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GUSTAVO CORREIA XAVIER

# INVESTMENT PLANS AND EXPECTED RETURNS: INSIGHTS FROM THE LIFE-CYCLE THEORY

JOÃO PESSOA

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Orientador: Márcio André Veras Machado

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**ATA DE DEFESA DE TESE**

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Ata da Sessão Pública de Defesa de Tese do(a) Doutorando(a) **Gustavo Correia Xavier** como requisito final para obtenção do grau de Doutor em Administração, Área de Concentração em Administração e Sociedade e na Linha de Pesquisa em Informação e Mercado.

No dia 29 de junho de 2021, às 10h30 horas, na sala virtual do google meet, por meio do link: meet.google.com/jsu-zdss-qug, reuniu-se a banca examinadora homologada pelo Colegiado do Programa de Pós-Graduação em Administração, composta pelos membros: Prof.(ª). Dr.(ª) Márcio André Veras Machado (Orientador(a) – PPGA/UFPB), Prof.(ª) Dr.(ª) Cassio da Nobrega Besarria (Examinador(a) Interno(a) – PPGA/UFPB) e Prof.(ª) Dr.(ª) Anderson Luiz Resende Mol (Examinador(a) Externo(a) – PPGA- UFRN), Sandro Cabral (Examinador Externo - INSPER) e Herbert Kimura (Examinador Externo - UNB), com a finalidade de julgar a tese do(a) aluno(a) **Gustavo Correia Xavier** intitulada "EXPECTED RETURNS: INSIGHTS FROM THE LIFE-CYCLE THEORY"**,** para obtenção do grau de Doutor em Administração. O desenvolvimento dos trabalhos seguiu o roteiro de sessão de defesa estabelecido pela coordenação do curso, com abertura, condução e encerramento da sessão solene de defesa realizados pelo(a) presidente Prof.(ª) Dr.(ª) Márcio André Veras Machado. Após haver analisado o referido trabalho e arguido o(a) candidato(a), os membros da Banca Examinadora deliberaram por unanimidade e atribuíram o conceito ( X ) aprovado, (  ) insuficiente, (  ) reprovado.

| **Observações da Banca**: |
|---|
| A banca, por maioria de votos, decidiu por aprovar a tese, condicionado à uma revisão dos aspectos mencionados na defesa e enviados por e-mail ao discente. Ficou decidido, ainda, que o discente enviaria a versão final, no prazo de até 60 dias, para homologação dos membros da banca, no sentido de atestarem se a reformulação feita atende ao solicitado na defesa. |

Proclamados os resultados, o Presidente da Banca Examinadora encerrou os trabalhos, e para constar eu, Prof.(ª) Dr.(ª) Márcio André Veras Machado, presidente da sessão, confiro e assino a presente ata, juntamente com os membros da Banca Examinadora e o(a) aluno(a).

Prof.(ª) Dr.(ª) Márcio André Veras Machado
Orientador(a) – PPGA/UFPB

Prof.(ª) Dr.(ª) Cassio da Nobrega Besarria Examinador(a)
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Gustavo Correia Xavier

Doutorando(a)

*Dedico esta tese à minha esposa, Raissa, e à minha filha, Cecília.*

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# Resumo

Esta tese tem como objetivo analisar como o Expected Investment Growth (EIG), uma medida dos planos de investimento, se relaciona com os retornos futuros em diferentes estágios do ciclo de vida. Para facilitar o alcance desse objetivo, a pesquisa está dividida em três estudos. O primeiro estudo (Capítulo 1 da Parte II) propõe uma nova medida de planos de investimento, no nível da firma, combinando o procedimento de Han et al. (2020) com a ideia de dicionário flexível de Lima, Godeiro and Mohsin (2020). A medida é estimada com base em dados de texto da MD&A contidos nos relatórios 10-K. Neste estudo, a amostra inclui todas as empresas americanas de capital aberto no período entre janeiro de 1995 e dezembro de 2019. Os dados são extraídos de diferentes bases, dados financeiros e contábeis anuais são extraídos da COMPUSTAT, os relatórios 10-K são extraídos da SEC EDGAR e os retornos mensais das ações dos EUA do Center for Research in Security Prices (CRSP). A principal conclusão do capítulo é que as palavras importam para prever os fundamentos da empresa, o no caso dos planos de investimento o método usado pode produzir previsões melhores com base apenas em informações públicas no momento da previsão, incluindo dados do MD&A. O segundo estudo (Capítulo 2 da Parte II) incorpora o conceito de ciclo de vida como forma de contribuir com o nosso entendimento sobre a relação entre planos de investimento e retornos acionário. Os dados financeiros e contábeis são extraídos das bases CRSP e COMPUSTAT. Empresas com patrimônio líquido negativo e empresas de utilidade pública foram excluídas da amostra deste estudo. O período é de 1962 a 2018. Os resultados empíricos não confirmam a ($H_{1a}$), que prevê que as empresas diminuirão seus planos de investimento à medida que amadurecem. Por outro lado, os resultados parecem levar a uma conclusão de que há uma extrapolação das expectativas dos gestores de empresas não-maduras, ampliando o que foi documentado por Gennaioli, Ma and Shleifer (2016). Apesar dos resultados contrários em ($H_{1a}$), as evidências estão alinhados com as demais hipóteses, uma vez que as proxies para o ciclo de vida parecem melhorar a previsão fora da amostra de planos de investimento ($H_{1b}$), o prêmio EIG de empresas em crescimento parece ser mais forte do que o prêmio EIG de empresas maduras ($H_{2a}$) e uma parte considerável do prêmio EIG pode ser explicada pelo sentimento do investidor ($H_{2b}$). Finalmente, o terceiro estudo (Capítulo 3 da Parte II), examina o papel das ciclo de vida e do nível de desenvolvimento do mercado acionário na relação entre os planos de investimento agregado e retorno do mercado, conduzindo uma pesquisa empírica que expande as evidências atuais para o mercado internacional. Neste estudo, é realizado testes em séries temporais individuais para cada país com o intuito de analisar em quais países o efeito é mais provável de ocorrer. Os dados de retorno acionário mensais internacionais são do Thomson Reuters Datastream e os dados contábeis são do banco de dados Worldscope. O período analisado varia de país para país e depende da disponibilidade de dados. Os principais resultados desta pesquisa é que a capacidade preditiva do EIG agregado não é exclusiva do mercado dos EUA, e nos mercados emergentes parece ser ainda mais forte, o que é um indício de que o fundamento racional do risco parece não ser a maior parte do poder preditivo do EIG.

**Palavras-chaves**: planos de investimento; crescimento esperado do investimento; previsão em cross-section; ciclo de vida das empresas; retorno acionário

# Abstract

This thesis aim to analyze how the expected investment growth, a measure of investment plans, relates to future returns at different life-cycle stages. In order to facilitate the achievement of this aim, I divide it into three studies. The first study (Chapter 1 of Part II) propose a novel measure of investment plans in the firm-level by using an approach based on text data and supervised machine learning. By combining the procedure of Han et al. (2020) with the idea of flexible dictionary of Lima, Godeiro and Mohsin (2020), I test a novel measure of investment plans based on text data from Management Discussion and Analysis disclosure in 10-K filings. In this study, the sample includes all US publicly traded firms in the period between January 1995 and December 2019. I build a unique dataset by merging information from multiple data sources. The annual firm-level financial and accounting data, I obtain from Compustat. The firms' 10-K filings are from the SEC Edgar database and the monthly US stock returns from the Center for Research in Security Prices (CRSP). The main find of this chapter is that words matter to predict firm fundamentals, and can produce a more accurate measure of investment plans based only on public information at the time of the forecast by including data from MD&A. The second study (Chapter 2 of Part II) incorporate the life-cycle concept to contribute to our understand about the relation between investment plans and stock returns. The financial and accounting data I obtain from the merged CRSP and COMPUSTAT database. The financial firms, firms with negative book equity and, utility firms are excluded from the sample in this study. The period is between of 1962 and 2018 including only firms with CRSP share codes 10 and 11, that refer to ordinary common shares with no special status. The empirical results shows evidence against the assumptions of $H_{1a}$, which predicts that firms will decrease their investment plans as they become more mature. In opposite, the results, which may be a result of find a extrapolative expectations of the growth firms managers (GENNAIOLI; MA; SHLEIFER, 2016), since mature firms have smaller investment plans on average, but also smaller standard deviation. Despite the opposite evidence on $H_{1a}$, the results is in line others assumptions as proxies for life cycle can improve out-of-sample prediction of investment plans $H_{1b}$, the EIG premium of growth firms seems to be stronger than EIG premium of mature firms $H_{2a}$, and a portion of the EIG premium is explained by investor sentiment $H_{2b}$. Finally, in the third study (Chapter 3 of Part II) examine the role of life-cycle firms and market development in the relationship between a country's aggregate investment plans and the wide stock market return by conducting an empirical research expanding actual evidence to international stock markets. For this study I perform individual time-series tests for each country, to analyze in which countries the effect is most likely to occur. The the international monthly stock data are from the Thomson Reuters Datastream, and accounting data are from the Worldscope database. The analyzed period varies from country to country and depends on data availability. The main results of this research is that the expected growth predictability is not exclusive to U.S market, and in emerging markets seems to be stronger, which imply that the rational risk explanation is not the most part of the predictability power of the aggregate expected growth investment.

**Key-words**: investment plans; expected investment growth; cross-section forecast; firm life-cycle; stock returns.

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# Part I

# Introduction

# Introduction

In events like trade tensions between the USA and China in 2018 and the COVID-19 pandemic in 2020, firms tend to fall your actual investment, which becomes a planned investment. While some of this comes back in the future as promising projects, another part will be permanently lost (e.g., R&D projects that are shelved or factories that never open), which implies costs to the long-run economic growth (FRANCIS; GRYTA, 2019; ROMEI, 2020). Beyond these consequences in the real economy, investment plans seem to influence the stock price as well, since there is a well-documented relation between investment plans and future stock returns (LAMONT, 2000; HOU et al., 2020; LI; WANG; YU, 2020).

However, the literature diverges about behavioral and rational explanations for the relation between investment plans and expected returns (LI; WANG; YU, 2020; JIANG et al., 2019). Specifically on the rational side, there is little discussion about the difference between the negative relation on aggregate-level (discount rate channel) and the positive relation on firm-level (cash flow news channel) (LAMONT, 2000; COCHRANE, 1991). In addition, there is an empirical challenge to measure investment plan on the firm-level, which is fundamentally a problem of prediction (HOU et al., 2020).

In this thesis, I propose a novel measure of investment plans based on machine learning tools, which are suitable for the prediction problem (GU; KELLY; XIU, 2020). And using this measure, I analyze how the ability of investment plans to predict future returns varies at different life cycle stages. In other words, I use the growth opportunities concept from the life-cycle theory to contribute to our understanding of the relation between investment plans and stock returns. In predicting stock returns, the literature of investment plans (investment growth) and about the current level of investment (asset growth) has common strands. For example, the intuition behind the predictive power of each one is a good starting point.

The net present value rule of corporate finance can be the intuition behind the relation between current level of investment and expected returns. A fall in the discount rate increase the number of projects with positive net present value, which raises investment in response to the cost of capital change (ZHANG, 2017). However, lags in the investment processes (such as delays in planning, delivery, and construction) limit firms from immediately adjust investment. In this sense, when managers decide to invest but cannot implement them immediately, those decisions become planned investments and a change in discount rate increase the investment plans rather than the current investment (LAMONT, 2000).

In a multiperiod neoclassical model built under the Q-theory of investment, the seminal work of Cochrane (1991) suggests that if investment plans will be implemented in the subsequent year, the expected stock returns can be written as a function of the expectations about 1-year ahead investment growth. Since managers' expectations are unobservable, one way to measure investment plans is by using survey answers about future capital expenditures growth, which are available only to a limited number of firms. Hence, most of the previous studies have analyzed investment plans at the aggregate- or industry-level (LI; WANG, 2018).

Evidence at the aggregate- and industry-level has confirmed negative relation between the future return of stock market and investment plans, which is consistent with the argument of Lamont (2000) that investment plans change in response to the time-varying risk premium due to frictions of investment lags. There is evidence that future return is more correlated with investment plans than with current capital expenditures (LAMONT, 2000), the aggregate investment plans also negatively covary with average stock returns of portfolios sorted by capital investment, book-to-market and earnings surprises (LIU; WHITED; ZHANG, 2009). The ability of aggregate investment plans to predict future market return is robust, both in-sample and out-of-sample, even after controlling for other macroeconomic return predictors (such as Treasury bill rate, asset growth, and dividend yield) (LI; WANG; YU, 2020).

As opposed to the aggregate-level relation, the firm-level investment plans should be positively related to future returns, as stated by the theoretical multiperiod model of Cochrane (1991). However, it is challenging to test this relation empirically due to the difficult to measure firm-level investment plans. Despite that, two recent studies use a predicted value of one year ahead investment growth as a measure of investment plans (hereafter referred to as "*Expected Investment Growth*" or "*EIG*"), and they indeed find a positive relation (HOU et al., 2020; LI; WANG, 2018). In other words, firms with large investment plans have higher expected returns than firms with smaller investment plans, which is a premium for the *EIG*. This premium is not explained by the leading asset pricing models (HOU et al., 2019), and for Hou et al. (2020) it is a new dimension of the expected return that has been largely ignored by previous studies in asset pricing.

Although the growing body of evidence about the role of investment plans, there is little discussion that explore this inverse relation of the different levels. One explanation is that the aggregate investment plans are mainly driven by the discount rate channel, while the firm-level is mostly due to the cash flow channel (LI; WANG, 2018). Cash flow channel means that the actual stock price is affected by shocks to expected cash flow, whereas discount rate channel means that the stock price is influenced by shocks to expected returns (VUOLTEENAHO, 2002). Thus, the stock returns may be driven by cash flow expectations and/or expected risk premium (CAMPBELL, 1991; CAMPBELL; AMMER, 1993). For instance, Vuolteenaho (2002) documents that at the firm-level the stock return often is mainly driven by the cash flow channel.

Different explanations that can be linked to cash flow and discount rate channel have been suggested by some studies about investment plans. Li and Wang (2018) use the finds of Vuolteenaho (2002) to argue that firm-level investment plans predict positively returns due to the firm idiosyncratic productivity (i.e., cash flow channel). For Hou et al. (2020), this positive relation is justified by the multiperiod model of Cochrane (1991). In contrast, Lamont (2000) argue that the negative relation is due to investment lags that increase investment plans in response to the cost of capital falls (i.e., discount rate channel), which is consistent with the large body of evidence that aggregate investment plans predict negatively returns (LIU; WHITED; ZHANG, 2009; JONES; TUZEL, 2013; LI; WANG; YU, 2020).

Despite the explanations, none of these studies about investment plans go deeper into the relative importance of cash flow and discount rate channel at each level. For example, Hirshleifer, Hou and Teoh (2009) explore a similar inverse relation in different levels existing in the accruals and cash flow effect. The authors find evidence consistent with both behavior bias and market efficiency explanation, this last one related to the discount rate channel. Then, is difficult to understand the importance of each channel without considering the role of behavioral bias, which in investment plans literature there is mixed evidence (JIANG et al., 2019; LI; WANG; YU, 2020).

The discount rate and cash flow channels are rational explanations for stock returns. However, the predictive power of investment plans may be consistent with both rational and behavioral explanations (LI; WANG; YU, 2020). The behavior models predicts that some individuals beliefs about future performance are biased because they tend to overextrapolate past price changes in the stock market (BARBERIS et al., 2015; HIRSHLEIFER; LI; YU, 2015). In the investment plans role, Gennaioli, Ma and Shleifer (2016) find a extrapolative structure of expectations about future growth and suggest that this expectations may not be rational.

Beyond the Lamont's (2000) rational explanation, the return predictability of investment plans can also be explained by investor sentiment. When the sentiment is high both current stock prices and corporate investment plans go up, leading to mispricing that gets corrected by economic fundamentals soon. This effect rises the negative correlation between investment plans and future stock market returns (LI; WANG; YU, 2020). There is evidence that manager sentiment are also related to investment growth, suggesting that a higher manager sentiment leads to overinvestment of current and planned investment, due to investment lags and managers' overly optimistic expectations about future performance (JIANG et al., 2019).

Both by the behavior and rational side, investment plans reflect expectations about future growth. Therefore, firms with larger investment plans should be those with more growth opportunities (LI; WANG, 2018), which is a concept widely debated by life-cycle theory (GRULLON; MICHAELY; SWAMINATHAN, 2002). This theory proposes that firms evolve and transition from one stage of development to another (PORTER, 2008). The studies essentially identify four phases for a firm's life: introduction, growth, maturity, and decline (QUINN; CAMERON, 1983; SMITH; MITCHELL; SUMMER, 1985). Specifically, the earlier stages are characterized by larger growth opportunities and less information available (CAI; LI; ZHANG, 2018), two features that can be linked to the behavior and rational explanations of investment plans' ability to predict return.

In addition, the life-cycle literature provide evidence of two aspect related to investment plans: the future growth and the decision to invest. For instance, Vorst and Yohn (2018) documents that life-cycle stages can improve predictability of growth in net operating assets and growth in the book value of common equity as well. In addition, Faff et al. (2016) shows that corporate policies follow a patterns related to life-cycle stages that is independent of the preferences of corporate managers and other firm characteristics. Specifically, cash holdings increase in the earlier stages and decrease in the later stages and the investments decline with firm life-cycle evolve.

In summary, there is a growing consensus about the importance of the investment plans, however some issues it remains open. First, since the firm-level investment plans are unobservable, there is still an empirical challenge to find a reliable proxy (LI; WANG, 2018; LIN; LIN, 2018). Second, since the investment plans respond to both discount rate change and cash flow expectations it is little discussion to understand the role of each channel (LAMONT, 2000; LI; WANG, 2018). Lastly, despite the agreement about the investment plans' ability to predict future return, there is mixed evidence to support rational and behavioral explanations (JIANG et al., 2019; LI; WANG; YU, 2020).

To shed light on the unclear issues mentioned above, I propose to incorporate the concept of growth opportunities of life-cycle theory. The key-assumption is that both firms with larger investment plans and firms in the earlier stages have more growth opportunities (LI; WANG, 2018; VORST; YOHN, 2018). Specifically, I intend to answer this central research question: **How the ability of investment plans to predict future return varies at different life cycle stages?** This main problem can be divided into three supporting questions: (*i*) First, how the life-cycle stages relate to investment plans? (*ii*) Second, how the life-cycle stages help to explain the relation between firm-level of investment plans and the stock returns? (*iii*) Lastly, how the life-cycle stages help to explain the relation between aggregate-level of investment plans and the stock market returns?

## Research Objectives

My research aim in this thesis is: **to analyze how the expected investment growth, a measure of investment plans, relates to future returns at different life-cycle stages**. In order to facilitate the achievement of this aim, I divide it into six research objectives, which I summarize in three main groups.

First, to answer the supporting question *i* by examining how the life-cycle stages relate to investment plans, I intend to conduct an analysis in-sample (*objective one*) and out-of-sample (*objective two*) by using U.S. data. Specifically in the out-of-sample analysis, I propose a new measure of investment plans.

Second, to answer the supporting question *ii* I incorporate the life-cycle concept in the analysis of the relation between firm-level investment plans and the U.S. stock returns. Then, I hope to better understand how the growth opportunities of firms in the early life-cycle stages (*objective three*) and the behavior bias (*objective four*) help to explain the EIG premium in the cross-section of stock returns.

Third, to answer the supporting question *iii* and better understand the role of firms in the later life-cycle stages (*objective five*) and the market efficiency (*objective six*) on the relation between the aggregate investment plans and future wide market return, I analyze this relation across countries by using global data. Hence, I present my research objectives as follow:

1. Examine how the life-cycle stages are related to the investment plans;

2. Investigate whether life-cycle proxies contain information beyond investment-based predictors, and therefore can improve the out-of-sample predictability of investment growth;

3. Analyze how the firm-level expected investment growth relates to future stock returns at different life-cycle stages;

4. Examine, in the firm-level, how the behavior bias influence the relation between investment plans and future stock return at different life-cycle;

5. Analyze how the aggregate expected investment growth, conditioned to different life-cycle stages, relates to future wide market returns;

6. Examine how the behavior bias explain the relation between the aggregate level investment plan, conditioned to different life-cycle stages, and the future stock market return.

# Contributions and Thesis Statement

The main contribution of my thesis is to analyze the holistic relation between firms' life cycle, investment plans, and stock returns. Similarly, the life-cycle theory has been used to better understand certain aspects of corporate finance such as forecasting, corporate policies, and asset pricing (HRIBAR; YEHUDA, 2015; VORST; YOHN, 2018; FAFF et al., 2016). This thesis is different from these previous studies in three ways: First, I intend to forecast investment growth by using machine learning tools instead of classic predictive regression. Second, among corporate policies, I focus on investment decisions. However, rather the current investment, I analyze those decisions that cannot be implemented immediately due to investment lags. Third, I use a similar approach of Hribar and Yehuda (2015) to study how a firm characteristic is priced at different life-cycle stages, but instead accruals and cash flow I analyze investment plans.

Conceptually, my contribution in this thesis is threefold: First, I add to the investment theory by including the role of corporate life-cycle as an explanatory variable for investment plans, since the previous studies use only predictors based on the investment literature (HOU et al., 2020; LI; WANG, 2018). For example, growth firms usually have a more intense investing cash flow than operating cash flow (DICKINSON, 2011), which is ignored by the previous studies that consider just the operating cash flow as predictor of future investment growth (LI; WANG, 2018; HOU et al., 2020). In short, these recent studies only focus on the investment literature predictions about firm idiosyncratic opportunities to generate new cash flow, and no one considered the relation with firms' life cycle. This project aims to fill this gap.

Second, the asset pricing literature can be benefited by the use life-cycle stages as a conditional variable, since they can shed new light to the relation of investment plans and future stock return. This is important because at the aggregate-level changes in the discount rate can cause a negative correlation between planned investment and the future market return (LAMONT, 2000). In contrast, firm-level investment plans predict positive stock returns in the cross section mainly in response to cash flow innovations (HOU et al., 2020; LI; WANG, 2018). In addition, beyond this rational explanation, behavioral bias seems to play an important role in this phenomenon and is difficult to know the real source since the evidence is mixed (JIANG et al., 2019; LI; WANG; YU, 2020).

Lastly, I contribute to the life-cycle literature by analyzing the difference between corporate decisions in the early and later stages since there is evidence that corporate policies, such as investment decision that have followed firms' life cycles (FAFF et al., 2016). Specifically, firms in the earlier stages tend to be more intense in their investment policies than mature firms (DICKINSON, 2011). Although the evidence about the investment decisions immediately implemented, it is unknown whether this relation expands to those that become planned investment due to investment lags.

Moreover, developing a novel measure of investment plans considering the firms' life-cycle perspective can improve both the scientific understanding of price behavior and as well the practical decisions of managers, investors, and policymakers. With my results managers may be encouraged to present out investment plans clearly in their financial reports, and as a result, investors can better price future opportunities. Managers also can understand how the market creates expectations about their company's investment plans, improving their decision-maker.

In addition, investors can make better portfolio management decisions by improving their analysis of firms' plans considering local or international diversification. I also hope that the policymakers may improve their understanding of what information related to investment plans is priced, then they are more able to create rules and regulations that facilitate analysis of firms' future investment expectations. Also, they can improve their understanding of the role of developing a stock market in the pricing efficiency of risks related to investment plans.

Therefore, to better understand the role of investment plans, I develop three main hypotheses regarding the holistic relation between firms' life cycle, investment plans, and stock returns. First, due to the decrease in investment opportunities (FAFF et al., 2016), firms will decrease their investment plans as they become more mature. This relation suggests that life cycle proxies contain information beyond investment-based predictors in an out-of-sample model to forecast investment plans.

In addition, I expect that investment plans of firms in earlier stages is a stronger predictor of stock returns than investment plans of mature firms, driven by the high degree of growth opportunities (GRULLON; MICHAELY; SWAMINATHAN, 2002). Lastly, since mature firms have less growth opportunities they are more consistent to the time varying explanation of the discount rate channel (LAMONT, 2000), the aggregate investment plans' ability to forecast stock returns are stronger when I consider a measure based on mature firms.

Given all the above, I argue that life cycle theory provides new insights to the prediction of the Q-theory of investment and, in addition of previous studies, I defend the following thesis: **Consistent with the models based on Q-theory** of investment, both "cash flow news" and "discount rate" channels explain the relation between investment plans and future stock return. However, in the early stages of the firms' life-cycle, the main source of this relation are the expectations about cash flow innovations (cash flow effect) while in the later stages of firms' life-cycle the time varying risk premium (discount rate effect) dominates the predictive power.

# Thesis Outline

The remainder of this thesis is structured in different sections, summarized as follows. Present introduction includes the context, research motivation, objectives, contributions and thesis statement. Chapter 1 presents a study to propose a novel measurement of investment plans in the firm-level by using an approach based on text data and supervised machine learning. Chapter 2 incorporate the life-cycle concept to contribute to our understand about the relation between investment plans and stock returns. Finally, to examine the role of life-cycle firms and market development in the relationship between a country's aggregate investment plans and the wide stock market return, chapter 3 endeavors empirical research expanding actual evidence to international stock markets.

# Part II

# Three Studies

# Chapter 1

# Measuring Firms Investment Plans: A text-based analysis

## 1 Introduction

In this chapter, I propose a novel measure of firm-level investment plans based on text data from MD&A (Management Discussion and Analysis) disclosure in 10-K filings, which I do by using a combination of the forecast procedure of Han et al. (2020) with the idea of time varying dictionary developed by Lima, Godeiro and Mohsin (2020). A reliable measure is relevant because despite the literature provide support to the importance of investment plans in both aggregate-level and firm-level (LI; WANG; YU, 2020; HOU et al., 2020), this last one receives less attention since it is empirically challenging to measure firm-level investment plans (LIN; LIN, 2018). Then, analyze investment plans in a firm-level is not an easy task, due to the plans are not observable.

