorted by size and book-to-market ratio are tested with the restriction that the zero-beta expected rate equals the risk-free rate, for example, the adjusted R^2 of the single-factor model with the conditional (unconditional) interest rate factor is 43.53% (-2.63%), which is even higher than 42.92% of the Fama-French three factor model. The average of absolute pricing error from our conditional factor model is 1.38%, which is comparable to 1.12% of the Fama-French three factor model. We find that across test assets, the estimated risk premium of the conditional interest rate risk is significant and robust, and has the theory-predicted sign. In contrast, the model with the unconditional interest rate factor has substantially lower R^2s and larger total pricing errors, and the estimated risk premium is not always significant. The results are robust to the restriction on the zero-beta rate and the sub-period analysis.

To confirm that our suggested factor is a valid stochastic discount factor, we further conduct the two analyses as follows. First, in Merton (1973)'s ICAPM framework, a state variable relates to changes in the investment opportunity set and the innovations in the state variable should be a priced factor in the cross-section (Maio and Santa-Clara, 2012). It implies that a state variable can work as a valid factor in the ICAPM framework only if it predicts future consumption growth. To test the consumption predictability, we run the regressions in which the dependent variable is the per capita real consumption growth rate, and the independent variables include the shocks to interest rates, standardized inflation, and their interaction. We measure the consumption growth over various horizons from one to twelve months. We show that neither interest rate nor inflation rate can individually predict the future consumption growth, but they collectively have significant predictability. Specifically, we find that neither an interest rate nor an inflation rate is individually significant, but their interaction term has a significantly negative coefficient, implying that a positive innovation in the interest rate predicts a decrease (increase) in the future consumption growth when the inflation rate is high (low). This finding justifies the use of the interaction between interest rate and inflation, rather than the interest rate itself, as an ICAPM pricing factor.

Second, we examine the Sharpe ratio of the conditional interest rate factor-mimicking portfolio. Note that in an incomplete market, there are infinitely many SDFs but the one in the payoff space is unique and has the smallest variance (Cochrane, 2009). Also note that Hansen and Jagannathan (1991)'s volatility bound implies that the SDF in the payoff space has the largest Sharpe ratio. Combined, if our suggested conditional interest rate factor is a valid SDF, its mimicking portfolio should have as high Sharpe ratio as the tangency portfolio. We construct the mimicking portfolio by a linear combination of the Fama-French six portfolios sorted by size and book-to-market ratio, and find that its annualized Sharpe ratio is 0.878. We compare it with the Sharpe ratio of the tangency portfolio in the efficient frontier generated with the six size and book-to-market portfolios and the four benchmark equity factors (RmRf, SMB, HML and UMD). We find that the Sharpe ratio of the conditional interest rate factor-mimicking portfolio is comparable to that of the tangency portfolio (1.242) and is much higher than those of standard equity factors.

Little prior research has analyzed the direct effects of the interest rate risk on stock markets, while there is ample empirical evidence of the relationship between monetary policy and stock prices. In aggregate contexts, Jensen et al. (1996) show that business conditions explain future stock returns only in expansive monetary policy periods, and Thorbecke (1997) finds that ex-post stock returns particularly increase with expansionary monetary policy. Bernanke and Kuttner (2005) show that a hypothetical expansionary monetary policy is associated with the increase in broad stock indexes, through the channel of expected stock returns. More related to our works, Lioui and Maio (2014) and Maio and Santa-Clara (2017) use an interest rate risk factor to help explain the cross section of stock returns. Chava and Hsu (2020) find that unanticipated interest rate changes affect the cross-section of stock returns with financially constrained firms. In this study, we analyze whether the interest rate risk affects the cross-section of stock returns conditioning on inflation rate.

Our analysis behind conditional interest rate risk upon inflation rate is motivated by the literature that studies how inflation risk could impact asset prices. Chen et al. (1986), Ferson and Harvey (1991), and Ang et al. (2012) examine the impact of inflation risk on stock returns. Boons et al. (2020) analyzes a time-varying risk premium is priced in the cross-section of stock returns. In particular, Lioui and Maio (2014) argue that high interest rate risk on asset prices is associated with inflation expectations. However, past work has not studied whether the inflation risk is conditionally associated with the effect of interest rate risks on asset prices. This study contributes to this literature by providing direct evidence that the interest rate risk is priced in the cross-section of stock returns conditioning on the prevailing inflation rates.

Our study also joins a growing literature on stock and bond correlations. The stock and bond returns had been positively correlated until the late 1990s, but the correlation turned negative since then. Interestingly, this correlation tends to switch its sign in the early 2020s and this kind of cycles is ascribed to the inflation rate. Most macro-finance studies examine aggregate asset pricing implications of the comovement between stocks and bonds. For example, Baele et al. (2010) show that while macro factors, such as interest rates, inflation, output gap, and cash flow growth, contribute little to explaining stock and bond correlations, they are important to determine the risk premia of the comovement. Campbell et al. (2017) explain the sign-switching stock-bond correlation by arguing that the nominal bonds can work as either bets for inflation or hedges against deflation. Campbell et al. (2020) use a consumption-based habit model to explain the risk premia on stock and bond return comovement with the correlation between inflation and output gap. These papers commonly point out inflation as a crucial factor in determining the direction of the impact of bond market shocks on the overall stock market. However, to the best of our knowledge, there is no study that draws implications for the cross section of stock returns. We hope that this research can fill the gap.

The remainder of this paper is organized as follows. Section 2 describes how our sample data are constructed. Section 3 presents the empirical methodology and the results. Section 4 discusses the validity of our proposed factor. Finally, we conclude in Section 5.

2 Data

As discussed in the introduction, we consider the innovation to the interest rate multiplied by the standardized level of inflation as a proxy for shocks to the stochastic discount factor (SDF). We denote this newly proposed pricing kernel as $IntInf$, indicating that it is the interaction of an *int*erest rate and *inf*lation, and argue that it can effectively represent the conditional interest rate risk. We use the three-month Treasury bill secondary market rate (i_{TB3}) as the primary measure of an interest rate. We also examine the Federal funds effective rate (i_{FFR}) for a robustness check, as in Maio and Santa-Clara (2017). The innovations to the interest rates (Int) are obtained from the $ARMA(1,1)$ residuals, following the literature (Vassalou, 2000; Campbell and Viceira, 2002; Boons et al., 2020).

For a measure of inflation, we use the monthly percentage change in the seasonally adjusted consumer price index (CPI) for all urban consumers. To measure the perceived level of prevailing inflation, we first compute the annualized inflation geometrically averaged over the past 36 months (π). Then, we standardize it by subtracting the mean and dividing it by the standard deviation. Since the perceived level of inflation depends on the historic experiences, the mean and standard deviation at month t are computed by using an expanding window that includes the observations since 1913 up to month t. This method allows time-varying means and standard deviations, so that the standardized inflation (Inf) can effectively indicate the extent to which a point in time is considered as a high or low inflation period. For example, the upper panel in Figure 1 depicts that the inflation rates in April 1986 and November 2021 were similar at 3.23% and 3.30%, respectively, but in the former case, the inflation rate gradually fell to 3.23% after the high inflation era in early 1980s, while in the latter case, it was a time when the low inflation period was over and prices were rising in earnest. Therefore, the inflation perceived by economic agents must be different. The lower panel confirms that the standardized inflation is indeed negative for April 1986, but positive for November 2021. Data for interest rate and inflation are downloaded from the Federal Reserve Economic Data (FRED) of the Federal Reserve Bank of St. Louis.

To examine the cross section of stock returns, we obtain the data from the Center for Research in Security Prices (CRSP). We use the stocks incorporated in the U.S. and listed on the NYSE, AMEX, or NASDAQ. We drop observations unless the CRSP share code is 10 or 11, and the trading status is active. The market return is defined as the value-weighted return of the above individual stocks. We compute the excess return by subtracting the one-month Treasury bill rate. To control for widely used stock market risk, we use the Fama-French five factors and the Carhart momentum factor, downloaded from Kenneth French's data library.

To confirm its validity as a priced factor in the ICAPM framework, we test whether the suggested factor ($IntInf$) has a predictive power for the future consumption growth. For this test, we use the growth rate of the per capita real consumption (ΔC), which is measured as follows. First, we obtain the aggregate real consumption by dividing the personal consumption expenditures (PCE) of nondurable goods and services by their associated PCE price indices respectively and summing them up. Then, we compute the per capita consumption by dividing the aggregate real consumption by the number of populations. Finally, the per capita real consumption growth is obtained as its monthly percentage change. These variables are obtained from the Bureau of Economic Analysis. We measure the consumption growth over various horizons from one to twelve months. Our sample starts from January 1959 because the monthly consumption data are available since then.[5] We use the data until December 2022.

Table 1 presents the descriptive statistics of our sample data. Panel A shows that from 1959 to 2022, the average short-term interest rate is 4.34% and the three-year moving average of inflation rate is 3.65%, expressed as an annual percentage. The monthly excess return of the market factor is 0.549%, equivalent to 6.588% per annum. Other risk factors also have substantial annualized excess returns from 2.424% (SMB) to 8.076% (UMD). Panel B presents the pairwise correlation among variables.

Note that equity factors are highly correlated one another. For example, the correlation between HML and CMA factors is as high as 0.683. Even among Fama-French three factors, RmRf and SMB have a correlation coefficient of 0.28. Interestingly, our conditional interest rate factor ($IntInf$) is barely correlated with these equity factors, where the largest absolute correlation is only 0.107 with the HML factor. It implies that the return predictability of $IntInf$, if any, is not an artifact of the correlation with

[5] When computing the standardized inflation, we use a longer sample of the monthly CPI data from 1913 for more accurate estimation.

existing asset pricing factors.

