Expected Investment Growth and the Cross Section of Stock Returns *

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Abstract

We propose a measure of corporate investment plans, namely, the expected investment growth (EIG). We document a robust finding that firms with high EIG have larger future investment growth and earn significantly higher returns than firms with low EIG, which cannot be fully explained by leading factor models. Further analyses reveal that EIG is closely related to distress risk, especially at short-run horizons up to one year. Detailed comparisons with traditional distress risk measures highlight the distinction between the short-run and long-run horizons in reconciling the opposite signs of distress premium documented in the literature.

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1 Introduction

Corporate investment plans have been shown to be important for economic fluctuations and stock market. For instance, Cochrane (1991) and Lamont (2000) document that the friction of investment plans can explain the negative contemporaneous covariation between aggregate investment and stock returns, as well as the insignificant covariation between aggregate investment and future stock returns. Using a survey of capital expenditure plans conducted by the Commerce Department, Lamont (2000) further shows that aggregate investment plans are forward looking and negatively predict stock market returns. More recently, the asset pricing literature documents that several firm characteristics, including cash-based operating profitability and R&D-to-market, that have a predictive power for stock returns beyond standard factor exposures can also predict future investment with the same sign, hinting a positive correlation between investment plans and stock returns in the cross section (e.g., Hou, Xue, and Zhang (2017)). However, micro-level investment plans are unobservable,[1] so this cross-sectional relation has not been directly established in the empirical asset pricing literature. In this paper, we attempt to fill this gap by proposing a measure of corporate investment plans, namely, the expected investment growth (EIG), solely based on public information, and we study its relation with future stock returns.[2]

Motivated by the existing studies on the determinants of corporate investment (e.g., Barro (1990), Morck, Shleifer, Vishny, Shapiro, and Poterba (1990), Gennaioli, Ma, and Shleifer (2016), Liu and Zhang (2014), and Fazzari, Hubbard, and Petersen (1988)), we construct EIG as the out-of-sample predicted value from the cross-sectional regression of the future one-year growth rate of capital expenditure on the prior 2- to 12-month stock return (i.e., momentum), Tobin's q, and cash flow, which capture firms' past stock and accounting performance as well as their investment opportunities. Our estimation results

[1]One exception is Gennaioli, Ma, and Shleifer (2016). Using micro data from Duke University quarterly survey of Chief Financial Officers (CFO), Gennaioli, Ma, and Shleifer (2016) show that corporate investment plans and the actual investment are well explained by CFOs' expectations of earnings growth. However, the CFO survey does not publicize the detailed firm-level data and only starts in 1998, which limits its application to asset pricing studies.

[2]There are many aspects of corporate investment plans, such as the selection of investment projects, the determination of project locations, durations, and starting time, as well as the allocation of funds among different projects. All of these decisions are important for a company. Throughout this paper, we focus on the overall capital expenditure and define a firm's investment plan as the expected investment growth in the subsequent year, as in Lamont (2000).

indicate that all three explanatory variables positively and significantly predict investment, and the constructed EIG strongly predicts future investment growth. In the decile portfolios sorted by EIG, the difference in the average realized investment growth between high and low EIG firms is 45% in the subsequent year, comparable to the difference of 66% in the sorting variable EIG. Furthermore, EIG alone can explain almost 70% of the cross-sectional variation in the future realized investment growth across EIG decile portfolios, confirming its validity as a proxy for investment plans.

In contrast to the negative correlation between investment plan and future stock return at the aggregate level, we find firms with higher investment plans (i.e., high EIG) have much higher future stock returns than firms with less investment plans (i.e., low EIG). A long-short investment strategy that takes a long position in high EIG firms and a short position in low EIG firms generates an average return of 20.7% per year, with a Sharpe ratio of 1.01, in the US sample between July 1953 and December 2015. To illustrate its historical performance, Figure 1 plots the cumulative returns of this long-short investment strategy. As a comparison, we also plot the cumulative returns of the market, value, and momentum strategies, which are normalized to have the same return standard deviation as the EIG strategy.[3] Though outperformed by the market strategy in the years prior to the mid-1960s, the EIG strategy has generated the best performance since then. Starting from $1 in the beginning of the sample period (July 1953), the cumulative wealth for the EIG strategy is $101,313 at the end of 2015, which is significantly greater than $108.2 for the market strategy, $19 for the value premium strategy, and $3,113.4 for the momentum strategy. Leading asset pricing factors do not fully capture the superior performance of the EIG strategy. The annualized abnormal returns from the capital asset pricing model (CAPM), Fama and French (1993) three-factor model, and Carhart (1997) four-factor model are 21.6% (t-statistic = 8.42), 24.0% (t-statistic = 9.11), and 13.1% (t-statistic = 5.06), respectively. Even controlling for the more recent Hou, Xue, and Zhang (2015) four factors and the Fama and French (2015) five factors, our EIG strategy remains largely profitable: the corresponding abnormal returns are 14.7% (t-statistic = 4.48) and 22.0% (t-statistic = 6.77), respectively. In addition, this return predictability holds in subperiods and in subsamples of firms, as well as in the other

[3]This normalization allows us to compare the performance while holding risk (i.e., standard deviation) constant across different investment strategies. The average return by itself is not a useful performance indicator since investors can always boost the average return by taking a higher leverage.

G7 countries.

[Insert Figure 1 Here]

Given that EIG is a linear function of momentum, q, and cash flow, which are known to predict future stock returns, we further investigate whether the EIG premium is a simple "repackaging" of these existing investment strategies. Specifically, we examine the role played by each of these three predictive variables (i.e., momentum, q, and cash flow) as well as the dependant variable (i.e., investment growth) in the construction of EIG. Our analysis suggests that it is not one, but rather the interaction of these three variables, that generates this strong return predictive power of EIG. When we keep only one of the three independent variables in the cross-sectional investment predictive regression and construct alternative EIG measures, the performance of these alternative long-short EIG strategies are much weaker than that of our benchmark EIG strategy. Meanwhile, the investment growth on the left-hand side of the cross-sectional regression contains important information about how the interaction of these predictive variables is related to future stock returns. When we replace future investment growth with future sales growth or gross profit growth while keeping the same three independent variables, the return predictive power of these alternative expected growth measures is considerably weaker.

A closer look at the difference in the past stock and accounting performance and leverage ratios between high and low EIG firms reveals that EIG may be related to financial distress risks. Using two traditional distress risk measures – failure probability (FP hereafter, from Campbell, Hilscher, and Szilagyi (2008)) and distance to default (DD hereafter, based on Merton (1974)) – we find that firms with low EIG are more financially distressed than firms with high EIG. However, there is an important difference between EIG and these traditional measures: while traditional measures are highly persistent and capture financial distress risks at both short and long horizons, EIG is short-lived with additional predictive power for corporate bankruptcies and failures only at horizons up to one year. In other words, if we decompose distress risks into a short-run and long-run components, EIG better captures the short-run component than the long-run component when compared with FP and DD. Nevertheless, the profitability of the buy-and-hold strategy based on EIG or traditional distress risk measures is significantly positive only in the first year following the strategy construction. Beyond the first year, the distress premium becomes much smaller and turns negative.[4] The short life of the positive distress premium indicates that this premium is mainly driven by the short-run component of distress risks. It also implies that, to the extent that the traditional distress measures and EIG both contain information about the distress premium, the variable that contains "cleaner" information about the short-run component should have stronger return predictive power and better captures distress premium because it is less "contaminated" by the long-run component. Indeed, in the 5-by-5 portfolios double-sorted by these traditional distress measures and EIG, we find that conditional on FP and DD, EIG strongly predicts future returns with a conditional annual EIG premium of 8.52% and 11.53%, respectively. In contrast, the FP and DD premiums conditional on EIG are no longer statistically significant.

The differentiation in horizons also sheds lights on the seemly contradictory findings on the signs of the distress premium in the existing literature. On the one hand, studies such as Campbell, Hilscher, and Szilagyi (2008) find a positive distress premium, i.e., more distressed stocks having lower future returns than less distressed stocks. Intuitively, Campbell, Hilscher, and Szilagyi (2008) focus on the return predictive power of distress risks at a shorter horizon, which presumably better captures the short-run component of distress risks. On the other hand, Chava and Purnanandam (2010) document a negative distress premium when implied cost of capital (ICC) is used as a measure of the expected stock return. Since ICC assumes a constant discount rate at all horizons and potentially better captures the long-run component than the short-run component of distress risks, it is not surprising that the relation between ICC and distress risks can be positive.

We consider several possible interpretations for this large EIG premium, from both rational and behavioral perspectives. On the risk side, the positive cross-sectional relation between investment plans and future stock returns can be consistent with the prediction of Li (2017), who directly models the investment plans friction at the firm level in an investment-based asset pricing framework. In Li (2017), firms that have experienced positive idiosyncratic productivity shocks in the recent past initiate greater investment plans and have higher exposure to stochastic price of investment goods and hence bear higher risk premium. This positive relation can also be consistent with the valuation model in John-

[4]Throughout the paper, we define the distress premium as the average return difference between less distressed firms and more distressed firms, as in Campbell, Hilscher, and Szilagyi (2008), so that a positive distress premium means that more distressed stocks earn an average lower return than stocks that are less financially distressed.

son (2002), which predicts that firms with greater expected growth have higher expected returns. In the data, we find that while the payoff of low EIG firms is countercyclical, their cash flow risk is strongly procyclical, suggesting that time-varying cash flow growth risks can provide an effective hedge to business cycle fluctuations for low EIG stocks. On the behavioral side, investors' preference for lottery-like stocks can also be related to the EIG premium (Conrad, Kapadia, and Xing (2014)). The lottery preference of investors can lead to overpricing of lottery-like assets and hence their subsequent low returns. Empirically, we find that low EIG stocks have low stock prices but high past maximum daily return, predicted jackpot probability, expected idiosyncratic skewness, and idiosyncratic volatility, suggesting that low EIG stocks indeed behave like lotteries and are potentially attractive to investors with lottery preferences. With the above interpretations considered, we believe that all of these mechanisms may have contributed to the strong return predictive power of EIG.

We would like to emphasize that our cross-sectional result does not necessarily contradict the negative correlation between investment plans and future stock returns at the aggregate level (Lamont (2000)).[5] Lamont (2000) argues that when there are lags between the decision to invest and the actual investment expenditure, investment plans are responsive to variations in the discount rate and negatively predict market returns. However, this argument is based on the assumption that the change in the discount rate is exogenous, holding cash flow constant. While this assumption can be valid at the aggregate level (see, e.g., Campbell and Shiller (1988a), Campbell and Shiller (1988b), Campbell (1991), and Campbell and Vuolteenaho (2004)), it may not hold in the cross section. In particular, the literature (e.g., Vuolteenaho (2002)) has shown that, compared to the discount rate news, the cash flow news may have played a much more important role for the firm-level stock returns. Therefore, the stock return, investment decision, and risk premium can all be endogenous in response to firm-specific cash flow news.[6] Indeed, Li, Wang, and Yu (2017) show that when firm-level EIG are aggregated across all firms, this bottom-up aggregate investment plan measure has

[5]In fact, the opposite signs in predicting stock returns at the aggregate level and at the firm level have been documented for several other firm characteristics, for example, accruals (Hirshleifer, Hou, and Teoh (2009)), default risks (e.g., Fama and French (1989), Campbell, Hilscher, and Szilagyi (2008)), and etc..

[6]For instance, in the investment-based model of Li (2017), when a firm experiences positive shocks to the idiosyncratic productivity which is assumed to be persistent, it will optimally choose a greater investment plan and hence higher future investment growth, despite an increase in the firm's risk premium.

a strong negative, rather than positive, correlation with future market returns, consistent with the findings in Lamont (2000).

This paper adds to the fast-growing literature of investment-based asset pricing. Most studies from this literature focus on the implication from the q theory of investment that firms with high realized investment have low future returns because of higher cost of capital. For instance, Titman, Wei, and Xie (2004) document that firms that substantially increase capital investments earn subsequently negative benchmark-adjusted returns. Xing (2008) finds that an investment growth factor, defined as the difference in returns between low-investment stocks and high-investment stocks, can explain the value premium about as well as the value premium factor from Fama and French (1992). Cooper, Gulen, and Schill (2008) find that a broader measure of investment, namely asset growth, can strongly predict future stock returns. Hou, Xue, and Zhang (2015) propose a four-factor asset pricing model based on the q theory of investment with an emphasis on the profitability factor and the investment factor.[7] Different from these papers, we focus on the cross-sectional relation between expected investment and stock returns.

Our paper is also closely related to the strand of literature that studies financial distress risks. Altman (1968) and Ohlson (1980) explore accounting variables that predict corporate bankruptcy. Shumway (2001), Chava and Jarrow (2004), and more recently, Campbell, Hilscher, and Szilagyi (2008) estimate dynamic logit or hazard models by including both accounting and stock market variables. In particular, Campbell, Hilscher, and Szilagyi (2008) document that a failure probability measure that incorporates firm characteristics including profitability, leverage, cash flow, stock returns, and volatility can strongly predict corporate bankruptcy and future stock returns. Our result is consistent with the positive distress premium in Campbell, Hilscher, and Szilagyi (2008), but it highlights an important dimension of distress risks that has been largely ignored in the existing literature: the horizon. Our findings suggest that while both short-run and long-run components of distress risk predict future bankruptcies and failures, it is the short-run component that drives the significantly lower returns of distressed stocks in the subsequent year.

[7]Other papers that study the implications of investment-based asset pricing models on cross-sectional stock returns include Cochrane (1996), Zhang (2005), Anderson and Garcia-Feijóo (2006), Liu, Whited, and Zhang (2009), Belo (2010), Kogan and Papanikolaou (2013), andKogan and Papanikolaou (2014). Cochrane (2005) and Zhang (2015) provide excellent reviews on this literature. See Nagel (2013) for a review of the broader literature on the empirical cross-sectional asset pricing.

The rest of the paper proceeds as follows. In Section 2, we describe the data sources and how we construct our EIG measure. Section 3 examines the return predictive power of EIG. In Section 4, we relate EIG to financial distress risks. We discuss several possible interpretations for the EIG premium from both risk-based and behavioral perspectives in Section 5. Section 6 concludes.

2 Data and the EIG measure

Our data come from several sources. Stock data are from the monthly and daily Center for Research in Security Prices (CRSP) database. Accounting data are from the Compustat Annual database. The Fama and French factors are from the Fama and French data library. The Hou, Xue, and Zhang (2015) factors are from the authors.[8] The international stock and accounting data come from the Compustat Global database. Our benchmark US sample includes all NYSE/AMEX/NASDAQ stocks (excluding financial stocks, utility stocks, and American depositary receipt (ADR) shares) from July 1953 to December 2015.

Our main variable, EIG, is computed in two steps, which are illustrated in the timeline of Figure 2. In the first stage, at the end of each year t, we run the following annual cross-sectional investment predictive regression using all NYSE/AMEX/NASDAQ stocks (excluding financial stocks, utility stocks, and ADR shares) with a December fiscal year end:[9]

$$\mathrm{IG}_{it} = b_{0,t} + b_{\mathrm{MOM},t} \times \mathrm{MOM}_{it-1} + b_{\mathrm{q},t} \times \mathrm{q}_{it-1} + b_{\mathrm{CF},t} \times \mathrm{CF}_{it-1} + \epsilon_{it}, \tag{1}$$

where investment growth (IG_{it}) is firm i's growth rate of investment expenditure (Compustat item CAPX) in year t (i.e., $\mathrm{IG}_{it} = \log(\mathrm{CAPX}_{it}/\mathrm{CAPX}_{it-1})$), momentum ($\mathrm{MOM}_{it}$) is the cumulative stock return from January to November in the previous year $t-1$, q_{it} is the log of the market value of the firm (sum of market equity, long-term debt, and preferred stock minus inventories and deferred taxes) divided by capital stock (Compustat item PPEGT) in year $t-1$, and cash flow (CF_{it}) is the sum of depreciation (Compustat item DP) and income before extraordinary items (Compustat item IB) divided by capital stock (Compustat item

[8] We thank Lu Zhang for sharing their factors data with us.

[9] We only include firms with a December fiscal year end to minimize estimation errors in the first-stage regressions. The result is slightly weaker when we use all firms, potentially because of the timing misalignment.