In this sense, most of the studies choose to examine investment plans in aggregate level data (LAMONT, 2000; LI; WANG; YU, 2020) and empirical investigations of firm-level investment plans are exceptions. One of then use micro data available in a quarterly survey of Chief Financial Officers (CFOs) and consider expectations about future investment growth as a measure of investment plans (GENNAIOLI; MA; SHLEIFER, 2016). Recently, Hou et al. (2020) and Li and Wang (2018) try to predict future investment change by using the Fama and MacBeth (1973) cross-sectional predictive regression based on current variables.

Both approaches at the firm-level have limitations. For example, the data used by Gennaioli, Ma and Shleifer (2016) is only available from 1998, which is a limitation for asset pricing studies (LI; WANG, 2018). The measure of Hou et al. (2020) may contain misspecification errors, since they use Fama and MacBeth (1973) approach (LIN; LIN, 2018). For Lin and Lin (2018), the expected investment change measure of Hou et al.

(2020) is a poor proxy for future investment growth because of the limitations on the regression model and the potential choose of weak predictors.

To better illustrate this argument, Hou, Xue and Zhang (2018) did an extensive empirical analysis of how the major pricing models explain the already documented anomalies. Their model, called q-factor, capture most of the anomalies. However, they find some that remain unexplained, including 46 not captured by the "q-factor" model (the q-anomalies). In an earlier version (NBER working paper 23394, May 2017), the authors suggest that q-anomalies may not be explained by the q-factor model because it ignores the inclusion of an expected growth factor (an EIG factor related to investment plans), and also mention, that Hou, Xue and Zhang (2015) option of not to include the EIG factor was due to concerns about the lack of reliable proxies for this variable.

In finance, the difficulty of measuring certain variables has been overcome with the use of more advanced techniques such as text regression and machine learning. For instance, Frankel, Jennings and Lee (2016) analyzed Management's Discussion and Analysis (MD&A) in the 10-K report to identify the most important words to explain firm-level accruals. Manela and Moreira (2017) created an implied volatility measure based on news that made it possible to understand the relationship between risk and disasters concerns using a much larger sample than that provided by options implied volatility (VIX). Lima, Godeiro and Mohsin (2020) analyzed textual data found on FED minutes and created a time-varying dictionary to predict GDP growth that allowed us to understand how predictive words change over time.

In this work, I propose a way to minimize the measurement problem of investment growth expectations by using the same cross-section forecast method of Han et al. (2020), but here with text data as did by Lima, Godeiro and Mohsin (2020) in time-series domain. Hence, to suggest a novel measure for investment plans may be a substantial contribution. To be more specific, by using machine learning and text regression to predict investment plans, I add to a growing literature that applies machine learning tools to analyze economic questions (MULLAINATHAN; SPIESS, 2017). In addition, I also contribute to a better understanding of an asset pricing puzzle related to the role of expected investment growth in explain returns. If the EIG is indeed an important and new dimension of expected return (HOU et al., 2020), finding better ways to measure it is essential for the asset pricing literature.

# 2 Methodology

## 2.1 Sample and Data

I analyze the US publicly traded firms in the years between 1995 to 2019, due to the availability of 10-k filings. I build a unique dataset by merging information from multiple data sources. The annual firm-level financial and accounting data, I obtain from Compustat. The firms' 10-K filings are from the SEC Edgar database. To analyze if investment plans are priced, I obtain monthly US stock returns from the Center for Research in Security Prices (CRSP).

In many cases, the MD&A section is incorporated by reference to the annual report, which is difficult to accurately parse since it usually appears in an exhibit that is part of the filing, the beginning and especially the ending position for the MD&A session typically is not obvious. So, as Loughran and McDonald (2011), I require at least 250 words in the MD&A section to leave the document at the sample.

## 2.2 Measure of Investment Plans

Since the firm's investment plans are not observable, I need to estimate it by using models that consider in each time t only the publicly available information up to time t. This is important because the investment theory assumptions predicts that the market investor use only available information in order to be able to price investment plans. In this sense, I estimate the benchmark measure using the classic Fama and MacBeth (1973) approach as the recent study of Hou et al. (2020), which I explain in sub section 2.3. For the text-based measures, I perform two main tests, the first one estimated each year (sub section 2.4) and the last one estimated by month (sub section 2.5). In the annual tests, I use four different approach to estimate the model, each one is explained in sub section 2.4. I also test the flexibility of the approach with others firms fundamentals (see sub section 3.1.3). However do to the limitation of the statistical tests in annual estimation, I propose to forecast the investment growth monthly, which I explain the procedure in sub section 2.5.

## 2.3 Benchmark Measure

The Equation (1) is the benchmarking of expected investment growth computed as Hou et al. (2020), referred to as the Expected Investment Growth of HMXZ ($EIG_{HMXZ}$). As shown in the Equation 1. Hou et al. (2020) used as predictors the log of Tobin's Q, a measure of operating cash flow, and the change in return on equity (dROE). This last one is an attempt to capture the short-term dynamic of the investment-to-assets change. the out-of-sample prediction of change. The investment-to-assets changes are be obtained from the average slopes estimated from the prior 120-month rolling window with the most recent winsorized predictors. Here, I require a minimum of 30 months to estimate the EIG.

$$E_{i,t}[IG] = b_{0,t} + b_{dROE,t} dROE_{i,t-1} + b_{q,t} Q_{i,t-1} + b_{CF,t} CF_{i,t-1} + \epsilon_{i,t} \tag{1}$$

where:

$E_{i,t}[IG]$ = the change in investment-to-assets ($I/A_{i,t}$) year ending in calendar year $t$ ($IG_{i,t} = I/A_{i,t} - I/A_{i,t-1}$);
$dROE_{i,t-1}$ = change in return on equity over the past four quarters;
$Q_{i,t-1}$ = the log of the market value of the firm divided by total assets in the fiscal year ending in calendar year $t-1$;
$CF_{i,t-1}$ = the operating cash flow in the fiscal year ending in calendar year $t-1$ divided by lag total assets.

## 2.4 Text-based Measure - Annual Estimation

To construct a text-based measure of investment plan, I use the model similar to Lima, Godeiro and Mohsin (2020). They propose a method to enable the content of dictionaries to vary over time, making it entirely determined by the predictive power of its words, which maximizes the predictive ability of the dictionary, then is suitable to the problem of forecasting. One of advantages of this methodology, is that is not necessary a pres-specified fixed dictionary because the model decide from the data which words are more important to predict investment growth over time.

In order to do this procedure, I follow three steps: First, the words are transformed into numerical values, which create a high dimensional and sparse matrix. Second I use a supervised machine learning to reduct the dimensionality by selecting the most predictive words and use them to construct new predictor(s). Lastly, in the third step, the out-of-sample forecasts are made from the new predictor(s) selected in the prior step. This three procedure is repeated recursively up to the end of the sample. In short, the content of the dictionary (the most predictive words) changes over time (LIMA; GODEIRO; MOHSIN, 2020).

### Step 1 - Pre-process the textual data

The first step in extracting meaningful information from textual data contained in the 10-k report, is to pre-process the text. In this work, the goal is to reduce the form of unstructured data to a numerical data readable by a statistical tool. In order to do this, first I grab all available 10-k reports from 1994 to 2019 in a collection of text, which the literature calls "corpus". Than I remove all stop words (e.g. also, but, did, would, etc), punctuation and numbers. After that, I perform a common natural language approach called stemming, which assigning morphological variants to common root words, for example, the words economic, economics, economically are all replaced by the common root economic.

After the pre-processing steps, I identify what the literature calls as collocations or n-grams. In this work I choose to identify collocations with no more then 2 words and whose frequency is above 100, this approach is similar to others research ((LIMA; GODEIRO; MOHSIN, 2020; FRANKEL; JENNINGS; LEE, 2016; MANELA; MOREIRA, 2017). Then I generate a vector $X_s$ where each element shows the frequency that a given 1-word or 2-words phrases $j$ appears on texts published at year $t$ by firm $i$.

Thus, with no using a pre-determined word list (fixed dictionary) this step converts words into numerical values for each firm $i$ and year $t$, although p is very large and some words are not observed for some individuals/periods. So, this numerical representation is high dimensional and sparse, which is not suitable to the classic approach used in previous work (HOU et al., 2018; LI; WANG, 2018; GEORGE; HWANG; LI, 2018) and, dimension reduction techniques as (e.g., regularization, principal components analysis) can be a suitable solution.

However, before the dimension reduction I apply a tf-idf weight for each term as (LOUGHRAN; MCDONALD, 2011). The tf-idf is commonly used as a filter removes less important words either because they are rare or because they are too frequent (GENTZKOW; KELLY; TADDY, 2019). However (LOUGHRAN; MCDONALD, 2011) use as weighting scheme, which is useful to consider all words and instead remove rare or too frequent word, I set a low value for that word. In addition, use tf-idf as a filter give to the researcher an ad-hoc cut-off to choose, which I avoid in this research and leave the data choose which words is important despite be rare or too frequent.

To compute each term weight consider N as the total number of 10-Ks in the sample, $tf_{i,j}$ as the raw count of the $i^{th}$ word in the $j^{th}$ document, $df_i$ the number of documents containing at least one occurrence of the *i-th* word, and $a_j$ the average word count in the document $j$, then the weighted measure is:

$$w_{i,j} = \begin{cases} \frac{(1+log(tf_{i,j}))}{1+log(a_j)} log\frac{N}{df_i} & if \quad tf_{i,j} \geq 1 \\ 0 & othersise \end{cases} \tag{2}$$

The first term attenuates the influence of high-frequency words with a log transformation. For instance, the word "adverse" appears 28776 times in the sample while the word phrase "credit loss" appears only 20 times. It is unlikely that the influence of the collocation "adverse" is more than 1438 times that of "credit loss". The second term of equation (2) alters the impact of a word phrase based on its commonality. For example, the word "adverse" appears in more than 80% of the documents, which implies that the second term of equation will decrease the first term by more than 80%. On the other hand, because "credit loss" appears in comparatively few documents, the second term of equation now rises the first by a factor of approximately six.

**Step 2 - Select high predictive words**

For the yearly estimation, I adapted the Lima, Godeiro and Mohsin (2020) time-series approach and use a cross-section and industry estimation as Frankel, Jennings and Lee (2016), but instead of Support Vector Regression I use Elastic Net, which is simpler and suitable to our problem. To estimate a model to forecast the expected investment growth ($y_{i,t+h}$) in time $h$ for each firm $i$, each year $t$ I use a set of information available up to year $t$ and estimate the equation (6).

$$y_{i,t|t-s} = \phi_t X'_{i,t-s} + \beta_{i,t} Z'_{i,t-s} + \varepsilon_{i,t} \tag{3}$$

Where $X_{i,t}$ is the $p \times 1$ vector with $p$ traditional variables, $Z_{i,t}$ is the $k \times 1$ vector with $k$ word count for each $i$ on year $t$. The forecasting horizon is $h > 0$. Finally, the $\hat{\beta}_{i,h}$ is estimated by minimizing the following objective function:

$$\min_{\beta_{i,h}} \frac{1}{nT} \sum_{i}^{n} \sum_{t}^{T} (y_{i,t+h} - X'_{i,t}\phi_{i,h} - Z'_{i,t}\beta_{i,h}) + \frac{\lambda}{nT} \left[ (1-\alpha) \left\| \beta_{i,h} \right\|_{\ell_1} + \alpha \left\| \beta_{i,h} \right\|_{\ell_2} \right] \tag{4}$$

The $\ell_1$ and $\ell_2$ are the elastic-net penalty, which is controlled by the two hyperparameters $\lambda$ and $\alpha$. I tune this parameters in a rolling window of train, validation and test set, which recursively the model is estimated on train data to minimize the mean squared forecast error on validation set. The test set is used to evaluate the model. I use two ways of estimation, one estimated by cross-section with all firms and another estimated by industry. For the cross-section estimation of the most predictive words I use $YEAR_{t-2}$ to train the model, while the industry estimation use the $YEAR_{t-5}$ to $YEAR_{t-2}$ as train data. The $YEAR_{t-1}$ is always used as validation set. This approach is similar to used by Frankel, Jennings and Lee (2016). I also perform a third model using a dimension reduction with the cross-section estimation.

### Step 3 - Forecast Investment Growth

To forecast investment growth annually, I perform three different approach. In the first one I use the model estimated on previous step with a cross-section regression and forecast next year investment growth as equation (5) using $\hat{\alpha}$, $\hat{\phi}$ and $\hat{\beta}$ estimated in previous step with the $\mathbf{X}$ and $\mathbf{Z}$ predictors of year $t$. I also use each industry model and compute the next year expected investment growth also as equation (5), but here there is one model for each industry.

$$IG_{i,t+h|t} = \hat{\alpha} + \hat{\phi}_t X'_{i,t} + \hat{\beta}_{i,t} Z'_{i,t} \tag{5}$$

The last one approach is to get the high predictive words selected by equation (3) and define a $Z_t^* \subset Z_t$ for each year t, which Lima, Godeiro and Mohsin (2020) calls time-varying dictionary. One difference from this work and the Lima, Godeiro and Mohsin (2020) is that here I estimate each matrix $Z_t^*$ by a cross-section regression. Even so, the dictionary tend to change over time. The $Z_t^*$ is a high-dimensional matrix, and a dimensional reduction can improve forecast using this predictors. So bring insight from time-series approach of Lima, Godeiro and Mohsin (2020), I pool the $Z_{t-2}^*$, $Z_{t-1}^*$ and $Z_t^*$ to define a a large matrix in which I estimate common factors by principal components. Than I take insight from Lima, Godeiro and Mohsin (2020) on time-series domains and select the optimal number of factors via eigenvalue ratio approach of Ahn and Horenstein (2013). Then, I keep only the factors with p-value less than or equal to 0.01 in prediction equation applied on year $t-1$ as Bai and Ng (2008).

## 2.5 Monthly Text-based Measure

I also perform a monthly estimation of a text-based measure, which is more appropriate to do a cross-section statistical evaluation and to examine an economic value performance in time-series portfolio analysis. For the monthly estimation, I match monthly and year date as Hou et al. (2020) and George, Hwang and Li (2018), that is that all accounting variables at month t is from the most recent fiscal year ending at least four months ago. One exception is the dRoe that is computed using earnings from the most recent announcement dates (item RDQ), and if not available, from the fiscal quarter ending at least four months ago. The word count from MD&A is from the most recent 10-k available for firm firm i at month t, using the SEC Edgars filing date.

With that, for each month I build three matrix to estimate the forecast model to predict investment growth from $t$ to $t+h$ ($IG_{t+h|t}$). For example, to forecast investment growth from $t$ to $t+12$ ($h=12$), I define a matrix $\mathbf{Y}$ with the most recent available investment growth at month $t$ (i.e. investment-to-assets change from $t-12$ to $t$), a matrix $\mathbf{X}$ with the most recent traditional predictors at month $t-12$ (e.g. Tobin's q, cash flow and change in return on equity from the fiscal year(quarter) ending at least six months(four months) ago) and, a large matrix $\mathbf{Z}$ for words in most recent MD&A available at month $t-12$.

The matrix $\mathbf{Z}$ with the word count is a high dimensional sparse matrix, and is not suitable to use as predictors in the traditional OLS regression. So I estimate a forecast model by using regularization method in a cross-section manner, which is similar to the approach of Han et al. (2020) that applied this idea to structured data. In analogous way I follow similar steps for text data.

Therefore, I implement a model to forecast the expected investment growth ($y_{i,t+h}$) in time $h$ for each firm $i$, each month $t$ I use a set of information available up to time $t$, so I estimate a cross-section model by using elastic net procedure as the linear prediction equation (6).

$$y_{i,t|t-s} = \phi_t X'_{i,t-s} + \beta_{i,t} Z'_{i,t-s} + \varepsilon_{i,t} \tag{6}$$

Where $h>0$ is the forecasting horizon and $\hat{\beta}_{i,h}$ is estimated by minimizing the following objective function:

$$\min_{\beta_{i,h}} \frac{1}{nT} \sum_{i}^{n} \sum_{t}^{T} (y_{i,t+h} - X'_{i,t}\phi_{i,h} - Z'_{i,t}\beta_{i,h}) + \frac{\lambda}{nT} \left[ (1-\alpha) \left\| \beta_{i,h} \right\|_{\ell_1} + \alpha \left\| \beta_{i,h} \right\|_{\ell_2} \right] \tag{7}$$

Where $X_{i,t}$ is the $p \times 1$ vector with $p$ variables, and $\ell_1$ and $\ell_2$ are the elastic-net penalty, which is controlled by the two hyperparameters $\lambda$ and $\alpha$. The $\alpha$ bridges the gap between lasso ($\alpha = 1$) and ridge ($\alpha = 0$) regression and, the tuning parameter $\lambda$ controls the overall strength of the penalty.

The Elastic Net estimation involves two non-negative hyperparameters, which imply in two well known regularizers as special cases. The LASSO case ($\alpha = 1$), which use absolute value, or $\ell 1$, as parameter penalization. And the Ridge Regression case ($\alpha = 0$), which uses $\ell 2$ parameter penalizaion to draw all coefficients estimates closer to zero but does not impose exact zero anywhere. By generating linear models through both shrinkage and selection, Elastic Net seems to be suitable to my research problem, since I have a high dimensional sparse matrix as predictor.

For the monthly estimations, I set the tuning parameters with the intention of maximizing the prediction accuracy while maintaining the low computational intensity of the method. Than, I set $\alpha = 0.5$ and choose $\lambda$ using the Hurvich and Tsai (1989) corrected version of the AIC (Akaike Information Criterion). Which is a similar approach used by Rapach and Zhou (2020), but here applied to text data.

By setting $\alpha = 0.5$, there is a stronger tendency for the model to select highly correlated predictors as a group (HASTIE; QIAN; TAY, 2016; RAPACH; ZHOU, 2020). For the $\lambda$, I select via corrected AIC as Rapach and Zhou (2020) and Han et al. (2020). Despite the K-fold cross-validation be a popular way for tunning the parameters, setting the number of folds and their definitions can be extensively arbitrary, and the results can be sensitive to these decisions (HAN et al., 2020). In addition, AIC procedure is more computationally scalable approach and, as doccumented by Flynn, Hurvich and Simonoff (2013) and Taddy (2017), select $\lambda$ via corrected AIC outperforms conventional five-fold cross-validations.

## 2.6 Performance Evaluation

For the yearly estimations, I compute the root mean squared forecast error (RMSFE) as equation (8), which compares from a conditional model (my propose) to that from the unconditional model (the benchmark). A similar approach is used by Lima, Godeiro and Mohsin (2020) in the time-series domain, however here I apply the RMSE to pools prediction errors across firms and over time. As Gu, Kelly and Xiu (2020), I perform assessment of each model by applying the out-of-sample evaluation measure into a panel-level.

$$RMSFE_j^h = \frac{\sqrt{\Sigma_{i=1}^{P}(IG_{t+h,i} - f_{t+h,i}^{j})^2}}{\sqrt{\Sigma_{i=1}^{P}(IG_{t+h,i} - f_{t+h,i})^2}} \tag{8}$$

where:

$IG_{t+h,i}$ = future realized investment growth from year $t$ to $t+h$ for firm $i$;
$f_{t+h,i}^{j}$ = expected investment growth for $t+h$ of firm $i$ predicted by elastic net model by using MD&A session of 10-K filings;
$f_{t+h,i}$ = expected investment growth for $t+h$ of firm $i$ predicted by benchmark model. That is, classic Fama and MacBeth (1973) procedure as Hou et al. (2020).

For the monthly estimation, I follow Han et al. (2020) to evaluate models by computing the cross-sectional MSFE (mean square forecast errors) by specify in terms of deviations from the mean as equation (9).

$$MSFE_{\hat{f},t+h} = \frac{1}{N}\sum_{i=1}^{N}\left[(IG_{i,t+h} - \overline{IG}_{i,t+h}) - (\hat{f}_{i,t+h|t} - \overline{\hat{f}}_{i,t+h|t})\right]^2 fot \;\; t = 1, ..., T \tag{9}$$

where:

$IG_{t+h,i}$ = future realized investment growth from month $t$ to $t+h$ for firm $i$;
$\hat{f}_{i,t+h|t}$ = expected investment growth for $t+h$ of firm $i$ predicted by elastic net model by using MD&A session of 10-K filings;
$\overline{\hat{f}}_{i,t+h|t}$ = is the cross-sectional mean for $\hat{f}_{i,t+h|t}$;
$\overline{IG}_{i,t+h}$ = is the cross-sectional mean for $IG_{t+h,i}$.

That is as relevant metric for assessing cross-sectional forecasts because is concerned with relative expected growth across firms, in other words, I measure the cross-sectional differences in expected growth. For instance, consider the traditional MSFE as equation (10).

$$MSFE_{\hat{f},t+h}^{\dagger} = \frac{1}{N}\sum_{i=1}^{N}\left(IG_{i,t+h} - \hat{f}_{i,t+h|t}\right)^2 fot \;\; t = 1, ..., T \tag{10}$$

If the forecast if perfect (i.e. $IG_{i,t+h} = \hat{f}_{i,t+h|t}$ for $i = 1, ..., N$), then it is obvious that both MSFE measures in equations (9) and (10) are equal zero. However, if $\hat{f}_{i,t+h|t} = IG_{i,t+h} + c$ for $i = 1, ..., N$, then by equation (10) the traditional $MSFE_{\hat{f},t+h}^{\dagger} = c^2$, oppositely, according to the cross-section MSFE used here, the $MSFE_{\hat{f},t+h} = 0$ by the equation (9).

### Modified Diebold-Mariano for cross-section

As Gu, Kelly and Xiu (2020), I addapt the Diebold and Mariano (1999) test from time-series domain, to perform the out-of-sample differences in cross-section predictive accuracy between two models. Specifically, to test forecast performance of model A versus B, I use the equation (11).

$$DM_{AB} = \frac{\bar{d}_{AB}}{\hat{\sigma}_{\bar{d}_{AB}}} \tag{11}$$

where:

$$d_{AB,t+h|t} = \frac{1}{N}\sum_{i=1}^{N}\left(\left(\hat{e}^{A}_{t+h|t}\right)^2 - \left(\hat{e}^{B}_{t+h|t}\right)^2\right) \tag{12}$$

The $\hat{e}^{A}_{t+h|t}$ and $\hat{e}^{B}_{t+h|t}$ are the cross-section prediction error at time t using each model. The $\bar{d}_{AB}$ and $\hat{\sigma}_{\bar{d}_{AB}}$ is the time-series mean and Newey and West (1994) standard error of $\hat{\sigma}_{\bar{d}_{AB,t}}$. So the modified Diebold-Mariano test is now based on a single time series $\bar{d}_{AB,t+h|t}$ and is more likely to satisfy the conditions needed for asymptotic normality, and than, gives appropriate p-values for test of model comparison (GU; KELLY; XIU, 2020).

### Cross-section Forecast Encompassing

Han et al. (2020) propose a forecast encompassing test for comparing the information content of two competing cross-section forecasts. The test is based on Harvey, Leybourne and Newbold (1998) from time-series domain. To compute the test, we perform the OLS regression as equation (13).

$$\hat{e}^{A}_{i,t+h|t} = \eta_t + \theta_t(\hat{e}^{A}_{i,t+h|t} - \hat{e}^{B}_{i,t+h|t}) + \epsilon_{i,t}\ for\ i = 1, ..., N; t = 1, ..., T, \tag{13}$$

where

$$\hat{e}^{k}_{i,t+h|t} = IG_{i,t+h} - \hat{f}_{i,t+h|t}\ \ for\ k = A, B. \tag{14}$$

Han et al. (2020) shows that estimate of $\theta_t$, $\hat{\theta}_t$, in the equation (13) is identical to mimizes the month-t cross-sectional $MSFE^*$ of a forecast composite by two competing models as equation (15).

$$MSFE_t^* = \frac{1}{N}\sum_{i=1}^{N}\left[(IG_{i,t+h} - \overline{IG}_{i,t+h}) - (\hat{f}^*_{i,t+h|t} - \overline{\hat{f}}^*_{i,t+h|t})\right]^2 fot \;\; t = 1, ..., T \tag{15}$$

where

$$\hat{f}^*_{i,t+h|t} = (1-\zeta)\hat{f}^A_{i,t+h|t} + \zeta\hat{f}^B_{i,t+h|t} \;\; for \; i = 1, ..., N; t = 1, ..., T; 0 \leq \zeta \leq 1. \tag{16}$$

Finally using the Fama and MacBeth (1973) procedure, I take the time-series average of the monthly slope coefficient of equation (13) and test the null hypothesis that model A encompasses B ($\theta > 0$) and the null hypothesis that model B encompass A ($\theta < 1$). For this procedure, I compute the robust standard errors of Newey and West (1994) for $\{\hat{\theta}_t\}_{t=1}^T$ in the equation (17).

$$\hat{\theta} = \frac{1}{T}\sum_{t=1}^{T}\hat{\theta}_t \tag{17}$$

**Modified Clark-West for cross-section nested model**

One of the disadvantages of the last two tests is that they are not suitable for nested models, so I use the same procedure of Gu, Kelly and Xiu (2020) and Han et al. (2020) to perform a modified Clark and West (2007) for cross-secion nested models. In other words, I compute the Clark and West (2007) on each cross-section as equation (18).

$$CW_{\hat{f},t+h} = (IG_{i,t+h} - \hat{f}^{benchmark}_{i,t+h|t})^2 - \left[(IG_{i,t+h} - \hat{f}^{text}_{i,t+h|t})^2 - (\hat{f}^{benchmark}_{i,t+h|t} - \hat{f}^{text}_{i,t+h|t})\right] \tag{18}$$

where:

$IG_{t+h,i}$ = future realized investment growth from month $t$ to $t+h$ for firm $i$;
$\hat{f}^{text}_{i,t+h|t}$ = expected investment growth for $t+h$ of firm $i$ predicted by elastic net model by using MD&A session of 10-K filings;
$\hat{f}^{text}_{i,t+h|t}$ = expected investment growth for $t+h$ of firm $i$ predicted by benchmark model.