3 Empirical analysis

3.1 Estimation of exposure to risk

We use a linear factor model to test the validity of our suggested factor, the conditional interest rate risk ($IntInf$), in the cross-section of asset returns. In other words, we assume that an SDF is affine in the factor:

$$SDF_t = 1 + b \cdot IntInf_t, \tag{1}$$

where $b > 0$. Note that unlike other conventional factors, the sign in front of b is positive because the increase in $IntInf$ indicates a bad state. Since an SDF can price any assets, $0 = E[SDF_t \cdot R^e_{it}]$ holds, where R^e_i is the excess return of asset i. Plugging in Equation (1),

$$\begin{aligned} 0 &= E[(1 + b \cdot IntInf_t)R^e_{it}] \\ &= E[R^e_{it}] + bE[IntInf_t \cdot R^e_{it}]. \end{aligned}$$

Rearranging the terms, we obtain

$$\begin{aligned} E[R^e_{it}] &= -bCov[IntInf_t, R^e_{it}] \quad (2) \\ &= \lambda^{IntInf} \beta^{IntInf}_i, \quad (3) \end{aligned}$$

where $\beta^{IntInf}_i = \frac{Cov[IntInf_t, R^e_{it}]}{Var[IntInf_t]}$ is the exposure of stock i's excess return to the conditional interest rate risk, and $\lambda^{IntInf} = -bVar[IntInf_t]$ is its associated risk premium. Note that the equation above implies that the risk premium associated with the conditional interest rate risk is negative. Intuitively, the stocks that perform well when $IntInf$ is large (as in the year of 2022) can work as a hedge, so that the required return for those stocks is supposedly low.

We estimate the risk exposure by running the following time series regressions:

$$R_{it} = a_i + \beta_i' \mathbf{F}_t + \epsilon_i, \quad i = 1, \cdots, N, t = 1, \cdots, T,$$

where $\mathbf{F}$ is a vector of risk factors in consideration. As a main analysis, we examine a single factor model: $\mathbf{F} = IntInf$. To compare the performance of the *conditional* factor with an *unconditional* factor, we also examine the case of $\mathbf{F} = Int$, the innovation to interest rate. For robustness checks, we also consider multi-factor cases in which $\mathbf{F}$ includes a market factor.

Following Boons et al. (2020), we estimate β on a monthly basis by using an expanding window for each stock. Specifically, we use all observations available up to month t but assign exponentially decaying weights, so that we use as much information as possible and put larger weights on more recent observations.[6] We require that stocks have return data for at least five years (60 monthly observations). To address the estimation error and mitigate highly noisy estimates, we transform the estimated exposure by a Vasicek (1973) adjustment, which follows the literature (Cosemans et al., 2016; Levi and Welch, 2017; Boons et al., 2020).[7] Our empirical findings are robust to this adjustment process.

[6]We minimize $\sum_{\tau=1}^{t} K(\tau)(R_{it}^e - a_i - \beta_i' \mathbf{F}_t)^2$, where $K(\tau) = \frac{\exp(-|t-\tau|h)}{\sum_{\tau=1}^{t-1} \exp(-|t-\tau|h)}$ and $h = \log(2)/60$. This specification makes the half-life of $K(\tau)$ converge to 60 months.

[7]The transformed exposure is a weighted average of the originally estimated exposure and their cross-sectional average in the month t. The weight is computed based on the standard error from time series regressions and the cross-sectional variation of estimates. For more details, see Vasicek (1973).

3.2 Portfolio analysis

Since the data starts from 1959 and at least five years of observations are required for beta estimation, the portfolio analysis begins from January 1964. Specifically, in the beginning of each month, we form decile portfolios based on the risk exposure estimated in the end of the previous month. The breakpoints are the 20th, 40th, 60th, and 80th percentiles of the adjusted risk exposure of the NYSE stocks. For robustness checks, we try various ways to form the portfolios: single-sorting by risk exposure, two-way-sorting based on size and exposure, etc. and confirm the robustness of the findings. Then, we compute the long-short portfolio return and check its statistical significance.

Table 2 presents the returns of portfolios sorted by the conditional interest rate beta. Portfolio 1 is composed of stocks with the smallest (most negative) ex ante exposure to the conditional interest rate risk. The table confirms that the post-formation sensitivity is the smallest for Portfolio 1 and exhibits an almost monotonically increasing pattern. The table also shows that the excess returns are generally decreasing from the 1st decile to the 10th decile, and the excess return of the portfolio that long the 1st decile and short the 10th decile is positive at the 1% significance level. The monthly excess return is 0.428%, which corresponds to 5.136% in an annual term. In Table 3, we examine whether the significantly positive excess return of the long-short portfolio is a simple reflection of high risk. For this purpose, we regress the long-short excess return on the standard risk factors such as Fama-French (FF) five factors and the Carhart momentum factor. We find that even after controlling for these risk factors, the excess return remains significant. When all five FF factors and the momentum factor are controlled for, the risk-adjusted excess return is even greater (0.637% per month), implying that the exposure to the conditional interest rate risk indeed explains the cross-section of stock returns.

Since the innovation in the interest rate may indicate good or bad economic states depending on the prevailing inflation rate, we expect that if we consider the *unconditional* interest rate risk which does not incorporate the inflation information, its exposure cannot generate a significant return difference cross-sectionally. To test this hypothesis, we repeat a similar portfolio analysis, in which the portfolios are formed based on β^{Int}, the exposure to the innovation in the interest rate. Tables 4 and 5 show that although the post-formation exposures to the considered factor are significantly different between Portfolios 1 and 10, the long-short portfolio return is not significantly different from zero regardless of the risk adjustment, confirming that the interest rate risk is priced only conditionally but not unconditionally.

3.3 Two-pass cross-sectional regressions

In the previous subsection, we find evidence that the exposure to the conditional interest rate risk can generate a substantial return difference in the cross section of stocks. In this subsection, we conduct formal two-pass regressions using the classical Fama-French 25 portfolios as the test assets.

Table 6 presents the results of the Fama-MacBeth regressions of $E[R^e] = \lambda_0 + \beta_F' \lambda_F$, where F is a vector of factors. The 25 equity portfolios sorted by size and book-to-market (BM) ratio are used as test assets. We consider six groups of factors: (1) market factor ($RmRf$), (2) Fama-French three factors ($RmRf$, SMB, HML), (3) $RmRf$ and unconditional interest rate factor (Int), (4) $RmRf$ and conditional interest rate factor ($IntInf$), (5) Int, and (6) $IntInf$. Each column describes the risk premium (λ) of the corresponding factor, measures of goodness-of-fit (R^2 and Adj-R^2), and the mean absolute pricing error ($MAPE$). The value in parenthesis is the t-statistic based on the Shanken-corrected standard error. In Panel A, we impose a restriction that the zero-beta excess rate (λ_0) equals zero, while there is no such restriction in Panel B. *Intercept* in Panel B is the annualized zero-beta excess rate, and *Total* is the sum of *Intercept* and *MAPE*, representing the size of total pricing error. The sample period from January 1964 to December 2022.

Column (1) shows that the CAPM fails to explain the size- and BM-sorted portfolios, re-confirming the existence of anomalies. When the model is estimated without the restriction of $\lambda_0 = 0$ (Panel B)[8], the adjusted R^2 is 0.68%. In addition, the zero-beta excess rate is significant, while the price of the market risk is insignificant, meaning that the difference in market betas cannot explain the difference in excess returns. Column (4) shows that when the conditional interest rate factor ($IntInf$) is added, the pricing performance is enhanced substantially. The adjusted R^2 increases to 51.22% and the zero-beta excess rate becomes insignificant. The price of the conditional interest rate risk has the sign predicted by theory and is highly significant. The total pricing error is only 2.12% per annum. This pricing performance is remarkable in that it is comparable or even superior to that of the Fama-French three factor model (FF3) in Column (2). Although FF3's adjusted R^2 is slightly higher (59.98%) than the two-factor model with $RmRf$ and $IntInf$, its factors except for HML are insignificant. Instead, FF3 has an economically and statistically significant zero-beta excess rate (14.02% per annum), leading to the high total pricing error (15.89%). Column (6) presents the results when $IntInf$ is used as a *single* pricing factor. We find the decent pricing performance of this single factor in that the adjusted R^2 is still high (52.37%), the zero-beta excess rate is insignificant, and $IntInf$ remains significant with the predicted sign. Finally, we compare the performance of the conditional interest rate factor with its unconditional counterpart (Int). We find from Column (3) that the inclusion of Int to CAPM improves

[8]Throughout the section, the main explanations are based on the case of no restriction on zero-beta excess rate (Panel B), but the main results do not qualitatively change in Panel A.

the goodness-of-fit and the risk premium of Int is significant. But the R^2 improvement and the significance of the risk premium of Int are not as much as those of $IntInf$. When Int is used as a single factor (Column (5)), the risk premium still has the theory-predicted sign but loses the significance. To sum, our conditional interest rate factor well explains the cross-section of the classical test assets regardless of whether it is together with the market factor or works as a single factor, and clearly outperforms its unconditional counterpart. Its performance is comparable with that of the Fama-French three factor model.