PPEGT) in year $t-1$.[10] MOM and CF contain information about stock and accounting performances, whereas q is generally considered as a measure of growth opportunities. These variables have been shown in the literature to have strong predictive power for investment. For example, Lamont (2000) argues that when there is investment lag friction, firms that experience firm-specific productivity shocks have contemporaneous response in stock returns and delayed response in the actual capital expenditure, giving rise to a positive correlation between stock returns and future investment.[11] Empirically, Barro (1990), Morck, Shleifer, Vishny, Shapiro, and Poterba (1990), and Liu and Zhang (2014) document that past stock returns are informative about future investment growth at both the aggregate level and the firm level. Furthermore, Fazzari, Hubbard, and Petersen (1988), among many other papers, show that Tobin's q is a strong predictor for the future investment rate, consistent with the q theory of investment (e.g., Hayashi (1982)). In our benchmark specification, we avoid including too many predictive variables to create an in-sample overfitting in the first stage, which tends to be associated with poor out-of-sample predictions.[12]

[Insert Figure 2 Here]

In the second stage, we compute the monthly EIG as the out-of-sample predicted value of investment growth from Model (1) using the most up-to-date q, CF, and momentum for all NYSE, AMEX, and NASDAQ stocks (excluding financial stocks, utility stocks, and ADR shares). Specifically, at the end of each month from June of year $t+1$ to May of year $t+2$, the out-of-sample EIG for firm i uses the accounting information (i.e., q_{it} and CF_{it}) from fiscal year end in calendar year t, following the standard Fama and French (1992) timing, and the prior 2- to 12-month cumulative stock returns (momentum), along with the time series average of the cross-sectional regression coefficients ($\hat{b}_{0,t}$, $\hat{b}_{\mathrm{MOM},t}$, $\hat{b}_{\mathrm{q},t}$, and $\hat{b}_{\mathrm{CF},t}$) estimated up

[10]Our measure of investment uses capital expenditures, which ignores the investment in R&D. To confirm that our result holds for a broader measure of investment taking into account the R&D expense, acquisition cost, and sale of property, we construct an alternative EIG measure based on this broad measure of investment and obtain a similar pattern. These results are reported in Table IA2 in the Internet Appendix.

[11]The positive correlation between stock returns and future investment can also be consistent with the feedback effect in Dow, Goldstein, and Guembel (2017) and Bond, Edmans, and Goldstein (2012).

[12]In Table IA2 of the Internet Appendix, we consider two alternative specifications by adding lag investment growth and the change in stock return volatility in the first-stage predictive regression, which have been used in Gennaioli, Ma, and Shleifer (2016) to predict future investment growth. These alternative EIG strategies generate even better performance than our benchmark specification.

to year t.[13] Our estimation procedure ensures that we only use publicly available information to construct EIG and guarantees that the EIG investment strategy we develop in the next section is tradable.

To confirm the roles of momentum, q, and CF in predicting investment growth, Table 1 reports the time series average coefficients from Model (1) using the full sample.[14] The first three columns are for the univariate regression of future investment growth on each predictive variable, and Column (4) is our benchmark case that includes all three variables. Consistent with our expectation, the estimated coefficients on CF, MOM, and q are all positive and statistically significant. Based on the estimation in Column (4), a one-standard-deviation increase in MOM, q, and CF is associated with an increase in future investment growth by 13.3%, 3.5%, and 6.3%, respectively.

[Insert Table 1 Here]

To validate this firm-level EIG measure, Table 2 reports average future investment growth for portfolios sorted by EIG. Panel A presents the results from the EIG deciles in the first four quarters (Q1-Q4), as well as the first year (Y1), second year (Y2), third year (Y3), and the fifth year (Y5) after the portfolio formation.[15] Consistent with our conjecture that investment is highly predictable, firms with high EIG have higher future growth rates in capital expenditure than firms with low EIG in the first four quarters. For the bottom EIG decile, average investment growth is consistently negative and statistically significant from zero in all four quarters, which is in sharp contrast with consistently positive and significant investment growth for the top EIG decile. The difference in the investment growth rate between the high and low EIG deciles is 12.1% in the first quarter, 13.1% in the second quarter, 9.8% in the third quarter, and 9.3% in the fourth quarter. However, this difference is relatively short-lived. Even though the investment growth spread between the high and

[13] We use the time series average of the estimated coefficients from historically available data to reduce estimation errors and avoid look-ahead bias. In Table IA2 in the Internet Appendix, we report similar results based on the average coefficients from the prior 5-year, 10-year, or 20-year rolling window, as well as a full sample average (despite the look-ahead bias), when we calculate the out-of-sample predicted value of investment growth in constructing EIG.

[14] Note the coefficients reported in Table 1 are different from those used in the EIG investment strategy in the next section, which are the time series average based only on the historical data.

[15] The investment data from Compustat quarterly database are only available from 1984, so we use the sample from 1984Q4 to 2015Q4 in our tests on quarterly investment growth.

low EIG deciles is 45% in the first year, the spread shrinks to only 7.6% in the second year and becomes negative afterward.

[Insert Table 2 Here]

Furthermore, all three variables in the construction of EIG (i.e., MOM, q, and CF) contribute to this predictability on future investment growth. To illustrate this, we create 5-by-5 portfolios sequentially double-sorted by each one of the constructing variables and then EIG. Panel B of Table 2 reports the spread of investment growth in the next year between high and low EIG quintiles conditioning on MOM, q, and CF. For the MOM and EIG sorts, the difference in investment growth between high and low EIG firms ranges from 2.7% in MOM quintile 4 to 23.3% in MOM quintile 1 (i.e., momentum losers), and the average conditional investment growth spread is 11.2% and significantly different from zero (t-statistic = 10.9). Therefore, although a large fraction of investment growth predictability comes from past stock performance, our measure of EIG contains additional predictive power for future investment beyond momentum. On the other hand, the average spread in investment growth conditioning on q or CF is generally much stronger. The average spread in investment growth between high and low EIG quintiles is 37.0% conditioning on q and 35.9% conditioning on CF.

One possible concern about our EIG measure is the low explanatory power of the three predictive variables in the first stage estimation, with an average cross-sectional R^2 of 6.7% from Specification (4) of Table 1. One may argue that this low R^2 indicates that the majority of the variation in the firm-level EIG is measurement errors, which can contaminate the relation between EIG and cross-sectional stock returns that is examined in the subsequent sections. In what follows, we would like to point out several possible reasons that can contribute this low explanatory power and provide further justification for our EIG measure. First, EIG is a measure constructed solely based on public information and serves as a proxy for firms' investment plans, whereas corporate managers are likely to make investment decisions based on both public information and their private information that is unobservable by investors or econometricians. In other words, our EIG measure can, at best, capture the part of investment plans based on public information and does not intend to reflect the part based on managers' private information. Second, even if we have perfect information about firms' actual investment plans, these plans do not have to be exactly the same as the actual investments in the future, because any changes in macroeconomic conditions or firms' own business environments may result in deviations of the actual capital expenditure from the planned investment. Third, non-convex capital adjustment costs can make the firm-level investment quite lumpy (e.g., Doms and Dunne (1998)). Even though there are debates in the macroeconomics literature on the importance of the adjustment cost to the dynamics of aggregate quantities,[16] the existence of this type of friction can create substantial measurement errors for firm-level investment plans, considering the fluctuations in business conditions (the second point above) and the potential real option effect from time variation in uncertainties (e.g., Bloom (2009)). However, for investors who use portfolios to diversify firm-level idiosyncratic risks, what matters is whether these measurement errors can be smoothed out at the portfolio level and, in particular, whether the portfolio-level EIG captures the portfolio future investment growth. To address this question, Figure 3 plots the time series of future one-year investment growth for the EIG deciles 1, 5, and 10 from 1953 to 2014. It is clear from this figure that for most of the time in our sample period, firms with high EIG indeed have higher future investment growth, and the portfolio ranking of the actual investment growth is consistent with the ranking of EIG. In untabulated analyses, we find when firms are sorted into EIG deciles, the average R^2 from the Fama-MacBeth cross-sectional regressions of portfolio-level realized investment growth on the portfolio-level EIG is 69.8%, much larger than that obtained from firm-level Fama-MacBeth regressions. These findings provide strong support for our EIG measure in capturing corporate investment plans.

[Insert Figure 3 Here]

3 EIG and future stock returns

In this section, we document that EIG can strongly predict stock returns. This predictive power is robust to different subsamples and is not captured by leading factor models including the recent Hou, Xue, and Zhang (2015) four-factor model and the Fama and French (2015) five-factor model. We perform extensive robustness checks for this return predictability.

[16]See, for example, Caballero and Engel (1999), Cooper, Haltiwanger, and Power (1999), Thomas (2002), and Khan and Thomas (2008).

3.1 Benchmark results

Panel A of Table 3 reports the characteristics of decile portfolios sorted by EIG. The portfolios are rebalanced every month based on the most up-to-date information about EIG. High EIG firms have better past stock performance (MOM) and accounting performance (CF) than low EIG firms. The average prior 2- to 12-month cumulative return is 93% (-37%) for high (low) EIG firms, and the corresponding CF is 0.41 and -0.98, respectively. This pattern is consistent with the positive and statistically significant coefficients on MOM and CF in the investment growth predictive regression from Table 1. Firms with low EIG are also smaller. The average market value is $34.4 million for firms in the low EIG decile, as compared with $238.2 million for firms in the high EIG decile. The book-to-market ratio (BM), investment rate (IK), and book leverage (LEV) are not monotonic across the EIG portfolios, with high EIG firms having a lower BM and LEV, but slightly higher IK than low EIG firms. Finally, the gross profitability (GP) increases with EIG.

[Insert Table 3 Here]

In Panel B of Table 3, we report the mean, standard deviation, Sharpe ratio, skewness, and kurtosis of the value-weighted excess return of the decile EIG portfolios and the long-short portfolio that takes a long (short) position in the high (low) EIG decile. The average excess return of the low EIG portfolio is -5.66% per year with a standard deviation of 27.03%. This performance is in contrast with a 15.03% mean and 22.57% standard deviation of the excess return of the high EIG portfolio. Consistent with the relatively smooth path of the cumulative return of the EIG strategy reported in Figure 1, the long-short EIG strategy (Hi-Lo) generates an average return of 20.69% per year with a Sharpe ratio of 1.01. In addition, the strategy does not suffer from large negative skewness in the realized return distribution, as in other investment strategies such as momentum.[17]

Table 4 reports the results from leading factor asset pricing model tests. The factor models we consider include the unconditional CAPM, Fama and French (1993) three-factor model, Carhart (1997) four-factor model, Hou, Xue, and Zhang (2015) four-factor model, as

[17] For example, Daniel and Moskowitz (2016) document a skewness of -4.7 for the momentum strategy based on the monthly data from January 1927 to March 2013. They also find that the crash of the momentum profit is partly forecastable by market declines and elevated market volatility, and is contemporaneous with market rebounds.

well as the Fama and French (2015) five-factor model, which adds two additional factors that are based on the gross profitability premium (Novy-Marx (2013)) and asset growth premium (Cooper, Gulen, and Schill (2008)) to their classical three-factor model. Panels A, B, and C of Table 4 report the test results from CAPM, Fama and French (1993) three-factor model, and Carhart (1997) four-factor model. The market factor (MKT), size premium factor (SMB), and value premium factor (HML) are all in the wrong direction in explaining the EIG portfolio spread. For the long-short EIG portfolio in the Fama and French (1993) three-factor model test, the market beta is -0.11 (t-statistic $= -1.67$), the SMB beta is -0.46 (t-statistic $= -4.13$), and the HML beta is -0.4 (t-statistic $= -3.56$). These negative betas imply an even greater profitability after controlling for these factors. Indeed, the Fama and French (1993) three-factor alpha is 24.01% per year with a t-statistic of 9.11.[18] Adding a momentum factor (UMD) weakens the performance of our strategy because an important predictive variable in the investment growth predictive regression is momentum. However, Panel C shows that even after including the UMD factor in the factor model, our strategy still generates a four-factor alpha of 13.14% per year with a t-statistic of 5.06, suggesting that our EIG-based investment strategy is beyond the standard momentum.

[Insert Table 4 Here]

Panels D and E report the results from the tests based on the more recent Hou, Xue, and Zhang (2015) four-factor model and Fama and French (2015) five-factor model. Again, we find that these new factors cannot fully explain the return spread between the high and low EIG portfolios. The abnormal return for the long-short EIG portfolio is 14.67% (t-statistic $= 4.48$) for the Hou, Xue, and Zhang (2015) four-factor model and 22.0% (t-statistic $= 6.77$) in the Fama and French (2015) five-factor model. In terms of the factor loadings, the long-short portfolio return has positive and significant correlations with the gross profitability premium (RMW) and return-on-equity (ROE) premium, indicating that firms with higher

[18] In the paper, we report the t-statistics based on White (1980) standard errors, but in untabulated tests, we also check the t-statistics based on Newey and West (1987) standard errors with up to 12 lags. The results are similar and even stronger if we use Newey and West (1987) standard errors. For example, the t-statistics for the Fama and French (1993) three-factor alphas for the long-short EIG portfolio are 9.37, 9.37, and 9.56 when we use standard errors based on Newey and West (1987) 3, 6, and 12 lags, respectively. This insensitivity is consistent with the low serial correlations of the returns on the EIG portfolios. The first-order autocorrelation for the long-short EIG portfolio is only 1.7%. All of the results based on Newey and West (1987) standard errors are available upon request.

EIG also tend to have higher profitability. The estimated coefficient on the ROE factor in the Hou, Xue, and Zhang (2015) four-factor model is 1.28 (t-statistic = 9.65). However, the large four-factor model abnormal return of the EIG premium suggests that EIG contains additional information about future stock returns beyond the expected profitability and past investment rate.[19]

3.2 Robustness checks

In this subsection, we report the results from several robustness checks. We start with subperiod analyses. In Table 5, we report the mean and Sharpe ratio of the EIG portfolio returns, as well as the abnormal returns from asset pricing tests for the early and late half subperiods.[20] The performance of our EIG strategy across these two subperiods is quantitatively similar. The average annual return is 18.24% in the early sample and 23.15% in the late sample, with a Sharpe ratio about 0.93 and 1.09, respectively. The EIG premium remains statistically and economically significant, even after controlling for the asset pricing factors. For example, in the Hou, Xue, and Zhang (2015) four-factor model test, the alpha is 11.15% per year (t-statistic = 2.25) for the early subsample and 15.65% per year (t-statistic = 3.6) for the late subsample. For the Fama and French (2015) five-factor model, the annualized abnormal returns are 25.76% and 19.98%, respectively, for these two sample periods.

[Insert Table 5 Here]

Table 6 reports the results from the same analyses using alternative portfolio formation approaches and subsamples of firms. In Panel A, we use the breakpoints from the NYSE firms

[19] In Table IA1 in the Internet Appendix, we also report the results from the tests based on two recent behavioral factor models, the Stambaugh and Yuan (2017) mispricing-factor model and the Daniel, Hirshleifer, and Sun (2017) short- and long-horizon behavioral model. The abnormal return for the long-short EIG portfolio remains significant at 12.76% per year (t-statistic = 4.15) for the Stambaugh and Yuan (2017) mispricing-factor model test and 9.14% per year (t-statistic = 2.41) for the Daniel, Hirshleifer, and Sun (2017) behavioral model test.

[20] Specifically, we use the midpoint to divide the full sample period into two subperiods: July 1953 to September 1984 for the early subsample and October 1984 to December 2015 for the late subsample. Because of the data availability, the two subperiods are January 1967 to June 1991 and July 1991 to December 2015 for the Hou, Xue, and Zhang (2015) four-factor model test, and July 1963 to September 1989 and October 1989 to December 2015 for the Fama and French (2015) five-factor model test.

to construct decile portfolios and calculate the value-weighted portfolio returns. Despite the lower weight on small firms with NYSE breakpoints, the EIG strategy still generates an average return of 13.96% per year, with a Sharpe ratio of 0.71. The abnormal returns of the EIG premium from the CAPM, Fama and French (1993) three-factor model, Carhart (1997) four-factor model, Hou, Xue, and Zhang (2015) four-factor model, and Fama and French (2015) five-factor model are 15.2 (t-statistic = 6.31), 19.02 (t-statistic = 7.87), 6.24 (t-statistic = 3.8), 6.81 (t-statistic = 2.17), and 16.41 (t-statistic = 5.26), respectively. Similar results are found when we focus on the all-but-micro subsample of stocks, that is, stocks with a market cap below 20% of the NYSE size breakpoint in the previous month, and calculate equal-weighted portfolio returns (Panel B). The average EIG premium is 14.52% with a Sharpe ratio of 0.78, which is unable to be fully explained by the leading factor models. Interestingly, a large fraction of this premium comes from the high EIG decile, with abnormal returns being significant for all factor models. In Panel C, we exclude stocks with a share price less than $5 at the end of the previous month. Again, we find very similar results. The annual EIG premium and Sharpe ratio for this subsample of stocks are 17.27% and 0.83, respectively.