Then I take the time-series average as equation (19) to test the null hypothesis $CW_{\hat{f},t+h} \geq 0$ by using the robust standard errors of Newey and West (1994). In sum, the error differences are based on a single time series with little autocorrelation and is more possible to satisfy the mild regularity conditions needed for asymptotic normality, and in turn, gives appropriate p-values for comparison of the nested models (GU; KELLY; XIU, 2020). Although, any potential autocorrelation problem is mitigated by the Newey and West (1994) procedure.

$$CW = \frac{1}{T}\sum_{t=1}^{T} CW_t \tag{19}$$

## 2.7 Economic Value

Additionally, I analyze the performance of portfolios formed based on the proposed investment growth measure. So, in order to evaluate the economic implication of the cross-sectional out-of-sample investment growth forecasts, I construct long-short portfolios by sorting stocks according to their text-based investment growth measure. Precisely, at the end of each month, I sort stocks into equal-weighted quintiles based on their subsequent forecasted investment growth. I then construct a zero-investment portfolio that goes long (short) the highest (lowest) quintile.

# 3 Empirical Results

In this session, I show that the most predictive words are not always the most obvious and that they change according to the sector and over time, which shows how important it is to use a more flexible method to deal with a text-based forecast.

## 3.1 Models Estimated Recursively by Year

### 3.1.1 High predictive words

The Table 1.1 presents the most relevant words in the cross-section predictive model, the table displays the average coefficients ordered by the most positive (negative) value. The results are presented in the table by sub-sample (1994 to 2006 and 2007 to 2019) and full sample, which help to understand how the time-varying dictionary updates the most predictive words with the main objective of obtaining the best forecast. Another important insight from this table is that the coefficients are all very close to zero in the cross-section model. Although it still improves the forecast compared to the benchmark model, the textual model in the cross-section estimation seems to have difficulty to finding a strong pattern between MD&A and investment growth, probably due to the large variation in the firms financial reports with different characteristics, such as life cycle and industry.

Table 1.1 – High predictive words in different periods

| | 1995-2006 | | 2007-2019 | | All Sample | |
|---|---|---|---|---|---|---|
| | Positive words | coeff | Positive words | coeff | Positive words | coeff |
| 1 | compare december | 0.02 | dac | 0.06 | dac | 0.06 |
| 2 | interestbearing | 0.02 | consolidate statement | 0.02 | consolidate statement | 0.02 |
| 3 | entertainment | 0.01 | apollo | 0.02 | apollo | 0.02 |
| 4 | accounting principle | 0.01 | percent million | 0.02 | percent million | 0.02 |
| 5 | obtained | 0.01 | basel | 0.01 | compare december | 0.02 |
| 6 | acquire business | 0.01 | material cost | 0.01 | basel | 0.01 |
| 7 | electronics | 0.01 | portfolios | 0.01 | entertainment | 0.01 |
| 8 | follows | 0.01 | gas price | 0.01 | material cost | 0.01 |
| 9 | mariner health | 0.01 | loan facility | 0.01 | accounting principle | 0.01 |
| 10 | earning share | 0.01 | fiscal due | 0.00 | obtained | 0.01 |
| 11 | funded | 0.01 | annum | 0.00 | acquire business | 0.01 |
| 12 | work | 0.01 | increase percent | 0.00 | portfolios | 0.01 |
| 13 | recovery | 0.01 | risks | 0.00 | electronics | 0.01 |
| 14 | operation | 0.01 | commissions | 0.00 | follows | 0.01 |
| 15 | restructuring plan | 0.01 | oil gas | 0.00 | mariner health | 0.01 |
| | Negative words | coeff | Negative words | coeff | Negative words | coeff |
| 1 | earning | -0.03 | clinical development | -0.03 | earning | -0.03 |
| 2 | revenue fiscal | -0.02 | ownership product | -0.02 | clinical development | -0.03 |
| 3 | contract manufacturer | -0.02 | mortgages | -0.01 | revenue fiscal | -0.02 |
| 4 | nonrecurring | -0.02 | precious metal | -0.01 | contract manufacturer | -0.02 |
| 5 | opportunities | -0.01 | cost sell | -0.01 | ownership product | -0.02 |
| 6 | severance | -0.01 | month period | -0.01 | nonrecurring | -0.02 |
| 7 | solid waste | -0.01 | period january | -0.01 | opportunities | -0.01 |
| 8 | gas property | -0.01 | aggregate principal | -0.01 | severance | -0.01 |
| 9 | business combination | -0.01 | supplementary data | -0.01 | solid waste | -0.01 |
| 10 | internet | -0.01 | statement supplementary | -0.01 | mortgages | -0.01 |
| 11 | share common | -0.01 | senior unsecured | -0.00 | gas property | -0.01 |
| 12 | telecommunications | -0.01 | servicing | -0.00 | business combination | -0.01 |
| 13 | million share | -0.01 | delaware basin | -0.00 | internet | -0.01 |
| 14 | six | -0.01 | lenders | -0.00 | share common | -0.01 |
| 15 | wells | -0.01 | december increase | -0.00 | precious metal | -0.01 |

This table present average coefficients ordered by the most positive (negative) value of the words in the cross-section model, which is estimated using $YEAR_{t-2}$ as training data and $YEAR_{t-1}$ as validation data.

For better understand the estimation by industry, the Table 1.2 shows the high predictive words in four different industries: Health Care Equipment & Supplies (GICS 351010), Household Durables (GICS 252010), Containers & Packaging (GICS 151030) and Metals & Mining (GICS 151040). This results shows that in all industries the coefficients shows a larger value than in cross-section estimation, which inply that the approach used by Frankel, Jennings and Lee (2016) seems to estimate better models.

Some positive words seems to have a intuitive relation to investment growth such as the positive word “investing” in Containers & Packaging (GICS 151030) and the negative word “unrealized” for Household Durables (GICS 252010). However, as in Frankel, Jennings and Lee (2016) there is also counter intuitive words or with no clear relation such as the word “small” classified as positive in Health Care Equipment & Supplies (GICS 351010) and “procedures” classified as relevant word for both Household Durables (GICS 252010) and Metals & Mining (GICS 151040). See the high predictive words of others industries in Appendix B.

Table 1.2 – High predictive words and phrases by Industry.

| | GICS 351010 | | GICS 252010 | | GICS 151030 | | GICS 151040 | |
|---|---|---|---|---|---|---|---|---|
| | Positive words | Coeff. | Positive words | Coeff. | Positive words | Coeff. | Positive words | Coeff. |
| 1 | interestearning | 0.19 | safety | 0.06 | providers | 0.10 | procedures | 0.26 |
| 2 | broadband | 0.11 | andor | 0.04 | delivered | 0.08 | discounts | 0.13 |
| 3 | tier | 0.09 | solutions | 0.03 | audit | 0.08 | county | 0.12 |
| 4 | tenant | 0.07 | external | 0.02 | small | 0.08 | networks | 0.10 |
| 5 | charter | 0.05 | candidates | 0.02 | investing | 0.07 | barrel | 0.10 |
| 6 | refined | 0.04 | amortized | 0.02 | entertainment | 0.07 | interestbearing | 0.08 |
| 7 | small | 0.02 | agency | 0.01 | increasing | 0.05 | reference | 0.07 |
| 8 | monthly | 0.02 | phases | 0.01 | auto | 0.04 | billing | 0.07 |
| 9 | commodity | 0.01 | employment | 0.01 | director | 0.04 | conditional | 0.05 |
| 10 | vessels | 0.01 | material adverse | 0.01 | radio | 0.04 | leasing | 0.04 |
| | Negative words | Coeff. | Negative words | Coeff. | Negative words | Coeff. | Negative words | Coeff. |
| 1 | derived | -0.08 | depletion | -0.18 | observable | -0.23 | satellite | -0.14 |
| 2 | practices | -0.03 | managements | -0.06 | week | -0.10 | patents | -0.14 |
| 3 | membership | -0.03 | procedures | -0.05 | whether | -0.06 | annuity | -0.07 |
| 4 | adverse effect | -0.03 | carried | -0.04 | expectations | -0.06 | guaranty | -0.07 |
| 5 | advisory | -0.02 | auto | -0.03 | branch | -0.05 | online | -0.06 |
| 6 | franchise | -0.02 | forth | -0.02 | salaries | -0.04 | generating | -0.04 |
| 7 | refinery | -0.02 | hotels | -0.02 | collateral | -0.04 | partnerships | -0.04 |
| 8 | warrant | -0.02 | materially | -0.01 | depend | -0.04 | gathering | -0.04 |
| 9 | stores | -0.02 | unrealized | -0.01 | supplies | -0.03 | predecessor | -0.04 |
| 10 | branch | -0.02 | inprocess | -0.01 | unpaid | -0.03 | weeks | -0.04 |

This table present average coefficients ordered by the most positive (negative) value of the words in the model estimated by industry, which use the $YEAR_{t-5}$ to $YEAR_{t-2}$ for each industry as train data and, the $YEAR_{t-1}$ is as the validation set. See the Appendix B for all industries.

Table 1.3 displays the high predictive words by life cycle. The words are ranked by the average coefficients of each one, and separated in positive and negative coefficients. The table shows the importance of a approach with no fixed dictionary, since most predictive words have no negative or positive connotation. However, there are some exception such as words that may charge a negative sentiment like “declines” in Introduction stage, “bad” in Shadec/Decline stage. And positive as well like “approvals” and "profitability" in Growth stage.

Table 1.3 – High predictive words and phrases by Life Cycle.

| | Introduction | | Growth | | Mature | | Shadec/Decline | |
|---|---|---|---|---|---|---|---|---|
| | Positive Words | coeff | Positive Words | coeff | Positive Words | coeff | Positive Words | coeff |
| 1 | interestearning | 0.090 | nonperforming | 0.297 | institution | 0.049 | casino | 0.227 |
| 2 | farmer | 0.084 | gap | 0.270 | noninterest | 0.019 | gaming | 0.227 |
| 3 | sensitivity | 0.047 | redevelopment | 0.114 | cement | 0.018 | premiums | 0.119 |
| 4 | duke | 0.045 | lae | 0.103 | percent million | 0.017 | served | 0.088 |
| 5 | compare december | 0.027 | riskbased | 0.084 | mortgages | 0.014 | mortgages | 0.061 |
| 6 | ongoing | 0.026 | aig | 0.064 | initial | 0.012 | interestearning | 0.058 |
| 7 | reflects | 0.025 | anticipate | 0.047 | indenture | 0.009 | electricity | 0.042 |
| 8 | electricity | 0.025 | mortgages | 0.040 | quoted | 0.008 | foreclosure | 0.038 |
| 9 | collateralized | 0.024 | approvals | 0.039 | trust | 0.006 | consists | 0.037 |
| 10 | mexico | 0.024 | profitability | 0.036 | unsecured | 0.006 | grade | 0.037 |
| | Negative Words | Coeff. | Negative Words | Coeff. | Negative Words | Coeff. | Negative Words | Coeff. |
| 1 | accruing | -0.113 | interestbearing | -0.097 | video game | -0.014 | registrants | -0.143 |
| 2 | central | -0.049 | bankruptcy | -0.089 | absolute | -0.013 | nasdaq | -0.082 |
| 3 | effectively | -0.044 | noncovered | -0.029 | foreclosure | -0.010 | reit | -0.050 |
| 4 | otherthantemporary | -0.036 | reit | -0.026 | certificates | -0.006 | bad | -0.044 |
| 5 | substantially | -0.035 | accident | -0.023 | impaired | -0.005 | generating | -0.044 |
| 6 | commission | -0.034 | business acquisition | -0.017 | order | -0.005 | annuity | -0.040 |
| 7 | declines | -0.034 | tobacco | -0.015 | rate note | -0.005 | requires | -0.031 |
| 8 | agency | -0.029 | annuity | -0.014 | clo | -0.004 | policy | -0.023 |
| 9 | currencies | -0.029 | support service | -0.012 | organic revenue | -0.004 | control | -0.021 |
| 10 | portfolio | -0.022 | unrecognized | -0.011 | auction rate | -0.004 | lien | -0.018 |

This table present average coefficients ordered by the most positive (negative) value of the words in the model estimated by life-cycle, which use the $YEAR_{t-5}$ to $YEAR_{t-2}$ for each life-cycle classification as train data and, the $YEAR_{t-1}$ is as the validation set.

### 3.1.2 Expected Investment Growth Forecasting Evaluation

The Table 1.4 present root mean squared forecast error computed as Equation (8). By these results, the combination of text regression with supervised machine learning to predict investment growth expectations from the MD&A section of 10-K filings leads to a better forecast. However, the first model shows a poor forecast for h = 1 and 2, which implies that using all firms to estimate the coefficient may not be a good approach when using words from financial reports as predictors.

Table 1.4 – RMSFE relative to the benchmark

| | $h = 1$ | $h = 2$ | $h = 3$ |
|---|---|---|---|
| $EIG_{fixed-dictionary}$ | 0.965** | 0.974* | 0.882*** |
| $EIG_{cross-section}$ | 0.955** | 0.957* | 0.873*** |
| $EIG_{by-industry}$ | 0.920*** | 0.928*** | 0.897*** |
| $EIG_{life-cycle}$ | 0.802*** | 0.829*** | 0.765*** |
| $EIG_{dimension-reduction}$ | 0.922*** | 0.906*** | 0.892*** |

This table present the root mean squared forecast error (RMSFE), computed as ($RMSFE_j^h = \sqrt{\Sigma_{i=1}^{P}(IG_{t+h,i} - \hat{f}_{t+h,i}^{model_j})^2} / \sqrt{\Sigma_{i=1}^{P}(IG_{t+h,i} - \hat{f}_{t+h,i}^{benchmark_j})^2}$) of pools prediction errors across firms and over time in a panel-level. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

The second and third models do a better job, when grouping firms by sector or life cycle, there is a greater similarity between the reports or in the relationship between words and fundamentals. In addition to grouping by industry, the model has a better performance according to Frankel, Jennings and Lee (2016), grouping by life cycle leads to a model with a relative performance even higher than that of the industry.

### 3.1.3 Applying this text-based forecast to others fundamentals

For check flexibility of the text-based forecast procedure proposed in this work, I try to add text information for three different models of firm fundamentals, two of than is a different approach for investment growth, and the last one is a model to predict the popular return on equity (ROE), which is vastly useful for investment professionals.

First, I perform here the same analysis as the previous section, but instead the investment-to-assets change as used by Hou et al. (2020), now I use the CAPEX growth as Li and Wang (2018) and CAPEX-to-capital growth as used by George, Hwang and Li (2018).

For the fist robustness check, I follow Li and Wang (2018) computing CAPEX growth in two steps. In the first step, I run the following annual cross-sectional predictive regression based on three predictors (Equation (20)). To reduce the impact of microcaps, the regression bellow is estimated by using weighted least squares with the market equity as the weights. Both the left- and right-hand side variables are winsorized each month at the 1% and 99% level.

$$E_{i,t}[IG_{LW}] = b_{0,t} + b_{MOM,t}MOM_{i,t-1} + b_{q,t}Q_{i,t-1} + b_{CF,t}CF_{i,t-1} + \epsilon_{i,t} \tag{20}$$

where:

| | |
|---|---|
| $E_{i,t}[IG]$ | = the growth rate of investment expenditure in the fiscal year ending in calendar year $t$ ($IG = log(CAPEX_{i,t}/CAPEX_{i,t-1})$); |
| $MOM_{i,t-1}$ | = the momentum cumulative stock returns over the past 12 months skipping one month before the end of last fiscal year; |
| $Q_{i,t-1}$ | = the log of the market value of the firm divided by total assets in the fiscal year ending in calendar year $t-1$; |
| $CF_{i,t-1}$ | = is the operating cash flow in the fiscal year ending in calendar year $t-1$ divided by lag total assets. |

In the second step, compute the monthly EIG as the out-of-sample predicted value of investment growth from Equation (20) using the most up-to-date momentum, q and CF for each firm with the historical average of the cross-sectional regression coefficients

$(b_{0,t}, b_{MOM,t}, b_{q,t}, b_{CF,t})$ estimated up to year $t$. Precisely, the accounting information as $Q$ and $CF$ are from fiscal year ending in calendar year $t$ and the $MOM$ (momentum) is the priour 2 to 12-month cumulative stock returns. I require a minimum of five years of regression coefficients to construct EIG in order to alleviate the impact of estimation errors. This proxy of investment plans used by Li and Wang (2018) is used as the first benchmark in this robustness check, namely here, as the Expected Investment Growth of LW ($E[IG_{LW}]$).

I also test whether my text forecast procedure is able to improve the prediction of the model used by George, Hwang and Li (2018), which measure investment growth as Liu, Whited and Zhang (2009) by using the annual investment-to-capital (I/K), where investment (I) is capital expenditures (annual item CAPX) minus sales of property, plant and equipment (annual item SPPE, set to zero if missing); and capital (K) is net property, plant and equipment (annual item PPENT). Note that investment can be negative if firms downsize. Consequently, the simple ratio of the current year's $I/K$ to the previous year's I/K can be negative even if investment is higher in the current year than in the previous year. To avoid this, we calculate the investment growth for fiscal year FY+1 ($IG_{FY+1}$) as Equation (21).

$$IG_{i,t} = \left[1 + \frac{I_t}{K_t}\right] / \left[1 + \left(\frac{I_{t-1}}{K_{t-1}}\right)\right] \tag{21}$$

The measure of George, Hwang and Li (2018) has two main difference with the previous model (Equation (20)). First, the estimation of the parameters is monthly rather than annual. Second, to estimate the parameters used to forecast investment growth, George, Hwang and Li (2018) used as dependent variable the CAPEX-to-capital change rather than just CAPEX growth. See Equation 22.

$$E_{i,t}[IG_{GHL}] = b_{0,t} + b_{ROE,t}ROE_{i,t-1} + b_{PTH,t}PTH_{i,t} + b_{PTL,t}PTL_{i,t} + \epsilon_{i,t} \tag{22}$$

where:

$E_{i,t+1}[IG_{GHL}]$ = the growth rate of investment-to-capital (as Equation 21) in the fiscal year ending in calendar year $t$;
$ROE_{i,t}$ = last available ROE, which is calculated by income before extraordinary items divided by two-year-lagged book equity;
$PTH_{i,t}$ = the ratio of current price to 12-month high price;
$PTL_{i,t}$ = the ratio of current price to 12-month low price.

Finally, to highlight the flexibility of the method proposed in this study, I apply the same approach of text regression and machine learning in order to use textual information from MD&A to predict others firms fundamentals, as return on equity (ROE). So I compete my text model with the Fama and MacBeth (1973) procedure used by George, Hwang and Li (2018) as equation (23).

$$E_{i,t}[ROE] = b_{0,t} + b_{ROE,t}ROE_{i,t-1} + b_{PTH,t}PTH_{i,t} + b_{PTL,t}PTL_{i,t} + \epsilon_{i,t} \tag{23}$$

where:

$E_{i,t+1}[IG_{GHL}]$ = the growth rate of investment-to-capital (as Equation 21) in the fiscal year ending in calendar year $t$;

$ROE_{i,t-1}$ = last available ROE, which is calculated by income before extraordinary items divided by two-year-lagged book equity;

$PTH_{i,t}$ = the ratio of current price to 12-month high price;

$PTL_{i,t}$ = the ratio of current price to 12-month low price.

The table 1.5 shows the RMSFE of the models for alternative measures. For the prediction of alternative measures, the model was not able to be as efficient. Perhaps a way of combining Li and Wang (2018) and George, Hwang and Li (2018) predictions with text prediction could yield better results. As for the prediction of other fundamentals, the text-based model proved to be much more efficient in predicting the ROE, indicating that the model can be flexible and applicable to other accounting fundamentals.

Table 1.5 – RMSFE of alternative fundamentals relative to respective benchmark.

| | cross-section | by industry | PCA |
|---|---|---|---|
| $E[IG_{i,t+1}]^{LWI}$ | 1.071 | 1.070 | 1.059 |
| $E[IG_{i,t+1}]^{GHL}$ | - | 1.033 | 1.026 |
| $E[ROE_{i,t+1}]$ | 0.965 | 0.971 | 0.975 |

This table present the root mean squared forecast error (RMSFE), computed as ($RMSFE_j^h = \sqrt{\Sigma_{i=1}^{P}(IG_{t+h,i} - \hat{f}_{t+h,i}^{model_j})^2} / \sqrt{\Sigma_{i=1}^{P}(IG_{t+h,i} - \hat{f}_{t+h,i}^{benchmark_j})^2}$) of pools prediction errors across firms and over time in a panel-level. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table 1.6 – Top 25 high predictive words on monthly estimation.

| | variable | coef | sentiment | variable | coef | sentiment |
|---|---|---|---|---|---|---|
| 1 | decrease | 3.68754 | | access service | -0.12242 | |
| 2 | reduce | 0.21439 | | electronic security | -0.12241 | |
| 3 | license fee | 0.09374 | | june | -0.10596 | |
| 4 | reduction | 0.07703 | | cable operator | -0.10388 | |
| 5 | supply chain | 0.05289 | | solid waste | -0.10165 | |
| 6 | source | 0.05045 | | fiber optic | -0.07430 | |
| 7 | total net | 0.04705 | | acquisition | -0.05921 | |
| 8 | companys | 0.03437 | | loan agreement | -0.05814 | |
| 9 | insurance | 0.03276 | | goodwill | -0.05634 | |
| 10 | thousand | 0.03088 | | vision system | -0.05619 | |
| 11 | patent | 0.03060 | | machine vision | -0.05353 | |
| 12 | series prefer | 0.02404 | | amortization | -0.05325 | |
| 13 | company genta | 0.02265 | | inprocess | -0.05228 | |
| 14 | genta jago | 0.01683 | | semiconductor | -0.05224 | |
| 15 | care | 0.01365 | | offer | -0.05061 | |
| 16 | medical | 0.01312 | | share series | -0.04585 | |
| 17 | research | 0.01156 | | avisof energy | -0.04411 | |
| 18 | rb falcon | 0.01050 | | public | -0.04054 | |
| 19 | fda | 0.00982 | | assurance | -0.04020 | |
| 20 | secure note | 0.00837 | | avisof utility | -0.03907 | |
| 21 | collaborative | 0.00501 | positive | convertible | -0.03816 | |
| 22 | termination | 0.00498 | negative | cost service | -0.03756 | |
| 23 | discontinue | 0.00306 | negative | technology | -0.03566 | |
| 24 | institution | 0.00306 | | senior note | -0.03564 | |
| 25 | yearend | 0.00009 | | system | -0.03468 | |
| 26 | web | -0.00232 | | product revenue | -0.03395 | |
| 27 | wireless | -0.00558 | | placement | -0.03130 | |
| 28 | assume | -0.00615 | uncertainty | warrant | -0.02921 | |
| 29 | absolute | -0.00708 | | july | -0.02808 | |
| 30 | drill | -0.00839 | | financial institution | -0.02747 | |

This table present average coefficients ordered by the most positive (negative) value of the words in the cross-section model estimated monthly. The third column exhibit if a specific word is sentiment charged using Loughran and McDonald (2011) dictionary.

## 3.2 Models Estimated Recursively by Month

### 3.2.1 High predictive words

The Table 1.6 presents the top-25 high predictive words ranked by the average sign. The table also presents the words that is sentiment charged according Loughran and McDonald (2011) dictionary. In this high predictive words only three is sentiment charged, in other words, the approach of Lima, Godeiro and Mohsin (2020) to not use a fixed dictionary seems to be suitable to cross-section forecast as well (in all words selected by the model, only 6.25% is sentiment charged). In addition, two important words to predict future investment growth is decrease and reduce, which can be associated increase in investment plans due to postpone projects, since this can be related to a reduction in a current asset.

### 3.2.2 Expected Investment Growth Forecasting Evaluation

To asses the accuracy of the monthly text-forecasts, Table 1.7 reports the time-series average of the monthly Diebold-Mariano statistic, $R^2_{OOS}$ and Clark West test for nested models. Also show the time-series average of $\theta$ and the null hypothesis test for $\theta = 0$ and $\theta = 1$, from the encompass test. All statistics is computed using robust standard errors of Newey and West (1994).

Table 1.7 – Forecast Evaluation for Monthly Estimated Models

| | |
|---|---|
| Diebold-Mariano | 0.0243* |
| $R^2_{OOS}$ | 2.68%** |
| Encompass Test ($\theta$) | 0.0784 |
| t-statistic ($\theta = 0$) | 3.05*** |
| t-statistic ($\theta = 1$) | 35.87*** |
| Clark West | 0.0426*** |

This table present time-series average of cross-sectional evaluation measures computed each month. $R^2$ out-of-sample ($R^2_{OOS}$) is computed as $1 - (MSFE^{text}/MSFE^{benchmark})$. The table also present $\theta$ estimation from the encompass test, the time-series average of $\theta$ and the null hypothesis test for $\theta = 0$ and $\theta = 1$. All statistics is computed using robust standard errors of Newey and West (1994).

The Diebold-Mariano test shows that our model outperform the benchmark. By the $R^2_{OOS}$ my model is 2.68% higher than classic model, which imply that words bring new set of information. The $\theta$ of 0.0784 shows that the benchmark model does not encompass the text model, which is confirmed by statistical test for null hypothesis that $\theta = 0$, and in contrast our model does not encompass the classic since the null hypothesis of $\theta = 1$ is rejected as well. Finally, the null hypothesis that the forecast error of my model is higher than the forecast error of benchmark is rejected by the test of Clark West, which account for difference in nested models.