We further explore whether any other anomalies that have been documented in the literature can be explained by the conditional interest rate risk. To the extent that the discount rate is linked to the interest rate, we conjecture that the anomalies related to the discount rate, such as valuation and investment, could be accounted for by the conditional interest rate risk. Specifically, we consider the equity portfolios sorted by long-run reversal and investment. The data are obtained from Kenneth French's data library. Tables 7 and 8 shows that the remarkable pricing performance of the conditional interest rate factor is not limited to particular anomaly portfolios but also applied to others in general. Specifically, we confirm that any model with the conditional interest rate factor has a considerably high adjusted R^2, the associated risk premium is significant, and the zero-beta excess rate is small and insignificant. Importantly, the conditional interest rate factor always exhibits a better pricing performance than its unconditional counterpart in terms of the R^2, the size of pricing error, and the significance of the risk premium.

3.4 Event Study

The results so far show that the stock returns are cross-sectionally priced with interest rate risk contingent upon inflation. In this section, we conduct an event study to analyze the reaction of the cross-sectional stock prices based on interest rate risk across inflation to changes in the Target Federal Funds Rate. Bernanke and Kuttner (2005) show that the stock returns negatively response to the unanticipated Target Federal Funds Rate increases on the FOMC announcement day and Chava and Hsu (2020) find that the negative response to the unanticipated interest rate changes is pronounced for financially constrained firms. Our event study tests whether the stock price reaction to the unanticipated Target Federal Funds Rate changes is heterogeneous across the firm's sensitivity of interest rate risk conditioning on inflation rate.

Following Kuttner (2001), Bernanke and Kuttner (2005), and Chava and Hsu (2020), we use the price of Fed funds futures contracts to compute the surprise components of monetary policy actions. The surprise components are measured by the changes in prices of the current-month futures contract right before and after the FOMC event days.[9] Specifically, the surprise components to monetary policy based on Fed futures are

$$FFRshock = \frac{D}{D-d}(f^0_{m,d} - f^0_{m,d-1}),$$

where $f^0_{m,d}$ is the month m futures contract price, D is the number of days in the month m, and d is the FOMC announcement day of the month.

To understand the differential impact of unanticipated interest rate changes in the cross-section of stock returns, we calculate post-announcement cumulative firm-level

[9] The surprise measure is available from June 1989 to June 2019 at Kenneth N. Kuttner's website: https://econ.williams.edu/faculty-pages/research/ and there are 266 FOMC event days in the sample.

returns around FOMC announcement. First, we run pooled regression of firm level cumulative returns by β^{Int}- and β^{IntInf}-sorted portfolios around the 266 FOMC announcement days. Table 9 presents the coefficient estimates of the pooled regression. We estimate the following regression model for the cumulative returns,

$$R(a,b)_{i,t} \quad = \quad \alpha + \delta FFRshock_t + \varepsilon_{i,t}$$

where, $R(a,b)_{i,t}$ is calculated with each firm i and each event date t over seven different event windows (a,b) and shown in Columns (1) to (7). Specifically, in Column (1), (0,0) denotes the return on the day of the FOMC announcement, and in Columns (2) to (7), (+1,+N) denotes the cumulative return in the posit announcement window up to N days. All regressions include firm and year fixed effects. Panel A reports the results with β^{Int}-sorted quintile portfolios, and Panel B reports the results with β^{IntInf}-sorted quintile portfolios. In line with Bernanke and Kuttner (2005), the coefficient loadings on the FFR shock are negative and significant. The negative effect of the FFR shock on stock returns is supposedly most pronounced in Portfolio 1 (with the most negative β^{Int} and β^{IntInf}). However, when the portfolios are formed based on β^{Int}, the cumulative return in Portfolio 1 is larger, rather than smaller, than the one in Portfolio 5, which is not consistent with the expected return response. On the other hand, when sorted by β^{IntInf}, Portfolio 1 has smaller cumulative returns than Portfolio 5, implying that β estimated by the interaction of interest rate innovation and standardized inflation can well explain the cross-section of return responses.

To confirm that the asymmetric impact of the FFR shock on the stock returns is consistent with $IntInf$-sorted portfolios but not with Int-sorted ones, we run the firm-level pooled regression with the FFR shock and the dummy of the negative β^{Int} (β^{IntInf}). We conjecture that a shock to monetary policy has heterogenous impacts on stock returns across firms. In particular, the negative return response to the unanticipated interest rate increase would be particularly pronounced for firms with the negative sensitivity to the interest rate risk. To analyze the differential effect, we regress the firm-level returns on the FFR shock, the negative beta dummy, and the interaction of the two:

$$\begin{aligned}
R(a,b)_{i,t} &= \alpha + \delta FFRshock_t + \gamma \mathbb{I}(\beta^{Int} < 0)_{i,t} + \theta FFRshock_t \times \mathbb{I}(\beta^{Int} < 0)_{i,t} + \varepsilon_{i,t}, \\
R(a,b)_{i,t} &= \alpha + \delta FFRshock_t + \gamma \mathbb{I}(\beta^{IntInf} < 0)_{i,t} + \theta FFRshock_t \times \mathbb{I}(\beta^{IntInf} < 0)_{i,t} + \varepsilon_{i,t}
\end{aligned}$$

for panels A and B in Table 10, respectively. All regressions include firm and year fixed effects. The coefficient on the interaction terms reflect the asymmetric of the FFR shock between positive interest rate beta and negative interest rate beta. Table 10 shows that a positive FFR shock yields negative return response for stocks with $\beta^{IntInf} < 0$, which is consistent with the conjecture. In contrast, a positive FFR shock leads to a positive return response for stocks with $\beta^{Int} < 0$, implying that the sensitivity to the unconditional interest rate risk cannot explain the heterogenous return responses to the unanticipated monetary shock. These findings mainly support our cross-sectional pricing results.

4 Mechanism

In this section, we provide supporting evidence that our suggested factor is a valid stochastic discount factor. First, note that in Merton (1973)'s ICAPM framework, a state variable relates to changes in the investment opportunity set and the innovations in the state variable should be a priced factor in the cross-section (Maio and Santa-Clara, 2012). It implies that a state variable can work as a valid factor, rather than a "fishing license (Fama, 1991)", in the ICAPM framework only if it predicts future consumption growth. To test the consumption predictability, we run the following regressions in which the dependent variable is the per capita real consumption growth rate, and the independent variables include the shocks to interest rates, standardized inflation and their interaction.

$$\Delta c_{t \to t+k} = a + b' X_t + u_{t \to t+k}, \quad k = 1, 3, 6, 12,$$

where $\Delta C_{t+1,t+K}$ is the real per capital consumption growth over K-month horizon. We measure the consumption growth over various horizons from one to twelve months ($K = 1, 3, 6, 12$). We consider Int, Inf and their interaction as the predictor X. The sample period from January 1959 to December 2022. To confirm the validity of the conditional interest rate factor and its superiority to the unconditional counterpart, it is important to show that the conditional factor has a predictive power for the future consumption growth, while the unconditional one does not.

Table 11 presents the results of the predictive regressions. The values in parentheses are the t-statistics using Newey-West standard errors with K lags. The results are supportive: neither interest rate nor inflation rate can individually predict the future consumption growth, but they collectively have significant predictability. Specifically, we find that the unconditional interest rate factor (Panel A) or the standardized inflation (Panel B) is not individually significant in predicting future consumption growth, but the conditional interest rate factor (Panel C) has a significantly negative coefficient except for the case $K = 1$, implying that a positive innovation in the interest rate predicts a decrease (increase) in the medium- or long-run consumption growth when the inflation rate is high (low). When the three predictors are simultaneously controlled for (Panel D), the interaction term ($IntInf$) remains significant over the medium or long horizon. This finding justifies the use of the interaction between interest rate and inflation, rather than the interest rate itself, as an ICAPM pricing factor.

As an additional validation, we examine the Sharpe ratio of the conditional interest rate factor-mimicking portfolio. Note that in an incomplete market, there are infinitely many SDFs but the one in the payoff space is unique and has the smallest variance (Cochrane, 2009). Also note that Hansen and Jagannathan (1991)'s volatility bound implies that the SDF in the payoff space has the largest Sharpe ratio. Combined, if our suggested conditional interest rate factor is a valid SDF, its mimicking portfolio should have the Sharpe ratio comparable to the tangency portfolio.

We construct the conditional interest rate factor-mimicking portfolio (IMP) by a linear combination of the Fama-French six portfolios sorted by size and book-to-market ratio (SH, SM, SL, BH, BM, BL). Specifically, we regress $IntInf$ on a constant and the excess returns of these six portfolios: $Basis = [R^e_{SH}, R^e_{SM}, R^e_{SL}, R^e_{BH}, R^e_{BM}, R^e_{BL}]'$, using the monthly data from January 1959 to December 2022.

$$IntInf_t = c_0 + c_1' Basis_t + \epsilon_t.$$

After normalizing the coefficient such that they sum to one, $\tilde{c}_{1i} = \frac{c_{1i}}{\sum c_{1i}}$, the mimicking portfolio is defined as $IMP_t = \tilde{c}_1' Basis_t$. Since IMP is a linear combination of six excess returns, it is also an excess return. Table 12 presents the averages and the standard deviations of IMP as well as the standard benchmark equity factors ($RmRf, SMB, HML, UMD$), and the resulting Sharpe ratios. The annualized Sharpe ratio is computed by multiplying $\sqrt{12}$. To examine whether IMP attains the maximum Sharpe ratio, we generate the efficient frontier with the six size and book-to-market portfolios and the four benchmark equity factors and find out the tangency portfolio. We find that the annualized Sharpe ratio of IMP is 0.878. Although it is smaller than the ex post maximum Sharpe ratio achieved from our sample (1.242), it is much higher than those of standard equity factors.