[Insert Table 6 Here]

The analyses so far are based on the portfolio approach. To better control for firm characteristics that are not included in the factor models, we test the return predictability of EIG using Fama-MacBeth cross-sectional regressions. Firm characteristics we control include firm size (ME), book-to-market ratio (BM), momentum (MOM), gross profitability (GP), asset growth (AG), and past investment growth (IG).[21] Table 7 reports the estimated coefficients and adjusted R^2 for the full sample in Panel A and the all-but-micro subsample in Panel B. In the univariate regression of future stock returns on EIG (Specification (1) of Panel A), the EIG coefficient is 1.68, which is more than five standard deviations from zero. Economically, a one-standard-deviation increase in EIG is associated with a 5.09% increase in the annual stock return. Controlling for firm size and book-to-market (Specification (2))

[21]In Table IA3 in the Internet Appendix, we also report the conditional EIG premium from double sorts. In particular, we create 5-by-5 portfolios double-sorted sequentially by each one of these firm characteristics and then by EIG. The conditional EIG premium is highly positive and statistically significant in all of the specifications. It ranges from 3.44% (t-statistic = 2.7) conditional on momentum to 13.16% (t-statistic = 7.38) conditional on size.

further increases the EIG coefficient to 2.02 (t-statistic = 6.8), whereas adding momentum to the regression (Specification (3)) weakens it to 0.97 (t-statistic = 2.75) because of the positive correlation between EIG and momentum. Specifications (4) and (5) of Panel A add additional characteristics including gross profitability, asset growth, and past investment growth, and we find that the return predictive power of EIG remains highly significant. Panel B of Table 7 repeats the same Fama-MacBeth regressions in all-but-micro firms. The EIG coefficient is even stronger than the full sample, ranging from 1.22 in Specification (3) when size, book-to-market, and momentum are controlled, to 2.5 in Specification (2) when only size and book-to-market are controlled. These results again confirm that the relation between EIG and stock returns is not restricted to micro firms.

[Insert Table 7 Here]

As a final robustness check, we repeat the main portfolio analysis in other G7 countries (Canada, France, Germany, Italy, Japan, and the United Kingdom). For each country, we compute firm-level EIG in the same way as we did for the United States. Stock returns are converted from local currency to US dollars, and excess returns are in excess of the one-month US T-bill rate.[22] The results, reported in Table 8, show a similar relation between EIG and future stock returns in all other G7 countries. In particular, firms with high EIG have higher average returns than firms with low EIG. The annualized EIG premium based on the long-short EIG strategy ranges from 7.68% (Sharpe ratio = 0.39) in Japan to 34.76% (Sharpe ratio = 0.82) in Canada. The result in Japan is very interesting given that the literature has documented that momentum strategies are not profitable in many Asian countries including Japan (e.g., Chui, Titman, and Wei (2010)). Controlling the Fama and French global three factors further improves the strategy performance, whereas adding the global momentum factor tends to weaken the performance. Nevertheless, the economic magnitudes of the EIG premium and abnormal returns are significant in these countries.

[Insert Table 8 Here]

[22]See Appendix for more details on the international data.

3.3 Importance of first-stage estimation

As discussed in Section 2, EIG is estimated from the cross-sectional regression of firms' investment growth on momentum, q, and cash flow. In other words, EIG is a linear combination of these explanatory variables. A natural question arises: Given the return predictive power of EIG, what are the roles played by each of these explanatory variables and the dependent variable (i.e., realized investment growth) in the first-stage estimation?

Our next set of analyses provides an answer to this question. In Panels A, B, and C of Table 9, we report the average excess returns and Sharpe ratio of decile portfolios sorted separately by EIG constructed from each one of these three components. In particular, we run a univariate regression of realized investment growth on each one of these three components in the first stage, and use the out-of-sample predicted value as momentum-only EIG, q-only EIG, or cash flow-only EIG. Panel A is for the momentum-only EIG portfolios. Consistent with the momentum literature (e.g., Jegadeesh and Titman (1993)), high momentum-only EIG firms outperform low momentum-only EIG firms by 21.39% per year, but part of this large return spread is due to the high standard deviation, as the Sharpe ratio of 0.76 is much lower than 1.01 for our benchmark EIG premium. Panels B and C report the results for the portfolios sorted by q-only EIG and cash flow-only EIG, respectively. Firms with high q-only EIG (low cash flow-only EIG) have lower average returns than firms with low q-only EIG (high cash flow-only EIG). The average returns for the long-short portfolio based on q-only EIG and cash flow-only EIG are -4.78% and 5.24%, and the corresponding Sharpe ratios are -0.26 and 0.3, respectively. None of these three components has stronger return predictive power than the benchmark EIG, indicating that the superior performance of EIG comes from the interaction of these three components, and therefore, the EIG premium is not a simple "repackaging" of strategies based on momentum, q, and cash flows.

[Insert Table 9 Here]

The coefficients in the linear combination of momentum, q, and cash flow for EIG are determined by future investment growth – the left-hand-side variable in the first-stage predictive regression. To illustrate the importance of this variable, we repeat our analysis but now replace the left-hand-side variable with future sales growth (Panel D) and gross profit growth (Panel E), so our portfolio sorting variables can be considered as expected sales growth and expected gross profit growth, respectively. In Panel D, the strategy based on the expected sales growth generates an average return of 9.56% per year with a Sharpe ratio of 0.41. The strategy return based on expected gross profit growth in Panel E is only 2.53% per year with a small Sharpe ratio of 0.13. This result suggests that the relative composition of momentum, q, and cash flow in creating EIG is important for predicting future stock returns, and this information is contained in investment decisions.

To further emphasize the importance of weights in the linear combination of momentum, q, and cash flow, we plot the performance of strategies that are based on different weights of these three predictive variables in Figure 4. For each linear combination, we assume the weights w(MOM), w(q), and w(CF) are constant throughout the sample period and sum up to one. In the top two panels, we plot the average annualized returns and Sharpe ratios along the dimensions of w(q) and w(CF), whereas w(MOM) is equal to 1−w(q)−w(CF) from the normalization restriction. Holding w(q) constant, the relation between the strategy performance and w(CF) is hump-shaped. A similar pattern is also found when we hold w(CF) constant and vary w(q). The bottom panels show the results along the dimensions of w(MOM) and w(CF). In general, the strategy performs better when both w(MOM) and w(CF) are closer to 1 than they are closer to −1, but again, this relation is non-monotonic. In each panel of this figure, we also mark the average weights from the EIG estimation Equation (1), denoted as "EIG". It is striking that these estimated weights are very close to the ex-post optimal weights among all possible linear combinations of these three variables. These findings again suggest that momentum, q, and cash flow, as well as the estimated coefficients from the first-stage EIG estimation are all informative about future stock returns.

[Insert Figure 4 Here]

4 EIG and financial distress risk

In Table 3, we have documented that firms with high EIG have better stock performance and accounting profitability than firms with low EIG. The bottom decile EIG portfolio has a past 12-month return of −37% and a cash flow-capital ratio of −0.98, as compared with 93% and 0.41, respectively, for the top decile EIG portfolio. In addition, the leverage ratio for low EIG firms is higher than high EIG firms. These characteristics have been shown to be associated with financial distress risk and able to predict bankruptcies and corporate failures (e.g., Altman (1968), Ohlson (1980), and Campbell, Hilscher, and Szilagyi (2008)). In this section, we investigate the relation between EIG and financial distress risks in more detail.

To get started, we first examine if EIG sorts create a large dispersion in traditional distress measures used in the existing literature. We consider two popular distress measures: failure probability (FP, 12-month-lag benchmark model, Table IV, page 2913, Campbell, Hilscher, and Szilagyi (2008)) and distance to default (DD, Merton (1974)), which measures the number of standard deviations of the asset value above the bankruptcy threshold.[23] From the definitions, a firm with higher FP and/or lower DD is more financially distressed. Panel A of Table 10 reports the average values of these distress measures across EIG decile portfolios. Consistent with our conjecture, we find that EIG is indeed closely related to these distress risk measures. For FP, it increases from −8.2 in the high EIG portfolio to −6.15 in the low EIG portfolio. Except for the top two deciles, the pattern is very monotonic. As a comparison, in an untabulated analysis, we find that the average FP in the top (bottom) decile of portfolios sorted by FP itself is −5.63 (−8.76). Therefore, the information content between EIG and FP indeed significantly overlaps. The pattern for DD across these portfolios is also similar: the average DD is 3.44 for the low EIG portfolio, which is much smaller than the average of 7.39 for the high EIG portfolio.[24]

[Insert Table 10 Here]

To formally test whether EIG predicts bankruptcies and corporate failures, we run logit models as in Section II of Campbell, Hilscher, and Szilagyi (2008). This analysis not only provides direct empirical evidence on the relation between EIG and distress risks; it also uncovers an important difference between EIG and traditional measures such as FP and DD, which we discuss shortly. Specifically, we assume for firm i that the probability of bankruptcy or failure in month j, conditional on its survival in month $j-1$, has the following logistic

[23]FP is not the actual failure probability. Instead, it is $\alpha_j + \beta_j x_{i,t-1}$ from Equation (2) below, which is a monotonic transformation of the failure probability. The construction of these variables is discussed in detail in Appendix.

[24]Although untabulated, we also look at other accounting-based distress risk measures, such as Altman (1968) Z-score and Ohlson (1980) O-score, and reach the same conclusion. For instance, the average Z-score increases monotonically from 1.77 in the low EIG portfolio to 4.03 in the high EIG portfolio. Similarly, the average O-score is 1.35 for the low EIG portfolio, which is much higher than −1.69 for the high EIG portfolio.

distribution:

$$P_{t-1}(Y_{i,t-1+j} = 1|Y_{i,t-2+j} = 0) = \frac{1}{1 + \exp(-\alpha_j - \beta_j x_{i,t-1})}, \tag{2}$$

where $Y_{i,t}$ is an indicator that equals one if the firm goes bankrupt or is in failure in month t, and $x_{i,t-1}$ are explanatory variables that include FP, DD, and EIG at the end of the previous month. As in Campbell, Hilscher, and Szilagyi (2008), we consider horizons of the next one month, six months and one, two, and three years. The data for the bankruptcy indicator are from Chava and Jarrow (2004), Chava (2014), and Alanis, Chava, and Kumar (2015), which equals one in a month if a firm files for bankruptcy under Chapter 7 or Chapter 11, and zero otherwise.[25] Following Campbell, Hilscher, and Szilagyi (2008), we also consider a broader measure of corporate failures that equals one in a month if a firm files for bankruptcy, is delisted for financial reasons, or receives a D rating. We construct FP following the procedure in Campbell, Hilscher, and Szilagyi (2008), and use the out-of-sample version of FP to predict corporate bankruptcy or failure.[26]

Panel B of Table 10 reports the estimation results, including the McFadden's pseudo-R^2, calculated as $1-L_1/L_0$, where L_1 is the log likelihood of the estimated model and L_0 is the log likelihood of a null model that includes only a constant term. In predicting bankruptcy and failure, the coefficient on EIG is strongly negative in the univariate regressions of all horizons (Specification 1), indicating that firms with lower EIG are more likely to go bankrupt or fail. When predicting bankruptcy in the next month (Panel B.1), the estimated coefficient for EIG is -9.87, which is more than 30 standard deviations from zero. This coefficient gradually decreases in magnitude with the predictive horizons: it becomes -6.93 in 6 months (t-statistic $= -31.19$), -5.09 in 1 year (t-statistic $= -25.84$), and even at a horizon of 3 years, the coefficient for EIG remains negative at -1.56 with a t-statistic of -8.67. The McFadden's pseudo-R^2 follows a similar pattern: it starts from 13.97% in 1 month, decays to 5.3% in 12 months, and becomes only 0.61% at the 3-year horizon. A similar but stronger pattern appears for the failure events (Panel B.2).

[25] We thank Sudheer Chava for sharing this dataset with us. The bankruptcy event includes all bankruptcy filings in the Wall Street Journal Index, the SDC database, SEC filings, and the CCH Capital Changes Reporter.

[26] Specifically, in each year from 1981 to 2014, we estimate the logistic regression using only historically available data to eliminate look-ahead bias. The estimated coefficients are used together with the most up-to-date values of the same predictive variables to construct the out-of-sample FP. The predictive variables are NIMTAAVG, TLMTA, EXRET, EXRETAVG, RSIZE, CAHMTA, MB, and PRICE. The detailed definitions and construction procedure of these variables can be found in Campbell, Hilscher, and Szilagyi (2008).

Panel B also reports the result from the univariate logistic regression using FP and DD (Specifications 2 and 3). Consistent with Campbell, Hilscher, and Szilagyi (2008), FP has very strong predictive power for corporate bankruptcy and failure. For example, when predicting bankruptcy in the next month, the coefficient of FP is 1.45 (t-statistic = 28.08) and the estimated pseudo-R^2 is 20.73%. This coefficient decreases with horizons at a lower speed than the coefficient for EIG. Even at the 3-year horizon, the coefficient on FP remains 58% of the 1-month estimate. The coefficient of DD in Specification 3 follows a very similar pattern, except the sign being negative, consistent with the definition of DD to capture the likelihood that firms are going bankruptcy and failure.

In the last specification of each predictive horizon, we include all three variables (EIG, FP, and DD) in the same logit regression and see whether EIG still has marginal predictive power for corporate bankruptcy or failure after controlling for FP and DD. Our estimation result suggests that the coefficient on EIG remains negative and statistically significant up to the next 12 months, so the additional predictive power is mainly concentrated at a shorter horizon. In predicting bankruptcy next month in Specification 4, the coefficient on EIG is -5.23 (t-statistic = -12.73) and the estimation pseudo-R^2 is 23.08%, as compared to 20.73% (14.65%) in the univariate regression using only FP (DD). However, the EIG coefficient decreases to -1.02 (t-statistic =-4.63) in the 12-month horizon, becomes only -0.1 (t-statistic = -0.52) in the 24-month horizon, and even turns positive at the 36-month horizon. In sharp contrast, the coefficients for FP and DD remain significant up to 36 months, even though their predict powers also decay with horizons.

The result in Table 10 suggests that although EIG, FP, and DD are all informative about future bankruptcies and failures, they have an important difference. If we use one year as the cutoff and decompose financial distress risks into a short-run and a long-run components, EIG better captures the short-run component than the long-run component when compared with FP and DD. To further illustrate this, we look into the dynamics of these variables at the portfolio level. We create decile portfolios using the current, prior one-year, two-year, three-year, and four-year values of EIG, FP, or DD, and report the average spread in the sorting variable of the two extreme portfolios for each sort. The relation between the average spread in characteristics and the sorting periods mimics their dynamics for these buy-and-hold portfolios over the corresponding horizons. Panel A of Table 11 reports the results. Consistent with the relative predictive power across horizons in Table 10, we find that FP

(Panel A.2) and DD (Panel A.3) are highly persistent. The initial difference in FP (DD) between low and high FP (DD) portfolios is −3.13 (20.1), and it decreases in magnitude to −2.37 (15.97) after one year and −1.96 (13.95) after two years. Even four years after the portfolio formation, the difference in FP (DD) is still −1.5 (11.47), representing 48% (57%) of the original spread. On the other hand, EIG is much less persistent (Panel A.1). One year following the portfolio formation, the EIG spread between the high and low EIG deciles shrinks to 34.8% of its initial spread.