## 3.3 Long-Short Portfolios Performance

To infer about the economic value of proposed forecast method, the economic value evaluation based on long-short portfolio performance are presented in Table 1.8. The table relates annualized mean, volatility and Sharpe ratio for each long-short portfolio. The portfolios go long (short) every month in stocks which the firm has the highest (lowest) investment growth forecast for the next fiscal year. The table shows the result for the value- and equal-weighting returns. The period is from 1996 to 2018, so is useful to compare the results with the wide market performance which has the lowest average return. However the volatility of the both portfolios are riskier than the wide market return, and only the equal weighting present a better Sharpe Ratio. Despite the poor performance of the value-weighting portfolio by the Sharpe ratio, the alpha of the Fama and French (2015) 5 factors model is positive and significant. For the equal-weighting portfolio, the performance in the period is better both by the Sharpe ratio (2.04) and the 5 factor annualized alpha (34.30).

Table 1.8 – Economic Value - Period 1996 to 2018

| Panel A | Market | Value weighting | Equal weighting |
|---|---|---|---|
| Annualized Mean (%) | 12.67 | 13.95 | 52.04 |
| Ann. Volatility (%) | 15.21 | 21.56 | 25.39 |
| Ann. Sharpe Ratio | 0.83 | 0.65 | 2.04 |
| **Panel B** | | **Value weighting** | **Equal weighting** |
| Annualized $\alpha$ (%) | | 10.65* | 34.30*** |
| MKT | | 0.132 | 0.188 |
| SMB | | -0.342 | 0.005 |
| HML | | -0.482 | -0.305 |
| RMW | | -0.254 | -0.373 |
| CMA | | 1.375*** | 1.140*** |

The table reports annualized summary statistics for long-short portfolios constructed from out-of-sample forecasts of cross-sectional investment growth based on the MD&A. At the end of each month, I sort all available stocks into quintiles according to their forecasted investment growth for the next fiscal year. The long-short portfolio goes long (short) the fifth (first) quintile. The quintiles for the long-short portfolios are value (equal) weighted according to market capitalization. Market return in Panel A is the CRSP value-weighted market portfolio return minus the risk-free return. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, according to t-statistics based Newey and West (1994) standard errors.

# 4 Conclusion

In this chapter, I propose a new measure of firm-level investment plans based on text data from MD&A (Management Discussion and Analysis) disclosure in 10-K filings. Specifically, I combine the idea of time varying dictionary of Lima, Godeiro and Mohsin (2020) with the cross-section forecast procedure of Han et al. (2020), which is adapted here to text data.

The contribution of this chapter is twofold. First, I show that the words matters even to predict investment growth, which is empirically challenging to measure in the firm-level. In addition, by adapting the Han et al. (2020) procedure to text data, I contribute to the forecast literature that lacks to explore unstructured data in cross-section forecast. Second, I add to the investment literature by proposing to use machine learning tools and text data to predict investment plans, which I show that to measure including text-data generate more accurate predictions and better performance in long-short portfolios.

Following Frankel, Jennings and Lee (2016), I also try some variations of yearly estimations, including the estimation using all firms in each year, the estimation by industry, by life-cycle and the estimation using all firms with dimensional reduction using principal component analysis.

By this annual tests, I could conclude that estimate the coefficients by using all 10-K filings firms at once did not present a tolerable forecast, mainly in the short term. Possibly this result in the cross-section estimation occur due to the variability that exists between reports from different firms.

Therefore, separating firms into groups is a solution that leads to better forecasting. That is, words are important and machine learning models can lead to better prediction, but for that to separate firms by industry makes machine learning models find a stronger pattern between words and fundamentals. Another insight is that the results shows, according to common sense, that industry and life cycle are good ways to set the training sample. But in addition, I present new evidence that to predict expected growth in life-cycle investment appears to be more important than industry.

# Chapter 2

# Investment Plans and Stock Returns at Different Life-Cycle Stages

## 1 Introduction

There is a growing literature showing that investment plans are related to future stock returns. However, there is mixed evidence about the drivers of the investment plan ability to predict return (LAMONT, 2000; COCHRANE, 1991; HOU et al., 2020; LI; WANG; YU, 2020). In this chapter, I use the concept of growth opportunities, from the life-cycle theory, to contribute to our understanding of the relation between investment plans and stock returns. Specifically, I investigate how that relation varies at different life-cycle stages.

Faff et al. (2016) document evidence about the effect of life-cycle on corporate investment decision. Precisely, investment decreases monotonically over a firm's life-cycle stage. Since the lags in the investment process (e.g. lag in delivery) generate investment plans from an actual decision of investment that cannot be implemented immediately (LAMONT, 2000), it is expected that the planned investment is impacted to some degree by the same characteristics that influence actual investment.

In this sense, it is possible to extend the finds of Faff et al. (2016) from actual investment to the context of planned investment. In addition, the use of life cycle to predict expected investment growth are consistent to the study of Vorst and Yohn (2018), since they find in life cycle a strong predictability of the growth, which is related to investment plans. Therefore, I develop the hypothesis $H_{1a}$.

$H_{1a}$: Due to the decrease in investment opportunities, firms will decrease their investment plans as they become more mature.

The expected investment growth is a measure of investment plans based on out-of-sample predictive regressions (HOU et al., 2020; LI; WANG, 2018). In addition, it is well known that many traditional return forecasting variables perform poorly out of sample (GOYAL; WELCH, 2008). Motivated by these issues, I extend the last assumption to infer that just as in the in-sample relation, life-cycle information can also improve out-of-sample prediction of investment growth. Then, I propose the hypothesis $H_{1b}$.

$H_{1b}$: Proxies for life cycle can improve out-of-sample prediction of expected investment growth (investment plans).

Firms in earlier stages usually have relatively more growth opportunities than mature firms, which are characterized as having less growth opportunity, but long histories, large size, and more information available (CAI; LI; ZHANG, 2018). For instance, Hou et al. (2020) show that firms with larger investment plans should experience high expected returns, which is attributed to rising in cash flow news expectations that come from growth opportunities (LI; WANG, 2018). This characteristic connects the life cycle theory and investment-based asset pricing by suggesting that the growth opportunities of the firms in the earlier stages are priced. This argument leads to our second hypothesis that investment plans of firms in earlier stages predict positively stock returns, while those of firms in later stages does not.

This assumption suggests that both "cash flow news" and "discount rate changes" are the source of the expected investment growth premium. In order words, growth firms as opposed to mature firms should experience a stronger positive expected investment growth premium. This is because firms in earlier life cycle stages increase their investment plans mainly because they have greater growth opportunities, while mature firms do not have the same degree of growth opportunities and therefore increase their investment plans mainly in response to changes in the discount rate. Then, I propose the hypothesis $H_{2a}$.

$H_{2a}$: Through the cash flow news channel, the relation between the investment plans of growth firms and future stock return are stronger than relation with investment plans of mature firms.

Although firms in the earlier life cycle stages have larger growth opportunities, they also are habitually characterized as younger and smaller (CAI; LI; ZHANG, 2018). Then, they have more limited information available, which suggest that they are more prone to extrapolative expectations about future growth (GENNAIOLI; MA; SHLEIFER, 2016; HIRSHLEIFER; LI; YU, 2015). So, I propose the following hypothesis:

$H_{2b}$: Due to the extrapolative expectations about growth opportunities, the stronger EIG premium of the growth firms is, at least partially, explained by investor sentiment.

# 2 Methodology

## 2.1 Sample Selection and Data Source

The data comes from several sources, the general financial and accounting data I obtain from the merged CRSP (Center of Research and Security Price) and COMPUSTAT database. For construct the Fama and French (2016) factors I use data from Keneth French's website. The sample include NYSE, AMEX, and NASDAQ common stocks. The financial firms (SIC 6000-6999) and firms with negative book equity are excluded from sample. Following Faff et al. (2016), utility firms (SIC 4900-4949) also are excluded since they are under government regulation. Following other asset pricing studies, the sample covers the period of 1962 to 2018 (HOU; XUE; ZHANG, 2015; FAMA; FRENCH, 2015), including only firms with CRSP share codes 10 and 11, that refer to ordinary common shares with no special status.

Table 2.1 shows descriptive statistics. Panel A contains the statistics of the dependent variables, which present mean values close to zero, however, the current investment level represented here by investment-to-assets ($I/A$) is slightly higher than the change in $I/A$ here represented by $d^1I/A$. The standard deviation of the change in investment is greater than investment-to-assets. My main variable of interest is the E[$d^1I/A$], my measure of expected investment growth (or investment plan), it was computed using the realized value of the future investment growth ($d^1I/A$) so it presents similar values with the predicted variable, in addition Panel C show the correlations and the expected investment growth ($E[d^1I/A]$) exhibits a correlation of 0.41 with the future investment made ($d^1I/A$).

In Panel B, the variables sales, total assets, and market value are in logarithmic form, so total assets and equity market values presented very similar distributions, and that is why each model considers only one of them to represent the size of the company as a predictor or control. The CF and the cop are variables that refer to the cash flow, and although the averages are close, the CF has a standard deviation well above the cop.

Panel C shows the mean and standard deviation of the dependent variables after being classified into four different life-cycles: Introduction, growth, maturity, and the last one, shakeout/decline. The growth firms had higher average investment-to-assets ($I/A$) values than mature firms, both current and one year ahead. In opposite, companies in the initial stages present average negative values of the change in investment-to-assets ($D^1I/A$), which are lower than that of mature ones. But despite the negative averages, growth firms have higher standard deviations of $D^1I/A$ and E$[D^1I/A]$, than this variation suggests that companies in the growth stage may have both more aggressive investment and disinvestment plans than mature firms.

## 2.2 Investment Plans Measurement

To measure the investment plans, which is the dependent variable of in-sample analyses ($E[d^1I/A]$ in Panel A, Table 2.1), I conduct an out-of-sample procedure to forecast the firm's investment growth of one year-a-head, then I use the predicted value of that model as the expected investment growth, in other words, the firm's investment plans.

In order to implement the out-of-sample procedure, I apply the Elastic Net method using, in prior years, a moving window training data for all firm-year observations in $Y_{t-5}$ to $Y_{t-2}$ and an out-of-sample validation test sample $Y_{t-1}$ to generate a model for expected investment growth. Then I apply that model to the current-year ($Y_t$) out-of-sample data to estimate the firm's investment plans, which I use as the expected investment growth in Equation 4 to conduct our in-sample analysis to test $H_{1a}$.

Therefore, I implement a model to forecast the expected investment growth ($y_{i,t+h}$) in time $h$ for each firm $i$, using a set of information available up to time $t$, so I apply elastic net to estimate the following linear prediction equation:

$$y_{i,t+h} = X'_{i,t} + \varepsilon_{i,t+h} \tag{1}$$

Where $h > 0$ is the forecasting horizon and $\hat{\beta}_{i,h}$ is estimated by minimizing the following objective function:

$$\min_{\beta_{i,h}} \frac{1}{nT} \sum_{i}^{n} \sum_{t}^{T} (y_{i,t+h} - X'_{i,t}\beta_{i,h}) + \frac{\lambda}{nT} \left[ (1-\alpha) \left\|\beta_{i,h}\right\|_{\ell_1} + \alpha \left\|\beta_{i,h}\right\|_{\ell_2} \right] \tag{2}$$

Where $X_{i,t}$ is the $p \times 1$ vector with $p$ variables, and $\ell_1$ and $\ell_2$ are the elastic-net penalty, which is controlled by the two hyperparameters $\lambda$ and $\alpha$. The $\alpha$ bridges the gap between lasso ($\alpha = 1$) and ridge ($\alpha = 0$) regression and, the tuning parameter $\lambda$ controls the overall strength of the penalty.

The Elastic Net estimation involves two non-negative hyperparameters, which imply in two well known regularizers as special cases. The LASSO case ($\alpha = 1$), which

Table 2.1 – Descriptive Statistics and Correlation Matrix

Panel A - Dependent Variables.

| | N | Mean | Min | Pctl(25) | Median | Pctl(75) | Max | St. Dev. |
|---|---|---|---|---|---|---|---|---|
| $I/A$ | 83,586 | 0.08 | −0.38 | −0.03 | 0.05 | 0.17 | 0.62 | 0.19 |
| $d^1I/A$ | 83,586 | 0.01 | −0.65 | −0.12 | 0.001 | 0.12 | 1.09 | 0.25 |
| $\mathrm{E}[d^1I/A]$ | 33,174 | −0.01 | −1.53 | −0.08 | 0.001 | 0.06 | 2.00 | 0.15 |

Panel B - Predictors / Control Variables.

| | N | Mean | Min | Pctl(25) | Median | Pctl(75) | Max | St. Dev. |
|---|---|---|---|---|---|---|---|---|
| CF | 83,586 | 0.11 | −3.17 | 0.05 | 0.15 | 0.32 | 1.42 | 0.58 |
| cop | 83,586 | 0.13 | −0.17 | 0.07 | 0.13 | 0.21 | 0.39 | 0.11 |
| q | 83,586 | 0.26 | −0.96 | −0.19 | 0.17 | 0.66 | 1.87 | 0.60 |
| dROE | 83,586 | −0.004 | −0.29 | −0.01 | 0.00 | 0.01 | 0.25 | 0.05 |
| Leverage | 83,586 | 0.22 | 0.00 | 0.03 | 0.19 | 0.35 | 0.73 | 0.19 |
| log(Sales) | 83,586 | 5.78 | 1.87 | 4.32 | 5.77 | 7.21 | 9.97 | 1.93 |
| log(AT) | 83,586 | 5.88 | 2.26 | 4.37 | 5.76 | 7.29 | 10.50 | 1.91 |
| log(ME) | 83,586 | 5.82 | 2.55 | 4.24 | 5.70 | 7.23 | 10.56 | 1.91 |

Panel C - Mean and Standard Deviation by Life-Cycle

| | Mean | | | | Standard Deviation | | | |
|---|---|---|---|---|---|---|---|---|
| | $I/A$ | $I/A_{t+1}$ | $d^1I/A$ | $\mathrm{E}[d^1I/A]$ | $I/A$ | $I/A_{t+1}$ | $d^1I/A$ | $\mathrm{E}[d^1I/A]$ |
| Introduction | 0.14 | 0.04 | -0.07 | -0.07 | 0.23 | 0.22 | 0.30 | 0.22 |
| Growth | 0.20 | 0.10 | -0.07 | -0.06 | 0.18 | 0.18 | 0.25 | 0.14 |
| Maturity | 0.03 | 0.07 | 0.05 | 0.02 | 0.11 | 0.15 | 0.18 | 0.11 |
| Shakeout/Decline | -0.05 | 0.01 | 0.07 | 0.04 | 0.17 | 0.19 | 0.26 | 0.18 |

Panel D - Correlation matrix

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| (1) $I/A$ | 1 | | | | | |
| (2) $d^1I/A$ | -0.47 | 1 | | | | |
| (3) $\mathrm{E}[d^1I/A]$ | -0.46 | 0.41 | 1 | | | |
| (4) CF | 0.34 | -0.11 | -0.1 | 1 | | |
| (5) cop | 0.06 | 0.07 | 0.21 | 0.41 | 1 | |
| (6) q | 0.24 | 0.09 | 0.06 | 0.03 | 0.23 | 1 |
| (7) dROE | 0.05 | 0.04 | 0.06 | 0.14 | 0.06 | 0.01 |
| (8) Leverage | -0.03 | -0.06 | -0.01 | -0.04 | -0.11 | -0.2 |
| (9) log(Sales) | 0.01 | -0.07 | 0 | 0.3 | 0.24 | -0.18 |
| (10) log(ME) | 0.12 | -0.04 | 0.04 | 0.23 | 0.26 | 0.25 |
| (11) log(AT) | 0.01 | -0.08 | 0.02 | 0.2 | 0.15 | -0.16 |
| | (7) | (8) | (9) | (10) | (11) | |
| (8) Leverage | -0.05 | 1 | | | | |
| (9) log(Sales) | 0.05 | 0.27 | 1 | | | |
| (10) log(ME) | 0.06 | 0.1 | 0.82 | 1 | | |
| (11) log(AT) | 0.04 | 0.32 | 0.93 | 0.89 | 1 | |

This table reports descriptive statistics and correlation matrix for this study. For more details about variable definitions, see Appendix A.

use absolute value, or $\ell1$, as parameter penalization. And the Ridge Regression case ($\alpha = 0$), which uses $\ell2$ parameter penalizaion to draw all coefficients estimates closer to zero but does not impose exact zero anywhere. So, the Elastic Net generates linear models through both shrinkage and selection, which is suitable to the propose of this research where I need a model that can be stable even with different predictors that are potentially correlated (LI, 2015).

To test $H_{1b}$ and investigate whether life cycle proxies contain information beyond investment-based predictors in an out-of-sample approach, I estimate an additional expected investment growth using the same procedure above with one difference, here I add new predictors based on life cycle theory and I expected that the life cycle information improve the predictability of the model, see the evaluation in section 3.3.

## 2.3 Classification of Life-Cycle Stage

To reduce concerns about data availability I capture the firm life-cycle by following Faff et al. (2016) that used Multiclass Linear Discriminant Analysis (MLDA) to predict the life-cycle stages. In order to do this procedure I employ two steps. First I classify the firms using the cash flow based proxy developed by (DICKINSON, 2011), which assigns firms into Introduction, Growth, Maturity, Shakeout, and Decline. Specifically in this chapter, I consider Shakeout and Decline as the same group. Consistent with life cycle theory (MILLER; FRIESEN, 1984), this measure takes in account the cash flow patterns that are usual for firms in different life cycle stages. The table (2.2) reports the Dickinson (2011) classification. One advantage of this approach is it allows the analysis of the time firms spend in each stage and allows that firms move through the stages in a non-sequential manner, which is possible to do with the Faff et al. (2016) procedure.

Table 2.2 – Life Cycle Classification

| Cash Flow Type | Introduction | Growth | Mature | Shake-Out | | | Decline | |
|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Operating Activities | - | + | + | - | + | + | - | - |
| Investing Activities | - | - | - | - | + | + | + | + |
| Financing Activities | + | + | - | - | + | - | + | - |

Second, I estimate the MLDA by employing the Equation 3 with the firms that cash flow information is available.

$$Group_{i,t} = \alpha_0 + \alpha_1 AGE_{i,t} + \alpha_2 RETA_{i,t} + \alpha_4 AGrth_{i,t} + \varepsilon_{i,t} \tag{3}$$

where:

$Group_{i,t}$ = the change in investment-to-assets (I/A) year ending in calendar year $t$ ($EIG = I/A_{i,t} - I/A_{i,t-1}$);
$AGE_{i,t}$ = is the firm i age adjusted for industry and size effects;
$RETA_{i,t}$ = is the ratio of retained earnings to total assets;
$AGrth_{i,t}$ = is the asset growth of firm i.

For the first one life-cycle proxy, I use the CRSP listed firm age adjusted for size and industry. That is important because the time required for firms to mature differs per industry, and the time of existence before listing may vary between firms (FAFF et al., 2016). Since a large firm tends to exist longer, I adjust the firm age for size to control for the age differences before listing.

## 2.4 Empirical Framework

In this section, I present the empirical models to test the three main hypotheses of this project: First, firms will decrease their investment plans as they become more mature ($H_1$). Second, investment plans of firms in earlier stages is a stronger predictor of stock returns than investment plans in mature firms ($H_2$). Lastly, a bottom-up measure of aggregate investment plans based on mature firms has stronger predictive ability than based on growth firms ($H_3$).

### Firm Life Cycle and Investment Plans

To test $H_{1a}$ and examine the impact of life cycle on planned investment, I follow DeAngelo, DeAngelo and Stulz (2010) and Faff et al. (2016) by using an empirical model as present by the Equation 4.

$$E[d^1 I/A]_{i,t} = \alpha_0 + \alpha_1 D_{i,t}^{intro} + \alpha_2 D_{i,t}^{growth} + \alpha_3 D_{i,t}^{shadec} + \Sigma \alpha X_{i,t} + \epsilon_{i,t} \tag{4}$$

where:

$E[d^1 I/A]$ = is the expected investment growth of firm $i$ at time $t$;
$D_i^{intro}$ = is a life cycle dummy which takes a value of one if the firm $i$ at time $t$ is in introductory stage and zero otherwise;
$D_i^{growth}$ = is a life cycle dummy which takes a value of one if the firm $i$ at time $t$ is in growth stage and zero otherwise;
$D_i^{shadec}$ = is a life cycle dummy which takes a value of one if the firm $i$ at time $t$ is in shadec stage and zero otherwise;
$\alpha X_i$ = Xi are the control variables for investment plans. Like investment decisions, planned investments can be explained by some variables added as control variables.

Following DeAngelo, DeAngelo and Stulz (2010) and Faff et al. (2016), I use robust standard errors based on the two-way (firm and year) clustering method in Petersen (2009) for this regression. In addition to controlling for size (neperian logarithm of total assets) and financial leverage, I intend to control for cash flow and Tobin's Q, respectively because of the well documented investment sensitivity to cash flow (FAZZARI; HUBBARD; PETERSEN, 1987; KAPLAN; ZINGALES, 1997) and future opportunities (KOGAN; PAPANIKOLAOU, 2014). By the $H_{1a}$, I expect all $\alpha$ of the earlier stages are more significant that the intercept and $\alpha_3$.

To test $H_{1b}$ and investigate whether life cycle proxies contain information beyond investment-based predictors in an out-of-sample approach, I conduct an empirical horse race between the benchmark ($EIG_{HMXZ}$); the measure estimated by Elastic Net and traditional predictors ($EIG_{ENet}$); and the last one also with Elastic Net, but now adding predictors based on life-cycle theory ($EIG_{LC}$).

### Firm-Level Investment Plans and Cash Flow Channel

To test my hypothesis that there is a higher EIG premium for firms with larger growth opportunities ($H_{2a}$), which are those in the early life-cycle stages, I implement a set of analyses by using decile portfolios sorted by EIG, rebalanced monthly based on the most up-to-date estimated EIG. Initially, I examine the value-weighted average excess returns, standard deviation and Sharpe ratio for each decile and the spread High minus Low EIG (consider the four measures). In addition, I do this analysis with the portfolios conditioned to my four classifications of life cycle (introduction, growth, mature and decline).

I also analyse the adjusted return of each decile controlled by risk factors of the leading asset pricing models. Specifically, I consider the three-factor model of Fama and French (1993), four-factor model of Carhart (1997), four-factor "q-factor" model of Hou, Xue and Zhang (2015) and the five-factor model of Fama and French (2015). The Equation 5 is the general specification and I am interested in the intercept of this regression. All the t-statistcs are calculated based on heteroskedasticity and autocorrelation consistent standard errors of Newey and West (1987).

$$R_{p,t} = \alpha_p + \sum_{K}^{j=1} \beta_p F_{j,t} + \varepsilon \tag{5}$$

where:

$R_{p,t}$ = is the difference between the value-weighted monthly return on stocks ranked in the bottom decile and the return on those in the top decile sorted by each measure of EIG conditioned to life cycle stages;
$\alpha_p$ = the adjusted return of portfolio p;
$F_{j,t}$ = is the risk factor $j$.

The $H_{2b}$ is tested including sentiment measures as explanatory variables of the EIG premium as the Equation 6. Where I analyze two sentiment measures, which is done separately. First I analyze that model presented in 6 by using the investor sentiment (ISent) proposed and made available online by Baker and Wurgler (2007). In a second analysis, I examine the same empirical model by using the measure of manager sentiment (MSent) proposed and made available online by Jiang et al. (2019).

$$R_{p,t} = \alpha_{p,t} + \sum_{K}^{j=1} \beta_p F_{j,t} + \beta_{sent} S_t + \varepsilon \tag{6}$$

where:

$R_{p,t}$ = is the difference between the value-weighted monthly return on stocks ranked in the bottom decile and the return on those in the top decile sorted by each measure of EIG conditioned to life cycle stages;
$\alpha_{p,t}$ = the adjusted return of portfolio p;
$F_{j,t}$ = is the risk factor $j$;
$S_t$ = is a sentiment measure (ISent or MSent).

By the $H_{2b}$ I expect that $\beta_{sent}$ of EIG portfolios based in growth firms is significant. Suggesting that EIG premium of the growth firms is, at least partially, explained by both sentiment measures.

# 3 Empirical Results

## 3.1 In-Sample Analysis of Investment Growth and Life-Cycle Stages

The Table 2.3 presents the results estimated by the Equation 4. My $H_{1a}$ predict a linear relation which firms will decrease their investment plans as they become more mature, but the empirical model exhibit a non-linear relation between life-cycle and expected investment growth (EIG), by the column (5) growth firms shows lower EIG than introduction and mature firms. In sum, this result imply that investment plans exhibit a "U" shape across life-cycle stages.

This relation is robust even if I use realized investment growth instead the expected as in column (3) and (4) of the Table 2.3. Also this results is robust when is used another proxy for investment growth as show in Table 2.4 where the CAPEX growth ($\log(CAPEX_t/CAPEX_{t-1})$ is used instead investment-to-assets change.

One explanation for these results is the predominance of disinvestment in growth firms. As seen in the descriptive statistics (Table 2.1), the average EIG by growth firms is negative despite the level of future investment being higher than that of mature firms. Also, the standard deviation is greater, implying that growth firms may have both higher investment plans (as predicted by $H_{1a}$) and more aggressive disinvestment as well. Column (1) and (2) of the Table 2.3 shows the relation between the current investment level and the life cycle and corroborates the findings of Faff et al. (2016), which the current investment level increases across the life-cycle stages. To alleviates the concerns with unobserved firm-level heterogeneity, which is time-varying and firm unobserved heterogeneity, I use a fixed effect specification, which is presented in table 2.5 and shows similar results.