To sum up, we validate our suggested factor by showing that it predicts the future consumption growth and its mimicking portfolio has the Sharpe ratio comparable to the tangency portfolio.

5 Conclusion

This study examines whether the interest rate risk is priced in the cross-section of stock returns conditioning on the prevailing inflation rates. When the Federal Reserve raises interest rates with high inflation state, investors seem to require higher premium to compensate for the interest rate risk. As a result, expected stock returns increase with interest rate risk, controlling for prevailing inflation level. This implication justifies current global market conditions with high inflation and high interest rate regime and makes robust relation of interest rate risk accompanied with inflation rate and stock prices. Thus, our study highlights the role of interest rate risk in understanding the current global bear markets and calls for more attention to be given to inflation rate when assessing interest rate risk. Further, the practical inference from our study is that investors' interest rate risk is conditionally related to the inflation rate in asset prices, which is crucial for their investment decisions.

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Table 1: **Descriptive statistics**

Panel A. Summary statistics	Mean	St.Dev.	Skewness	Kurtosis	Min	Q25	Median	Q75	Max	Obs
i_{TB3} (%)	4.343	3.170	0.766	3.874	0.01	1.88	4.415	5.98	16.3	768
Int	0.000	0.382	-1.283	21.339	-3.265	-0.087	-0.016	0.108	2.263	768
π (%)	3.652	2.472	1.524	4.831	0.626	2.042	2.836	4.526	11.869	768
Inf	0.096	0.538	1.401	4.284	-0.655	-0.257	-0.106	0.318	1.783	768
$IntInf$	0.012	0.500	-2.256	46.733	-5.212	-0.015	0.005	0.024	3.927	768
RmRf	0.549	4.456	-0.496	4.712	-23.24	-1.97	0.98	3.365	16.1	768
SMB	0.202	2.953	0.353	6.257	-15.35	-1.51	0.08	1.92	18.34	768
HML	0.316	2.909	0.111	5.444	-13.97	-1.345	0.265	1.75	12.75	768
RMW	0.282	2.223	-0.280	14.245	-18.73	-0.79	0.24	1.31	13.09	714
CMA	0.301	2.056	0.321	4.382	-6.94	-1	0.105	1.52	9.05	714
UMD	0.673	4.089	-1.304	13.220	-34.3	-0.875	0.79	2.91	18.2	768

Panel B. Correlation matrix	i_{TB3} (%)	Int	π (%)	Inf	$IntInf$	RmRf	SMB	HML	RMW	CMA
i_{TB3} (%)	1									
Int	0.121	1								
π (%)	0.754	0.049	1							
Inf	0.751	0.058	0.987	1						
$IntInf$	0.058	0.867	0.026	0.026	1					
RmRf	-0.086	-0.084	-0.045	-0.053	-0.104	1				
SMB	-0.027	0.006	0.047	0.053	-0.022	0.280	1			
HML	0.066	-0.078	0.063	0.067	-0.107	-0.209	-0.026	1		
RMW	-0.013	0.093	-0.021	-0.029	0.088	-0.180	-0.348	0.091	1	
CMA	0.057	-0.082	0.061	0.061	-0.070	-0.366	-0.097	0.683	-0.019	1
UMD	0.081	0.060	0.055	0.059	0.067	-0.165	-0.061	-0.204	0.080	-0.021

Note: Table 1 presents the descriptive statistics of the interest rate, inflation and equity risk factors. The sample period from January 1959 to December 2022.

Table 2: β^{IntInf}-**sorted deciel portfolios**

	Pt1	Pt2	Pt3	Pt4	Pt5	Pt6	Pt7	Pt8	Pt9	Pt10	Pt1-Pt10
Excess return	0.765***	0.641***	0.628***	0.598***	0.608***	0.625***	0.445**	0.516***	0.475**	0.337*	0.428**
	(3.20)	(3.13)	(3.11)	(3.14)	(3.29)	(3.43)	(2.43)	(2.76)	(2.49)	(1.72)	(2.47)
Post-formation beta	-1.193***	-1.034***	-1.067***	-1.051***	-0.699*	-0.830**	-0.744*	-1.045**	-0.877*	-0.549	-0.644*
	(-3.25)	(-3.06)	(-3.25)	(-2.86)	(-1.74)	(-2.39)	(-1.93)	(-2.46)	(-1.85)	(-0.95)	(-1.72)
Market capitalization	2816.3***	3411.3***	1710.4***	1561.1***	1985.8***	2192.5***	2112.3***	2004.9***	2206.8***	2174.2***	642.1**
	(11.02)	(13.55)	(15.54)	(20.88)	(19.13)	(18.98)	(16.80)	(13.11)	(10.46)	(9.74)	(2.23)
Obs.	708	708	708	708	708	708	708	708	708	708	708

Note: Table 2 presents the portfolio analysis results. The portfolio 1 (Pt1) represents the stocks with the smallest (most negative) β^{IntInf}, while the portfolio 10 (Pt10) represents the stocks with the largest β^{IntInf}. Pt1-Pt10 is the portfolio that goes long on Pt1 and goes short on Pt10. The numbers are the time-series averages of the portfolio excess return, post-portfolio formation exposure to the conditional interest rate risk ($IntInf$), and the average market capitalization in $ thousands. The numbers in the parenthesis are the t statistics based on the Newey-West standard error. The lag length is chosen to be one. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively. The sample period from January 1964 to December 2022.

Table 3: **Risk-adjusted excess returns of β^{IntInf}-sorted long-short portfolio**

	Pt1-Pt10	Pt1-Pt10	Pt1-Pt10	Pt1-Pt10	Pt1-Pt10	Pt1-Pt10
Risk-adjusted α	0.428**	0.316*	0.286*	0.386**	0.578***	0.637***
	(2.47)	(1.84)	(1.69)	(2.11)	(3.22)	(3.35)
RMRF		0.207***	0.147**	0.124**	0.0807	0.0678
		(3.48)	(2.38)	(2.06)	(1.29)	(1.08)
SMB			0.298***	0.297***	0.157*	0.160*
			(2.70)	(2.58)	(1.80)	(1.82)
HML			-0.0246	-0.0656	0.195*	0.153
			(-0.24)	(-0.64)	(1.92)	(1.50)
UMD				-0.116		-0.0815
				(-1.42)		(-1.14)
RMW					-0.564***	-0.550***
					(-4.41)	(-4.26)
CMA					-0.436***	-0.407***
					(-2.78)	(-2.69)
Obs.	708	708	708	708	708	708

Note: Table 3 presents the risk-adjusted excess return of the long-short portfolio. RmRf, SMB, HML, RMW and CMA are Fama-French five factors and UMD is the Carhart momentum factor. The values in parenthesis are the t statistics based on the Newey-West standard error. The lag length is chosen to be one. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively. The sample period from January 1964 to December 2022.

Table 4: β^{Int}**-sorted deciel portfolios**

	Pt1	Pt2	Pt3	Pt4	Pt5	Pt6	Pt7	Pt8	Pt9	Pt10	Pt1-Pt10
Excess return	0.514***	0.432**	0.553***	0.611***	0.606***	0.613***	0.593***	0.614***	0.549**	0.729***	-0.215
	(3.01)	(2.48)	(3.23)	(3.50)	(3.41)	(3.35)	(3.05)	(2.93)	(2.47)	(2.85)	(-1.19)
Post-formation beta	-1.172***	-1.052***	-1.016***	-0.916**	-0.919**	-0.750**	-0.851**	-0.944**	-0.929**	-0.569	-0.603*
	(-3.27)	(-3.04)	(-2.73)	(-2.41)	(-2.42)	(-2.10)	(-2.37)	(-2.46)	(-2.08)	(-0.98)	(-1.68)
Market capitalization	2679.1***	3028.2***	3030.4***	2638.5***	2365.7***	2217.0***	1889.3***	1749.3***	1491.3***	1085.9***	1593.1***
	(12.61)	(13.73)	(13.80)	(17.75)	(16.82)	(17.53)	(16.33)	(16.11)	(16.32)	(17.49)	(8.73)
Obs.	708	708	708	708	708	708	708	708	708	708	708

Note: Table 4 presents the portfolio analysis results. The portfolio 1 (Pt1) represents the stocks with the smallest (most negative) β^{IntInf}, while the portfolio 10 (Pt10) represents the stocks with the largest (most positive) β^{Int}. Pt1-Pt10 is the portfolio that goes long on Pt1 and goes short on Pt10. The numbers are the time-series averages of the portfolio excess return, post-portfolio formation exposure to the conditional interest rate risk (Int), and the average market capitalization in $ thousands. The numbers in the parenthesis are the t statistics based on the Newey-West standard error. The lag length is chosen to be one. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively. The sample period from January 1964 to December 2022.