[Insert Table 11 Here]

Panel A of Table 11 also reports the dynamics of the average return spread across these portfolios. A striking feature is that the return spread is short-lived for all three strategies. For the EIG strategy (Panel A.1), the initial annualized return is 20.69% but decays fast to 0.76% after one year and remains small or becomes negative in subsequent years. Similar results hold for FP deciles in Panel A.2 and DD deciles in Panel A.3. The average FP and DD strategy returns are both positive and large initially (13.92% for the FP strategy and 12.35% for the DD strategy), then become negative one year later.[27] For instance, the average annualized FP (DD) premium is −2.33% (−1.35%) in year 1 and −0.46% (−1.19%) in year 2 following the portfolio formation.

Given the aforementioned decomposition of distress risks, the short life of the EIG, FP, and DD premiums in Panel A of Table 11 implies that while both the short-run and long-run components of distress risks predict future bankruptcies and corporate failures, it is the short-run component that drives the lower returns of distressed stocks within the subsequent year. In contrast, the average returns at longer horizons suggests that the long-run component may have a positive predictive power for future stock returns. It also implies that, to the extent that all three variables are related to distress risks, the one that contains better information about the short-run component should have a stronger negative return predictive power

[27] The positive DD premium we document here is different from a negative premium in Vassalou and Xing (2004), partly because in constructing DD, we follow Campbell, Hilscher, and Szilagyi (2008) and use a constant of 6% as the stock expected return, whereas Vassalou and Xing (2004) estimate the average return on each stock based on realized stock returns. Da and Gao (2010) examine the implication of the estimation procedure of Vassalou and Xing (2004) and find the large negative distress premium is largely driven by short-term return reversals rather than systematic default risk. In addition, Da and Gao (2010) document a significant positive premium in the horizon of 2-12 months following portfolio formations, which is consistent with our finding.

because it is least "contaminated" by the long-run component. Clearly, EIG is better than FP and DD from this perspective.

We confirm the previous conjecture in Panel B of Table 11. We create 5-by-5 portfolios double-sorted on one of the traditional distress measures and EIG.[28] Panel B.1 reports the EIG premium within each FP (DD) quintile, their average across quintiles (Con. Prem.), which can be interpreted as the EIG premium conditional on FP (DD). As a comparison, we also report the unconditional EIG premiums (Unc. Prem.) from one-way quintile sorts on EIG. Conditional on the FP and DD, the EIG premium remains positive and highly significant in four out of five FP and DD quintiles. The average conditional EIG premium is 8.52% and 11.53%, compared with the 14.04% and 14.24% unconditional EIG premium, for these two sample periods corresponding to FP and DD, respectively. In contrast, conditional on EIG, the average FP and DD premiums are no longer significant at the 5% level, as reported in Panel B.2 of Table 11. For example, across EIG quintiles, the conditional FP premium is only significant in the low EIG quintile. The average FP premium decreases from 9.12% unconditionally to only 4.64% when we condition on EIG, representing an almost 50% decline.

In sum, the results from this section highlight an important dimension of financial distress risk that has been largely ignored in the existing literature: the horizon. Intuitively, persistent variables such as market-to-book and financial leverage are more likely to predict corporate bankruptcy in the longer horizon, consistent with Fama and French (1993) and Fama and French (1996) which find that value firms have persistently lower earnings than growth firms and interpret the value premium as a premium for a state variable related to relative distress. On the other hand, transitory variables such as short-run stock performance are more likely to predict corporate bankruptcy at shorter horizons. Our analyses suggest that it is the short-run component of expected bankruptcy that is closely associated with the significantly lower future stock returns of those distressed stocks.

The separation in horizons of distress risk can also potentially reconcile the seemly contradictory findings in the existing literature on the sign of the distress premium. While Campbell, Hilscher, and Szilagyi (2008) document that firms that are more financially dis-

[28]To better compare with the FP strategy in the previous literature, instead of using the out-of-sample FP in the predictive regression of bankruptcy, we compute FP based on the benchmark model in Campbell et al. (2008) (Table IV, 12-month lag, page 2913).

tressed have lower average stock returns than firms that are less financially distressed, Chava and Purnanandam (2010) find a higher average return for more distressed stocks. Our findings suggest that horizons can be important in understanding these results. On the one hand, Campbell, Hilscher, and Szilagyi (2008) focus on the return predictive power of failure probability at a shorter horizon up to one year, which presumably better captures the short-run expected return. In contrast, Chava and Purnanandam (2010) examine the relation between measures of distress risks and implied cost of capital (ICC), which assumes a constant discount rate and can be considered as a weighted average of expected returns at all horizons. When the long-run component of distress risk (e.g., book-to-market ratio) persistently predicts higher future returns, ICC would contain more information about the long-run component than the short-run component. By focusing on different components of distress risks and expected returns differentiated by horizons, these papers naturally reach different conclusions.

5 Discussions

In this section, we discuss possible interpretations for this large EIG premium.

On the rational side, the EIG premium can be consistent with the prediction of the investment-based asset pricing model in Li (2017). By incorporating the investment plan friction to the neoclassical framework of Zhang (2005), Li (2017) shows that firms with positive firm-specific productivity shocks in the recent past initiate greater investment plans and have higher exposure to the stochastic price of investment goods and hence higher risk premium than firms with negative productivity shocks. When the firm-level productivity is highly persistent, the cash flow channel from the productivity shocks dominate the discount rate channel from investment plan friction, so productivity shocks and stock returns are positively correlated, generating momentum profits. Since investment plan is more fundamental than realized stock returns, the model also implies that EIG has a stronger return predictive power than momentum, a prediction which we have confirmed in Section 2. In addition, the EIG premium provides empirical support for the investment CAPM (Zhang (2015)): holding the expected profitability and past investment rate constant, firms with higher expected investment growth have higher expected returns.

The return predictive power of EIG can also be consistent with the theoretical model in Johnson (2002). Johnson (2002) argues that the expected return of a stock can increase with its expected growth when the stock's valuation ratio is convex with respect to the expected growth. If aggregate consumption growth is correlated with the pricing kernel, as standard consumption-based asset pricing models assume, and if EIG also captures firm-level expected cash flow growth, high EIG firms would have higher aggregate consumption risk exposure and hence higher expected returns than low EIG firms. In Tables IA4 and IA5 in the Internet Appendix, we report the future cash flow growth and consumption betas of the EIG decile portfolios. Indeed, we find that EIG positively predicts future cash flow growth. Furthermore, while the payoff of the low EIG portfolio is countercyclical, its consumption beta is strongly procyclical: the consumption exposure of low EIG firms is especially more negative in bad times when consumption is low and the risk premium is high (e.g., Campbell and Cochrane (1999), Case II of Bansal and Yaron (2004)).[29] This behavior of low EIG stocks provides an effective hedge for business cycle fluctuations, so the risk premium demanded by investors can be low or even negative.

Lastly, given the close relation between EIG and distress risks, existing risk-based explanations of the distress premium can potentially be applied to the EIG premium. These explanations include shareholder recoveries in Garlappi and Yan (2011), financial distress costs and optimal capital structure decisions in George and Hwang (2010), nonlinearity of equity betas in O'Doherty (2012) and Boualam, Gomes, and Ward (2017), and investor learning in Opp (2015), among others.

On the behavioral side, the EIG premium can be related to investors' lottery preferences, which have been shown to be related to the distress premium (e.g., Conrad, Kapadia, and Xing (2014)). Since low EIG stocks have high distress risk, lottery preferences may be a potential source for their low returns. We examine the lottery feature of the EIG portfolios in Panel A of Table IA6 in the Internet Appendix. Indeed, compared to high EIG stocks, low EIG stocks have lower stock prices but higher maximum daily return, predicted jackpot probability, expected idiosyncratic skewness, and idiosyncratic volatility. In other words, they are lottery-like assets and can be overpriced if investors have lottery preferences. Further, investors may have more severe expectation errors by overestimating the probability of

[29]An incomplete list of studies on consumption-based explanations of the cross-sectional stock returns includes: Lettau and Ludvigson (2001), Bansal, Dittmar, and Lundblad (2005), Malloy, Moskowitz, and Vissing-Jorgensen (2009), Da (2009), Roussanov (2014), and Li and Zhang (2017).

large return outcomes of these stocks, which make them attractive to investors with lottery preferences (e.g., Brunnermeier, Parker, and Gollier (2007)). Consistent with the expectation error channel, we find in the last two columns of Panel A that low EIG stocks indeed on average have more negative earnings surprise (SUE) and three-day cumulative abnormal returns (CAR) around firms' subsequent earnings announcement dates than high EIG stocks.

Of course, market frictions may also play a role. Because the turnover rate of the EIG investment strategy is similar to that of the momentum strategy, the transaction costs and bid-ask spreads can be responsible for a certain fraction of the EIG profitability in practice. Consistent with this argument, Panel B of Table IA6 in the Internet Appendix shows that the EIG premium is higher among firms with high limits-to-arbitrage/information uncertainty.

6 Conclusion

In this paper, we propose an empirical measure of corporate investment plans, namely, the expected investment growth (EIG), and document that EIG has strong predictive power for stock returns. Leading factor models including the CAPM, the Fama-French three-factor model, the Carhart four-factor model, the more recent Hou, Xue, and Zhang four-factor model, and the Fama and French five-factor model all fail to fully capture the profitability of this premium. The result is robust to subperiods and subsamples of firms. It also holds in the other G7 countries.

Further analyses suggest that EIG is closely related to financial distress risk. Compared with high EIG firms, low EIG firms have a high failure probability and low distance to default, so they are more financially distressed. However, different from these traditional measures of distress risks which are highly persistent, the additional predictive power of EIG for future bankruptcies and failures concentrates on short horizons up to one year. Interestingly, this horizon coincides with the horizon of the large negative return predictability of both EIG and traditional distress risk measures, indicating that EIG is a better return predictor than these traditional distress measures. Indeed, in portfolios double-sorted by EIG and these distress measures, the conditional EIG premium remains economically and statistically significant, whereas the conditional distress premiums are significantly weaker. It is an interesting and puzzling finding that while both the short-horizon and long-horizon components of financial distress risk predict corporate bankruptcies and failures, it is only the short-horizon component that has strong negative predictive power for future stock returns; we leave this question for future research. An equilibrium model with a rich cross section of firms making their financing, investment, and bankruptcy decisions can be potentially fruitful in understanding this pattern.

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Appendix

In this appendix, we provide details on how we construct the financial distress measures, as well as the data on the non-US G7 countries.

Financial distress measures:

FP: Following Campbell, Hilscher, and Szilagyi (2008), for each firm, we use the most recently available Compustat quarterly and CRSP data to compute a distress score:

$$\begin{aligned}\mathrm{FP}_t &= -9.16 - 20.26 \times \mathrm{NIMTAAVG}_t + 1.42 \times \mathrm{TLMTA}_t - 7.13 \times \mathrm{EXRETAVG}_t \\ &\quad + 1.41 \times \mathrm{SIGMA}_t - 0.045 \times \mathrm{RSIZE} - 2.13 \times \mathrm{CASHMTA}_t + 0.075 \times \mathrm{MB}_t - 0.058 \times \mathrm{PRICE}_t,\end{aligned}$$

where

$$\begin{aligned}\mathrm{NIMTAAVG}_{t-1,t-12} &= \frac{1-\phi^2}{1-\phi^{12}}(\mathrm{NIMTA}_{t-1,t-3} + \cdots + \phi^9\mathrm{NIMTA}_{t-10,t-12}) \\ \mathrm{EXRETAVG}_{t-1,t-12} &= \frac{1-\phi}{1-\phi^{12}}(\mathrm{EXRET}_{t-1} + \cdots + \phi^{11}\mathrm{EXRET}_{t-12}).\end{aligned}$$

The coefficient $\phi = 2^{-1/3}$ implies that the weight is halved each quarter. NIMTA is net income (Compustat quarterly item NIQ) divided by the sum of market equity and total liabilities (Compustat quarterly item LTQ). The moving average NIMTAAVG uses a longer history of losses that can better predict bankruptcy than a single month. EXRET $= \log(1+\mathrm{R}_{it}) - \log(1+\mathrm{R}_{\mathrm{S\&P500},t})$ is the monthly log excess return on each firm's equity relative to the S&P 500 index. To use its moving average, the model assumes that a sustained decline in stock market value could better predict bankruptcy than a sudden stock price decline in a single month. TLMTA is total liability divided by the sum of market equity and total liabilities. SIGMA is the volatility of daily stock returns over the past three months. RSIZE is the log ratio of each firm's market equity to that of the S&P 500 index. CASHMTA is the ratio of cash and short-term investments (Compustat quarterly item CHEQ) divided by the sum of market equity and total liabilities. MB is the market-to-book equity. PRICE is the log of stock price, winsorized at \$15.

Distance to Default (DD): Following Hillegeist, Keating, Cram, and Lunstedt (2004) and Campbell et al. (2008), distance to default is computed in two steps. In the first step, we solve a system of two nonlinear equations simultaneously:

$$\mathrm{ME} = \mathrm{TA_{DD}} \times N(\mathrm{d}_1) - \mathrm{BD} \times \exp(-\mathrm{R_{BILL}} \times T) \times N(\mathrm{d}_2)$$
$$\mathrm{SIGMA} = N(\mathrm{d}_1) \times \frac{\mathrm{TA_{DD}}}{\mathrm{ME}} \times \mathrm{SIGMA_{DD}},$$

where $\mathrm{TA_{DD}}$ is total assets, $\mathrm{SIGMA_{DD}}$ is the volatility of total assets, ME is market equity, BD is the face value of debt that matures at time T, $\mathrm{R_{BILL}}$ is the risk-free rate measured by the Treasury bill rate, T is assumed to be 1 following Vassalou and Xing (2004), and

$$\mathrm{d}_1 = \frac{\log(\mathrm{TA_{DD}}/\mathrm{BD}) + (\mathrm{R_{BILL}} + 0.5 \times \mathrm{SIGMA_{DD}^2}) \times T}{\mathrm{SIGMA_{DD}} \times T^{1/2}},$$
$$\mathrm{d}_2 = \mathrm{d}_1 - \mathrm{SIGMA_{DD}} \times T^{1/2}$$

We use $\mathrm{TA_{DD}} = \mathrm{ME{+}BD}$ and $\mathrm{SIGMA_{DD}} = \mathrm{SIGMA} \times \frac{\mathrm{ME}}{\mathrm{ME+BD}}$ as the initial value in iteration until we find $\mathrm{TA_{DD}}$ and $\mathrm{SIGMA_{DD}}$ that are consistent with their observed values. In the second step, we compute distance to default as

$$\mathrm{DD} = \frac{-\log(\mathrm{BD}/\mathrm{TA_{DD}}) + 0.06 + \mathrm{R_{BILL}} - 0.5 \times \mathrm{SIGMA_{DD}^2}}{\mathrm{SIGMA_{DD}}}.$$

Non-US G7 countries:

Following Gao, Parsons, and Shen (2015), for each country, we only include non-financial and non-utility stocks traded on its major national stock exchanges. Most countries have only one major exchange except for Canada, for which we use stocks from both the Toronto Stock Exchange and the TSX Ventures Exchange, and Japan, for which we include all stocks traded on the Osaka Securities Exchange, the Tokyo Stock Exchange, and JASDAQ. We convert all returns, prices, and accounting variables from local currency to US dollars. We further exclude micro-cap firms that have market equity below 5% per month in a country. To further eliminate erroneous observations, any return above 300% that is reversed within one month is set to missing. Lastly, returns are winsorized at 0.1 and 99.9 percentiles to avoid extreme values. To compute portfolio alphas, we use the Fama and French Global factors from the Fama and French data library.

Table 1: Predictive regressions of expected investment growth

This table reports the time series average of coefficients and adjusted R^2 of the Fama-MacBeth investment growth predictive regressions on momentum (MOM, column (1)), q (column (2)), cash flow (CF, column (3)), and all three variables together (column (4)). Every December from 1951 to 2014, we run cross-sectional predictive regressions of firms' investment growth on its lagged MOM, q, and CF, among NYSE/AMEX/NASDAQ stocks (excluding financial stocks, utility stocks, and ADR shares) with a December fiscal year end. Investment growth is computed as the growth rate in capital expenditures (Compustat data item CAPX). MOM is the prior 2- to 12-month cumulative return. q is computed as the log of the market value of the firm (sum of market equity, long-term debt, and preferred stock minus inventories and deferred taxes) divided by capital (Compustat data item PPEGT). CF is the sum of depreciation (Compustat data item DP) and income before extraordinary items (Compustat data item IB) divided by capital (Compustat data item PPEGT). Variables are winsorized cross-sectionally at the 5th and 95th percentiles. The adjusted R^2 is in percentages.