## 3.2 Address the Endogeneity Problem in the In-Sample Analysis

The previous models show that investment plans are, on average smaller than those of mature companies. To mitigate omitted variable bias, I include a collection of firm-level controls in the last analysis. I also use fixed effect specification to alleviates the concerns with unobserved firm-level heterogeneity, which is time-varying and firm unobserved heterogeneity. Despite that, there is a concern that my empirical model omits some variables that might affect the outcome variable (i.e., expected investment growth) and simultaneously the main independent variables of interest (i.e., life-cycle stages). The instrumental variable (IV) approach is often used to address the endogeneity problem.

Table 2.3 – Life-cycle stages, investment-to-assets and expected investment growth

| | $I/A_{i,t}$ | $I/A_{i,t+1}$ | $d^1I/A$ | | $E\left[d^1I/A\right]$ |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Constant | 0.008 | 0.078*** | 0.100*** | 0.096*** | 0.032*** |
| | (1.223) | (10.193) | (10.658) | (8.911) | (3.122) |
| $D_i^{intro}$ | 0.138*** | −0.014*** | −0.134*** | −0.151*** | −0.118*** |
| | (22.011) | (−3.665) | (−16.792) | (−17.818) | (−11.852) |
| $D_i^{growth}$ | 0.159*** | 0.036*** | −0.107*** | −0.119*** | −0.078*** |
| | (50.047) | (12.889) | (−37.155) | (−37.059) | (−16.975) |
| $D_i^{shadec}$ | −0.051*** | −0.041*** | 0.014*** | 0.007 | −0.001 |
| | (−17.969) | (−14.662) | (3.011) | (1.547) | (−0.293) |
| CF | 0.110*** | 0.053*** | −0.060*** | −0.064*** | −0.044*** |
| | (12.951) | (8.610) | (−8.196) | (−6.649) | (−4.179) |
| q | 0.060*** | 0.069*** | 0.045*** | 0.038*** | 0.022*** |
| | (25.628) | (28.288) | (7.350) | (8.171) | (3.223) |
| dROE | 0.082** | 0.267*** | 0.262*** | 0.346*** | 0.183*** |
| | (2.289) | (8.259) | (5.039) | (5.647) | (4.121) |
| log(sale) | −0.010*** | 0.013*** | 0.019*** | 0.022*** | −0.009*** |
| | (−5.890) | (5.016) | (5.128) | (4.629) | (−3.604) |
| Leverage | −0.027*** | −0.025*** | 0.001 | −0.014 | 0.018* |
| | (−2.759) | (−2.597) | (0.128) | (−1.107) | (1.750) |
| log(at) | 0.009*** | −0.018*** | −0.027*** | −0.028*** | 0.008*** |
| | (4.833) | (−6.031) | (−6.816) | (−5.551) | (2.595) |
| $N$ | 83,586 | 83,586 | 83,586 | 33,174 | 33,174 |
| $R^2$ | 0.363 | 0.134 | 0.084 | 0.097 | 0.104 |
| Adjusted $R^2$ | 0.363 | 0.133 | 0.083 | 0.097 | 0.103 |

This table present the coefficients for the following regression: $DependentVariable_{i,t} = \alpha_0 + \alpha_1 D_{i,t}^{intro} + \alpha_2 D_{i,t}^{growth} + \alpha_3 D_{i,t}^{shadec} + \Sigma\alpha X_{i,t} + \epsilon_{i,t}$, where the $DependentVariable_{i,t}$ is investment-to-assets ($I/A$), realized future investment growth ($d^1I/A$) and expected investment growth ($E[d^1I/A]$). All predictive variables are winsorized at the 5% and 95% levels. The t-statistics are reported in parentheses with robust standard errors based on the two-way (firm and year) clustering method in Petersen (2009). The sample is annual from 1989 to 2018.

Table 2.4 – CAPEX Growth as Investment Growth

| | *Dependent variable:* | | |
|---|---|---|---|
| | $IG^{CAPEX}_{h=1\|t}$ | $IG^{CAPEX}_{h=2\|t}$ | $IG^{CAPEX}_{h=3\|t}$ |
| | (1) | (2) | (3) |
| Constant | 0.195*** | 0.223*** | 0.321*** |
| | (3.779) | (4.419) | (5.025) |
| $D_i^{intro}$ | −0.137 | −0.143 | −0.210* |
| | (−1.458) | (−1.553) | (−1.730) |
| $D_i^{growth}$ | −0.101*** | −0.098*** | −0.123*** |
| | (−4.600) | (−4.500) | (−4.908) |
| $D_i^{shadec}$ | −0.171*** | −0.149** | −0.185** |
| | (−2.874) | (−2.425) | (−2.574) |
| CF | 0.255*** | 0.238*** | 0.226*** |
| | (6.915) | (7.112) | (6.733) |
| q | 0.100*** | 0.104*** | 0.094*** |
| | (3.933) | (4.125) | (3.381) |
| dROE | 1.995*** | 1.928*** | 2.081*** |
| | (12.082) | (12.491) | (11.149) |
| at | −0.022*** | −0.026*** | −0.034*** |
| | (−2.920) | (−3.371) | (−3.835) |
| Observations | 30,530 | 30,530 | 30,530 |
| $R^2$ | 0.042 | 0.039 | 0.033 |
| Adjusted $R^2$ | 0.041 | 0.038 | 0.033 |
| F Statistic (df = 7; 30522) | 189.604*** | 174.807*** | 150.822*** |

This Table present the coefficients for the following regression: $DependentVariable_{i,t} = \alpha_0 + \alpha_1 D^{intro}_{i,t} + \alpha_2 D^{growth}_{i,t} + \alpha_3 D^{shadec}_{i,t} + \Sigma\alpha X_{i,t} + \epsilon_{i,t}$, where the $DependentVariable_{i,t}$ is expected investment growth ($E[IG]$) using CAPEX growth. All predictive variables are winsorized at the 5% and 95% levels. The t-statistics are reported in parentheses with robust standard errors based on the two-way (firm and year) clustering method in Petersen (2009). The sample is annual from 1989 to 2018.

Table 2.5 – Fixed Effect Specification to analyze Life-cycle stages, investment-to-assets and expected investment growth

| | I/A | I/A t+1 | d1I/A | | E[d1I/A] |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| LCintro | 0.107*** | −0.042*** | −0.095*** | −0.112*** | −0.089*** |
| | (11.687) | (−5.169) | (−6.011) | (−6.194) | (−4.148) |
| LCgrowth | 0.292*** | 0.007*** | −0.256*** | −0.267*** | −0.139*** |
| | (79.749) | (2.954) | (−57.642) | (−55.884) | (−14.214) |
| LCshadec | −0.112*** | −0.021*** | 0.086*** | 0.101*** | 0.056*** |
| | (−24.695) | (−4.195) | (10.442) | (9.887) | (4.857) |
| CF | 0.084*** | 0.029*** | −0.052*** | −0.061*** | −0.017** |
| | (19.775) | (5.531) | (−6.469) | (−6.484) | (−2.345) |
| q | 0.056*** | 0.098*** | 0.088*** | 0.093*** | 0.049*** |
| | (20.900) | (29.340) | (10.302) | (11.742) | (3.621) |
| dROE | 0.057** | 0.195*** | 0.186*** | 0.193*** | 0.020 |
| | (2.153) | (8.211) | (4.414) | (4.466) | (0.508) |
| log(sale) | −0.030*** | 0.046*** | 0.083*** | 0.088*** | −0.073*** |
| | (−8.702) | (15.175) | (15.536) | (9.419) | (−9.617) |
| Leverage | −0.042*** | −0.141*** | −0.152*** | −0.159*** | −0.031 |
| | (−4.727) | (−10.305) | (−6.883) | (−6.801) | (−1.458) |
| log(at) | 0.039*** | −0.094*** | −0.160*** | −0.174*** | 0.041*** |
| | (9.164) | (−22.148) | (−16.651) | (−14.449) | (6.500) |
| *N* | 91,890 | 91,890 | 91,890 | 42,739 | 42,739 |
| $R^2$ | 0.588 | 0.155 | 0.244 | 0.265 | 0.128 |
| Adjusted $R^2$ | 0.535 | 0.046 | 0.146 | 0.129 | −0.034 |

This table present the coefficients for the following regression: $DependentVariable_{i,t} = \alpha_0 + \alpha_1 D^{intro}_{i,t} + \alpha_2 D^{growth}_{i,t} + \alpha_3 D^{shadec}_{i,t} + \Sigma\alpha X_{i,t} + \epsilon_{i,t}$, where the $DependentVariable_{i,t}$ is investment-to-assets ($I/A$), realized future investment growth ($d^1 I/A$) and expected investment growth ($E[d^1 I/A]$). All predictive variables are winsorized at the 5% and 95% levels. The t-statistics are reported in parentheses with robust standard errors based on the two-way (firm and year) clustering method in Petersen (2009). The sample is annual from 1989 to 2018.

However, the possibility of selecting an inappropriate instrument can result in a biased estimation (JIANG, 2017).

Therefore, it is not easy to find (at least four) suitable instruments for my empirical model since my main variable of interest is the life-cycle stages. One solution for this problem is the multiple mismeasured regressor errors-in-variables model of Erickson and Whited (2002) and Erickson, Jiang and Whited (2014), which is a valuable solution when suitable instruments are not available (ERICKSON; PARHAM; WHITED, 2017; HASAN et al., 2021). Also the recent finance literature have been using this procedure to overcoming measurement error (JAVAKHADZE; RAJKOVIC, 2019; LYANDRES et al., 2019), specifically (HASAN et al., 2021) apply in an analysis of the relation between firm life cycle and trade credit. This method produce consistent estimation based on the original and the unaugmented set of observable variables.

Here I use fifth-order cumulants as instruments and treat four life-cycle stages as misspecified variables. The Table 2.6 presents the coefficients $\alpha_0$, $\alpha_1$, $\alpha_2$ and $\alpha_3$ for the same regression of 2.3, but here using the multiple mesmeasured regressor error-in-variables model of Erickson, Jiang and Whited (2014). The statistics reported is computed by using robust bootstrep standard errors, clustered at the firm level. Based on these results, the introduction and growth stages have, on average smaller expected investment growth. In all models the J-statistic for the test of overidentifying restrictions is quite large, which indicates a violation of one of the conditions where likely culprit being a regression error, $u_i$, that is independent of the regressors, $X_i$ and $Z_i$ (ERICKSON; PARHAM; WHITED, 2017). In other words, it is very likely that my initial empirical model is not well specified. Even so, the initial conclusions remain after the robust test accounting for the endogeneity problem.

Table 2.6 – Endogeneity test

| | $I/A_{i,t}$ | $I/A_{i,t+1}$ | $d^1I/A$ | | $E\left[d^1I/A\right]$ |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Constant | 0.011*** | 0.062*** | 0.076*** | 0.085*** | 0.014*** |
| | (7.137) | (22.144) | (18.616) | (17.724) | (7.710) |
| $D_i^{intro}$ | −0.212*** | −0.114*** | −0.103*** | −0.142*** | −0.048*** |
| | (−22.521) | (−15.278) | (−6.494) | (−6.09) | (−3.983) |
| $D_i^{growth}$ | 0.347*** | 0.047*** | −0.225*** | −0.220*** | −0.112*** |
| | (76.559) | (22.432) | (−45.572) | (−30.912) | (−30.557) |
| $D_i^{shadec}$ | −0.233*** | −0.086*** | 0.057*** | 0.054*** | 0.05*** |
| | (−39.357) | (−15.817) | (5.729) | (3.752) | (7.637) |
| Other controls | Yes | Yes | Yes | Yes | Yes |
| Firm effects | Yes | Yes | Yes | Yes | Yes |
| $N$ | 83,586 | 83,586 | 83,586 | 42,739 | 42,739 |
| *J statistic* | 2420.621 | 4736.769 | 6880.370 | 3337.358 | 1719.466 |

This table present the coefficients $\alpha_0$, $\alpha_1$, $\alpha_2$ and $\alpha_3$ for the following regression: $DependentVariable_{i,t} = \alpha_0 + \alpha_1 D_{i,t}^{intro} + \alpha_2 D_{i,t}^{growth} + \alpha_3 D_{i,t}^{shadec} + \Sigma\alpha X_{i,t} + \epsilon_{i,t}$, where the $DependentVariable_{i,t}$ is investment-to-assets ($I/A$), realized future investment growth ($d^1I/A$) and expected investment growth ($E[d^1I/A]$). The statistics are reported in parentheses with robust bootstrep standard errors clustered at the firm level as the multiple mesmeasured regressor error-in-variables model of Erickson, Jiang and Whited (2014). The sample is annual from 1989 to 2018.

## 3.3 Out-of-sample Analysis of Investment Growth and Life-Cycle Stages

In this subsection, I add Life-Cycle Proxies as predictor in the Elastic Net model to estimate the expected investment growth and conduct an out-of-sample analysis to understand if the life-cycle information are indeed useful to predict investment plans. By the $H_{1b}$, I expect that MSE of first model with only predictors based on investment literature is inferior to the new model which I add life-cycle proxies as predictors. The Panel A of Table 2.7 exhibit MSE of both model, their difference and t statistic as well. The t-statistics are computed using robust standard errors of Newey and West (1987).

Panel B of Table 2.7 presents a ranking of the importance of the variables in each model based on the average of the coefficients over all periods. The average of the coefficients of each variable estimated in each model over all periods is indicative of the importance of the variables, as the model optimizes the use of data in the training sample to achieve the best forecast in the validation sample and this procedure was performed recursively every year. The table shows that different types of proxies were relevant

Table 2.7 – MSE Evaluation

Panel A - MSE Evaluation

| $MSE_1$ | $MSE_2$ | $MSE_2 - MSE_1$ |
|---|---|---|
| 0.084 | 0.075 | 0.009 |
| | | (3.848) |

Panel B - High Predictive Variables in each model.

| | EIG with traditional predictors | | | EIG with Life-Cycle Proxies | |
|---|---|---|---|---|---|
| | variables | coefficients | | variables | coefficients |
| 1 | IGt0 | -0.22 | 1 | IGt0 | -0.13 |
| 2 | cop | 0.22 | 2 | Ret | 0.12 |
| 3 | SG | -0.15 | 3 | cop | 0.11 |
| 4 | Ret | 0.10 | 4 | dROE | 0.10 |
| 5 | Id | -0.09 | 5 | SG | -0.08 |
| 6 | dROE | 0.07 | 6 | $D_i^{growth}$ | -0.08 |
| 7 | CF | -0.03 | 7 | $LC^{MDA}$ | 0.05 |
| 8 | EG | 0.02 | 8 | Id | -0.04 |
| 9 | Ie | 0.01 | 9 | q | 0.04 |
| 10 | CFG | 0.01 | 10 | $D_i^{mature}$ | 0.03 |
| 11 | q | 0.01 | 11 | $D_i^{shadec}$ | 0.02 |
| 12 | PG | -0.00 | 12 | $LC^{reta}$ | -0.02 |
| | | | 13 | $D_i^{intro}$ | -0.02 |
| | | | 14 | Ie | 0.01 |
| | | | 15 | CFG | -0.00 |

in terms of out-of-sample forecasting, such as the dummy variables of Dickinson (2011) ($D_i^{intro}$, $D_i^{growth}$, $D_i^{mature}$ and $D_i^{shadec}$), the proxy based on the Faff et al. (2016) model ($LC^{MDA}$) and profit retention ($LC^{straight}$). Only age did not appear among the relevant variables.

## 3.4 Portfolio Sort

To the portfolio sort analysis I expect that EIG premium of growth firms are greater than EIG premium for mature firms ($H_{2a}$), which I test first in Table 2.8 and second in Table 2.9. I also expect that investor sentiment help to explain the EIG premium of growth firms (table 2.10). In Table 2.8, I analyse the expected investment growth premium controlled by the q-factor, columns (1), (2) and (3), and the augmented q-factor, columns (4), (5) and (6). In all models the $\alpha$ is significant, and the proeminent portfolio are the formed by mature firms. Which has higher investment growth on average.

The 2.10 table shows the expected investment growth premium results based on 10 minus 1 top deciles computed for each life cycle. In this analysis controlled by the Fama and French (2015) five factor. The empirical model shows that the expected growth premium persist across the life-cycle stages and is predominant in mature firms. The $\alpha$

Table 2.8 – EIG across the life-cycle stages and q-factor models

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | EIG | | | | | |
| | All | Growth | Mature | All | Growth | Mature |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\alpha$ | 1.836*** | 2.660*** | 1.570*** | 1.506*** | 2.143*** | 1.404*** |
| | (7.066) | (5.582) | (8.045) | (7.066) | (5.582) | (8.045) |
| $\beta_{Mkt}$ | −0.005 | 0.143*** | −0.007 | 0.041 | 0.217*** | 0.016 |
| | (0.819) | (3.427) | (0.262) | (0.819) | (3.427) | (0.262) |
| $\beta_{ME}$ | 0.105 | 0.206 | 0.212 | 0.143 | 0.266 | 0.231 |
| | (0.880) | (1.553) | (1.351) | (0.880) | (1.553) | (1.351) |
| $\beta_{I/A}$ | 0.361 | 0.014 | 0.187 | 0.283 | −0.109 | 0.148 |
| | (1.420) | (−0.392) | (1.044) | (1.420) | (−0.392) | (1.044) |
| $\beta_{Roe}$ | −0.102** | −0.174** | 0.118 | −0.268** | −0.434** | 0.035 |
| | (−2.470) | (−2.451) | (0.313) | (−2.470) | (−2.451) | (0.313) |
| $\beta_{EG}$ | | | | 0.508*** | 0.798*** | 0.255* |
| | | | | (3.763) | (3.889) | (1.786) |
| Observations | 528 | 528 | 528 | 528 | 528 | 528 |
| $R^2$ | 0.043 | 0.038 | 0.033 | 0.081 | 0.070 | 0.043 |
| Adjusted $R^2$ | 0.036 | 0.030 | 0.026 | 0.073 | 0.061 | 0.033 |

Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively. The t-statistics in parentheses are calculated based on heteroskedasticity-consistent standard errors of Newey and West (1987) with an automatic lag selection procedure of Newey and West (1994).

of the column (3) is 2.097 with a t-statistic of 8.164 while the growth firms shows an $\alpha$ of 2.493 with a t-statistic of 6.233. So, by this test is not possible to infer that growth firms shows greater premium as predicted by $H_{2b}$.

## 3.5 Expected Investment Growth and Investor Sentiment

The 2.10 table shows the expected investment growth premium results based on 10 minus 1 top deciles computed for each life cycle. I regress that premium with a model that contain the q-factor risk factors and an investor sentiment beta. The $H_{2b}$ predicts that due to the extrapolation of expectations, investor sentiment helps explain the premium when considering only companies in the growth stage. In column (1) that involves all firms, the $\beta_{Sent}$ is significant with a t statistic of 2,375, and as predicted by $H_{2b}$ it also appears as a singular in only column (2) with t statistics of 2,204 and not in column (3)

Table 2.9 – EIG across the life-cycle stages and Fama-French 5 factor model

| | *Dependent variable:* | | |
|---|---|---|---|
| | | EIG | |
| | All | Growth | Mature |
| | (1) | (2) | (3) |
| $\alpha$ | 1.934*** | 2.493*** | 2.097*** |
| | (6.444) | (6.233) | (8.164) |
| Mkt | 0.066 | 0.156 | 0.026 |
| | (1.010) | (1.632) | (0.351) |
| SMB | 0.244** | 0.079 | 0.307*** |
| | (2.057) | (0.422) | (2.675) |
| HML | −0.034 | 0.236 | −0.156 |
| | (−0.229) | (0.953) | (−1.135) |
| RMW | −0.089 | −0.155 | −0.190 |
| | (−0.414) | (−0.761) | (−0.936) |
| CMA | 0.561** | −0.183 | 0.420* |
| | (2.113) | (−0.474) | (1.831) |
| Observations | 528 | 528 | 528 |
| $R^2$ | 0.069 | 0.020 | 0.084 |
| Adjusted $R^2$ | 0.060 | 0.011 | 0.075 |

Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively. The t-statistics in parentheses are calculated based on heteroskedasticity-consistent standard errors of Newey and West (1987) with an automatic lag selection procedure of Newey and West (1994).

of only mature firms. Which implies that at least partially the premium for the EIG is explained by the behavioral factor. And mostly of the behavioral part of EIG premium is explained by the growth firms.

In the literature, there is some evidence that the return predictability of investment plans can also be explained by investor sentiment (LI; WANG; YU, 2020; JIANG et al., 2019), but none of them contemplate the firms life-cycle. Therefore, the empirical evidence of this work adds to the literature by showing that the portion of predictive power related to investor sentiment is mainly related to growth firms. Possibly this is because managers of firms in introductory stages are more likely to extrapolate their expectations (GENNAIOLI; MA; SHLEIFER, 2016). This assumptions also add to finds of Jiang et al. (2019). They documents that moments of optimism lead to overinvestment of current and planned investment, due to investment lags and managers' overly optimistic expectations about future performance.

Table 2.10 – EIG and Investor Sentiment Index

| | *Dependent variable: EIG Premium* | | |
|---|---|---|---|
| | | 10 - 1 deciles | |
| | All | Growth | Mature |
| | (1) | (2) | (3) |
| $\alpha$ | 1.486*** | 2.117*** | 1.403*** |
| | (7.027) | (5.412) | (7.997) |
| $\beta_{Sent}$ | 0.519** | 0.636** | 0.030 |
| | (2.375) | (2.204) | (0.130) |
| $\beta_{Mkt}$ | 0.044 | 0.220*** | 0.016 |
| | (0.890) | (3.469) | (0.262) |
| $\beta_{ME}$ | 0.149 | 0.273 | 0.231 |
| | (0.933) | (1.634) | (1.320) |
| $\beta_{I/A}$ | 0.265 | −0.131 | 0.147 |
| | (1.345) | (−0.475) | (0.981) |
| $\beta_{Roe}$ | −0.282*** | −0.452** | 0.034 |
| | (−2.598) | (−2.575) | (0.301) |
| $\beta_{EG}$ | 0.499*** | 0.787*** | 0.255* |
| | (3.759) | (3.811) | (1.805) |
| Observations | 528 | 528 | 528 |
| $R^2$ | 0.095 | 0.077 | 0.043 |
| Adjusted $R^2$ | 0.085 | 0.067 | 0.032 |

Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively. The t-statistics in parentheses are calculated based on heteroskedasticity-consistent standard errors of Newey and West (1987) with an automatic lag selection procedure of Newey and West (1994).

# 4 Conclusion

This study extends the knowledge about the expected investment growth premium. Previous studies find evidence that there is a strong relation between future stock returns and expected investment growth. However there is a little discussion about the drivers of investment growth premium. In the current study, I examine the impact of firm life-cycle dynamics on the observed association between expected investment growth and stock returns in the cross-section. I show that the expected investment growth premium is on average stronger in the growth stages than in mature stages.

I also document that the relation between investment plans and future return in growth firms is partially explained by investor sentiment. Which is consistent with the theoretical prediction that both rational and behavioral side explain the positive relation between expected investment growth and stock returns. The investment growth premium of both life-cycle is robust to the lead asset pricing models, such as the five factor model of Fama and French (2015) and the augmented q factor model of Hou et al. (2020).

Despite most of my theoretical predictions are not denied, this work presents empirical evidence against the assumptions of my $H_{1a}$, which is that non-mature firms have more aggressive investment plans because they have more growth opportunities. In opposite, the results show that mature (non-mature) firms have larger (smaller) investment plans, on average, that is considering both periods of investment and disinvestment. This evidence add new insights to the literature by showing that non-mature firms indeed have larger investment plans as my previous assumptions, however also have stronger disinvestment, which seems to be attributed to the not rational extrapolation expectation of managers (GENNAIOLI; MA; SHLEIFER, 2016), consequently, managers are forced to reverse bad investment projects in the future (disinvestment).

Empirical evidence that mature firms have larger investment plans gives two important implications for the literature. First, the difference between mature and non-mature firms shows that life-cycle stages are an important characteristic to predict future investment growth, both in- and out-of-sample. Moreover, it contributes to our knowledge with the indication that firms in the introductory stages of the lifecycle may be more susceptible to the extrapolative structure of expectations pointed by Gennaioli, Ma and Shleifer (2016).

# Chapter 3

# Mature Firms, Aggregate Investment Plans and Market Returns

## 1 Introduction

The future return of stock market and and the aggregate-level of investment plans has a negative relation, which is consistent with the argument of Lamont (2000) that investment plans change in response to the time-varying risk premium due to frictions of investment lags. There is recent evidences to corroborate that argument, Li, Wang and Yu (2020) documents the ability of aggregate investment plans to predict future market return, both in-sample and out-of-sample, even after controlling for other macroeconomic return predictors (such as Treasury bill rate, asset growth, and dividend yield).

However, most of the studies are based only on U.S. market data and none of them analyze in the context of firm life-cycle. So in this chapter, I add to the literature by analyzing how the aggregate investment plans, conditioned to different life-cycle stages, relates to future wide market returns using a global data. I also examine how the behavior bias explains the relation between the aggregate-level investment plan, conditioned to different life-cycle stages, and the future stock market return.

The contribution of this chapter is threefold. First, by analyzing global data instead of merely the U.S. market I try to expand knowledge about the evidence of the explanatory power of investment plans at the aggregate level. Second, by comparing emerging and developed markets, it is possible to understand whether explanatory power is stronger in more efficient markets. Third, I expand the analysis of Chapter 2 by testing how the relationship between market return and aggregate investment plans changes when considering only firms in each life cycle.

Therefore, this chapter is quite different from the previous one because I investigate how the expected investment growth on aggregate-level (instead of firm-level) explains market-wide return (instead of individual firms returns). In addition, I employ another approach in a different data-set (i.e., global stock data) to answer a new question, which is how the aggregate expected investment growth, conditioned to different life-cycle stages, relates to future market returns.

# 2 Related Literature and Hyphoteses Development

Three research streams are directly related to this chapter. The first relates to investment-based asset pricing. These studies focus on the supply side of asset pricing in a general equilibrium model. They are the theoretical background for the expected investment growth premium.