Table 5: **Risk-adjusted excess returns of β^{Int}-sorted long-short portfolio**

	Pt1-Pt10	Pt1-Pt10	Pt1-Pt10	Pt1-Pt10	Pt1-Pt10	Pt1-Pt10
Risk-adjusted α	-0.215	-0.00141	-0.125	-0.168	-0.272	-0.295
	(-1.19)	(-0.01)	(-0.79)	(-0.94)	(-1.58)	(-1.57)
RMRF		-0.391***	-0.289***	-0.278***	-0.253***	-0.248***
		(-7.82)	(-5.44)	(-5.33)	(-4.42)	(-4.34)
SMB			-0.247***	-0.247***	-0.181**	-0.182**
			(-2.93)	(-2.87)	(-2.35)	(-2.33)
HML			0.404***	0.421***	0.281***	0.298***
			(4.85)	(4.87)	(2.65)	(2.76)
UMD				0.0502		0.0320
				(0.66)		(0.43)
RMW					0.264***	0.259**
					(2.66)	(2.55)
CMA					0.249*	0.237
					(1.69)	(1.64)
Obs.	708	708	708	708	708	708

Note: Table 5 presents the risk-adjusted excess return of the long-short portfolio. RmRf, SMB, HML, RMW and CMA are Fama-French five factors and UMD is the Carhart momentum factor. The values in parenthesis are the t statistics based on the Newey-West standard error. The lag length is chosen to be one. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively. The sample period from January 1964 to December 2022.

Table 6: **Pricing the 25 equity portfolios sorted by size and book-to-market**

	(1) CAPM	(2) FF3	(3) CAPM+Int	(4) CAPM+IntInf	(5) Int	(6) IntInf
Panel A. Restriction on zero-beta excess rate ($\lambda_0 = 0$)						
RmRf	0.665	0.518	0.662	0.619		
	(3.469)	(2.974)	(3.275)	(3.073)		
Int			-0.400		-0.642	
			(-2.070)		(-1.866)	
IntInf				-0.506		-0.652
				(-2.369)		(-2.122)
SMB		0.242				
		(1.975)				
HML		0.370				
		(3.139)				
R^2	-43.59%	49.77%	36.57%	55.28%	1.47%	45.79%
Adj-R^2	-49.58%	42.92%	31.06%	51.39%	-2.63%	43.53%
MAPE	2.03%	1.12%	1.42%	1.22%	1.91%	1.38%
Panel B. No restriction on zero-beta excess rate						
λ_0	1.077	1.169	0.081	0.021	0.374	0.216
	(1.935)	(3.084)	(0.131)	(0.031)	(0.835)	(0.486)
RmRf	-0.310	-0.600	0.589	0.600		
	(-0.543)	(-1.446)	(0.872)	(0.834)		
Int			-0.382		-0.332	
			(-2.179)		(-1.525)	
IntInf				-0.501		-0.471
				(-2.327)		(-1.992)
SMB		0.199				
		(1.627)				
HML		0.341				
		(2.906)				
R^2	4.82%	64.98%	36.69%	55.29%	35.00%	54.36%
Adj-R^2	0.68%	59.98%	30.94%	51.22%	32.18%	52.37%
MAPE	1.87%	1.87%	1.87%	1.87%	1.87%	1.87%
Intercept	12.93%	14.02%	0.97%	0.25%	4.49%	2.59%
Total	14.79%	15.89%	2.84%	2.12%	6.36%	4.46%

Note: Table 6 presents the risk premiums (λ) from 25 equity portfolios sorted by size and book-to-market ratio. λ's are obtained from the Fama-MacBeth regression of $E[R^e] = \lambda_0 + \beta_F' \lambda_F$, where each column indicates the considered factors (F). In Panel A, we impose a restriction that the zero-beta excess rate (λ_0) equals zero, while there is no such restriction in Panel B. The values in parentheses are Shanken t-statistics. MAPE is the mean absolute pricing error. Intercept in Panel B is the annualized zero-beta excess rate, and Total is the sum of Intercept and MAPE. The sample period from January 1964 to December 2022.

Table 7: **Pricing the 25 equity portfolios sorted by size and long-run reversal**

	(1) CAPM	(2) FF3	(3) CAPM+Int	(4) CAPM+IntInf	(5) Int	(6) IntInf
Panel A. Restriction on zero-beta excess rate ($\lambda_0 = 0$)						
RmRf	0.726	0.556	0.699	0.658		
	(3.763)	(3.157)	(3.522)	(3.355)		
Int			-0.301		-0.658	
			(-2.196)		(-1.890)	
IntInf				-0.478		-0.685
				(-2.615)		(-2.146)
SMB		0.171				
		(1.235)				
HML		0.524				
		(2.473)				
R^2	0.25%	71.59%	34.83%	60.19%	-19.80%	47.97%
Adj-R^2	-3.91%	67.71%	29.16%	56.73%	-24.79%	45.80%
MAPE	1.56%	0.78%	1.24%	0.90%	1.65%	1.10%
Panel B. No restriction on zero-beta excess rate						
λ_0	0.393	0.412	-0.077	-0.093	0.463	0.213
	(1.042)	(0.914)	(-0.148)	(-0.166)	(1.316)	(0.588)
RmRf	0.367	0.161	0.768	0.741		
	(0.837)	(0.351)	(1.327)	(1.221)		
Int			-0.316		-0.281	
			(-1.864)		(-1.779)	
IntInf				-0.497		-0.506
				(-2.091)		(-2.069)
SMB		0.185				
		(1.318)				
HML		0.466				
		(1.910)				
R^2	8.32%	75.59%	35.04%	60.56%	21.97%	55.17%
Adj-R^2	4.33%	72.10%	29.14%	56.98%	18.58%	53.22%
MAPE	1.57%	0.71%	1.22%	0.91%	1.41%	0.93%
Intercept	4.72%	4.94%	-0.93%	-1.12%	5.55%	2.56%
Total	6.29%	5.65%	2.15%	2.03%	6.97%	3.49%

Note: Table 7 presents the risk premiums (λ) from 25 equity portfolios sorted by size and long-run reversal. λ's are obtained from the Fama-MacBeth regression of $E[R^e] = \lambda_0 + \beta_F' \lambda_F$, where each column indicates the considered factors (F). In Panel A, we impose a restriction that the zero-beta excess rate (λ_0) equals zero, while there is no such restriction in Panel B. The values in parentheses are Shanken t-statistics. MAPE is the mean absolute pricing error. Intercept in Panel B is the annualized zero-beta excess rate, and Total is the sum of Intercept and MAPE. The sample period from January 1964 to December 2022.

Table 8: **Pricing the 25 equity portfolios sorted by size and investment**

	(1) CAPM	(2) FF3	(3) CAPM+Int	(4) CAPM+IntInf	(5) Int	(6) IntInf
Panel A. Restriction on zero-beta excess rate ($\lambda_0 = 0$)						
RmRf	0.674	0.565	0.684	0.648		
	(3.553)	(3.285)	(3.496)	(3.218)		
Int			-0.341		-0.674	
			(-2.297)		(-1.807)	
IntInf				-0.588		-0.704
				(-2.912)		(-2.035)
SMB		0.174				
		(1.445)				
HML		0.699				
		(4.350)				
R^2	-47.90%	65.58%	3.20%	35.45%	-53.74%	31.88%
Adj-R^2	-54.06%	60.89%	-5.22%	29.84%	-60.15%	29.04%
MAPE	2.14%	0.99%	1.72%	1.39%	2.06%	1.43%
Panel B. No restriction on zero-beta excess rate						
λ_0	1.015	0.671	0.612	0.333	0.525	0.221
	(2.493)	(1.568)	(1.499)	(0.600)	(1.372)	(0.550)
RmRf	-0.244	-0.077	0.126	0.351		
	(-0.533)	(-0.168)	(0.266)	(0.572)		
Int			-0.201		-0.214	
			(-1.679)		(-1.385)	
IntInf				-0.490		-0.503
				(-2.337)		(-2.403)
SMB		0.164				
		(1.370)				
HML		0.544				
		(2.881)				
R^2	3.58%	70.24%	13.53%	38.79%	13.29%	38.30%
Adj-R^2	-0.61%	65.99%	5.67%	33.22%	9.52%	35.61%
MAPE	1.78%	0.83%	1.73%	1.39%	1.73%	1.37%
Intercept	12.18%	8.06%	7.35%	4.00%	6.30%	2.65%
Total	13.96%	8.89%	9.08%	5.38%	8.03%	4.02%

Note: Table 8 presents the risk premiums (λ) from 25 equity portfolios sorted by size and investment. λ's are obtained from the Fama-MacBeth regression of $E[R^e] = \lambda_0 + \beta_F' \lambda_F$, where each column indicates the considered factors (F). In Panel A, we impose a restriction that the zero-beta excess rate (λ_0) equals zero, while there is no such restriction in Panel B. The values in parentheses are Shanken t-statistics. MAPE is the mean absolute pricing error. Intercept in Panel B is the annualized zero-beta excess rate, and Total is the sum of Intercept and MAPE. The sample period from January 1964 to December 2022.