Variables	(1)	(2)	(3)	(4)
Intercept	2.52	2.68	1.14	-0.77
	(1.54)	(1.2)	(0.68)	(-0.44)
MOM	40.05			35.52
	(26.81)			(26.64)
q		5.93		3.13
		(10.65)		(5.47)
CF			23.10	10.82
			(5.55)	(4.79)
Adj. R^2	5.59	1.62	1.52	6.65

Table 2: EIG and future investment growth

This table reports the future investment growth of EIG portfolios. Panel A reports the average (i.e., the time series mean of cross-sectional median) investment growth in the first four quarters (Q1-Q4), as well as in the first year (Y1), second year (Y2), third year (Y3), and fifth year (Y5) following EIG decile formations. In Panel B, we create 5-by-5 portfolios by sequentially sorting stocks by one conditioning variable and then by EIG, where the conditioning variable is momentum (MOM), q, or cash flow (CF). We then report the average conditional spread in investment growth between the top and bottom EIG quintiles in the first year following portfolio formations. We also report the average conditional investment growth spread (Ave.) across all quintiles in the first sorting dimension. Annual (quarterly) investment growth (in percentages) is computed as the growth rate in capital expenditures from the previous year (quarter). We use the past four-quarter moving average of capital expenditure as the quarterly adjusted capital expenditure to smooth out seasonality. The t-statistics in parentheses are calculated based on the heteroskedasticity-consistent standard errors of Newey and West (1987). The sample includes NYSE/AMEX/NASDAQ stocks (excluding financial stocks, utility stocks, and ADR shares) with a December fiscal year end from 1984Q4 to 2015Q5 for quarterly growth and from 1953 to 2015 for annual growth.

Panel A: Future investment growth for EIG deciles

Port.	Lo	2	3	4	5	6	7	8	9	Hi	Hi-Lo
Q1	-5.51	-4.56	-1.99	-0.43	0.81	1.36	1.89	2.74	4.33	6.59	12.10
	(-8.16)	(-8.02)	(-3.91)	(-1.12)	(2.33)	(3.76)	(11.55)	(13.16)	(12.05)	(8.16)	(10.74)
Q2	-5.69	-5.28	-2.24	-0.73	0.69	1.18	2.24	3.01	4.95	7.37	13.06
	(-8.97)	(-9)	(-4.51)	(-1.91)	(2.34)	(4.73)	(10.21)	(9.66)	(11.62)	(12.85)	(29.48)
Q3	-3.71	-4.46	-2.07	-0.87	0.81	1.28	2.06	2.76	4.15	6.09	9.80
	(-7.44)	(-12.65)	(-3.07)	(-2.43)	(2.71)	(4.85)	(8.27)	(8.82)	(9.52)	(9.59)	(25.61)
Q4	-4.54	-4.08	-2.33	-0.70	0.54	1.33	2.13	2.31	3.86	4.71	9.25
	(-7.67)	(-6.49)	(-4.16)	(-1.54)	(1.83)	(4.36)	(4.75)	(6.76)	(11.68)	(6.64)	(14.96)
Y1	-17.28	-10.76	-4.10	1.20	6.21	6.86	10.25	14.26	19.03	27.74	45.02
	(-5.06)	(-2.44)	(-1.42)	(0.5)	(2.97)	(4.19)	(7.62)	(14.54)	(13.75)	(18.67)	(12.74)
Y2	2.89	3.76	3.87	6.19	6.49	6.87	7.35	9.64	8.75	10.54	7.64
	(1.19)	(2.17)	(1.92)	(2.84)	(4.03)	(4.44)	(5.42)	(8.46)	(8.17)	(7.65)	(3.28)
Y3	9.05	9.15	7.26	5.45	6.17	6.34	6.65	6.44	7.38	6.97	-2.08
	(4.44)	(4.97)	(3.34)	(3.93)	(3.73)	(5.56)	(3.95)	(5.35)	(6.7)	(7.06)	(-1.24)
Y5	7.93	7.92	6.22	7.99	6.23	5.76	6.59	5.51	5.66	5.44	-2.49
	(4.89)	(6.94)	(4.55)	(4.26)	(5.05)	(3.78)	(4.53)	(4.98)	(3.38)	(3.56)	(-2.27)

Panel B: Conditional spread in one-year investment growth between high and low EIG quintiles

Cond. Var.	Lo	2	3	4	Hi	Ave.
MOM	23.32	10.74	4.43	2.67	14.62	11.15
	(10.43)	(6.91)	(4.27)	(1.56)	(8.14)	(10.9)
q	39.11	36.18	34.37	41.38	33.74	36.96
	(13.12)	(13.42)	(7.5)	(11.7)	(7.25)	(11.28)
CF	41.69	39.07	33.22	35.30	30.33	35.92
	(12.22)	(6.33)	(18.38)	(13.47)	(9.31)	(11.77)

Table 3: Characteristics of EIG portfolios

This table reports the time series average of the cross-sectional median firm characteristics in Panel A and the value-weighted average excess returns (Ret^e), standard deviation (Std), Sharpe ratio (SR), skewness (Skew), and kurtosis (Kurt) of the decile EIG portfolios in Panel B. At the beginning of every month, we sort NYSE/AMEX/NASDAQ stocks (excluding financial stocks, utility stocks, and ADR shares) into EIG deciles. ME is market equity in million dollars. BM is the book value of equity divided by market value at the end of the last fiscal year. IK is investment (Compustat data item CAPX) over capital (Compustat data item PPEGT). CF is the sum of depreciation (Compustat data item DP) and income before extraordinary items (Compustat data item IB) divided by capital (Compustat data item PPEGT). Gross profitability (GP) is defined as income (Compustat data item REVT minus Compustat data item COGS) divided by total assets (Compustat data item AT). Leverage (LEV) is the book value of debt divided by total assets. The sample period is from July 1953 to December 2015.

Panel A: EIG portfolio characteristics

Port.	EIG	MOM	ME	BM	CF	IK	GP	LEV
Lo	-0.22	-0.37	34.42	0.70	-0.98	0.14	0.20	0.19
2	-0.08	-0.25	62.10	0.84	0.07	0.11	0.29	0.22
3	-0.03	-0.13	108.73	0.81	0.14	0.11	0.32	0.21
4	0.01	-0.03	164.82	0.77	0.16	0.11	0.33	0.21
5	0.05	0.05	225.58	0.75	0.17	0.11	0.35	0.20
6	0.08	0.13	287.16	0.70	0.20	0.11	0.36	0.19
7	0.12	0.22	328.81	0.67	0.22	0.12	0.37	0.19
8	0.17	0.33	363.43	0.63	0.25	0.12	0.39	0.18
9	0.25	0.51	334.98	0.58	0.29	0.13	0.40	0.16
Hi	0.44	0.93	238.24	0.55	0.41	0.15	0.40	0.15

Panel B: Portfolio excess returns

Port.	Lo	2	3	4	5	6	7	8	9	Hi	Hi-Lo
Ret^e	-5.66	0.57	4.76	6.09	6.46	6.18	7.02	8.07	11.27	15.03	20.69
	(-1.66)	(0.17)	(1.8)	(2.75)	(3.04)	(3.02)	(3.44)	(3.9)	(4.88)	(5.27)	(8)
Std	27.03	26.95	20.94	17.53	16.82	16.22	16.16	16.38	18.25	22.57	20.46
SR	-0.21	0.02	0.23	0.35	0.38	0.38	0.43	0.49	0.62	0.67	1.01
Skew	-0.09	0.60	0.11	0.00	-0.31	-0.46	-0.40	-0.46	-0.56	-0.30	-0.43
Kurt	2.13	9.00	4.31	2.73	1.93	1.93	1.98	1.77	2.01	1.94	2.23

Table 4: Asset pricing model tests

This table reports the results of asset pricing tests from the following factor models: CAPM (Panel A), Fama-French three-factor model (Panel B), Carhart four-factor model (Panel C), Hou, Xue, and Zhang four-factor model (Panel D), and Fama-French five-factor model (Panel E). At the beginning of every month, we sort NYSE/AMEX/NASDAQ stocks (excluding financial stocks, utility stocks, and ADR shares) into value-weighted EIG deciles. The abnormal returns are annualized and reported in percentages. The t-statistics in parentheses are calculated based on the heteroskedasticity-consistent standard errors of White (1980). The sample period is from July 1953 to December 2015 in Panel A to C, and from January 1967 to December 2015 in Panel D, and July 1963 to December 2015 in Panel E due to the factor availability.

Port.	Lo	2	3	4	5	6	7	8	9	Hi	Hi-Lo
					Panel A: CAPM						
α^{CAPM}	-15.46	-9.21	-3.44	-1.03	-0.71	-0.89	-0.06	0.95	3.57	6.14	21.60
	(-7.08)	(-4.37)	(-2.4)	(-0.92)	(-0.76)	(-1.13)	(-0.07)	(1.17)	(3.43)	(3.88)	(8.42)
MKT	1.39	1.38	1.16	1.01	1.01	1.00	1.00	1.01	1.09	1.26	-0.13
	(26.78)	(21.44)	(30.75)	(33.18)	(46.03)	(50.96)	(55.76)	(51.01)	(41.76)	(36.19)	(-2.02)
R^2	59.09	59.12	68.91	74.27	81.50	85.33	86.18	85.04	80.01	69.78	0.75
					Panel B: Fama-French three-factor model						
α^{FF3}	-15.09	-11.23	-5.12	-2.17	-1.59	-1.22	0.03	1.62	5.19	8.92	24.01
	(-7.5)	(-5.49)	(-3.57)	(-1.94)	(-1.71)	(-1.52)	(0.04)	(2.03)	(5.4)	(6.61)	(9.11)
MKT	1.21	1.36	1.18	1.03	1.04	1.01	1.02	0.99	1.03	1.11	-0.11
	(25.15)	(21.23)	(31.28)	(34.03)	(48.22)	(51.04)	(57.31)	(52)	(43.24)	(35.65)	(-1.67)
SMB	0.81	0.41	0.15	0.05	-0.02	-0.03	-0.09	-0.03	0.07	0.36	-0.46
	(10.8)	(4.18)	(2.34)	(1.03)	(-0.49)	(-0.71)	(-2.76)	(-0.82)	(1.77)	(5.83)	(-4.13)
HML	-0.20	0.33	0.31	0.21	0.18	0.07	0.00	-0.13	-0.33	-0.60	-0.40
	(-2.26)	(2.7)	(4.47)	(4.15)	(4.36)	(1.73)	(-0.1)	(-3.4)	(-7.89)	(-10.64)	(-3.56)
R^2	68.68	61.96	70.79	75.41	82.39	85.50	86.44	85.49	82.91	78.92	7.31
					Panel C: Carhart four-factor model						
α^{CARH}	-8.80	-0.20	1.87	2.79	1.34	0.00	-0.58	-0.53	1.61	4.35	13.14
	(-4.24)	(-0.12)	(1.6)	(3.15)	(1.6)	(0.01)	(-0.73)	(-0.66)	(1.97)	(3.34)	(5.06)
MKT	1.12	1.20	1.08	0.96	1.00	1.00	1.02	1.02	1.08	1.17	0.05
	(28)	(34.84)	(37.16)	(48.84)	(54.27)	(49.81)	(56.87)	(57.58)	(55.06)	(42)	(0.94)
SMB	0.80	0.38	0.14	0.04	-0.03	-0.04	-0.09	-0.02	0.08	0.37	-0.44
	(13.3)	(7.95)	(3.52)	(1.16)	(-0.86)	(-0.85)	(-2.59)	(-0.64)	(2.07)	(7.91)	(-6.24)
HML	-0.39	-0.01	0.09	0.06	0.08	0.03	0.02	-0.06	-0.22	-0.46	-0.06
	(-5.32)	(-0.19)	(1.97)	(1.7)	(2.45)	(0.86)	(0.52)	(-1.76)	(-6.06)	(-9.25)	(-0.76)
UMD	-0.54	-0.95	-0.60	-0.43	-0.25	-0.11	0.05	0.19	0.31	0.39	0.94
	(-6.63)	(-14.75)	(-16.92)	(-15.65)	(-10.38)	(-4.18)	(2.38)	(6.48)	(12.01)	(8.25)	(8.14)
R^2	75.88	84.26	85.62	86.07	86.42	86.24	86.61	87.78	88.00	84.37	44.82

Port.	Lo	2	3	4	5	6	7	8	9	Hi	Hi-Lo
					Panel D: Hou, Xue, and Zhang four-factor model						
α^{HXZ}	-7.15	-0.78	0.86	1.79	-1.02	-1.54	-2.69	-0.79	1.34	7.52	14.67
	(-2.83)	(-0.28)	(0.4)	(1.21)	(-0.82)	(-1.33)	(-2.73)	(-0.8)	(1.08)	(3.86)	(4.48)
MKT	1.13	1.30	1.14	1.01	1.05	1.03	1.03	1.02	1.05	1.13	0.00
	(22.41)	(22.33)	(28)	(32.72)	(43.25)	(42.24)	(52.78)	(51.47)	(41.12)	(28.9)	(-0.07)
ME	0.48	0.05	-0.02	-0.07	-0.06	-0.03	-0.04	0.04	0.16	0.37	-0.10
	(6.56)	(0.48)	(-0.31)	(-1.47)	(-1.24)	(-0.51)	(-1.07)	(1.18)	(3.57)	(4.53)	(-0.86)
IA	-0.63	0.00	0.10	0.12	0.20	0.19	0.13	0.00	-0.26	-0.76	-0.13
	(-4.78)	(-0.01)	(0.77)	(1.34)	(2.66)	(2.55)	(2.49)	(-0.07)	(-3.45)	(-6.94)	(-0.79)
ROE	-1.02	-1.21	-0.62	-0.38	-0.11	0.02	0.20	0.26	0.38	0.26	1.28
	(-8.51)	(-6.97)	(-5.34)	(-4.85)	(-1.95)	(0.4)	(5.75)	(5.62)	(7.19)	(3.29)	(9.65)
R^2	75.52	72.79	74.65	77.66	83.14	86.03	87.80	87.49	84.41	78.18	28.60
					Panel E: Fama-French five-factor model						
α^{FF5}	-11.03	-8.40	-4.31	-1.57	-2.75	-2.38	-2.09	0.56	4.23	10.97	22.00
	(-4.89)	(-3.18)	(-2.32)	(-1.13)	(-2.45)	(-2.53)	(-2.33)	(0.62)	(3.65)	(6.73)	(6.77)
MKT	1.13	1.33	1.18	1.04	1.07	1.05	1.03	1.01	1.01	1.06	-0.07
	(20.46)	(18.15)	(25.77)	(31.35)	(44.1)	(49)	(51.51)	(49.02)	(37.2)	(28.91)	(-0.96)
SMB	0.54	0.25	0.10	0.03	0.03	0.03	-0.02	0.05	0.15	0.33	-0.21
	(5.94)	(2.27)	(1.48)	(0.55)	(0.79)	(0.73)	(-0.52)	(1.46)	(3.34)	(5.34)	(-1.59)
HML	-0.17	0.50	0.36	0.23	0.15	-0.04	-0.09	-0.18	-0.32	-0.43	-0.27
	(-1.35)	(2.88)	(3.51)	(3.4)	(3.03)	(-0.8)	(-2.14)	(-4.03)	(-5.82)	(-5.93)	(-1.6)
RMW	-1.05	-0.54	-0.17	-0.02	0.20	0.23	0.24	0.22	0.18	-0.25	0.81
	(-8.12)	(-2.72)	(-1.38)	(-0.28)	(3.01)	(3.35)	(4.85)	(4.03)	(2.8)	(-2.79)	(4.28)
CMA	-0.27	-0.39	-0.11	-0.04	0.09	0.26	0.20	0.15	-0.01	-0.38	-0.11
	(-1.61)	(-1.6)	(-0.65)	(-0.39)	(1.14)	(3.39)	(3.49)	(2.28)	(-0.1)	(-3.59)	(-0.51)
R^2	74.01	62.74	70.23	75.11	83.25	86.62	87.67	86.49	83.66	80.05	12.53

Table 5: Subperiod analyses

This table reports the returns and asset pricing test results for decile EIG portfolios in subperiods. The sample period for Panel A is from July 1953 to September 1984, except for α^{HXZ} , which is from January 1967 to June 1991, and α^{FF5}, which is from July 1963 to September 1989. The sample period for Panel B is from October 1984 to December 2015, except for α^{HXZ} , which is from July 1991 to December 2015, and α^{FF5}, which is from October 1989 to December 2015. At the beginning of every month, we sort NYSE/AMEX/NASDAQ stocks (excluding financial stocks, utility stocks, and ADR shares) into EIG deciles. We report the value-weighted excess returns (Ret^{e}), Sharpe ratio (SR), and the abnormal return from CAPM (α^{CAPM}), Fama-French three-factor model (α^{FF3}), Carhart four-factor model (α^{CARH}), Hou, Xue, and Zhang (2015) four-factor model (α^{HXZ}), and Fama-French five-factor model (α^{FF5}). The returns and alphas are annualized and reported in percentages. The t-statistics in parentheses are calculated based on the heteroskedasticity-consistent standard errors of White (1980).