The second literature stream relates to marketing efficiency and the existence of mispricing. Although the broad body of literature in defense of market efficiency, some studies observe a certain degree of mispricing, which is the deviation of the asset price from its fundamental value. These researchs may help explain the EIG phenomenon since they cover discussion about the influence of investor sentiment and the lower price efficiency of less developed markets.

The third stream of research relates to the firms' life cycle concept, which predicts that firms evolve in a nonlinear manner by four groups: introduction, growth, mature and decline. This classification is related to corporate finance decision and asset pricing as well.

## Investment-based Asset Pricing and Expected Growth

Built on the Q-theory of investment and predict that expected (investment) growth are related to the cross-sectional stock returns in a different dimension no captured by the profitability and actual investment. Specifically, lags in the investment process (such as delays in planning, delivery, and construction) limit firms from immediately adjusting investment when the cost of capital changes, but orders (or investment plans) increase immediately (COCHRANE, 1991). Hence, in an aggregate level changes in the discount rate can cause a negative correlation between planned investment and the future market return (LAMONT, 2000). Liu, Whited and Zhang (2009) confirm the aggregate relation found by Lamont (2000).

In understanding these literature gaps about *expected* investment (or investment plan), it useful to discuss prior studies about *realized* investment (or asset growth). Cochrane (1991) was one of the first to examine an investment effect onexpected returns. He propose that firms with larger observed investment must be those with lower discount rates. So, these firms experience a negative subsequent stock return. Since then, a large body of empirical evidence also suggests that this negative effect is due to a rational explanation based on Q-theory (COCHRANE, 1996; CHEN; NOVY-MARX; ZHANG, 2011; HOU; XUE; ZHANG, 2015; LAM; WEI, 2011; LIN; ZHANG, 2013).

However, existing works provide contradicting evidence for this conjecture. For example, Baker and Wurgler (2002) suggest that managers, opportunistically, issue stocks when their value is high and buy stocks otherwise. Lakonishok, Shleifer and Vishny (1994) argue that when investor value firms, there is an overreaction about prior firm's asset growth. Both papers offer a behavior explanation for the asset growth effect.

In order to distinguish conflicting interpretations, Watanabe et al. (2013) and Titman, Wei and Xie (2013), extend the evidence to international data. Both works conclude that the effect is more likely due to the rational explanation of optimal investment effect. They also suggest that Q-theory prediction, that managers align investment to cost of capital, are more likely to occur in countries with developed market. In the Brazilian market, Machado and Faff (2018) find results in line with Watanabe et al. (2013).

Also based on investment Q-theory, the Expected Investment Growth (EIG) premium is driven by a neoclassical model that, when expanded over several periods, suggests that firms with larger investment plans should have a higher expected returns (HOU et al., 2020; LI; WANG, 2018). Empirically, testing the role of EIG has been a challenge since investment plans are not an observable variable. (HOU; XUE; ZHANG, 2018), for example, in doing an extensive empirical analysis of how the major pricing models explain the already documented anomalies, find some that remain unexplained, including 46 not captured by the q-factor model. q-anomalies).

In an earlier version (NBER working paper 23394, May 2017), the authors suggest that q-anomalies may not be explained by the q-factor model because it ignores the inclusion of an expected growth factor (EIG factor), and also mentions, that Hou, Xue and Zhang (2015) option not to include the EIG factor was due to concerns about the lack of reliable proxies for this variable.

Despite the empirical challenges, two recent studies attempt to predict EIG from financial variables, and in fact they find a premium that is not fully captured by major pricing models (HOU et al., 2020; LI; WANG, 2018). While recent empirical evidence demonstrates the importance of the EIG premium, on the other hand the low predictability of investment growth raises questions about currently used EIG measures (LIN; LIN, 2018). And in oppose to previous studies about aggregate investment plan, the firm-level investment plans predict positive stock returns in the cross section (HOU et al., 2020; LI; WANG, 2018).

In other words, firms with large investment plans have a higher expected returns than firms with small investment plans. One explanation for this inverse relation is that while the aggregate investment plans are mainly drive by the discount rate channel, the firm-level is due to cash flow channel since firms' investment decisions depend on their idiosyncratic productivity (LI; WANG, 2018; LI; WANG; YU, 2020). More generally, this finds corroborate with Vuolteenaho (2002), which decompose stock return in two channels, and find that cash flow news dominate the firm-level.

## Market Efficiency and Behavior Bias

The basic idea of market efficiency is related to the assumption that security price always reflects all available information, which is called "efficient market" (FAMA, 1970). The term market efficiency has essentially two meanings: one related to the impossibility of any investor to systematically beat the market with abnormal returns and another to rational price formation by agents (STATMAN, 1999). The concept of impossibility to beat the market suggests that market participants demand a higher return on riskier assets. In other words, a market is efficient if is impossible for investors to achieve average higher return without taking more risk (MALKIEL, 2003).

Observing extreme market efficiency is difficult, given the assumptions of unlimited rationality, homogeneous expectations, and the absence of transaction costs. In addition, the inference about market efficiency is further affected by what is called by the "joint-hypothesis problem", which refers to the fact that market efficiency cannot be tested in conjunction with a pricing model. Then, an abnormal return may not be evidence of market inefficiency but a failure of a pricing model (FAMA, 1991).

Given the joint-hypothesis problem, there are two possible approaches to explaining abnormal returns. The rational approach, in which anomalies are attributed to a premium that investors expected for risk taken, since an asset pricing model may omit a specific risk factor (FAMA; FRENCH, 2015; HOU; XUE; ZHANG, 2015), and the behavioral approach, where pricing errors resulting from irrational expectations result in abnormal returns (STAMBAUGH; YUAN, 2016; DANIEL; HIRSHLEIFER; SUN, 2018).

While the behavioral approach argues that asset price deviations from their core values are caused by the presence of investors who are not fully rational (BARBERIS; THALER, 2002), classical finance theories assume that, in competitive financial markets, any investors behaviors bias are quickly eliminated by arbitrageurs.

However, the crises in financial markets, commonly called bubbles, are attributed to poor pricing efficiency and suggest that investor sentiment may influence asset prices. In other words, speculative bubbles come from the influence of investor sentiment (SMIDT, 1968). Lee, Shleifer and Thaler (1991) define investor sentiment as the component of bond prices that comes from expectations about returns that are not justified by their fundamentals.

The study of sentiment is relevant because it is a variable that tends to be persistent over time, as optimism is reinforced as more people adhere to the trend (BROWN; CLIFF, 2004). And although the arbitrage can eliminate short-term lucrative strategies, it cannot correct long-term price deviations (BROWN; CLIFF, 2005).

The first empirical evidence on investor sentiment comes in the 1990s, such as Lee, Shleifer and Thaler (1991), who found a significant negative relationship between returns and the change in Closed end Fund Discounts (CEFD), which is a clear measure of the distortion between the prices considered by investors and the fundamental prices.

Baker and Wurgler (2006) examined the relationship between investor sentiment and the return on stocks classified according to their arbitrage difficulty (e.g. less liquid, volatile, non-dividend paying stocks) and consequently their susceptibility. to speculation. The authors demonstrated that after periods of low (high) investor sentiment, subsequent returns from the stock group studied were relatively high (low) (BAKER; WURGLER, 2007).

Globally, the investor sentiment may have some influence on the returns of six countries (Germany, Canada, the United States, France, Japan, and the United Kingdom), as well as on a global index. In addition, there is a negative and significant relationship between the country's sentiment index and future returns, and contrary to the global sentiment index (BAKER; WURGLER; YUAN, 2012).

Yu (2013) also makes a study among 15 countries, however, relating the sentiment index to the exchange rate, observing a positive and significant relationship between high internal sentiment and exchange rate growth. Stambaugh, Yu and Yuan (2012) have shown that some market anomalies reflect mispricing, which in turn is more frequent in periods when the market is bullish (high investor sentiment indices).

Theses anomalies mispricing generate a power asset pricing model based on anomalies (STAMBAUGH; YUAN, 2016). Jacobs (2016) apply this concept to analyse the market maturity and mispricing, they find that the source of mispricing studied appears to be at least as prevalent in developed markets as in emerging markets, which imply that some anomalies there is a other form of risk factor.

In the perspective of firm investment and stock return, the evidence are mixed. The actual level of investment seems to be rational since the asset growth effect are stronger in more developed countries (WATANABE et al., 2013; TITMAN; WEI; XIE, 2013). However the for the investment plans there are evidence for the influence of overoptimistic of manages (GENNAIOLI; MA; SHLEIFER, 2016; JIANG et al., 2019) and as well as the influence of the investor sentiment, at least partially (LI; WANG; YU, 2020).

## Life Cycle Theory and Growth Opportunities

The second stream is related to the life-cycle concept, which proposes that firms evolve and transition from one stage of development to another (PORTER, 2008). The theory identifies essentially four phases for a firm's life: introduction, growth, maturity, and decline (QUINN; CAMERON, 1983; SMITH; MITCHELL; SUMMER, 1985). Each of the stages is characterized by a predictable pattern followed by the firms, and these phases of development cannot be quickly reversed (MILLER; FRIESEN, 1984).

The earlier phases are identified by more operating risk and high value of assets, mainly from future growth opportunities. While it is observed that revenues grow rapidly, the earnings are prone to lag. As the firm evolve toward maturity, cash flows from operations and earnings gradually become positive. On the other hand, profitable investment opportunities decrease, the firm faces more competition, and the demand for the products begins to saturate. Consequently, the firm will experience lower growth rates (MUELLER, 1972).

In the decline stage firms typically experience falling in sales and earnings, and hence production capacity. Investments are likely to remain producing cash flows at a diminishing rate. The firm do not have so relevant need to make new investments and the value of the firm derives mostly from the historical cost of assets (HABIB; HASAN, 2018).

The accounting literature on firm's life cycle essentially concentrates on the implications of corporate life cycle phases for the relevance and quality of financial and management accounting information. On the other hand, studies in the finance literature are interested how life cycle influences corporate policies like decisions of investment, financing and dividend policies as well as how the life cycle affects asset pricing (HABIB; HASAN, 2018).

In the literature accounting, Jenkins, Kane and Velury (2004) investigates the value-relevance of changes in operating, financing, and investing cash flows by life-cycle phases and find that investing cash flows is more value-relevant when firms are in the growth stage. Anthony and Ramesh (1992) show that market response to unexpected capital investment and unexpected sales growth decline as the firm matures. Dickinson (2011) provide a classification based on cash flow patters and show that investors do not fully incorporate information contained in firms life cycle. Lastly, Vorst and Yohn (2018), find that life cycle models improve the forecast accuracy of both earnings' growth and profitability forecasts, outperforming the benchmark models in forecasting a variety of profitability and growth measures both in the short- and the long-term.

In finance, Xu (2007) investigate risk factors and estimating expected rates of return interpreting according to life cycle stages and shows that capital markets incorporate information about firm life cycle stages. Da, Jagannathan and Shen (2013) provide support that firms in the same life cycle stage exhibit different stock return conditional on investors' optimism about sales growth. Hribar and Yehuda (2015) find that accruals and cash flow capture different information in the growth stage of the firm's life cycle and correlated information in the maturity and decline stages, suggesting that cash flows anomaly subsumes the accruals anomaly in the later stages. Chincarini, Kim and Moneta (2016) show that firm age (a proxy for corporate life cycle) is closely linked to the cost of equity capital and it captures the time-varying in systematic risk (beta).

Finally, Faff et al. (2016) show that corporate policies, in general, follow a predictable pattern that is independent of the preferences of corporate managers and other firm characteristics. Specifically, they find that cash holdings increase in the earlier stages and decrease in the later stages and the investments and equity issuance decline with firm life cycle evolve.

## Testable Hypotheses

The firm-level investment plans predict positively return trough the cash flow news channel (VUOLTEENAHO, 2002; LI; WANG, 2018). In contrast, the aggregate level of investment plans predict negatively return trough the discount rate channel (LAMONT, 2000; LIU; WHITED; ZHANG, 2009). If this is the case, I have the support to our third hypothesis that in aggregate level mature firms play a crucial role in the ability of investment plans to predict future returns. Then, I propose the following hypotheses:

$H_1$: Due to the greater exposition of mature firms to the discount rate channel, a bottom-up measure of aggregate investment plans based on mature firms has stronger predictive ability than based on growth firms.

The ability of aggregate investment plans to predicts stock returns can also be explained by a behavioral bias. When the investors overvalue the stock market due to being overly confident about the economy, managers tend to follow this optimism and as a result, investment plans initiated exceed the rationality. Then when investors recognize their previous expectation errors, they correct this mispricing (LI; WANG; YU, 2020; JIANG et al., 2019). Li, Wang and Yu (2020) studied the aggregate investment plans on the U.S. market and they have ruled out neither rational nor behavioral explanation. Therefore, I use the assumption of price efficiency to test the role of mispricing at investment plans, since the developed markets seem to have a more efficient market (BAI; PHILIPPON; SAVOV, 2016; TITMAN; WEI; XIE, 2013; JACOBS, 2016). So, I propose the following hypothesis:

$H_2$: In a cross-country analysis, the investment plans' ability to predict return increase with market development.

# 3 Methodology

In this section, I present the procedures to analyze, from the perspective of firms' life cycle how the aggregate investment plans based on mature firms differ from the growth of mature firms. To test the hypothesis that a bottom-up measure of aggregate investment plans based on mature firms has stronger predictive ability than based on growth firms, I follow three steps. First, I use a similar approach of Li, Wang and Yu (2018) to construct my benchmark: the aggregate measure of investment plans (AEIG-B), defined as the monthly value-weighted average of my firm-level measure of investment plans ($EIG$). Second, I follow the same approach to construct two other aggregate measures, on of them based on growth firms (AEIG-G) and another one on mature firms (AEIG-M). Lastly, I analyze how this tree measure can predict the future aggregate stock return both in-sample and out-of-sample across global stock market.

## 3.1 Data and Sample

For the cross-country analysis, both financial and accounting data are obtained from databases provided by Thomson Reuters, with the exception of the U.S. sample, which comes from the CRSP and COMPUSTAT . The international monthly stock data are from the Thomson Reuters Datastream, and accounting data are from the Worldscope database. The analyzed period varies from country to country and depends on data availability. The Table 3.1 present the periods analyzed for each country, most of then has a range from 1997 to 2019 due to data availability.

Table 3.1 – Period of each country

| nation | Period |
|---|---|
| AUSTRALIA | 1997 - 2019 |
| BELGIUM | 1997 - 2019 |
| BRAZIL | 2002 - 2019 |
| CANADA | 1997 - 2019 |

*Continued*

Table 3.1 continued from previous page

| | Period |
|---|---|
| CHILE | 1999 - 2019 |
| CHINA | 1997 - 2019 |
| DENMARK | 1997 - 2019 |
| EGYPT | 2002 - 2019 |
| FINLAND | 1997 - 2019 |
| FRANCE | 1997 - 2019 |
| GERMANY | 1997 - 2019 |
| GREECE | 2001 - 2019 |
| HONG KONG | 1997 - 2019 |
| INDIA | 1998 - 2019 |
| INDONESIA | 1997 - 2019 |
| IRELAND | 1997 - 2019 |
| ISRAEL | 1997 - 2019 |
| ITALY | 1997 - 2019 |
| JAPAN | 1997 - 2019 |
| KOREA (SOUTH) | 1998 - 2019 |
| MALAYSIA | 1997 - 2019 |
| MEXICO | 1997 - 2019 |
| NETHERLANDS | 1997 - 2019 |
| NEW ZEALAND | 1997 - 2019 |
| NORWAY | 1997 - 2019 |
| PAKISTAN | 1997 - 2019 |
| PHILIPPINES | 1998 - 2019 |
| POLAND | 1998 - 2019 |
| RUSSIA | 2001 - 2019 |
| SAUDI ARABIA | 2007 - 2019 |
| SINGAPORE | 1997 - 2019 |
| SOUTH AFRICA | 1997 - 2019 |
| SPAIN | 2003 - 2019 |
| SRI LANKA | 1998 - 2019 |
| SWEDEN | 1997 - 2019 |
| SWITZERLAND | 1997 - 2019 |
| TAIWAN | 1998 - 2019 |
| THAILAND | 1997 - 2019 |
| TURKEY | 1997 - 2019 |
| UNITED KINGDOM | 1997 - 2019 |
| VIETNAM | 2011 - 2019 |

The Table 3.2 present the correlation between the official Ibovespa Brazilian index and two measure from my sample data, the Aggregate Investment Growth and the Brazilian wide market return, which is computed as value-weighted return of all Brazilian stocks in the sample. Both wide market return has negative correlation with AEIG (-0.20), and a strong positive correlation between them (0.80). This correlation is the analysis of only one country, and despite being an indication that the data converge to the real, it cannot be extrapolated to other countries.

Table 3.2 – Correlation between my data and official Ibovespa Brazilian Index

| | $AEIG^{Brazil}$ | $MKT^{ibovespa}$ | $MKT^{calculated}$ |
|---|---|---|---|
| $AEIG^{Brazil}$ | 1 | | |
| $MKT^{ibovespa}$ | -0.12* | 1 | |
| $MKT^{calculated}$ | -0.20*** | 0.83*** | 1 |

The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

## 3.2 Construction of Aggregate Expected Investment Growth

The aggregate expected investment growth (AEIG) is a bottom-up measure from firm-level expected investment growth (EIG). So, to build AIEG I follow three steps as Li, Wang and Yu (2020). First, I estimate the parameters of the Equation 1 by the cross-sectional step of Fama and MacBeth (1973) procedure.

$$E_{i,t}[IG_{LW}] = b_{0,t} + b_{MOM,t}MOM_{i,t-1} + b_{q,t}Q_{i,t-1} + b_{CF,t}CF_{i,t-1} + \epsilon_{i,t} \tag{1}$$

where:

$E_{i,t}[IG]$ = the growth rate of investment expenditure in the fiscal year ending in calendar year $t$ ($IG = log(CAPEX_{i,t}/CAPEX_{i,t-1})$);

$MOM_{i,t-1}$ = the momentum cumulative stock returns over the past 12 months skipping one month before the end of last fiscal year;

$Q_{i,t-1}$ = the log of the market value of the firm divided by total assets in the fiscal year ending in calendar year $t-1$;

$CF_{i,t-1}$ = is the operating cash flow in the fiscal year ending in calendar year $t-1$ divided by lag total assets.

Second, compute the monthly EIG as the out-of-sample predicted the firm-level expected investment growth using the most up-to-date momentum, q and CF for each firm with the historical average of the cross-sectional regression coefficients $(b_{0,t}, b_{MOM,t}, b_{q,t}, b_{CF,t})$ estimated using all data up to year t. In the third and last step I compute aggregate expected investment growth (AEIG) as value-weighted average of the firm-level expected investment growth (EIG) estimated in the previous step.

The $MOM$ (momentum) prior 2 to 12-month cumulative stock returns is align to the account data ($Q$ and $CF$) following the standard Fama and French (1993) timing.

To reduce the impact of microcaps, the regression bellow is estimated by using weighted least squares with the market equity as the weights. Both the left- and right-hand side variables are winsorized each month at the 1% and 99% level.

Table 3.3 – Descriptive Statistics

| Panel A - Mean and Standard Deviation by Aggregate Investment Growth | | | | | | |
|---|---|---|---|---|---|---|
| | Mean | | | Standard Deviation | | |
| | All | Mature | Growth | All | Mature | Growth |
| Developed Markets | 0.0167 | 0.0198 | 0.0175 | 0.228 | 0.224 | 0.235 |
| Emerging Markets | 0.0249 | 0.0294 | 0.0106 | 0.690 | 0.582 | 0.839 |
| All Markets | 0.0201 | 0.0237 | 0.0137 | 0.480 | 0.408 | 0.587 |

For more details about variable definitions, see Appendix A.

## 3.3 Empirical Model

To test $H_1$ and $H_2$, I examine the role of the life cycle in stock return predictability through the discount rate channel of investment plans. So, I estimate to each measure a univariate time-series predictive regression of future cumulative market returns onto the aggregate investment plans and a multivariate predictive regression with several control variables. In order to do this, I run the follow econometric model showed at Equation 2. All the t-statistic are estimated by using Newey and West (1987) standard errors.

$$R_{t,t+1} = \alpha_t + \alpha_1[AEIG]_{i,y} + \sum \alpha X_{i,t} + \varepsilon_{i,t} \tag{2}$$

where:

$R_{t+1,t+h}$ = is the country i future cumulative market returns over h = 1, 6 and 12 months following month t;

$[AEIG]_{i,y}$ = is the y measure of aggregate expected investment plans for country i, where $[\text{AEIG}]_y \in$[AEIG-B, AEIG-G, AEIG-M];

$\sum \alpha X_{i,t}$ = are the control variables for the country i. See the appendix E for detailed description of the control variables.

To better understand how the life cycle firms has different information about future return I conduct an out-of-sample analysis understand the difference between two type of life cycle stages and the relation I estimate the abilities of AEIG-G versus AEIG-M to predict out-of-sample aggregate stock returns and compete with the benchmark measure

AEIG-B. The performance of each one is computed by out-of-sample R2 as used in session 2.4.

The $H_1$ are tested by competing the three measures, while $H_2$ are tested competing the performance of this measures in development and non devolopment countries.

# 4 Empirical Results

In this section, I analyze the ability to predict the market return by three measures of aggregate expected investment growth: one based on all firms of the sample, the other based only on mature firms, and the last one based on no mature firms. Initially, I analyze the difference between the two conditioned measures (mature and non-mature (growth)), and then I analyze how the relation between market return and aggregate expected investment growth occurs in emerging and developed markets.

## 4.1 The role of life-cycle stage on AEIG

The firm-level investment plans predict positively return trough the cash flow news channel (VUOLTEENAHO, 2002; LI; WANG, 2018). In contrast, the aggregate level of investment plans predict negatively return trough the discount rate channel (LAMONT, 2000; LIU; WHITED; ZHANG, 2009). If this is the case, I have the support to our third hypothesis that in aggregate level mature firms play a crucial role in the ability of investment plans to predict future returns.

For this analysis, each year I classified the firms as growth or mature, and from there I built a measure of aggregate expected investment growth (AEIG) based on growth firms and mature firms as well. Then I compute each relation between wide market return and each measure of AEIG. By my theoretical framework, I hope AEIG based on mature firms are a powerful predictor than AEIG based on growth firms.

Table 3.4 presents how the aggregate expected investment growth conditioned to each life cycle predicts the market return for the next month. The main results shows that there is no clear difference between the predictability of the AEIGm and AEIGg, in other words, theres is no evidence that mature firms dominate the predictability power of the aggregate expected investment. The relation between lifecycle conditioned AEIG measures and stock return is more common when considering the 12-month cumulative return and more proeminent in emerging markets. However this results are insufficient to make conclusions about the $H3_a$.

Table 3.4 – The role of life-cycle stage on AEIG

| Emerging Markets | $h = 1$ | $h = 3$ | $h = 6$ | $h = 12$ | Total |
|---|---|---|---|---|---|
| Growth ($AEIGg$) | 2 | 7 | 13 | 15 | 20 |
| Mature ($AEIGm$) | 1 | 5 | 10 | 12 | 20 |
| **Developed Markets** | $h = 1$ | $h = 3$ | $h = 6$ | $h = 12$ | Total |
| Growth ($AEIGg$) | 0 | 2 | 5 | 7 | 21 |
| Mature ($AEIGm$) | 0 | 2 | 6 | 7 | 21 |
| **All Markets** | $h = 1$ | $h = 3$ | $h = 6$ | $h = 12$ | Total |
| Growth ($AEIGg$) | 2 | 9 | 18 | 22 | 41 |
| Mature ($AEIGm$) | 1 | 7 | 16 | 19 | 41 |

This table presents, for each group of countries, the number of regressions with significant coefficients $b_t$ (at level of 5%) in the regression $R_{t,t+1} = a_t + b_t[AEIG]_y + \varepsilon_{i,t}$ where $R_{t+1,t+h}$ is the future cumulative market returns of the country over h = 1, 6 and 12 months following month t; $[AEIG]_y$ is the y measure of aggregate expected investment plans of the country, where $[\text{AEIG}]_y \in$[AEIG-G, AEIG-M]. The column Growth presents estimates for AEIG-G, which is a measure that aggregates EIG of all growth firms of the market. The column Mature presents estimates for AEIG-M, which is a measure that aggregates EIG of all mature firms of the market. All the t-statistic are estimated by using Newey and West (1987) standard errors. For a detailed results see Appendix C.

## 4.2 Difference between Emerging Markets and Developed Markets

The ability of aggregate investment plans to predicts stock returns can also be explained by a behavioral bias. When the investors overvalue the stock market due to being overly confident about the economy, managers tend to follow this optimism and as a result, investment plans initiated exceed the rationality. Then when investors recognize their previous expectation errors, they correct this mispricing (LI; WANG; YU, 2020; JIANG et al., 2019). Li, Wang and Yu (2020) studied the aggregate investment plans on the U.S. market and they have ruled out neither rational nor behavioral explanation. Therefore, I use the assumption of price efficiency to test the role of mispricing at investment plans, since the developed markets seem to have a more efficient market (BAI; PHILIPPON; SAVOV, 2016; TITMAN; WEI; XIE, 2013; JACOBS, 2016).