Table 9: **Return response of β^{Int}- and β^{IntInf}-sorted portfolios to shock of Fed Funds rates around FOMC event days**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Portfolio	(0,0)	(+1,+1)	(+1,+2)	(+1,+3)	(+1,+4)	(+1,+10)	(+1,+20)
			Panel A: β^{Int}-sorted portfolios				
1 (Low)	-0.003	-0.018**	-0.016	-0.003	-0.013	-0.062**	-0.118***
	(-0.24)	(-2.01)	(-1.49)	(-0.21)	(-0.72)	(-2.29)	(-3.11)
2	-0.005	-0.016*	-0.011	-0.002	-0.008	-0.039*	-0.087***
	(-0.45)	(-1.78)	(-1.02)	(-0.18)	(-0.53)	(-1.89)	(-3.05)
3	-0.004	-0.016**	-0.013	-0.007	-0.015	-0.046**	-0.092***
	(-0.43)	(-2.25)	(-1.30)	(-0.60)	(-1.00)	(-2.15)	(-2.92)
4	-0.005	-0.018**	-0.017	-0.009	-0.015	-0.060**	-0.112***
	(-0.43)	(-2.25)	(-1.49)	(-0.75)	(-0.94)	(-2.38)	(-3.06)
5 (High)	-0.007	-0.024***	-0.026**	-0.015	-0.024	-0.103***	-0.159***
	(-0.36)	(-3.04)	(-2.19)	(-1.03)	(-1.27)	(-2.70)	(-2.89)
			Panel B: β^{IntInf}-sorted portfolios				
1 (Low)	-0.009	-0.022***	-0.023*	-0.012	-0.021	-0.095***	-0.151***
	(-0.50)	(-2.62)	(-1.96)	(-0.81)	(-1.10)	(-2.62)	(-2.97)
2	-0.006	-0.020**	-0.013	-0.003	-0.011	-0.055**	-0.100***
	(-0.49)	(-2.20)	(-1.30)	(-0.32)	(-0.76)	(-2.37)	(-3.15)
3	-0.001	-0.017**	-0.015	-0.008	-0.013	-0.042*	-0.093***
	(-0.07)	(-2.09)	(-1.39)	(-0.72)	(-0.90)	(-1.91)	(-2.96)
4	-0.003	-0.019**	-0.016	-0.007	-0.014	-0.056**	-0.103***
	(-0.33)	(-2.39)	(-1.47)	(-0.57)	(-0.89)	(-2.23)	(-2.88)
5 (High)	-0.002	-0.017*	-0.0175	-0.006	-0.014	-0.063**	-0.119***
	(-0.13)	(-1.92)	(-1.54)	(-0.42)	(-0.80)	(-2.23)	(-2.91)

Note: Table 9 presents the coefficient estimates of the pooled regression of firm level returns by β^{Int}- and β^{IntInf}-sorted portfolios around the 266 FOMC event days. Panel A reports the results with β^{Int}-sorted portfolios, and Panel B reports the results with β^{IntInf}-sorted portfolios. The firm level returns are calculated over seven different event windows and shown in model (1) to (7) by each portfolio. We estimate the following regression model: $R(a,b)_{i,t} = \alpha + \delta FFRshock_t + \varepsilon_{i,t}$. $R(a,b)_{i,t}$ is calculated with each firm i and each event date t over seven different event windows (a,b). The explanatory variable, $FFRShock_t$, denotes the shock components of Fed Funds rates from Kenneth N. Kuttner's website. All regressions include firm and year fixed effects. The sample period from June 1989 to June 2019.

Table 10: **Firm level return response to shock of Fed Funds rates around FOMC event days**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	(0,0)	(+1,+1)	(+1,+2)	(+1,+3)	(+1,+4)	(+1,+10)	(+1,+20)
Panel A: Dummy Variables of negative β^{Int}							
FFRshock	-0.005	-0.023***	-0.023**	-0.016	-0.024*	-0.078***	-0.123***
	(-0.40)	(-3.50)	(-2.48)	(-1.32)	(-1.66)	(-3.04)	(-3.25)
$\mathbb{I}(\beta^{Int} < 0)$	-0.035	-0.059	-0.036	0.018	0.036	0.054	0.161
	(-0.62)	(-1.09)	(-0.56)	(0.24)	(0.42)	(0.36)	(0.64)
FFR $\times$ $\mathbb{I}(\beta^{Int} < 0)$	0.003	0.014	0.022*	0.029**	0.033**	0.051**	0.028
	(0.27)	(1.36)	(1.92)	(2.29)	(2.24)	(2.59)	(1.15)
Observations	1,243,401	1,242,985	1,243,036	1,243,049	1,243,057	1,243,082	1,243,098
Adjusted R^2	0.014	0.014	0.016	0.021	0.021	0.030	0.050
Panel B: Dummy Variables of negative β^{IntInf}							
FFRshock	-0.002	-0.018**	-0.016	-0.007	-0.013	-0.048*	-0.098***
	(-0.18)	(-2.09)	(-1.48)	(-0.60)	(-0.90)	(-1.96)	(-2.82)
$\mathbb{I}(\beta^{IntInf} < 0)$	0.016	0.012	0.036	0.141*	0.141*	-0.061	-0.032
	(0.34)	(0.31)	(0.74)	(1.66)	(1.66)	(-0.45)	(-0.12)
FFR $\times$ $\mathbb{I}(\beta^{IntInf} < 0)$	-0.008	-0.003	-0.004	-0.002	-0.005	-0.0475**	-0.054*
	(-0.91)	(-0.70)	(-0.61)	(-0.23)	(-0.49)	(-2.08)	(-1.85)
Observations	1,243,401	1,242,985	1,243,036	1,243,049	1,243,057	1,243,082	1,243,098
Adjusted R^2	0.014	0.014	0.016	0.021	0.021	0.030	0.050

Note: Table 10 presents the coefficient estimates of the pooled regression of firm level returns around the 266 FOMC event days. The firm level returns are calculated over seven different event windows and shown in model (1) to (7). We estimate the following regression models: $R(a,b)_{i,t} = \alpha + \delta FFRshock_t + \gamma\mathbb{I}(\beta^{Int} < 0)_{i,t} + \theta FFRshock_t \times \mathbb{I}(\beta^{Int} < 0)_{i,t} + \varepsilon_{i,t}$ and $R(a,b)_{i,t} = \alpha + \delta FFRshock_t + \gamma\mathbb{I}(\beta^{IntInf} < 0)_{i,t} + \theta FFRshock_t \times \mathbb{I}(\beta^{IntInf} < 0)_{i,t} + \varepsilon_{i,t}$, for panels A and B respectively. $R(a,b)_{i,t}$ is calculated with each firm i and each event date t over seven different event windows (a,b). $FFRShock_t$, denotes the shock components of Fed Funds rates from Kenneth N. Kuttner's website and $\mathbb{I}(\beta^{Int} < 0)_{i,t}$ and $\mathbb{I}(\beta^{IntInf} < 0)_{i,t}$ are the dummy variables denoting the negative values of β^{Int} and β^{IntInf}. All regressions include firm and year fixed effects. The sample period from June 1989 to June 2019.

Table 11: **Prediction of consumption growth**

Horizon K	1	3	6	12
Panel A. $X = Int$				
Int	0.196	0.008	0.049	-0.061
	(1.20)	(0.10)	(0.42)	(-0.40)
Const.	0.156***	0.468***	0.935***	1.867***
	(6.20)	(8.28)	(9.63)	(9.71)
R^2	1.19%	0.00%	0.02%	0.01%
Adj-R^2	1.06%	-0.13%	-0.11%	-0.12%
Panel B. $X = Inf$				
Inf	-0.005	-0.005	0.007	0.089
	(-0.12)	(-0.06)	(0.04)	(0.26)
Const.	0.157***	0.468***	0.934***	1.859***
	(5.56)	(7.57)	(9.03)	(9.30)
R^2	0.00%	0.00%	0.00%	0.06%
Adj-R^2	-0.13%	-0.13%	-0.13%	-0.07%
Panel C. $X = IntInf$				
IntInf	-0.008	-0.09*	-0.137***	-0.201***
	(-0.18)	(-1.94)	(-2.92)	(-2.70)
Const.	0.156***	0.469***	0.937***	1.870***
	(6.23)	(8.30)	(9.66)	(9.74)
R^2	0.00%	0.14%	0.24%	0.28%
Adj-R^2	-0.13%	0.01%	0.11%	0.14%
Panel D. $X = \{Int, Inf, IntInf\}$				
Int	0.765	0.387	0.760***	0.608
	(1.16)	(1.53)	(2.62)	(1.60)
Inf	-0.024	-0.013	-0.008	0.079
	(-0.68)	(-0.14)	(-0.05)	(0.24)
IntInf	-0.506	-0.337*	-0.632***	-0.599**
	(-1.10)	(-1.86)	(-3.10)	(-2.26)
Const.	0.164***	0.473***	0.945***	1.869***
	(6.92)	(7.74)	(9.41)	(9.49)
R^2	4.86%	0.60%	1.42%	0.73%
Adj-R^2	4.48%	0.21%	1.38%	0.34%
Obs.	767	765	762	756