Port.	Lo	2	3	4	5	6	7	8	9	Hi	Hi-Lo
					Panel A: Early subsample						
Ret^{e}	-1.80	1.70	4.02	5.35	5.49	5.21	8.14	7.97	12.66	16.44	18.24
	(-0.46)	(0.48)	(1.3)	(1.88)	(1.85)	(1.76)	(2.67)	(2.61)	(3.82)	(4.34)	(5.22)
SR	-0.08	0.09	0.23	0.34	0.33	0.31	0.48	0.47	0.68	0.78	0.93
α^{CAPM}	-9.41	-5.31	-2.47	-0.65	-0.98	-1.28	1.42	1.36	5.73	8.98	18.39
	(-4.26)	(-2.9)	(-1.76)	(-0.51)	(-0.86)	(-1.2)	(1.3)	(1.15)	(3.8)	(4.29)	(5.23)
α^{FF3}	-12.30	-7.84	-3.90	-1.70	-1.31	-1.22	2.13	2.68	7.97	11.25	23.56
	(-5.65)	(-4.21)	(-2.84)	(-1.34)	(-1.13)	(-1.12)	(1.87)	(2.22)	(5.48)	(5.71)	(6.55)
α^{CARH}	-3.47	1.09	2.04	2.88	1.20	-0.97	0.27	-1.39	1.35	1.85	5.32
	(-1.89)	(0.79)	(1.73)	(2.47)	(1.05)	(-0.76)	(0.22)	(-1.24)	(1.29)	(1.38)	(2.34)
α^{HXZ}	-8.58	-0.32	1.96	5.12	-0.14	-0.98	-1.54	-0.68	-0.39	2.57	11.15
	(-2.55)	(-0.12)	(0.92)	(2.61)	(-0.08)	(-0.62)	(-1.04)	(-0.46)	(-0.21)	(1.01)	(2.25)
α^{FF5}	-13.99	-7.67	-2.58	0.09	-1.94	-2.07	-0.45	2.56	7.31	11.77	25.76
	(-4.53)	(-2.82)	(-1.41)	(0.05)	(-1.37)	(-1.55)	(-0.34)	(1.67)	(3.99)	(4.56)	(5.14)
					Panel B: Late subsample						
Ret^{e}	-9.52	-0.56	5.50	6.84	7.43	7.16	5.90	8.18	9.88	13.63	23.15
	(-1.7)	(-0.1)	(1.28)	(2.02)	(2.44)	(2.52)	(2.17)	(2.92)	(3.07)	(3.19)	(6.08)
SR	-0.30	-0.02	0.23	0.36	0.44	0.45	0.39	0.52	0.55	0.57	1.09
α^{CAPM}	-21.70	-13.37	-4.52	-1.45	-0.40	-0.43	-1.44	0.60	1.43	3.23	24.94
	(-5.88)	(-3.64)	(-1.85)	(-0.78)	(-0.27)	(-0.38)	(-1.42)	(0.56)	(1.01)	(1.37)	(6.78)
α^{FF3}	-19.41	-14.64	-5.98	-2.42	-1.42	-0.92	-1.66	0.89	2.62	6.06	25.47
	(-6.22)	(-4.11)	(-2.47)	(-1.32)	(-1.01)	(-0.81)	(-1.65)	(0.86)	(2.1)	(3.35)	(6.84)
α^{CARH}	-14.41	-3.58	0.99	2.46	1.55	0.66	-1.64	-0.35	0.46	3.52	17.94
	(-4.63)	(-1.5)	(0.56)	(1.85)	(1.28)	(0.62)	(-1.65)	(-0.34)	(0.42)	(1.98)	(4.96)
α^{HXZ}	-8.17	-2.32	0.23	-0.16	-0.08	-0.66	-2.76	-0.82	0.53	7.47	15.65
	(-2.08)	(-0.56)	(0.07)	(-0.08)	(-0.05)	(-0.43)	(-2.17)	(-0.66)	(0.31)	(2.77)	(3.6)
α^{FF5}	-11.50	-10.13	-5.02	-3.18	-2.37	-1.86	-2.57	-0.58	1.19	8.48	19.98
	(-3.54)	(-2.38)	(-1.69)	(-1.48)	(-1.38)	(-1.39)	(-2.1)	(-0.51)	(0.77)	(3.98)	(4.58)

Table 6: Robustness check on sample selection

This table reports the returns and asset pricing test results for decile EIG portfolios for subsamples of firms. Panel A uses the NYSE breakpoints. Panel B uses the all-but-micro subsample which excludes stocks smaller than 20% of the NYSE size cutoff at the portfolio formation month. Panel C only includes NYSE/AMEX/NASDAQ stocks (excluding financial stocks, utility stocks, and ADR shares) with a lag price at least \$5 per share. At the beginning of every month, we sort stocks in each sample into EIG deciles. We report the excess returns (Ret^{e}), Sharpe ratio (SR), and the abnormal return from CAPM (α^{CAPM}), Fama-French three-factor model (α^{FF3}), Carhart four-factor model (α^{CARH}), Hou, Xue, and Zhang (2015) four-factor model (α^{HXZ}), and Fama-French five-factor model (α^{FF5}). Portfolios are value weighted in Panel A and C, and equally weighted in Panel B. The returns and alphas are annualized and reported in percentages. The t-statistics in parentheses are calculated based on the heteroskedasticity-consistent standard errors of White (1980). The sample period is from July 1953 to December 2015, except for α^{HXZ} which is from January 1967 to December 2015, and α^{FF5} which is from July 1963 to December 2015 due to the factor availability.

Port.	Lo	2	3	4	5	6	7	8	9	Hi	Hi-Lo
					Panel A: NYSE breakpoints						
Ret^{e}	-0.49	4.27	6.73	5.60	7.08	6.23	7.50	8.10	10.39	13.47	13.96
	(-0.15)	(1.65)	(2.94)	(2.66)	(3.41)	(3.12)	(3.77)	(3.99)	(4.76)	(5.16)	(5.62)
SR	-0.02	0.21	0.37	0.34	0.43	0.39	0.48	0.50	0.60	0.65	0.71
α^{CAPM}	-10.18	-3.64	-0.61	-1.35	0.06	-0.55	0.62	1.19	2.99	5.01	15.20
	(-5.54)	(-2.49)	(-0.54)	(-1.4)	(0.06)	(-0.66)	(0.81)	(1.41)	(3.3)	(3.84)	(6.31)
α^{FF3}	-11.56	-5.58	-2.36	-2.24	-0.71	-1.01	0.45	1.54	4.39	7.46	19.02
	(-6.38)	(-3.81)	(-2.16)	(-2.33)	(-0.79)	(-1.2)	(0.59)	(1.83)	(5.05)	(6.7)	(7.87)
α^{CARH}	-2.78	1.75	2.65	1.58	1.48	0.06	0.01	-0.48	1.48	3.46	6.24
	(-2)	(1.75)	(2.84)	(1.81)	(1.69)	(0.07)	(0.01)	(-0.6)	(1.88)	(3.35)	(3.8)
α^{HXZ}	-1.49	1.05	1.58	-0.13	-0.88	-1.20	-2.03	-1.64	0.27	5.32	6.81
	(-0.68)	(0.52)	(1.03)	(-0.1)	(-0.7)	(-0.94)	(-2.19)	(-1.66)	(0.27)	(3.32)	(2.17)
α^{FF5}	-8.00	-4.56	-2.01	-2.69	-1.94	-2.16	-1.69	-0.24	3.06	8.41	16.41
	(-3.58)	(-2.43)	(-1.49)	(-2.24)	(-1.84)	(-2.27)	(-2.06)	(-0.25)	(3.09)	(6.14)	(5.26)

Port.	Lo	2	3	4	5	6	7	8	9	Hi	Hi-Lo
					Panel B: All-but-micro subsample						
Ret^{e}	1.72	6.27	7.84	7.87	8.59	8.99	10.45	11.66	13.22	16.23	14.52
	(0.53)	(2.41)	(3.34)	(3.49)	(3.94)	(4.1)	(4.65)	(4.94)	(5.14)	(5.25)	(6.18)
SR	0.07	0.30	0.42	0.44	0.50	0.52	0.59	0.63	0.65	0.66	0.78
α^{CAPM}	-8.32	-2.22	-0.05	0.14	1.04	1.33	2.64	3.57	4.70	6.62	14.94
	(-4.74)	(-1.8)	(-0.05)	(0.15)	(1.25)	(1.69)	(3.16)	(3.81)	(3.95)	(3.87)	(6.59)
α^{FF3}	-10.32	-4.61	-2.16	-1.51	-0.41	0.20	2.00	3.51	5.57	8.47	18.79
	(-6.85)	(-4.31)	(-2.58)	(-2.08)	(-0.63)	(0.35)	(3.28)	(5.58)	(6.84)	(7.09)	(8.51)
α^{CARH}	-2.27	0.85	1.35	0.89	0.78	0.20	0.92	1.47	2.18	3.57	5.84
	(-2.06)	(1.18)	(2.05)	(1.41)	(1.25)	(0.35)	(1.52)	(2.47)	(3.16)	(3.48)	(4.59)
α^{HXZ}	-1.02	0.38	0.28	-0.32	-0.51	-0.28	0.43	2.21	3.22	5.33	6.35
	(-0.57)	(0.24)	(0.23)	(-0.32)	(-0.53)	(-0.4)	(0.63)	(2.97)	(2.84)	(2.96)	(2.07)
α^{FF5}	-7.38	-3.96	-2.49	-2.21	-1.54	-0.73	1.01	2.99	5.24	8.92	16.30
	(-3.99)	(-2.81)	(-2.41)	(-2.52)	(-2.02)	(-1.14)	(1.49)	(4.1)	(5.24)	(6.06)	(5.61)
					Panel C: Excluding stocks with lag price less than $5 per share						
Ret^{e}	-1.93	4.44	5.56	6.12	6.31	5.50	8.09	8.85	11.65	15.34	17.27
	(-0.63)	(1.77)	(2.58)	(3)	(3.11)	(2.77)	(3.88)	(4.2)	(4.82)	(5.23)	(6.6)
SR	-0.08	0.22	0.33	0.38	0.39	0.35	0.49	0.53	0.61	0.66	0.83
α^{CAPM}	-11.34	-3.47	-1.43	-0.72	-0.62	-1.35	0.95	1.68	3.64	6.32	17.66
	(-6.52)	(-2.61)	(-1.33)	(-0.79)	(-0.75)	(-1.8)	(1.11)	(1.93)	(3.27)	(3.8)	(6.76)
α^{FF3}	-12.78	-5.03	-2.82	-1.54	-0.95	-1.54	1.47	2.72	5.57	9.31	22.10
	(-7.42)	(-3.7)	(-2.64)	(-1.78)	(-1.11)	(-2.06)	(1.71)	(3.28)	(5.61)	(6.6)	(8.77)
α^{CARH}	-4.87	1.12	1.36	1.33	0.44	-1.64	-0.10	-0.10	2.19	4.57	9.45
	(-3.68)	(1.02)	(1.43)	(1.64)	(0.49)	(-2.16)	(-0.1)	(-0.14)	(2.41)	(3.43)	(5.01)
α^{HXZ}	-4.34	-0.32	0.12	-0.39	-1.82	-2.95	-1.38	0.03	2.62	8.31	12.65
	(-2.04)	(-0.19)	(0.08)	(-0.32)	(-1.37)	(-3.14)	(-1.28)	(0.03)	(1.94)	(3.84)	(3.45)
α^{FF5}	-10.04	-4.46	-2.96	-2.11	-2.41	-2.65	-0.59	1.97	5.42	11.70	21.74
	(-4.73)	(-2.71)	(-2.17)	(-2.01)	(-2.4)	(-3.11)	(-0.64)	(2.03)	(4.54)	(6.69)	(6.59)

Table 7: Fama-MacBeth regressions

Each month, we run a cross-sectional regression of excess returns (in percentages) on lagged variables. This table reports the time series average of the regression. Firm characteristics we consider include: expected investment growth (EIG), log of firm market value (LogME), log of book-to-equity ratio (LogBM), prior 2- to 12-month cumulative returns (MOM), gross profitability (GP), asset growth (AG), and investment growth (IG). The adjusted R^2 are reported in percentages. The sample includes NYSE/AMEX/NASDAQ stocks (excluding financial stocks, utility stocks, and ADR shares) in Panel A, and excludes micro stocks (stocks smaller than 20% of the NYSE size cutoff in the previous month) in Panel B. The right-hand-side accounting variables are winsorized cross-sectionally at 1st and 99th percentiles. The sample period is from July 1953 to December 2015. The t-statistics in parentheses are calculated based on White (1980).

	Panel A: Full sample					Panel B: All-but-micro subsample				
Spec.	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Intercept	0.74	1.47	1.44	1.34	1.27	0.52	0.86	0.87	0.80	0.84
	(3.58)	(4.94)	(5.03)	(4.22)	(4.19)	(2.74)	(2.56)	(2.66)	(2.33)	(2.47)
EIG	1.68	2.02	0.97	1.95	1.15	2.21	2.50	1.22	2.42	1.39
	(5.01)	(6.8)	(2.75)	(6.59)	(2.82)	(6.3)	(7.34)	(3)	(7.17)	(3.09)
LogBM		0.28	0.25	0.25	0.23		0.28	0.23	0.27	0.23
		(5.37)	(4.72)	(4.72)	(4.17)		(4.97)	(3.9)	(4.75)	(3.77)
LogME		-0.14	-0.14	-0.12	-0.13		-0.04	-0.05	-0.04	-0.05
		(-4.03)	(-4.22)	(-3.57)	(-3.75)		(-1.23)	(-1.48)	(-1.32)	(-1.66)
MOM			0.51		0.41			0.61		0.50
			(2.73)		(2.05)			(2.93)		(2.32)
GP				0.40	0.44				0.43	0.42
				(3.18)	(3.6)				(2.82)	(2.9)
AG				-0.94	-0.76				-0.62	-0.58
				(-7.45)	(-6.03)				(-4.39)	(-4.16)
IG					-0.06					-0.03
					(-2.77)					(-1.04)
Adj. R^2	1.25	3.08	3.49	3.69	4.12	1.92	3.96	4.61	5.03	5.69

Table 8: EIG portfolios for non-US G7 countries

This table reports the average returns (Ret^e), Sharpe ratio (SR), the global CAPM alphas (α^{CAPM}), the Fama-French global three-factor alphas (α^{FF3}), the Fama-French global four-factor alphas (α^{CARH}), and the Fama-French global five-factor alphas (α^{FF5}) of EIG deciles for non-US G7 countries (Canada, France, Germany, Italy, Japan, and United Kingdom). The returns and alphas are annualized and reported in percentages. The sample period is from July 2001 to December 2015 for Canada, from July 1992 to December 2015 for France and the United Kingdom, from July 1996 to December 2015 for Germany and Italy, and from July 2002 to December 2015 for Japan. The t-statistics in parentheses are calculated based on the heteroskedasticity-consistent standard errors of White (1980).