Table 3.5 presents how the aggregate expected investment growth (this one based on all firms) predicts the market return for the next month on emerging and expected economy. By my theoretical argument, I hope that in developed economies the power is strong. However, the predictability in emerging markets seems to be more common, especially on the accumulated returns for the next three and six months. In the cumulative return on the next 12 months, the difference between emerging and developed markets is

Table 3.5 – DM versus EM, Number of significant results

| | $h = 1$ | $h = 3$ | $h = 6$ | $h = 12$ | Total |
|---|---|---|---|---|---|
| Developed Markets | 1 | 3 | 4 | 5 | 20 |
| Emerging Markets | 2 | 10 | 9 | 15 | 21 |

This table presents, for each group of countries, the number of regressions with significant coefficients $b_t$ (at level of 5%) in the regression $R_{t,t+1} = a_t + b_t AEIG_t + \varepsilon_{i,t}$ where $R_{t+1,t+h}$ is the future cumulative market returns of the country over h = 1, 6 and 12 months following month t; $AEIG_t$ is the measure of aggregate expected investment growth of all firms in the market as Li, Wang and Yu (2020). All the t-statistic are estimated by using Newey and West (1987) standard errors. For a detailed results see Appendix D.

larger, since in emerging markets 15 countries of 21 shows strong predictability significant at level of 5% while in develop economies, only 5 countries of 20 shows similar results. In sum, emerging countries show a greater number of economies with statistically significant results, which indicates that the behavioral factor maybe is the main driver of AEIG predictability. This result can lead to new insights into the work of Li, Wang and Yu (2020), which study only U.S. market and argue that the driver of AEIG seems to be both rational and behavioral.

I also estimate a multivariate predictive regression of future cumulative market returns onto the aggregate investment plans controlled by others well-known predictors of the market return (i.e. Dividend Yield, Investment-to-capital, Inflation and Interest Rate). The results are quite similar and my conclusion remain even controlled by this predictors. For a detailed results see Appendix E.

# 5 Conclusion

In this chapter, I expand the empirical evidence about expected investment growth. Despite Li, Wang and Yu (2020) documents strong relation of aggregate stock returns on U.S., lacks evidence in other countries. In this sense, the question arises whether the effect is seen in other countries and what is the role of rational and behavioral in explaining the relationship between AEIG and the future return of the stock market.

I show that in a cross-country analysis the investment plans' ability to predict wide market return is higher in emerging than in develop countries, which indicates that the strong relationship may be much more driven by behavioral determinants than rational ones. I also construct two measures of aggregate investment plans, one based on mature firms and another based on introductory firms, than I document a stronger predictive ability for the measure conditioned to growth firms, probably, this occur due to the greater exposition of non-mature firms to the growth opportunities and, therefore, they are more likely to be influenced by extrapolation of expectations. However, there is no big difference between the two life cycles, then there is no clear evidence to support my assumptions about the greater power of mature firms.

By my theoretical formulation, firms in earlier stages has a high degree of idiosyncratic growth opportunities (GRULLON; MICHAELY; SWAMINATHAN, 2002), so the investment plans in mature firms is more susceptible to the time varying interest rate. In sum, the mature firms are more compatible with the discount rate channel interpretation (LAMONT, 2000). In opposite, the empirical results shows that the non-mature firms and their growth opportunities seems to have a crucial role to predict future stock returns, especially in emerging markets. This finds is similar to the study of Hirshleifer, Hou and Teoh (2009). They explore relation between stock returns and both accruals and cash flow. The authors find evidence consistent with both behavior bias and market efficiency explanation, this last one related to the discount rate channel.

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# Appendix

# APPENDIX A

# Variable Descriptions

## 1 Variables in Chapter 1

### 1.1 Predicted Variable

- $IG$: My main measure of investment growth, computed as Hou et al. (2020), which define investment growth as investment-to-assets change ($IG_{i,t} = I/A_{i,t+h} - I/A_{i,t}$).
  - Investment-to-assets ($I/A$) is measured as Cooper, Gulen and Schill (2008) and Hou, Xue and Zhang (2015), as total assets change (Compustat annual data item AT for the fiscal year end ing year t minus total assets of t-1) divided by total assets for the fiscal year in t-2 minus 1.
- $IG_{LW}$: Investment growth measure of Li and Wang (2018), defined as growth rate of investment expenditure in the fiscal year ending in calendar year t ($IG_{i,t} = log(CAPEX_{i,t}/CAPEX_{i,t-1})$. CAPEX is the Compustat annual item CAPX.
- $IG_{GHL}$: Investment growth measure of Gennaioli, Ma and Shleifer (2016), defined as growth rate of investment-to-capital ($IG_{i,t} = log([1 + I_{i,t}/K_{i,t}]/[1 + (I_{i,t-1}/K_{i,t-1})])$.

### 1.2 Standard Predictors

- AT: Is the log of total assets (Compustat annual item AT).
- CFG is defined as the change in cash flow (Compustat data items NI+DP) divided by capital (Compustat data item PPEGT) (LI, WANG, YU, 2020).
- dRoe: change in return on equity over the past four quarters. (. . . ) The change in return on equity, dRoe, is Roe minus the 4-quarter-lagged Roe. Roe is income before extraordinary items (Compustat quarterly item IBQ) scaled by 1-quarter-lagged

book equity. We compute dRoe with earnings from the most recent announcement dates (item RDQ), and if not available, from the fiscal quarter ending at least four months ago (Hou, Xue, and Zhang, 2019). Finally, missing dRoe values are set to zero in the cross-sectional forecasting regressions.

- cop: is a measure of operating cash flows. At the beginning of each month t, we measure current Cop as total revenue (Compustat annual item REVT) minus cost of goods sold (item COGS), minus selling, general and administrative expenses (item XSGA), plus research and development expenditures (item XRD, zero if missing), minus change in accounts receivable (item RECT), minus change in inventory item INVT), minus change in prepaid expenses (item XPP), plus change in deferred revenue (item DRC plus item DRLS), plus change in trade accounts payable (item AP), and plus change in accrued expenses (item XACC), scaled by book assets, all from the fiscal year ending at least four months ago. Missing annual changes are set to zero.

- q: Tobin‘s q measure as Kaplan and Zingales (1997) computed as market equity (CRSP price per share times the number of shares outstanding) plus long-term debt (Compustat item DLTT) and short-term debt (DLC), all scaled by books assets (Compustat annual item AT). I do that each month using the most recent fiscal year ending at least four months ago. For firms with multiple share classes, I merge the market equity of each class.

- Ret: as in Li, Wang and Yu (2020), is the prior 12-month cumulative returns.

# 2 Variables in Chapter 2

## 2.1 Dependent Variables

- $I/A$: investment-to-assets measure as Cooper, Gulen and Schill (2008) and Hou, Xue and Zhang (2015). Is defined as total assets (Compustat annual data item AT) for the fiscal year ending year t-1 divided by total assets for the fiscal year in t-2 minus 1.

- $d^{\tau}I/A$: Is defined as change in investment to assets from most recent $I/A$ to $I/A_{t+\tau}$.

- E[$d^{\tau}I/A$]: Is defined as the expected investment growth by using a specific approach to predict $d^{\tau}I/A$.

## 2.2 Proxies for Life-Cycle Stages

- RETA: Retained earnings (Compustat item RE) divided by total assets (Compustat item AT).
- AdjAge: CRSP firm age adjusted by industry and size.

## 2.3 Other Variables

- AT: Is the log of total assets (Compustat annual item AT).
- CFG is defined as the change in cash flow (Compustat data items NI+DP) divided by capital (Compustat data item PPEGT) (LI, WANG, YU, 2020).
- dRoe: change in return on equity over the past four quarters. (...) The change in return on equity, dRoe, is Roe minus the 4-quarter-lagged Roe. Roe is income before extraordinary items (Compustat quarterly item IBQ) scaled by 1-quarter-lagged book equity. We compute dRoe with earnings from the most recent announcement dates (item RDQ), and if not available, from the fiscal quarter ending at least four months ago (Hou, Xue, and Zhang, 2019). Finally, missing dRoe values are set to zero in the cross-sectional forecasting regressions.
- cop: is a measure of operating cash flows. At the beginning of each month t, we measure current Cop as total revenue (Compustat annual item REVT) minus cost of goods sold (item COGS), minus selling, general and administrative expenses (item XSGA), plus research and development expenditures (item XRD, zero if missing), minus change in accounts receivable (item RECT), minus change in inventory item INVT), minus change in prepaid expenses (item XPP), plus change in deferred revenue (item DRC plus item DRLS), plus change in trade accounts payable (item AP), and plus change in accrued expenses (item XACC), scaled by book assets, all from the fiscal year ending at least four months ago. Missing annual changes are set to zero.
- EG is defined as the change in earnings (Compustat data item IB) divided by capital (Compustar data item PPEGT) (LI, WANG, YU, 2020).
- Ie is equal to 1 if a firm increase its equity by more than 5% and 0 otherwise. New shares issues is defined as the sale of common and preferred stock (Compustat data tiem SSTK) divided by lag market equity after 1971, and the growth rate of the split-adjusted shares (Compustat data items CSHO x AJEX) before 1971 due to the data availability of SSTK (LI, WANG, YU, 2020).

- Id is equal to 1 if a firm increases its total debt by more than 10% and 0 otherwise. New debt issues is the change in total debt (Compustat data items DLTT+DLC) divided by lagged debt (LI, WANG, YU, 2020).
- Leverage: Total debt/Total equity (FAFF et al., 2016)
- PG is defined as the change in profitability (Compustat data items EBITDA-(XINT-IDIT)-(TXT-TXDC)) divided by capital.
- Ret: as in Li, Wang and Yu (2020), is the prior 12-month cumulative returns.
- Sales: Compustat item Sale / Total assets (Compustat annual item AT).
- SG is the log growth rate of sales (Compustat data item Sale) (LI, WANG, YU, 2020).

# 3 Variables in Chapter 3

## 3.1 Variables to Classify the Life-Cycle Stage

- $CFF$: is the net financing cash flow (Thomson Reuters Worldscope item 4890).
- $CFI$: is the net investment cash flow (Thomson Reuters Worldscope item 4870).
- $CFO$: is the net operational cash flow (Thomson Reuters Worldscope item 4860).

## 3.2 Variables to Estimate the Predictive Model of Expected Investment Growth (EIG)

### 3.2.1 Predicted Variable in the EIG model

- $IG_{LW}$: Investment growth measure of Li and Wang (2018), defined as growth rate of investment expenditure in the fiscal year ending in calendar year t ($IG_{i,t} = log(CAPEX_{i,t}/CAPEX_{i,t-1})$. CAPEX is the Thomson Reuters Worldscope item 4601.

### 3.2.2 Predictors used in the EIG model

- $ROE$: is the total percentage of return on equity (Thomson Reuters Worldscope item 8301).

- $Q$: is Q de tobin computed by Enterprise Value (Thomson Reuters Worldscope item 18100) divided by Total Asset (Thomson Reuters Worldscope item 7230)
- $CF$: is the net operational cash flow (Thomson Reuters Worldscope item 4860).

## 3.3 Variables used in the Time-series Regression Analysis

### 3.3.1 Dependent Variable of the Regression Analysis

- $R_{t,t+1}$: is the country wide market future cumulative returns over h=1, 6 and 12 months following month t.

### 3.3.2 Independent Variable of the Regression Analysis

- $AEIG$: is the y measure of aggregate expected investment plans for country i, where $[\text{AEIG}]_y \in$[AEIG-B, AEIG-G, AEIG-M].

### 3.3.3 Control Variables of the Regression Analysis

- $DY$: Dividend Yield (Thomson Reuters Worldscope item 9404)
- $I/K$: Capital Expenditures (Thomson Reuters Worldscope item 4601) divided by equity (Thomson Reuters Worldscope item 7220)
- $Interest$: Interest Rate available on the World Bank Data (Item FR.INR.DPST). Some high-income countries do not provide this data to World Bank, so I gather from FRED Economic Data of Federal Reserve Bank of St. Louis
- $Inflation$: Inflation Rate available on the World Bank Data (Item FP.CPI.TOTL.ZG). Some high-income countries do not provide this data to World Bank, so I gather from FRED Economic Data of Federal Reserve Bank of St. Louis

## 3.4 Others itens used as filter or to compute some variables

- $CAPEX$ is the capital expenditures (Thomson Reuters Worldscope item 4601).
- $SG$ is the net sales/revenues growth computed by Thomson Reuters Worldscope (item 8631).
- $AG$ is the total asset growth computed by Thomson Reuters Worldscope (item 8621).

- $AT$ is the total assets in U.S.$ (Thomson Reuters Worldscope item 7230).
- $MV$ is the market capitalization in U.S.$ (Thomson Reuters Worldscope item 7210).

# APPENDIX B

# High Predictive Words by Industry

Table B.1 – High Predictive Words for All Industries

| 101010 | Energy Equipment & Services | coeff |
|---|---|---|
| 1 | candidates | 0,32 |
| 2 | earning | 0,201 |
| 3 | q | 0,099 |
| 4 | mortgages | 0,063 |
| 5 | qualified | 0,061 |
| 6 | electronic | 0,048 |
| 7 | underwriting | 0,041 |
| 8 | asbestos | 0,036 |
| 9 | attract | 0,034 |
| 10 | approval | 0,03 |
| 1 | occupancy | -0,462 |
| 2 | file | -0,462 |
| 3 | exercised | -0,141 |
| 4 | inclusion | -0,102 |
| 5 | opened | -0,088 |
| 6 | ending | -0,084 |
| 7 | royalty | -0,079 |
| 8 | patent | -0,078 |
| 9 | accident | -0,058 |
| 10 | positions | -0,05 |
| 101020 | Oil, Gas & Consumable Fuels | coeff |
| 1 | tejas | 0,492 |
| 2 | dac | 0,353 |
| 3 | redevelopment | 0,223 |
| 4 | q | 0,116 |
| 5 | apartment | 0,076 |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 6 | test | 0,069 |
| 7 | wireless | 0,069 |
| 8 | telephone | 0,066 |
| 9 | brands | 0,061 |
| 10 | milestone | 0,051 |
| 1 | programming | -0,171 |
| 2 | code | -0,154 |
| 3 | portfolios | -0,143 |
| 4 | upfront | -0,139 |
| 5 | tobacco | -0,121 |
| 6 | earning | -0,105 |
| 7 | opening | -0,095 |
| 8 | devices | -0,088 |
| 9 | ready | -0,084 |
| 10 | invested | -0,081 |
| 151010 | Chemicals | coeff |
| 1 | collaborative | 0,517 |
| 2 | carolina | 0,21 |
| 3 | shall | 0,204 |
| 4 | impaired | 0,198 |
| 5 | coal | 0,116 |
| 6 | downturn | 0,105 |
| 7 | nuclear | 0,104 |
| 8 | mills | 0,1 |
| 9 | wells | 0,068 |
| 10 | protect | 0,064 |
| 1 | bankruptcy | -1,057 |
| 2 | depends | -0,268 |
| 3 | underwriting | -0,182 |
| 4 | training | -0,16 |
| 5 | contributions | -0,123 |
| 6 | herein | -0,115 |
| 7 | q | -0,099 |
| 8 | code | -0,093 |
| 9 | patents | -0,09 |
| 10 | lenders | -0,085 |
| 151030 | Containers & Packaging | coeff |
| 1 | training | 0,188 |
| 2 | entertainment | 0,085 |
| 3 | audit | 0,074 |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 4 | investing | 0,068 |
| 5 | director | 0,044 |
| 6 | radio | 0,035 |
| 7 | texas | 0,032 |
| 8 | certificates | 0,031 |
| 9 | increasing | 0,03 |
| 10 | wisconsin | 0,029 |
| 1 | opened | -0,291 |
| 2 | observable | -0,215 |
| 3 | week | -0,167 |
| 4 | apb | -0,129 |
| 5 | q | -0,086 |
| 6 | membership | -0,052 |
| 7 | expectations | -0,048 |
| 8 | retained | -0,048 |
| 9 | basic | -0,045 |
| 10 | storage | -0,043 |
| **151040** | **Metals & Mining** | **coeff** |
| 1 | certificates | 0,257 |
| 2 | commitment | 0,163 |
| 3 | barrel | 0,153 |
| 4 | relationships | 0,076 |
| 5 | trials | 0,069 |
| 6 | action | 0,055 |
| 7 | education | 0,037 |
| 8 | q | 0,034 |
| 9 | reflecting | 0,03 |
| 10 | proved | 0,03 |
| 1 | guaranty | -0,158 |
| 2 | principles | -0,136 |
| 3 | defined | -0,078 |
| 4 | partnerships | -0,057 |
| 5 | weeks | -0,057 |
| 6 | gathering | -0,049 |
| 7 | managements | -0,043 |
| 8 | online | -0,037 |
| 9 | developing | -0,036 |
| 10 | exit | -0,031 |
| **151050** | **Paper & Forest Products** | **coeff** |
| 1 | ending | 0,333 |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 2 | security | 0,049 |
| 3 | reimbursement | 0,044 |
| 4 | city | 0,04 |
| 5 | forth | 0,035 |
| 6 | electronic | 0,029 |
| 7 | storage | 0,022 |
| 8 | herein | 0,022 |
| 9 | title | 0,019 |
| 10 | media | 0,018 |
| 1 | japan | -0,584 |
| 2 | clients | -0,146 |
| 3 | illinois | -0,087 |
| 4 | trial | -0,083 |
| 5 | wells | -0,072 |
| 6 | disposition | -0,072 |
| 7 | regulation | -0,07 |
| 8 | directly | -0,069 |
| 9 | q | -0,06 |
| 10 | pacific | -0,059 |
| 201010 | Aerospace & Defense | coeff |
| 1 | station | 0,14 |
| 2 | laboratory | 0,124 |
| 3 | original | 0,111 |
| 4 | media | 0,105 |
| 5 | automobile | 0,105 |
| 6 | pharmaceutical | 0,103 |
| 7 | point | 0,094 |
| 8 | spread | 0,083 |
| 9 | junior | 0,074 |
| 10 | licensed | 0,067 |
| 1 | observable | -0,202 |
| 2 | relatively | -0,179 |
| 3 | institution | -0,122 |
| 4 | online | -0,12 |
| 5 | similar | -0,112 |
| 6 | residential | -0,086 |
| 7 | studies | -0,065 |
| 8 | ultimate | -0,065 |
| 9 | proved | -0,064 |
| 10 | continued | -0,054 |

**Table B.1 continued from previous page**

| 201020 | Building Products | coeff |
|---|---|---|
| 1 | retain | 0,128 |
| 2 | contribution | 0,11 |
| 3 | training | 0,081 |
| 4 | clients | 0,063 |
| 5 | differences | 0,058 |
| 6 | rental | 0,052 |
| 7 | core | 0,051 |
| 8 | temporary | 0,043 |
| 9 | either | 0,038 |
| 10 | grade | 0,037 |
| 1 | street | -0,21 |
| 2 | mine | -0,209 |
| 3 | opening | -0,175 |
| 4 | restaurant | -0,172 |
| 5 | deliverables | -0,109 |
| 6 | mortgages | -0,074 |
| 7 | events | -0,063 |
| 8 | central | -0,055 |
| 9 | direct | -0,054 |
| 10 | sensitive | -0,054 |