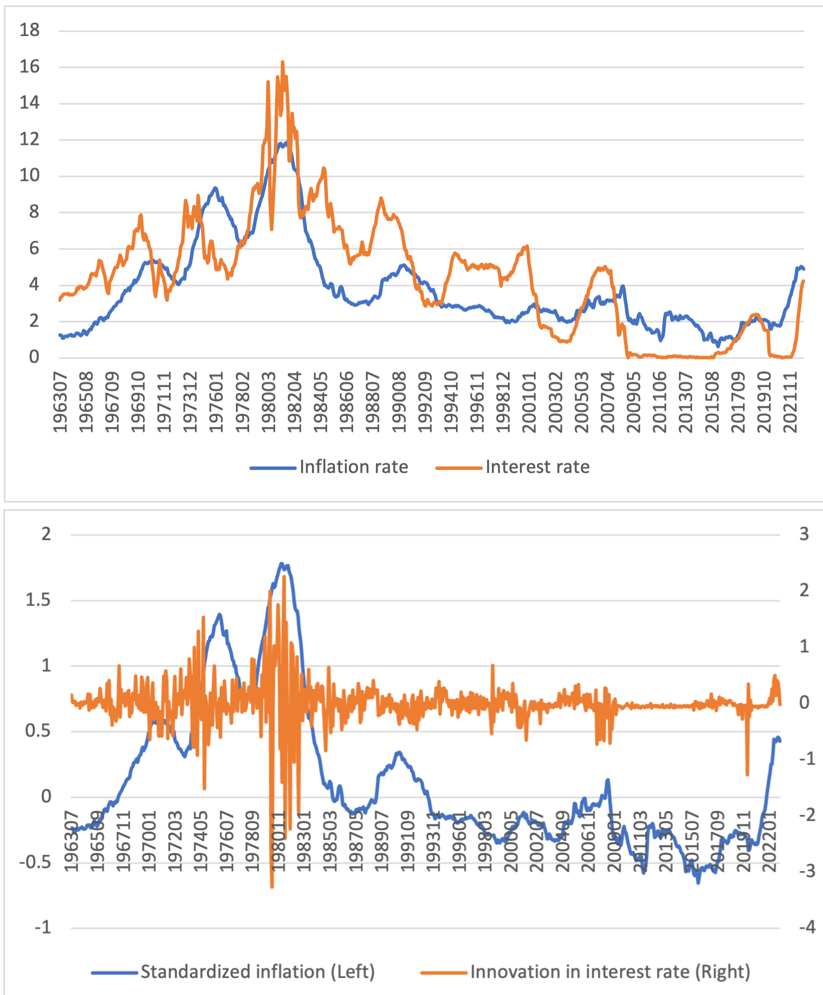
Note: Table 11 presents the results of the following predictive regressions: $\Delta C_{t+1,t+K} = c_0^K + c_1^K X_t + e_{t+1,t+K}$. $\Delta C_{t+1,t+K}$ is the real per capital consumption growth over K-month horizon ($K = 1, 3, 6, 12$). We consider Int, Inf and their interaction as the predictor X. The values in parentheses are the t-statistics using Newey-West standard errors with K lags. The sample period from January 1959 to December 2022.

Table 12: **Sharpe ratio of IMP and benchmark equity factors**

	Expected return (%)	Standard deviation (%)	Sharpe ratio	Annualized Sharpe ratio
RmRf	0.549	4.456	0.123	0.427
SMB	0.167	2.973	0.056	0.194
HML	0.316	2.909	0.109	0.376
UMD	0.673	4.089	0.164	0.570
IMP	1.369	5.400	0.254	0.878
Tangency	0.422	1.178	0.358	1.242

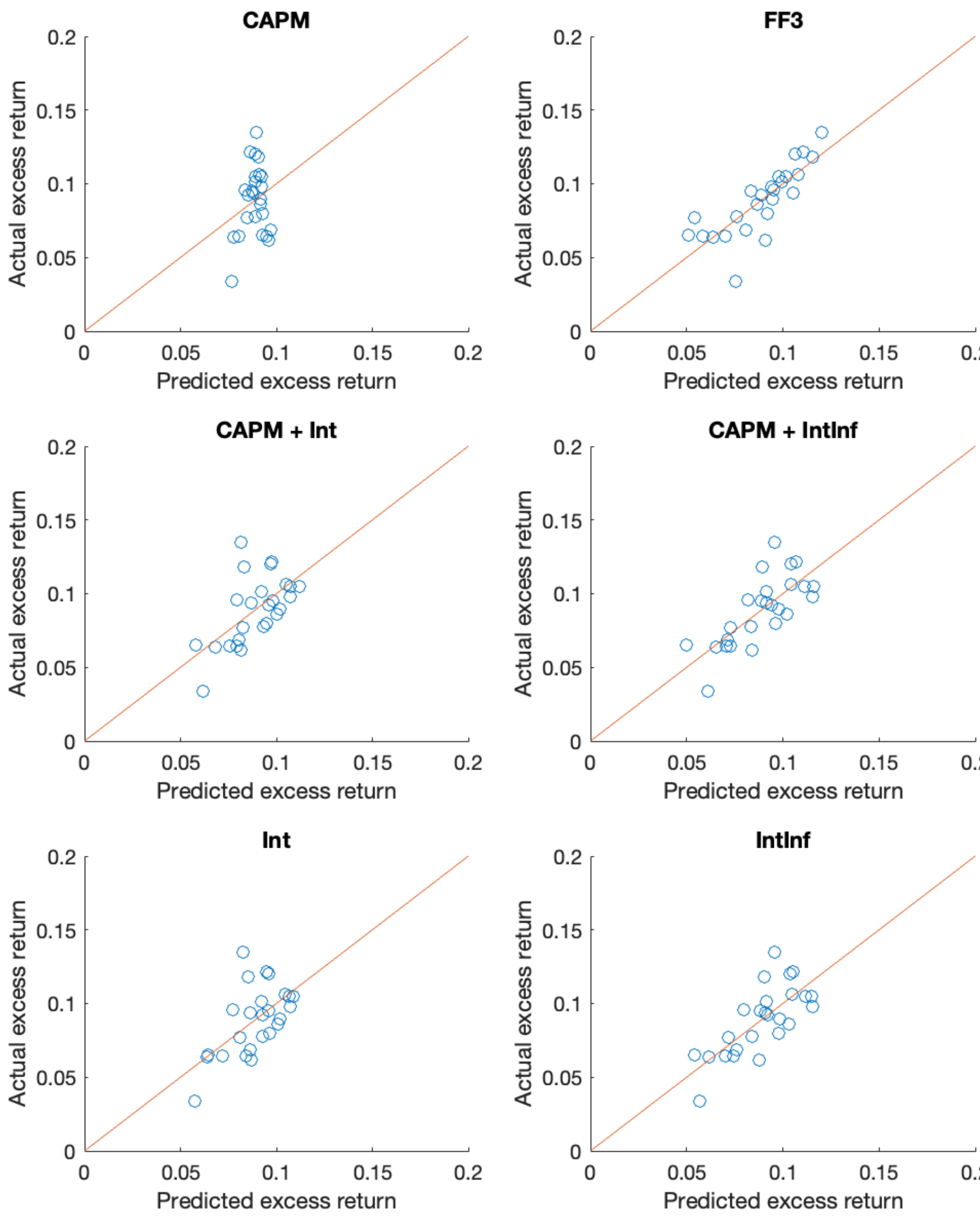
Note: Table 12 presents the monthly and annualized Sharpe ratios of IMP and four benchmark equity factors. Expected returns, standard deviations and Sharpe ratios are measured from monthly excess returns, while the annualized Sharpe ratio is computed by multiplying $\sqrt{12}$. The sample period from January 1959 to December 2022.

Figure 1: Interest rate and inflation



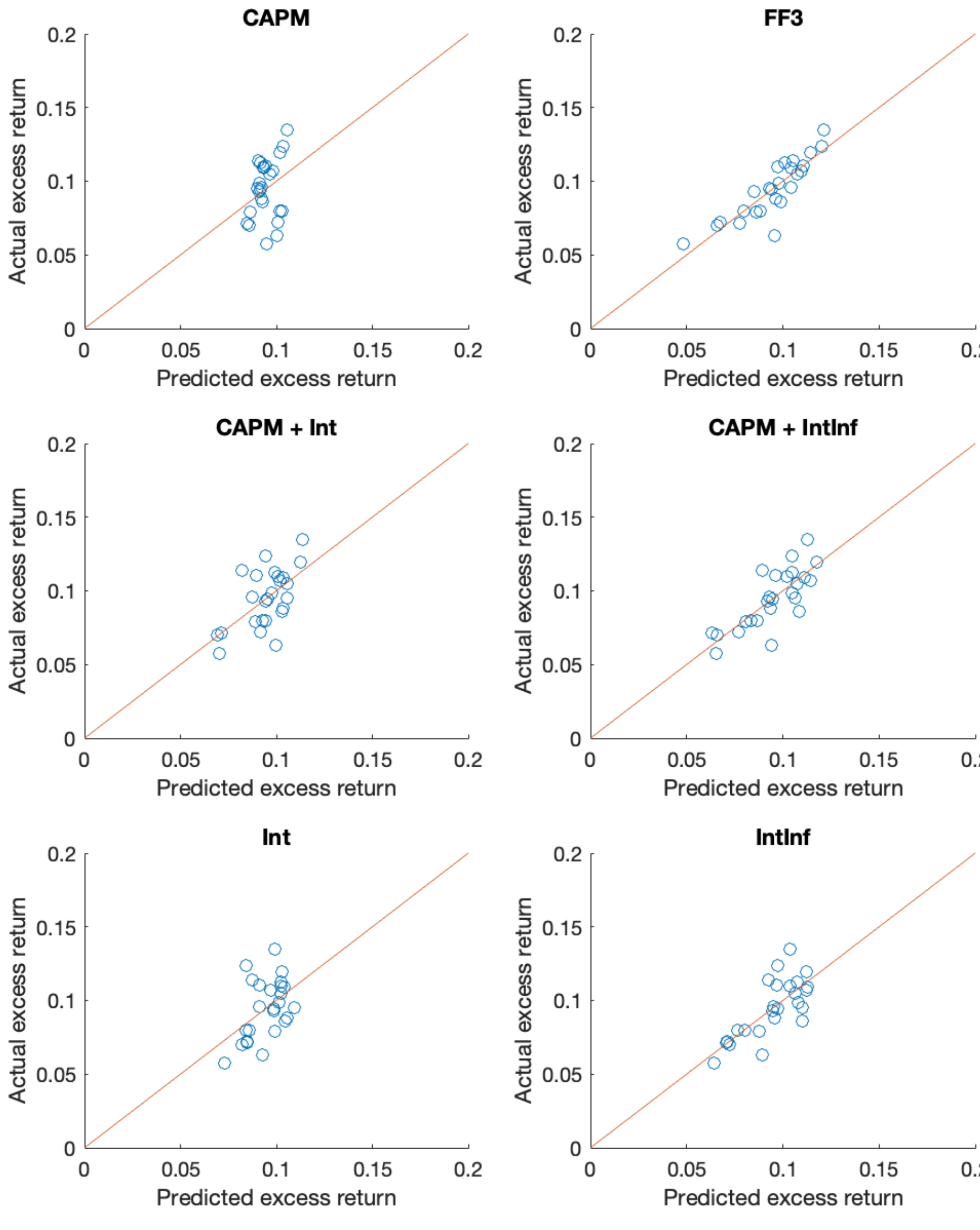
Note: The upper panel depicts the level of inflation (three-year annualized CPI inflation, %) and interest rates (annualized three-month treasury bill rates, %). The lower panel depicts the standardized inflation and the innovation in the interest rate. The innovation is obtained from the ARMA(1,1) residual. The data cover the period from July 1963 to December 2022.