Port.	Lo	2	3	4	5	6	7	8	9	Hi	Hi-Lo
					Canada						
Ret^e	-12.29	1.93	0.61	1.57	4.38	4.54	6.25	9.39	17.49	22.47	34.76
	(-1)	(0.17)	(0.08)	(0.23)	(0.68)	(0.81)	(1.05)	(1.66)	(2.5)	(2.77)	(3.11)
SR	-0.26	0.04	0.02	0.06	0.18	0.21	0.28	0.43	0.65	0.72	0.82
α^{CAPM}	-24.35	-9.58	-7.06	-4.81	-2.09	-1.18	-0.22	3.64	11.08	15.05	39.40
	(-2.72)	(-1.23)	(-1.21)	(-0.94)	(-0.46)	(-0.29)	(-0.05)	(0.89)	(2.04)	(2.37)	(3.76)
α^{FF3}	-23.23	-11.14	-10.64	-6.58	-4.14	-3.34	-2.56	2.72	7.90	12.66	35.90
	(-2.53)	(-1.4)	(-1.76)	(-1.23)	(-0.89)	(-0.84)	(-0.64)	(0.67)	(1.63)	(2.03)	(3.24)
α^{CARH}	-15.25	-2.09	-6.80	-4.66	-2.70	-4.48	-4.76	-0.92	2.43	7.82	23.07
	(-1.74)	(-0.28)	(-1.19)	(-0.9)	(-0.58)	(-1.12)	(-1.21)	(-0.24)	(0.53)	(1.25)	(2.25)
α^{FF5}	-8.04	3.32	-4.40	-4.37	-0.80	-4.63	-3.71	-1.78	5.89	10.68	18.72
	(-0.84)	(0.44)	(-0.73)	(-0.83)	(-0.18)	(-1.2)	(-0.96)	(-0.44)	(1.1)	(1.77)	(1.73)
					France						
Ret^e	-0.26	1.92	5.03	10.44	5.02	9.54	9.43	10.01	8.37	15.35	15.62
	(-0.03)	(0.29)	(0.97)	(2.39)	(1.12)	(2.25)	(2.43)	(2.37)	(1.89)	(2.73)	(2.15)
SR	-0.01	0.06	0.20	0.49	0.23	0.46	0.50	0.49	0.39	0.56	0.44
α^{CAPM}	-10.80	-7.62	-3.00	4.17	-1.55	3.18	3.73	3.75	2.03	7.53	18.33
	(-1.76)	(-1.58)	(-0.91)	(1.39)	(-0.5)	(1.15)	(1.39)	(1.33)	(0.65)	(1.85)	(2.63)
α^{FF3}	-11.30	-7.46	-4.24	3.06	-3.26	2.41	1.49	2.52	0.77	6.20	17.50
	(-1.69)	(-1.54)	(-1.29)	(0.99)	(-1.07)	(0.83)	(0.57)	(0.85)	(0.25)	(1.55)	(2.32)
α^{CARH}	-1.20	0.69	-0.47	4.06	-2.34	1.84	0.67	-1.02	-2.18	2.25	3.45
	(-0.17)	(0.14)	(-0.14)	(1.31)	(-0.76)	(0.66)	(0.25)	(-0.36)	(-0.71)	(0.56)	(0.47)
α^{FF5}	-5.02	-3.37	-5.54	0.52	-4.62	0.37	-0.84	-2.94	-1.56	4.59	9.61
	(-0.65)	(-0.63)	(-1.55)	(0.15)	(-1.47)	(0.12)	(-0.31)	(-1.02)	(-0.49)	(1.06)	(1.11)

Port.	Lo	2	3	4	5	6	7	8	9	Hi	Hi-Lo
					Germany						
$\mathrm{Ret}^{\mathrm{e}}$	-18.64	-7.18	-2.21	-1.90	1.82	3.89	5.84	10.82	10.97	14.75	33.39
	(-2.27)	(-0.94)	(-0.33)	(-0.37)	(0.37)	(0.88)	(1.18)	(2.48)	(2.36)	(2.14)	(4.39)
SR	-0.51	-0.21	-0.07	-0.08	0.08	0.20	0.27	0.56	0.53	0.48	0.99
α^{CAPM}	-27.01	-14.12	-8.39	-6.77	-2.27	-0.22	1.06	7.20	7.44	9.17	36.19
	(-4.38)	(-2.29)	(-1.52)	(-1.67)	(-0.54)	(-0.06)	(0.26)	(1.92)	(1.86)	(1.57)	(4.9)
α^{FF3}	-22.56	-15.07	-10.30	-8.98	-4.36	-2.87	-1.06	5.84	5.58	10.94	33.50
	(-3.82)	(-2.42)	(-2)	(-2.16)	(-1.03)	(-0.87)	(-0.25)	(1.58)	(1.42)	(1.85)	(4.47)
α^{CARH}	-17.84	-6.94	-4.94	-7.08	-3.32	-2.26	-3.44	4.96	3.11	7.90	25.74
	(-2.96)	(-1.06)	(-1)	(-1.59)	(-0.73)	(-0.67)	(-0.83)	(1.28)	(0.84)	(1.15)	(3.13)
α^{FF5}	-20.03	-9.86	-9.65	-9.55	-7.58	-4.93	-4.57	3.20	4.71	9.07	29.10
	(-3.14)	(-1.49)	(-1.56)	(-2.21)	(-1.62)	(-1.57)	(-0.99)	(0.84)	(1.17)	(1.35)	(3.41)
					Italy						
$\mathrm{Ret}^{\mathrm{e}}$	-8.57	-0.71	2.13	1.48	9.00	2.70	8.97	9.68	12.36	8.58	17.15
	(-0.91)	(-0.08)	(0.3)	(0.22)	(1.37)	(0.45)	(1.64)	(1.66)	(1.94)	(1.2)	(2.1)
SR	-0.20	-0.02	0.07	0.05	0.31	0.10	0.37	0.38	0.44	0.27	0.47
α^{CAPM}	-17.44	-8.66	-5.10	-5.64	2.45	-2.93	3.48	3.99	6.08	2.20	19.64
	(-2.37)	(-1.34)	(-0.98)	(-1.18)	(0.5)	(-0.64)	(0.83)	(0.89)	(1.28)	(0.39)	(2.53)
α^{FF3}	-17.68	-10.48	-8.64	-7.92	-0.89	-6.00	2.99	3.45	6.70	5.77	23.45
	(-2.39)	(-1.58)	(-1.7)	(-1.67)	(-0.19)	(-1.39)	(0.72)	(0.76)	(1.33)	(1.05)	(2.92)
α^{CARH}	-9.42	-5.68	-4.13	-4.92	1.37	-5.86	1.48	0.44	2.47	2.10	11.53
	(-1.34)	(-0.83)	(-0.81)	(-1.07)	(0.29)	(-1.32)	(0.35)	(0.11)	(0.54)	(0.36)	(1.55)
α^{FF5}	-13.36	-8.24	-10.86	-9.80	-0.82	-9.26	0.31	-1.20	2.19	3.22	16.58
	(-1.69)	(-1.15)	(-2.07)	(-2.12)	(-0.16)	(-2.16)	(0.07)	(-0.23)	(0.4)	(0.56)	(1.99)
					Japan						
$\mathrm{Ret}^{\mathrm{e}}$	2.00	4.66	5.13	6.94	6.84	5.85	5.58	8.55	4.96	9.67	7.68
	(0.34)	(1.01)	(1.17)	(1.69)	(1.67)	(1.46)	(1.32)	(1.95)	(1.04)	(1.59)	(1.43)
SR	0.09	0.27	0.32	0.46	0.45	0.40	0.36	0.53	0.28	0.43	0.39
α^{CAPM}	-4.81	-0.86	-0.10	2.12	1.98	0.97	0.97	4.15	0.43	4.68	9.49
	(-1.12)	(-0.26)	(-0.03)	(0.68)	(0.67)	(0.33)	(0.3)	(1.16)	(0.11)	(0.88)	(1.88)
α^{FF3}	-7.51	-2.99	-1.98	0.68	0.06	-0.31	-0.67	1.94	-1.75	1.67	9.18
	(-1.97)	(-0.99)	(-0.67)	(0.23)	(0.02)	(-0.11)	(-0.21)	(0.6)	(-0.48)	(0.36)	(1.87)
α^{CARH}	-4.51	-1.48	-0.53	0.47	0.49	-1.31	-1.88	-0.36	-4.22	-0.89	3.63
	(-1.18)	(-0.47)	(-0.18)	(0.15)	(0.18)	(-0.46)	(-0.6)	(-0.11)	(-1.23)	(-0.2)	(0.76)
α^{FF5}	-5.27	-2.20	-0.10	0.21	0.37	-1.86	-3.50	-2.00	-5.95	-2.20	3.07
	(-1.39)	(-0.76)	(-0.03)	(0.07)	(0.13)	(-0.64)	(-1.09)	(-0.61)	(-1.68)	(-0.46)	(0.57)
					United Kingdom						
$\mathrm{Ret}^{\mathrm{e}}$	-9.62	-4.24	6.21	3.53	5.01	7.81	6.76	8.61	7.13	12.99	22.61
	(-1.61)	(-0.62)	(1.25)	(0.8)	(1.23)	(2.24)	(1.87)	(2.52)	(1.79)	(2.83)	(4.78)
SR	-0.33	-0.13	0.26	0.17	0.25	0.46	0.38	0.52	0.37	0.58	0.98
α^{CAPM}	-17.96	-12.80	-1.15	-3.14	-1.30	2.84	1.41	3.89	1.94	6.93	24.90
	(-4.18)	(-2.45)	(-0.34)	(-1.07)	(-0.51)	(1.12)	(0.56)	(1.56)	(0.63)	(1.96)	(5.4)
α^{FF3}	-19.00	-15.30	-2.98	-4.60	-2.44	1.82	1.25	3.68	2.67	7.86	26.86
	(-4.39)	(-2.86)	(-0.88)	(-1.5)	(-0.99)	(0.71)	(0.49)	(1.5)	(0.91)	(2.32)	(5.91)
α^{CARH}	-14.82	-4.26	2.07	-0.91	-1.90	0.81	0.12	0.72	-2.86	4.80	19.62
	(-3.61)	(-0.81)	(0.61)	(-0.3)	(-0.68)	(0.32)	(0.04)	(0.29)	(-1.05)	(1.39)	(4.52)
α^{FF5}	-20.15	-10.93	-3.90	-5.74	-4.98	-1.45	-3.30	1.75	-0.84	7.26	27.41
	(-4.59)	(-1.96)	(-1.1)	(-1.87)	(-1.82)	(-0.55)	(-1.31)	(0.68)	(-0.27)	(2.09)	(5.44)

Table 9: Alternative expected growth measures

This table reports the average returns (Ret^e) and Sharpe ratio (SR) of EIG deciles based on alternative measures of expected growth. Panel A to Panel C are for portfolios sorted separately on the three alternative EIG proxies using only momentum (Panel A), q (Panel B), or cash flow (Panel C) in the first stage of EIG estimation. Panel D to Panel F are for portfolios sorted on four alternative measures of expected growth: expected sales growth (Panel D) and expected gross profit growth (Panel E). The returns are annualized and reported in percentages. The sample period is from July 1953 to December 2015. The t-statistics in parentheses are calculated based on the heteroskedasticity-consistent standard errors of White (1980).

Port.	Lo	2	3	4	5	6	7	8	9	Hi	Hi-Lo
Panel A: Momentum-only EIG portfolios											
Ret^e	-4.52	0.02	1.60	5.74	6.68	6.78	7.40	9.79	11.74	16.87	21.39
	(-1.13)	(0.01)	(0.59)	(2.4)	(3.12)	(3.33)	(3.57)	(4.75)	(5.02)	(5.72)	(6)
SR	-0.14	0.00	0.08	0.30	0.39	0.42	0.45	0.60	0.63	0.72	0.76
Panel B: q-only EIG portfolios											
Ret^e	11.23	9.86	9.52	7.38	7.37	7.64	6.59	7.10	7.10	6.45	-4.78
	(4.84)	(4.68)	(4.72)	(3.79)	(3.67)	(3.67)	(3.22)	(3.27)	(3.17)	(2.24)	(-2.03)
SR	0.61	0.59	0.60	0.48	0.46	0.46	0.41	0.41	0.40	0.28	-0.26
Panel C: Cash flow-only EIG portfolios											
Ret^e	3.29	5.08	6.51	8.23	7.69	6.83	8.12	7.68	8.03	8.53	5.24
	(0.95)	(1.75)	(2.73)	(3.84)	(3.92)	(3.38)	(3.97)	(3.77)	(3.74)	(3.23)	(2.37)
SR	0.12	0.22	0.35	0.49	0.50	0.43	0.50	0.48	0.47	0.41	0.30
Panel D: Expected sales growth portfolios											
Ret^e	4.43	6.36	7.03	5.46	6.10	7.07	5.69	7.42	8.98	13.99	9.56
	(1.47)	(2.61)	(3.24)	(2.62)	(2.93)	(3.48)	(2.75)	(3.53)	(3.84)	(4.72)	(3.26)
SR	0.19	0.33	0.41	0.33	0.37	0.44	0.35	0.45	0.48	0.60	0.41
Panel E: Expected gross profit growth portfolios											
Ret^e	8.55	6.37	7.69	9.03	7.37	7.05	5.90	7.84	8.45	11.08	2.53
	(2.92)	(2.54)	(3.27)	(4.1)	(3.66)	(3.5)	(2.92)	(3.65)	(3.29)	(3.21)	(0.99)
SR	0.37	0.32	0.41	0.52	0.46	0.44	0.37	0.46	0.42	0.41	0.13

Table 10: EIG and financial distress risk

Panel A reports the average distress risks, measured as failure probability (FP) from Campbell, Hilscher, and Szilagyi (2008) and distance to default (DD), for EIG deciles. The sample is from 1975 to 2015 for FP and 1971 to 2015 for DD in Panel A. Panel B reports the coefficients of EIG, FP, and DD, and McFadden's pseudo-R^2 (in percentages) in the out-of-sample logistic regression to predict corporate bankruptcy (Panel B.1) and failure (Panel B.2) in the 1-month, 6-month, 12-month, 24-month, and 36-month horizons. Corporate bankruptcy is a dummy variable from Chava and Jarrow (2004) that equals 1 if a firm files for bankruptcy, and 0 otherwise. Failure is a broader distress measure from Campbell et al. (2008) that equals 1 if a firm files for bankruptcy, is delisted for financial reasons, or receives a D rating, and 0 otherwise. To construct the out-of-sample FP, each year we estimate the logistic regression using only historically available data. The estimated coefficients are used together with the most up-to-date predictive variables to construct the out-of-sample FP. The sample period in Panel B is monthly from 1981 to 2014.