Figure 2: Actual versus predicted excess returns: 25 portfolios sorted by size and book-to-market



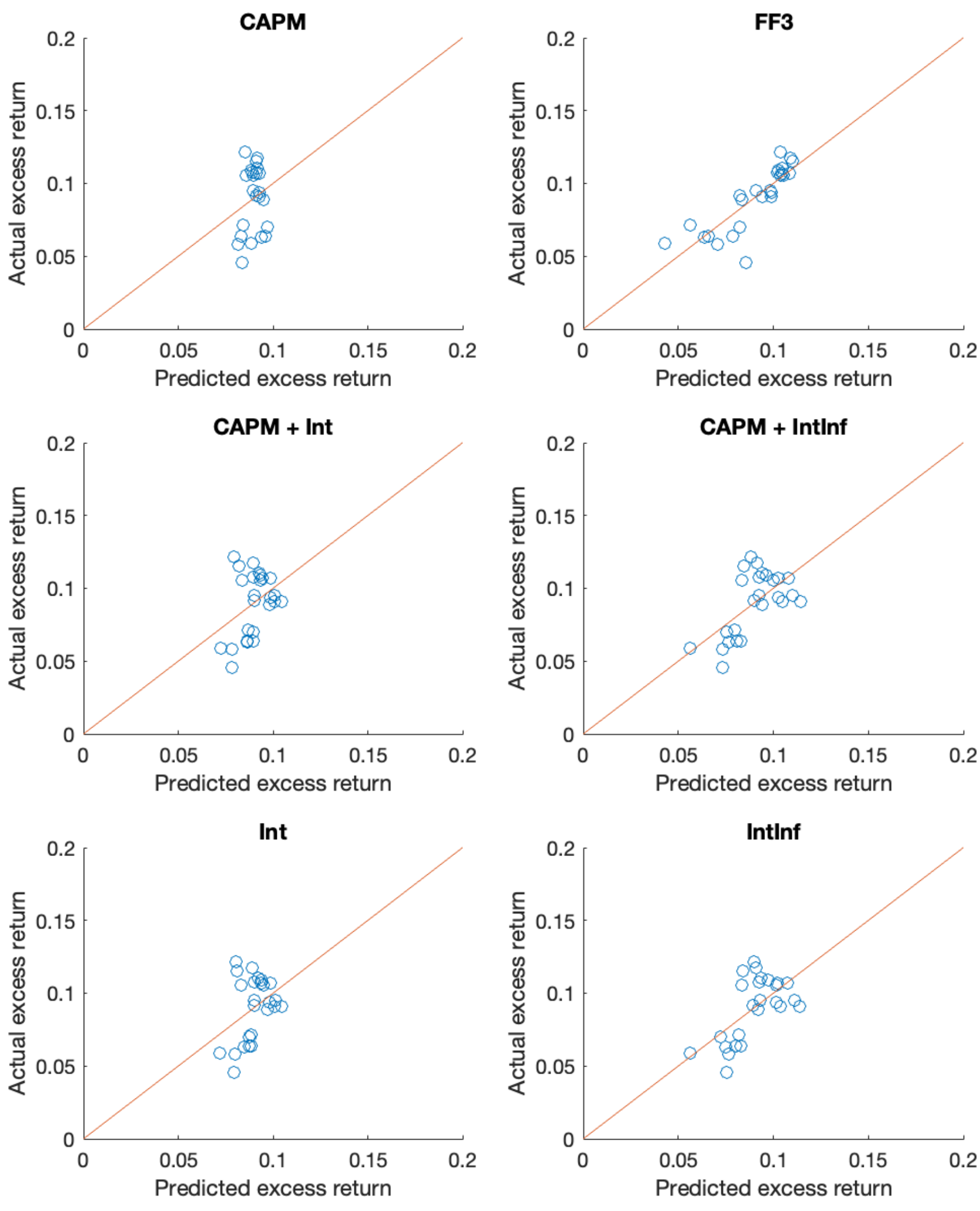
Note: Each panel in this figure plots the actual average excess returns of 25 equity portfolios sorted by size and book-to-market ratio against their average excess returns predicted by the corresponding model. The data cover the period from January 1964 to December 2022.

Figure 3: Actual versus predicted excess returns: 25 portfolios sorted by size and long-run reversal



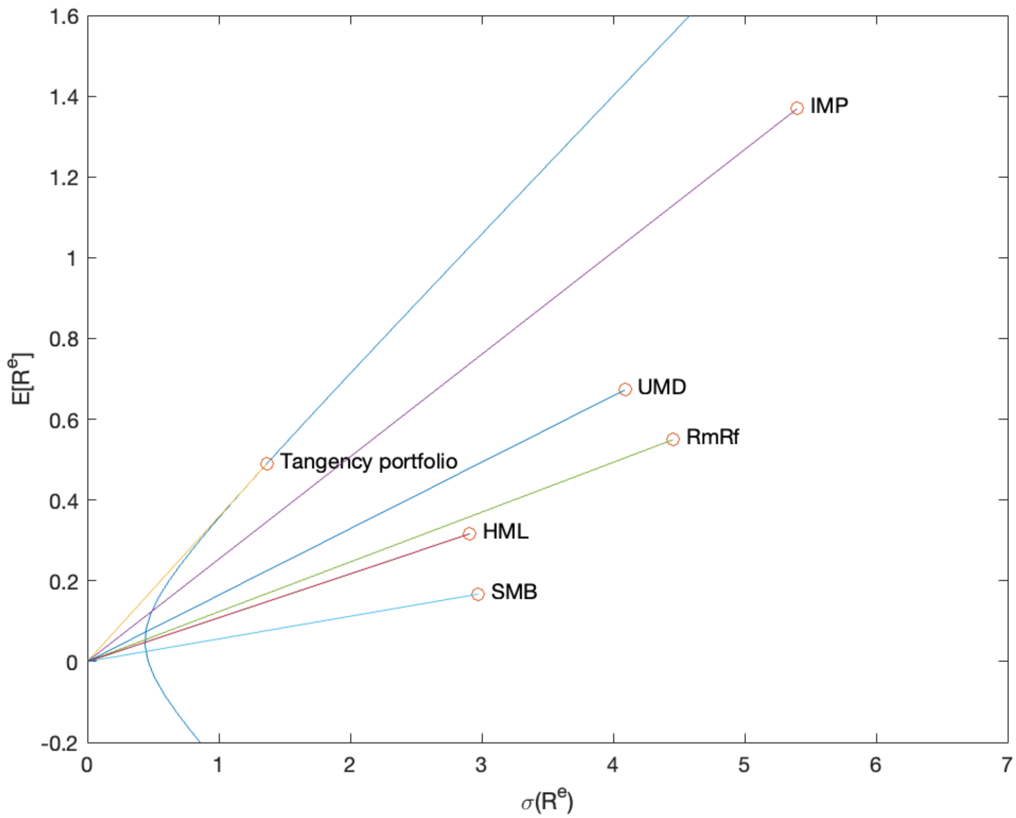
Note: Each panel in this figure plots the actual average excess returns of 25 equity portfolios sorted by size and long-run reversal against their average excess returns predicted by the corresponding model. The data cover the period from January 1964 to December 2022.

Figure 4: Actual versus predicted excess returns: 25 portfolios sorted by size and investment



Note: Each panel in this figure plots the actual average excess returns of 25 equity portfolios sorted by size and investment against their average excess returns predicted by the corresponding model. The data cover the period from January 1964 to December 2022.

Figure 5: Expectations and standard deviations of IMP and benchmark equity factors



Note: This figure depicts the expectations and standard deviations of interest rate risk mimicking portfolio (IMP) and four benchmark equity factors (RmRf, SMB, HML, UMD). IMP is constructed by a linear combination of the Fama-French six portfolios sorted by size and book-to-market ratio (SL, SM, SH, BL, BM, BH). For comparison, this figure also depicts the efficient frontier and the tangency portfolio. The efficient frontier is generated with the six size and book-to-market portfolios and the four benchmark equity factors but we drop SH and BH to prevent the perfect correlation. The data cover the period from January 1959 to December 2022.