Panel A: Distress risks of EIG portfolios

Port.	Lo	2	3	4	5	6	7	8	9	Hi
FP	-6.15	-6.81	-7.39	-7.70	-7.90	-8.04	-8.13	-8.20	-8.24	-8.20
DD	3.44	3.85	5.18	6.28	7.09	7.66	8.01	8.16	8.10	7.39

Panel B: Out-of-sample bankruptcy or failure predictive regressions

		Panel B.1: Bankruptcy				Panel B.2: Failure			
Horizon	Spec.	EIG	FP	DD	Pseudo R^2	EIG	FP	DD	Pseudo R^2
	1	-9.87				-10.51			
		(-30.19)			13.97	(-61.55)			18.03
	2		1.45				1.56		
			(28.08)		20.73		(52.45)		26.97
1-Month	3			-0.83				-0.78	
				(-23.22)	14.65			(-46.44)	16.66
	4	-5.23	0.93	-0.1583		-3.85	1.10	-0.16	
		(-12.73)	(14.62)	(-4.71)	23.08	(-18.98)	(32.1)	(-12.21)	28.73
	1	-6.93				-7.16			
		(-31.19)			8.75	(-55.7)			10.66
	2		1.42				1.42		
			(35.88)		17.21		(61.8)		21.37
6-Month	3			-0.56				-0.55	
				(-26.21)	11.14			(-45.72)	12.67
	4	-2.04	1.09	-0.09		-1.06	1.18	-0.09	
		(-7.81)	(20.11)	(-4.37)	17.86	(-7.79)	(39.94)	(-9.42)	21.79
	1	-5.09				-5.20			
		(-25.84)			5.30	(-44.52)			6.31
	2		1.28				1.23		
			(35.39)		12.20		(60.25)		14.88
12-Month	3			-0.40				-0.39	
				(-24.27)	8.04			(-40.88)	9.04
	4	-1.02	1.00	-0.08		-0.44	1.02	-0.08	
		(-4.63)	(18.88)	(-5.04)	12.55	(-3.65)	(36.21)	(-9.81)	15.21
	1	-2.47				-2.80			
		(-13.69)			1.45	(-25.3)			2.09
	2		1.05				1.03		
			(26.53)		5.60		(46)		7.43
24-Month	3			-0.23				-0.23	
				(-19.25)	4.42			(-31.74)	5.02
	4	-0.10	0.77	-0.09		0.09	0.84	-0.07	
		(-0.52)	(12.95)	(-6.41)	5.95	(0.79)	(26.64)	(-10.08)	7.79
	1	-1.56				-1.83			
		(-8.67)			0.61	(-16.16)			0.93
	2		0.84				0.82		
			(19.52)		3.15		(33.06)		4.06
36-Month	3			-0.16				-0.16	
				(-15.63)	2.75			(-24.59)	2.93
	4	0.15	0.58	-0.08		0.09	0.63	-0.07	
		(0.83)	(9.7)	(-7.02)	3.60	(0.82)	(19.57)	(-10.55)	4.50

Table 11: Distress risks and cross-sectional stock returns

This table compares the performance of EIG and traditional distress measures (FP and DD) in predicting stock returns. Panel A reports the difference in the sorting variable and the difference in average excess returns between high and low deciles in Panel A.1 and Panel A.3 (or between low and high deciles in Panel A.2) where deciles are based on the current, prior one-year, two-year, three-year, and four-year values of these sorting variables. The sample is from 1953 to 2015 for EIG, from 1975 to 2015 for FP, and from 1971 to 2015 for DD. In Panel B, we construct 5-by-5 portfolios double-sorted sequentially first on one of the distress measures and then EIG (Panel B.1), and first on EIG and then one of the distress measures (Panel B.2). Panel B.1 reports the conditional EIG premium within each distress quintile, their average across quintiles (Con. Prem.), and the unconditional EIG premium from the one-way quintile sort (Unc. Prem.). Panel B.2 reports the distress premium within each EIG quintile, their average across quintiles (Con. Prem.), and the unconditional distress premium from the one-way quintile sort (Unc. Prem.). The sample is monthly from 1975 to 2015 for FP related portfolios and from 1971 to 2015 for DD related portfolios. Returns are annualized and reported in percentages. The t-statistics in parentheses are calculated based on the heteroskedasticity-consistent standard errors of White (1980).

Panel A: Spread in average returns and sorting variable of EIG and distress risk portfolios over longer horizons

Year	0	1	2	3	4
			Panel A.1: EIG deciles		
EIG	0.66	0.23	0.16	0.13	0.10
Ret	20.69	0.76	-1.17	0.79	-2.16
			Panel A.2: FP deciles		
FP	-3.13	-2.37	-1.96	-1.69	-1.50
Ret	13.92	-2.33	-0.46	0.96	5.17
			Panel A.3: DD deciles		
DD	20.10	15.97	13.95	12.52	11.47
Ret	12.35	-1.35	-1.19	-1.86	-3.33

Panel B: Conditional and unconditional EIG and distress premium

Panel B.1: Conditional and unconditional EIG premium

Con. Var.	Lo	2	3	4	Hi	Con. Prem.	Unc. Prem.
FP	10.77	2.62	7.94	7.92	13.36	8.52	14.04
	(3.49)	(0.82)	(2.25)	(2.36)	(3.41)	(3.56)	(4.12)
DD	20.54	14.87	10.88	7.17	4.19	11.53	14.24
	(4.98)	(4.38)	(3.64)	(2.35)	(1.54)	(4.78)	(4.39)

Panel B.2: Conditional and unconditional distress premium

Sort. Var.	Lo	2	3	4	Hi	Con. Prem.	Unc. Prem.
FP	18.11	3.05	-1.07	-1.14	4.26	4.64	9.12
	(3.57)	(0.79)	(-0.36)	(-0.37)	(1.24)	(1.68)	(2.37)
DD	19.07	7.77	0.21	-1.93	-0.40	4.94	8.78
	(3.98)	(2.09)	(0.07)	(-0.65)	(-0.13)	(1.92)	(2.50)

Figure 1: Cumulative returns of EIG and alternative investment strategies

This figure plots the cumulative wealth of investing $1, at the beginning of July 1953, in the long-short portfolio based on three investment strategies (EIG, momentum, and value) and the passive market portfolio in excess of the risk-free rate. The long-short portfolio is the difference between the top and bottom decile EIG (MOM, or BM) portfolios. EIG, MOM, and BM are computed in the same way as in Table 3. The strategy returns are normalized to have the same standard deviation as that for the return of the EIG strategy. The sample includes all NYSE/AMEX/NASDAQ stocks (excluding financial stocks, utility stocks, and ADR shares) from July 1953 to December 2015.

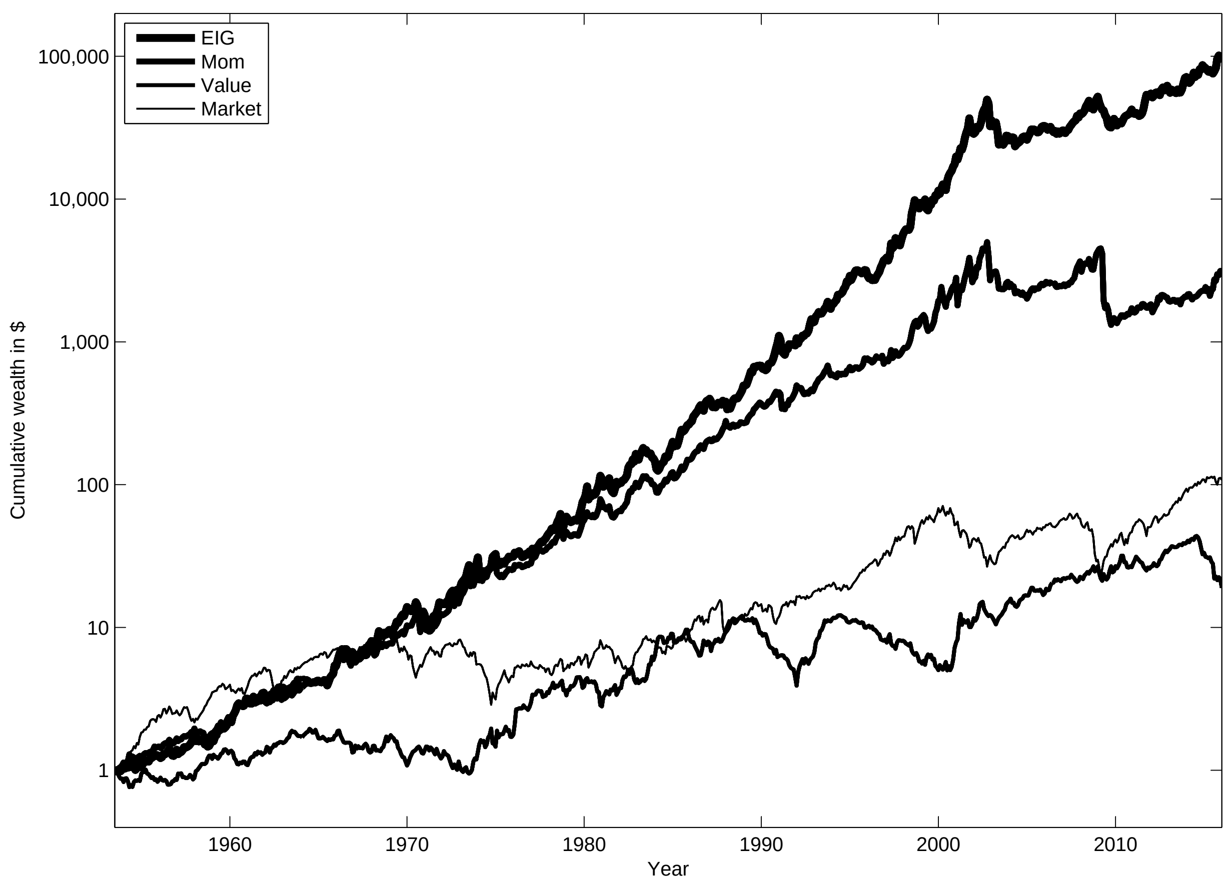

Figure 2: Timeline for EIG construction

This figure plots the timeline used in our estimation of expected investment growth (EIG). In the first stage, we run cross-sectional regressions of investment growth (IG) on momentum (MOM), Tobin's Q (q), and cash flow (CF) at each year t, and the estimated coefficients are $b_{0,t}$, $b_{\mathrm{MOM},t}$, $b_{\mathrm{q},t}$, and $b_{\mathrm{CF},t}$. On the second stage, EIG for firm i at year $t+1$ is the out-of-sample predicted value of investment growth using the most updated values of MOM, q, and CF for firm i, as well as the historical average of estimated coefficients from the first-stage estimations up to year t (i.e., $\hat{b}_{0,t}$, $\hat{b}_{\mathrm{MOM},t}$, $\hat{b}_{\mathrm{q},t}$, and $\hat{b}_{\mathrm{CF},t}$). Following Fama and French (1992) and Jegadeesh and Titman (1993), CF and q are updated at the end of every June, whereas MOM is updated every month.

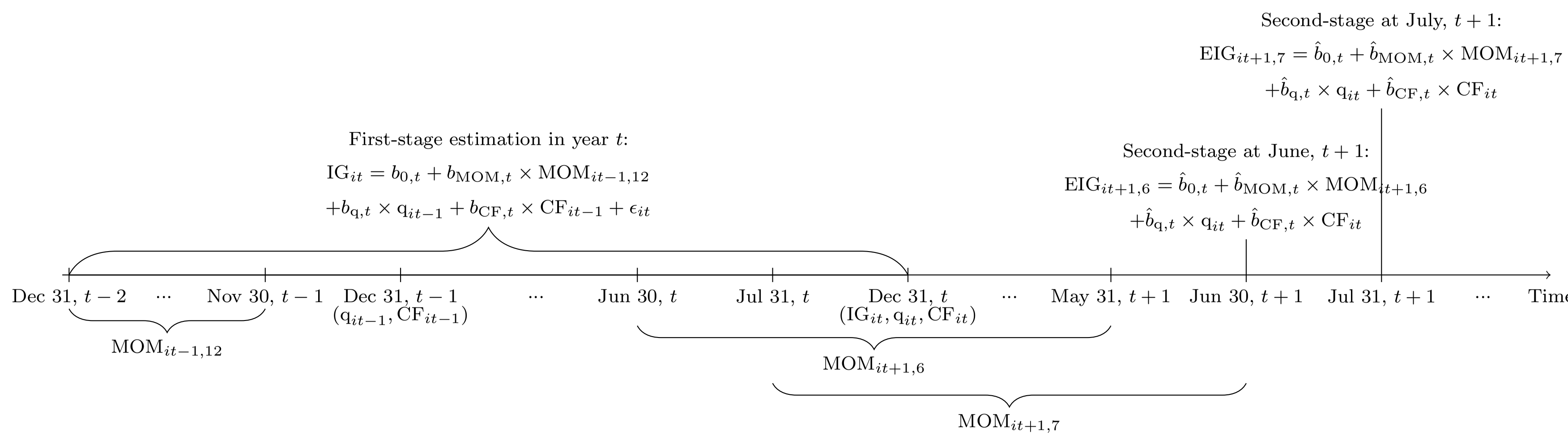

Figure 3: Times series of realized investment growth for EIG deciles

This figure plots the time series of the realized investment growth for the EIG deciles 1, 5 and 10. The realized investment growth is computed as the growth rate of investment expenditure (Compustata data item CAPX) in the subsequent year. We use the median firm-level realized investment growth as the portfolio investment growth. The sample is annual from 1953 to 2014 and includes all NYSE/AMEX/NASDAQ stocks (excluding financial stocks, utility stocks, and ADR shares) with a December fiscal year end.

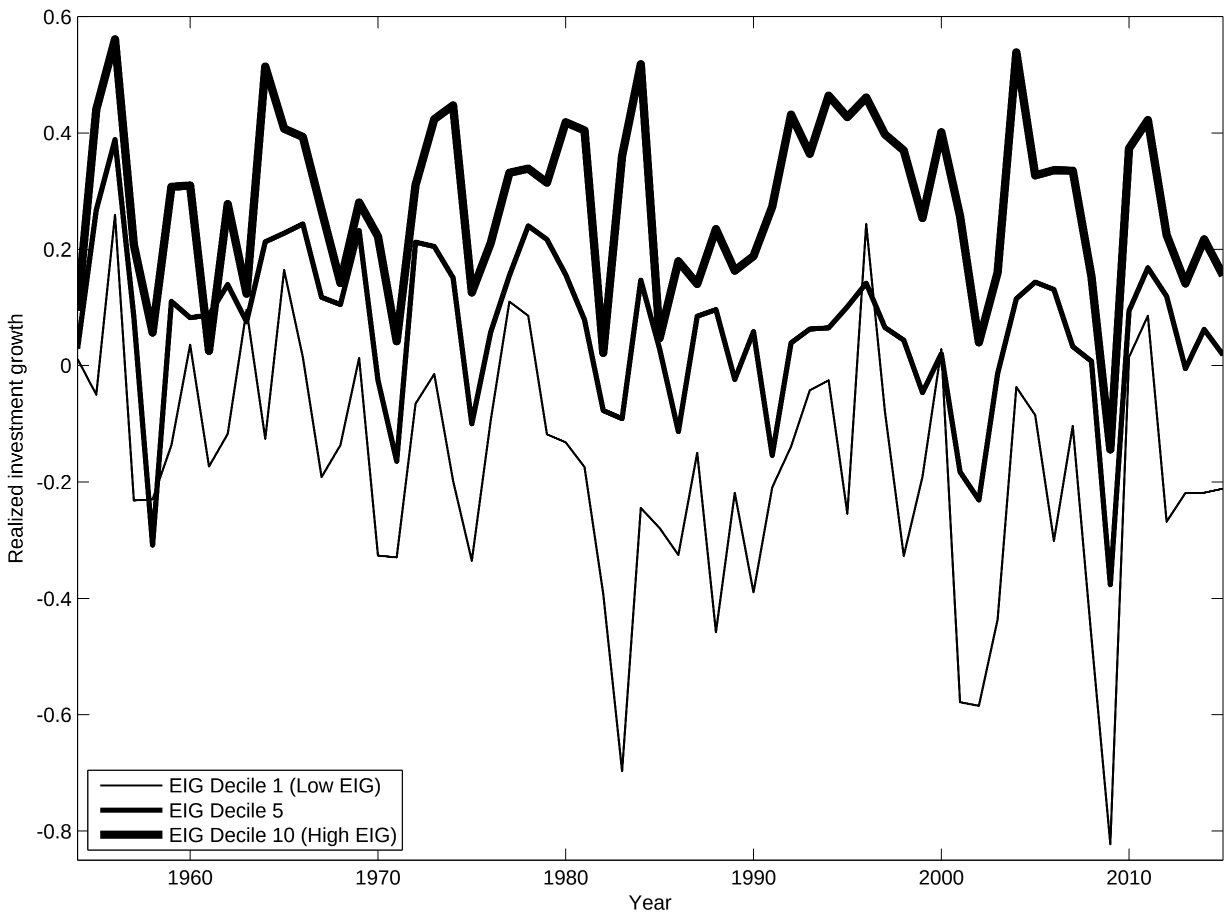

Figure 4: EIG premium with different weights on MOM, q, and CF

This figure plots the annualized average returns and Sharpe ratios of strategies based on different linear combinations of MOM, q, and CF. For each linear combination, the weights on MOM, q, and CF (w(MOM), w(q), and w(CF), respectively) are assumed to be constant throughout the sample period and are normalized to sum up to one. The top two panels plot the results along the dimensions of w(q) and w(CF). The bottom two panels plot the results along the dimensions of w(MOM) and w(CF). We mark "EIG" on these plots to indicate the corresponding results using estimated weights from Eq.(1). The sample includes all NYSE/AMEX/NASDAQ stocks (excluding financial stocks, utility stocks, and ADR shares) from July 1953 to December 2015.