| 201030 | Construction & Engineering | coeff |
|---|---|---|
| 1 | wells | 0,354 |
| 2 | spreads | 0,127 |
| 3 | discounts | 0,071 |
| 4 | hurricanes | 0,051 |
| 5 | restatement | 0,05 |
| 6 | misstatements | 0,04 |
| 7 | six | 0,036 |
| 8 | complete | 0,028 |
| 9 | relationships | 0,028 |
| 10 | euro | 0,026 |
| 1 | automotive | -0,384 |
| 2 | q | -0,087 |
| 3 | four | -0,081 |
| 4 | increasing | -0,073 |
| 5 | positions | -0,058 |
| 6 | agricultural | -0,055 |
| 7 | categories | -0,053 |
| 8 | floating | -0,052 |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 9 | upfront | -0,05 |
| 10 | allocation | -0,044 |
| 201040 | Electrical Equipment | coeff |
| 1 | exposures | 0,25 |
| 2 | depletion | 0,105 |
| 3 | rules | 0,096 |
| 4 | tier | 0,08 |
| 5 | junior | 0,071 |
| 6 | water | 0,064 |
| 7 | operational | 0,059 |
| 8 | calendar | 0,058 |
| 9 | milestone | 0,054 |
| 10 | professional | 0,054 |
| 1 | propane | -0,49 |
| 2 | inprocess | -0,253 |
| 3 | video | -0,223 |
| 4 | content | -0,163 |
| 5 | store | -0,157 |
| 6 | hospital | -0,154 |
| 7 | travel | -0,13 |
| 8 | partnership | -0,125 |
| 9 | yields | -0,122 |
| 10 | managements | -0,11 |
| 201060 | Machinery | coeff |
| 1 | shale | 0,076 |
| 2 | proved | 0,061 |
| 3 | satellite | 0,051 |
| 4 | attract | 0,045 |
| 5 | provider | 0,043 |
| 6 | personal | 0,04 |
| 7 | ars | 0,036 |
| 8 | groups | 0,035 |
| 9 | franchise | 0,035 |
| 10 | premium | 0,031 |
| 1 | homebuilding | -0,138 |
| 2 | startup | -0,098 |
| 3 | inprocess | -0,08 |
| 4 | gulf | -0,074 |
| 5 | merchant | -0,069 |
| 6 | television | -0,059 |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 7 | opportunities | -0,059 |
| 8 | mac | -0,047 |
| 9 | licensing | -0,044 |
| 10 | q | -0,04 |
| 201070 | Trading Companies & Distributors | coeff |
| 1 | mutual | 0,228 |
| 2 | patent | 0,153 |
| 3 | exit | 0,109 |
| 4 | semiconductor | 0,053 |
| 5 | idaho | 0,042 |
| 6 | offerings | 0,038 |
| 7 | crude | 0,036 |
| 8 | title | 0,029 |
| 9 | tenant | 0,028 |
| 10 | vehicle | 0,026 |
| 1 | offshore | -0,107 |
| 2 | wells | -0,107 |
| 3 | launch | -0,1 |
| 4 | food | -0,077 |
| 5 | cable | -0,055 |
| 6 | content | -0,052 |
| 7 | banking | -0,045 |
| 8 | corporations | -0,039 |
| 9 | automobile | -0,039 |
| 10 | partnership | -0,038 |
| 202010 | Commercial Services & Supplies | coeff |
| 1 | phases | 0,133 |
| 2 | producing | 0,133 |
| 3 | served | 0,099 |
| 4 | devices | 0,094 |
| 5 | programming | 0,086 |
| 6 | eps | 0,058 |
| 7 | electricity | 0,057 |
| 8 | indicated | 0,056 |
| 9 | fail | 0,046 |
| 10 | video | 0,037 |
| 1 | dental | -1,003 |
| 2 | channel | -0,254 |
| 3 | likely | -0,15 |
| 4 | semiconductor | -0,107 |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 5 | continues | -0,105 |
| 6 | merchant | -0,095 |
| 7 | platform | -0,094 |
| 8 | combination | -0,09 |
| 9 | subscriber | -0,087 |
| 10 | nine | -0,085 |
| 202020 | Professional Services | coeff |
| 1 | dental | 0,308 |
| 2 | chemical | 0,267 |
| 3 | largely | 0,257 |
| 4 | interestbearing | 0,246 |
| 5 | pension | 0,115 |
| 6 | nine | 0,114 |
| 7 | telephone | 0,088 |
| 8 | specialty | 0,082 |
| 9 | clinical | 0,081 |
| 10 | charged | 0,07 |
| 1 | looking | -0,188 |
| 2 | natural | -0,176 |
| 3 | vessel | -0,161 |
| 4 | proxy | -0,161 |
| 5 | inprocess | -0,125 |
| 6 | homes | -0,107 |
| 7 | spread | -0,097 |
| 8 | longlived | -0,096 |
| 9 | greater | -0,081 |
| 10 | without | -0,077 |
| 203020 | Airlines | coeff |
| 1 | q | 0,133 |
| 2 | satellite | 0,125 |
| 3 | acceptance | 0,066 |
| 4 | managements | 0,042 |
| 5 | controls | 0,04 |
| 6 | china | 0,037 |
| 7 | combination | 0,036 |
| 8 | countries | 0,035 |
| 9 | canadian | 0,034 |
| 10 | video | 0,028 |
| 1 | mutual | -0,385 |
| 2 | manufacture | -0,123 |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 3 | industrial | -0,111 |
| 4 | investigation | -0,079 |
| 5 | personal | -0,052 |
| 6 | businesses | -0,048 |
| 7 | plant | -0,045 |
| 8 | hurricanes | -0,041 |
| 9 | gulf | -0,041 |
| 10 | regulated | -0,04 |
| 203040 | Road & Rail | coeff |
| 1 | mills | 0,755 |
| 2 | surplus | 0,348 |
| 3 | manufacture | 0,203 |
| 4 | media | 0,176 |
| 5 | imaging | 0,154 |
| 6 | specialty | 0,152 |
| 7 | difficulties | 0,14 |
| 8 | world | 0,113 |
| 9 | availableforsale | 0,091 |
| 10 | disclosures | 0,084 |
| 1 | oem | -0,81 |
| 2 | opening | -0,284 |
| 3 | propane | -0,273 |
| 4 | distributors | -0,221 |
| 5 | warehouse | -0,181 |
| 6 | branch | -0,158 |
| 7 | borrowed | -0,135 |
| 8 | exploration | -0,127 |
| 9 | maine | -0,09 |
| 10 | earning | -0,087 |
| 251010 | Auto Components | coeff |
| 1 | travel | 0,247 |
| 2 | card | 0,144 |
| 3 | digital | 0,144 |
| 4 | semiconductor | 0,118 |
| 5 | treasury | 0,117 |
| 6 | converted | 0,087 |
| 7 | now | 0,075 |
| 8 | absolute | 0,069 |
| 9 | telecommunications | 0,068 |
| 10 | except | 0,063 |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 1 | individual | -0,175 |
| 2 | opening | -0,15 |
| 3 | payroll | -0,136 |
| 4 | status | -0,131 |
| 5 | candidates | -0,124 |
| 6 | depletion | -0,097 |
| 7 | earning | -0,085 |
| 8 | branch | -0,084 |
| 9 | derived | -0,08 |
| 10 | nonperforming | -0,073 |
| 252010 | Household Durables | coeff |
| 1 | approvals | 0,166 |
| 2 | employment | 0,085 |
| 3 | solutions | 0,078 |
| 4 | safety | 0,064 |
| 5 | city | 0,042 |
| 6 | rebates | 0,031 |
| 7 | station | 0,031 |
| 8 | external | 0,027 |
| 9 | forma | 0,026 |
| 10 | week | 0,026 |
| 1 | depletion | -0,169 |
| 2 | maine | -0,13 |
| 3 | mac | -0,102 |
| 4 | advance | -0,093 |
| 5 | small | -0,076 |
| 6 | hotel | -0,055 |
| 7 | japan | -0,042 |
| 8 | low | -0,038 |
| 9 | proposed | -0,033 |
| 10 | specialty | -0,026 |
| 252020 | Leisure Products | coeff |
| 1 | expanded | 0,303 |
| 2 | workers | 0,254 |
| 3 | fleet | 0,254 |
| 4 | underwriting | 0,239 |
| 5 | nil | 0,148 |
| 6 | station | 0,075 |
| 7 | collateralized | 0,06 |
| 8 | staffing | 0,051 |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 9 | claim | 0,045 |
| 10 | west | 0,045 |
| 1 | inprocess | -0,179 |
| 2 | housing | -0,151 |
| 3 | card | -0,116 |
| 4 | q | -0,11 |
| 5 | pool | -0,103 |
| 6 | energy | -0,093 |
| 7 | tobacco | -0,059 |
| 8 | milestone | -0,049 |
| 9 | yield | -0,047 |
| 10 | storage | -0,045 |
| 252030 | Textiles, Apparel & Luxury Goods | coeff |
| 1 | predecessor | 0,129 |
| 2 | collaborative | 0,115 |
| 3 | underwriting | 0,084 |
| 4 | guaranty | 0,077 |
| 5 | carried | 0,069 |
| 6 | field | 0,047 |
| 7 | establishes | 0,045 |
| 8 | partnerships | 0,041 |
| 9 | restated | 0,036 |
| 10 | distributions | 0,031 |
| 1 | devices | -0,106 |
| 2 | sensitivity | -0,084 |
| 3 | fully | -0,079 |
| 4 | corporations | -0,078 |
| 5 | q | -0,074 |
| 6 | book | -0,058 |
| 7 | presented | -0,057 |
| 8 | sublease | -0,056 |
| 9 | sop | -0,053 |
| 10 | agency | -0,053 |
| 253010 | Hotels, Restaurants & Leisure | coeff |
| 1 | divestiture | 0,027 |
| 2 | studies | 0,023 |
| 3 | defense | 0,017 |
| 4 | ecommerce | 0,016 |
| 5 | refining | 0,013 |
| 6 | brazil | 0,012 |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 7 | equivalent | 0,011 |
| 8 | plant | 0,009 |
| 9 | utilization | 0,009 |
| 10 | fiscal due | 0,008 |
| 1 | guaranty | -0,266 |
| 2 | theme park | -0,066 |
| 3 | sensitivity | -0,02 |
| 4 | pro forma | -0,018 |
| 5 | offshore | -0,012 |
| 6 | million related | -0,012 |
| 7 | manufacture | -0,011 |
| 8 | product segment | -0,011 |
| 9 | steel | -0,009 |
| 10 | ownership product | -0,009 |
| 253020 | Diversified Consumer Services | coeff |
| 1 | dated | 0,97 |
| 2 | casino | 0,379 |
| 3 | writedown | 0,127 |
| 4 | katrina | 0,044 |
| 5 | milestone | 0,036 |
| 6 | packaging | 0,027 |
| 7 | energy | 0,022 |
| 8 | stations | 0,021 |
| 9 | oil | 0,021 |
| 10 | regulated | 0,02 |
| 1 | medicare | -0,191 |
| 2 | commodity | -0,182 |
| 3 | websites | -0,114 |
| 4 | telecommunications | -0,098 |
| 5 | patents | -0,081 |
| 6 | manager | -0,076 |
| 7 | membership | -0,059 |
| 8 | thousand | -0,056 |
| 9 | q | -0,052 |
| 10 | region | -0,052 |
| 254010 | Media | coeff |
| 1 | milestone | 0,118 |
| 2 | defense | 0,088 |
| 3 | hedges | 0,079 |
| 4 | phase | 0,057 |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 5 | gulf | 0,042 |
| 6 | premiums | 0,039 |
| 7 | evidence | 0,037 |
| 8 | personal | 0,036 |
| 9 | regulation | 0,033 |
| 10 | treasury | 0,03 |
| 1 | yields | -0,13 |
| 2 | traffic | -0,122 |
| 3 | americas | -0,088 |
| 4 | supplies | -0,087 |
| 5 | remediation | -0,073 |
| 6 | expectations | -0,065 |
| 7 | establishes | -0,058 |
| 8 | comparison | -0,048 |
| 9 | utilities | -0,047 |
| 10 | principles | -0,044 |
| 255010 | Distributors | coeff |
| 1 | natural | 0,35 |
| 2 | department | 0,345 |
| 3 | epa | 0,301 |
| 4 | combination | 0,103 |
| 5 | maximum | 0,077 |
| 6 | semiconductor | 0,063 |
| 7 | rights | 0,062 |
| 8 | late | 0,061 |
| 9 | affiliate | 0,061 |
| 10 | impaired | 0,059 |
| 1 | reimbursement | -0,237 |
| 2 | installment | -0,217 |
| 3 | drug | -0,215 |
| 4 | former | -0,173 |
| 5 | successful | -0,129 |
| 6 | principles | -0,114 |
| 7 | indicated | -0,112 |
| 8 | q | -0,111 |
| 9 | managed | -0,107 |
| 10 | actual | -0,096 |
| 255020 | Internet & Catalog Retail | coeff |
| 1 | underwriting | 0,191 |
| 2 | institutional | 0,187 |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 3 | oem | 0,127 |
| 4 | others | 0,108 |
| 5 | portfolios | 0,104 |
| 6 | canadian | 0,099 |
| 7 | thousand | 0,093 |
| 8 | client | 0,077 |
| 9 | games | 0,05 |
| 10 | retirement | 0,049 |
| 1 | q | -0,207 |
| 2 | qualified | -0,179 |
| 3 | residential | -0,114 |
| 4 | exercisable | -0,109 |
| 5 | opportunities | -0,085 |
| 6 | mobile | -0,077 |
| 7 | energy | -0,066 |
| 8 | land | -0,065 |
| 9 | student | -0,052 |
| 10 | components | -0,05 |
| 255030 | Multiline Retail | coeff |
| 1 | managements | 0,513 |
| 2 | nonmonetary | 0,271 |
| 3 | advisory | 0,157 |
| 4 | treatment | 0,072 |
| 5 | slightly | 0,069 |
| 6 | television | 0,051 |
| 7 | licenses | 0,026 |
| 8 | forma | 0,025 |
| 9 | life | 0,023 |
| 10 | hedges | 0,021 |
| 1 | floating | -0,083 |
| 2 | intellectual | -0,066 |
| 3 | agreed | -0,05 |
| 4 | vessel | -0,049 |
| 5 | solutions | -0,04 |
| 6 | carryforwards | -0,038 |
| 7 | shareholders | -0,034 |
| 8 | sec | -0,028 |
| 9 | bearing | -0,025 |
| 10 | professional | -0,024 |
| 255040 | Specialty Retail | coeff |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 1 | exhibit | 0,091 |
| 2 | mortgagebacked | 0,089 |
| 3 | energy | 0,076 |
| 4 | largely | 0,072 |
| 5 | south | 0,033 |
| 6 | statutory | 0,031 |
| 7 | power | 0,03 |
| 8 | transportation | 0,022 |
| 9 | unusual | 0,018 |
| 10 | ltd | 0,017 |
| 1 | mining | -0,155 |
| 2 | search | -0,147 |
| 3 | sop | -0,095 |
| 4 | studies | -0,094 |
| 5 | collections | -0,093 |
| 6 | engineering | -0,077 |
| 7 | approvals | -0,067 |
| 8 | bad | -0,033 |
| 9 | placement | -0,025 |
| 10 | asbestos | -0,024 |
| 301010 | Food & Staples Retailing | coeff |
| 1 | relative | 0,161 |
| 2 | mortgage | 0,151 |
| 3 | gap | 0,123 |
| 4 | media | 0,108 |
| 5 | looking | 0,085 |
| 6 | transition | 0,073 |
| 7 | technologies | 0,061 |
| 8 | lenders | 0,053 |
| 9 | branch | 0,045 |
| 10 | commitment | 0,041 |
| 1 | suffer | -0,412 |
| 2 | ready | -0,237 |
| 3 | generation | -0,199 |
| 4 | qualified | -0,174 |
| 5 | programming | -0,167 |
| 6 | raw | -0,137 |
| 7 | holdings | -0,099 |
| 8 | billing | -0,086 |
| 9 | present | -0,074 |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 10 | telephone | -0,074 |
| 302010 | Beverages | coeff |
| 1 | advanced | 0,274 |
| 2 | origination | 0,207 |
| 3 | safety | 0,134 |
| 4 | borrower | 0,131 |
| 5 | studies | 0,127 |
| 6 | rule | 0,126 |
| 7 | bonus | 0,123 |
| 8 | agent | 0,115 |
| 9 | onetime | 0,085 |
| 10 | partnerships | 0,081 |
| 1 | internet | -0,488 |
| 2 | member | -0,272 |
| 3 | tobacco | -0,152 |
| 4 | q | -0,148 |
| 5 | ohio | -0,141 |
| 6 | site | -0,104 |
| 7 | pipeline | -0,1 |
| 8 | servicing | -0,087 |
| 9 | milestones | -0,08 |
| 10 | trial | -0,079 |
| 302020 | Food Products | coeff |
| 1 | metal | 0,291 |
| 2 | reinsurance | 0,111 |
| 3 | positive | 0,106 |
| 4 | chemical | 0,099 |
| 5 | farmer | 0,068 |
| 6 | institution | 0,058 |
| 7 | regulated | 0,033 |
| 8 | protection | 0,024 |
| 9 | ltd | 0,021 |
| 10 | approved | 0,017 |
| 1 | q | -0,115 |
| 2 | collection | -0,087 |
| 3 | recognize | -0,074 |
| 4 | hardware | -0,066 |
| 5 | positions | -0,048 |
| 6 | defense | -0,037 |
| 7 | affiliated | -0,037 |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 8 | vendors | -0,035 |
| 9 | disposal | -0,032 |
| 10 | bankruptcy | -0,032 |
| 303010 | Household Products | coeff |
| 1 | manufacture | 0,037 |
| 2 | trial | 0,036 |
| 3 | dated | 0,036 |
| 4 | agencies | 0,031 |
| 5 | japan | 0,028 |
| 6 | reorganization | 0,026 |
| 7 | principle | 0,022 |
| 8 | franchise | 0,021 |
| 9 | page | 0,018 |
| 10 | treatment | 0,016 |
| 1 | q | -0,282 |
| 2 | right | -0,07 |
| 3 | advisory | -0,045 |
| 4 | licensing | -0,023 |
| 5 | placement | -0,023 |
| 6 | acquire | -0,021 |
| 7 | harm | -0,017 |
| 8 | video | -0,017 |
| 9 | proprietary | -0,016 |
| 10 | unable | -0,015 |
| 303020 | Personal Products | coeff |
| 1 | edison | 0,377 |
| 2 | annuity | 0,355 |
| 3 | healthcare | 0,157 |
| 4 | lending | 0,129 |
| 5 | gold | 0,124 |
| 6 | networks | 0,078 |
| 7 | consideration | 0,077 |
| 8 | banking | 0,077 |
| 9 | field | 0,059 |
| 10 | scheduled | 0,052 |
| 1 | workers | -0,26 |
| 2 | capitalized | -0,229 |
| 3 | fuel | -0,215 |
| 4 | proxy | -0,154 |
| 5 | bps | -0,127 |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 6 | weather | -0,127 |
| 7 | pro | -0,108 |
| 8 | energy | -0,098 |
| 9 | rule | -0,095 |
| 10 | sharing | -0,085 |
| 351010 | Health Care Equipment & Supplies | coeff |
| 1 | branch | 0,365 |
| 2 | tier | 0,078 |
| 3 | tenant | 0,065 |
| 4 | debentures | 0,011 |
| 5 | east | 0,009 |
| 6 | networks | 0,009 |
| 7 | sensitivity | 0,008 |
| 8 | locations | 0,007 |
| 9 | closed | 0,004 |
| 10 | sell | 0,004 |
| 1 | refinery | -0,079 |
| 2 | origination | -0,079 |
| 3 | disposition | -0,049 |
| 4 | forma | -0,027 |
| 5 | competitors | -0,026 |
| 6 | practices | -0,025 |
| 7 | q | -0,025 |
| 8 | registration | -0,022 |
| 9 | ratings | -0,021 |
| 10 | event | -0,018 |
| 351020 | Health Care Providers & Services | coeff |
| 1 | redevelopment | 0,077 |
| 2 | nil | 0,063 |
| 3 | card | 0,048 |
| 4 | improvements | 0,039 |
| 5 | savings | 0,028 |
| 6 | networks | 0,024 |
| 7 | foot | 0,021 |
| 8 | parts | 0,018 |
| 9 | bps | 0,017 |
| 10 | labor | 0,017 |
| 1 | rose | -0,922 |
| 2 | collaborative | -0,23 |
| 3 | borrowed | -0,21 |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 4 | dental | -0,126 |
| 5 | retail | -0,12 |
| 6 | collaboration | -0,106 |
| 7 | q | -0,074 |
| 8 | cable | -0,052 |
| 9 | manufacturers | -0,044 |
| 10 | sga | -0,03 |
| 351030 | Health Care Technology | coeff |
| 1 | unconsolidated | 0,315 |
| 2 | servicing | 0,118 |
| 3 | shipments | 0,118 |
| 4 | properties | 0,107 |
| 5 | necessary | 0,099 |
| 6 | programming | 0,097 |
| 7 | premiums | 0,082 |
| 8 | relative | 0,082 |
| 9 | interestbearing | 0,076 |
| 10 | york | 0,065 |
| 1 | yearend | -0,632 |
| 2 | bearing | -0,294 |
| 3 | phases | -0,252 |
| 4 | dispositions | -0,218 |
| 5 | rating | -0,184 |
| 6 | specialty | -0,142 |
| 7 | prepayment | -0,13 |
| 8 | disposition | -0,129 |
| 9 | chief | -0,117 |
| 10 | plant | -0,105 |
| 352010 | Biotechnology | coeff |
| 1 | proved | 0,318 |
| 2 | dates | 0,105 |
| 3 | presented | 0,09 |
| 4 | opportunities | 0,086 |
| 5 | revolver | 0,078 |
| 6 | tobacco | 0,068 |
| 7 | q | 0,068 |
| 8 | terminal | 0,065 |
| 9 | municipal | 0,048 |
| 10 | servicing | 0,046 |
| 1 | postretirement | -0,328 |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 2 | derived | -0,239 |
| 3 | separation | -0,147 |
| 4 | present | -0,125 |
| 5 | predecessor | -0,109 |
| 6 | placement | -0,074 |
| 7 | wind | -0,064 |
| 8 | commerce | -0,063 |
| 9 | staff | -0,062 |
| 10 | lending | -0,046 |
| 352020 | Pharmaceuticals | coeff |
| 1 | noninterest | 0,207 |
| 2 | modifications | 0,184 |
| 3 | regions | 0,097 |
| 4 | sop | 0,093 |
| 5 | q | 0,084 |
| 6 | west | 0,069 |
| 7 | workers | 0,065 |
| 8 | file | 0,061 |
| 9 | environment | 0,056 |
| 10 | source | 0,051 |
| 1 | aircraft | -0,517 |
| 2 | brokerage | -0,375 |
| 3 | suffer | -0,345 |
| 4 | engineering | -0,308 |
| 5 | content | -0,284 |
| 6 | electricity | -0,218 |
| 7 | reorganization | -0,209 |
| 8 | grew | -0,181 |
| 9 | ending | -0,154 |
| 10 | steel | -0,138 |
| 352030 | Life Sciences Tools & Services | coeff |
| 1 | origination | 0,725 |
| 2 | insured | 0,179 |
| 3 | bonus | 0,084 |
| 4 | gaap | 0,048 |
| 5 | candidates | 0,033 |
| 6 | institution | 0,033 |
| 7 | measure | 0,032 |
| 8 | therapy | 0,026 |
| 9 | plants | 0,022 |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 10 | reduced | 0,021 |
| 1 | branch | -0,207 |
| 2 | consumers | -0,132 |
| 3 | merchandise | -0,132 |
| 4 | collateralized | -0,095 |
| 5 | largely | -0,07 |
| 6 | exploration | -0,067 |
| 7 | procedures | -0,063 |
| 8 | q | -0,059 |
| 9 | sensitivity | -0,057 |
| 10 | trust | -0,055 |
| 402010 | Diversified Financial Services | coeff |
| 1 | texas | 0,029 |
| 2 | electronic | 0,028 |
| 3 | materially | 0,021 |
| 4 | overhead | 0,018 |
| 5 | internet | 0,018 |
| 6 | utility | 0,016 |
| 7 | opportunities | 0,014 |
| 8 | majority | 0,014 |
| 9 | right | 0,013 |
| 10 | engineering | 0,011 |
| 1 | q | -0,071 |
| 2 | asia | -0,06 |
| 3 | planning | -0,054 |
| 4 | ready | -0,038 |
| 5 | successful | -0,028 |
| 6 | equivalent | -0,024 |
| 7 | directly | -0,02 |
| 8 | wells | -0,018 |
| 9 | volumes | -0,016 |
| 10 | mcf | -0,016 |
| 402020 | Consumer Finance | coeff |
| 1 | charter | 0,16 |
| 2 | q | 0,043 |
| 3 | indenture | 0,031 |
| 4 | membership | 0,03 |
| 5 | leased | 0,024 |
| 6 | technologies | 0,022 |
| 7 | square | 0,02 |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 8 | court | 0,019 |
| 9 | fasb | 0,018 |
| 10 | weather | 0,015 |
| 1 | backlog | -0,117 |
| 2 | trial | -0,057 |
| 3 | success | -0,052 |
| 4 | accruals | -0,05 |
| 5 | grants | -0,049 |
| 6 | commerce | -0,049 |
| 7 | attract | -0,049 |
| 8 | hardware | -0,045 |
| 9 | community | -0,044 |
| 10 | advertising | -0,042 |
| 402030 | Capital Markets | coeff |
| 1 | mine | 0,114 |
| 2 | bearing | 0,09 |
| 3 | staffing | 0,077 |
| 4 | dated | 0,062 |
| 5 | statutory | 0,061 |
| 6 | wells | 0,051 |
| 7 | startup | 0,05 |
| 8 | commerce | 0,043 |
| 9 | commercialization | 0,04 |
| 10 | introduction | 0,038 |
| 1 | msrs | -0,128 |
| 2 | restaurants | -0,112 |
| 3 | programming | -0,106 |
| 4 | packaging | -0,083 |
| 5 | station | -0,07 |
| 6 | foot | -0,067 |
| 7 | merchandise | -0,054 |
| 8 | accumulated | -0,052 |
| 9 | suppliers | -0,05 |
| 10 | tons | -0,039 |
| 403010 | Insurance | coeff |
| 1 | commerce | 0,337 |
| 2 | supplementary | 0,21 |
| 3 | carolina | 0,167 |
| 4 | additions | 0,081 |
| 5 | backlog | 0,044 |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 6 | qualified | 0,039 |
| 7 | users | 0,032 |
| 8 | offshore | 0,024 |
| 9 | patient | 0,023 |
| 10 | licenses | 0,023 |
| 1 | refining | -0,176 |
| 2 | media | -0,057 |
| 3 | nonperforming | -0,047 |
| 4 | proceedings | -0,035 |
| 5 | deliverables | -0,035 |
| 6 | indicated | -0,035 |
| 7 | intangibles | -0,034 |
| 8 | trial | -0,027 |
| 9 | technological | -0,025 |
| 10 | severance | -0,022 |
| 451010 | Internet Software & Services | coeff |
| 1 | claim | 0,244 |
| 2 | patient | 0,209 |
| 3 | canadian | 0,152 |
| 4 | imaging | 0,121 |
| 5 | ratios | 0,114 |
| 6 | sensitive | 0,113 |
| 7 | lending | 0,104 |
| 8 | described | 0,096 |
| 9 | initiatives | 0,085 |
| 10 | leasing | 0,07 |
| 1 | nine | -0,523 |
| 2 | approvals | -0,29 |
| 3 | anticipate | -0,201 |
| 4 | franchise | -0,184 |
| 5 | healthcare | -0,159 |
| 6 | floating | -0,154 |
| 7 | earning | -0,123 |
| 8 | feet | -0,103 |
| 9 | packaging | -0,101 |
| 10 | trust | -0,095 |
| 451020 | IT Services | coeff |
| 1 | ohio | 0,097 |
| 2 | oem | 0,08 |
| 3 | difficulties | 0,078 |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 4 | hotel | 0,075 |
| 5 | investors | 0,072 |
| 6 | nine | 0,069 |
| 7 | petroleum | 0,069 |
| 8 | west | 0,067 |
| 9 | practices | 0,065 |
| 10 | branch | 0,058 |
| 1 | dental | -0,406 |
| 2 | exercisable | -0,276 |
| 3 | generating | -0,188 |
| 4 | harmed | -0,08 |
| 5 | communities | -0,073 |
| 6 | necessary | -0,066 |
| 7 | modifications | -0,057 |
| 8 | content | -0,053 |
| 9 | digital | -0,051 |
| 10 | present | -0,047 |
| 451030 | Software | coeff |
| 1 | fuel | 0,192 |
| 2 | retirement | 0,099 |
| 3 | pension | 0,086 |
| 4 | central | 0,084 |
| 5 | clearing | 0,076 |
| 6 | restructured | 0,049 |
| 7 | generating | 0,047 |
| 8 | exploration | 0,045 |
| 9 | deposit | 0,044 |
| 10 | oil | 0,044 |
| 1 | interestearning | -0,325 |
| 2 | living | -0,261 |
| 3 | south | -0,234 |
| 4 | suffer | -0,173 |
| 5 | west | -0,169 |
| 6 | florida | -0,166 |
| 7 | registrant | -0,153 |
| 8 | noninterest | -0,132 |
| 9 | communities | -0,113 |
| 10 | opened | -0,108 |
| 452010 | Communications Equipment | coeff |
| 1 | drilling | 0,254 |

**Table B.1 continued from previous page**

| | | |
|---|---|---|
| 2 | accident | 0,183 |
| 3 | subsequent | 0,153 |
| 4 | community | 0,149 |
| 5 | writedown | 0,118 |
| 6 | borrowed | 0,102 |
| 7 | fda | 0,083 |
| 8 | forth | 0,074 |
| 9 | subscription | 0,073 |
| 10 | opportunities | 0,06 |
| 1 | premiums | -0,552 |
| 2 | block | -0,486 |
| 3 | largely | -0,187 |
| 4 | vehicle | -0,178 |
| 5 | noninterest | -0,158 |
| 6 | station | -0,15 |
| 7 | earning | -0,138 |
| 8 | except | -0,122 |
| 9 | underwriting | -0,112 |
| 10 | treatment | -0,094 |

| 452020 | Technology Hardware, Storage & Peripherals | coeff |
|---|---|---|
| 1 | offshore | 0,35 |
| 2 | produced | 0,196 |
| 3 | ebitda | 0,169 |
| 4 | steel | 0,164 |
| 5 | borrower | 0,095 |
| 6 | brokerage | 0,064 |
| 7 | refinancing | 0,061 |
| 8 | department | 0,06 |
| 9 | member | 0,06 |
| 10 | commercialization | 0,058 |
| 1 | throughput | -0,321 |
| 2 | games | -0,28 |
| 3 | fleet | -0,228 |
| 4 | tests | -0,128 |
| 5 | royalties | -0,113 |
| 6 | ipo | -0,095 |
| 7 | warehouse | -0,087 |
| 8 | restaurants | -0,084 |
| 9 | controls | -0,069 |
| 10 | automotive | -0,065 |

**Table B.1 continued from previous page**

| 452030 | Electronic Equipment | coeff |
|---|---|---|
| 1 | interestearning | 0,466 |
| 2 | regulated | 0,182 |
| 3 | tobacco | 0,159 |
| 4 | brokerage | 0,116 |
| 5 | medicare | 0,093 |
| 6 | tenant | 0,075 |
| 7 | mutual | 0,074 |
| 8 | origination | 0,066 |
| 9 | late | 0,053 |
| 10 | investing | 0,048 |
| 1 | disease | -0,3 |
| 2 | charter | -0,273 |
| 3 | fleet | -0,222 |

# APPENDIX C

# Life-cycle stage on AEIG (all markets)

Table C.1 – AEIG conditioned to Life Cycle (h = 1 month)

| | Growth | | | Mature | | |
|---|---|---|---|---|---|---|
| Country | Coeff. | | t statistic | Coeff. | | t statistic |
| AUSTRALIA | 0,0004 | | (0,018) | -0,0158 | | (-0,268) |
| BELGIUM | -0,0078 | | (-0,682) | 0,0168 | | (1,041) |
| BRAZIL | 0,0479 | ** | (2,424) | -0,0177 | | (-0,767) |
| CANADA | 0,0216 | * | (1,656) | 0,0136 | | (0,51) |
| CHILE | 0,0006 | | (0,044) | 0,0117 | | (0,411) |
| CHINA | -0,0049 | | (-0,47) | 0,0033 | | (0,267) |
| DENMARK | -0,0054 | | (-0,199) | 0,0032 | | (0,128) |
| EGYPT | -0,0381 | | (-0,937) | 0,0349 | | (1,234) |
| FINLAND | 0,0037 | | (0,051) | -0,0316 | | (-0,262) |
| FRANCE | -0,0172 | | (-0,8) | 0,0403 | | (0,795) |
| GERMANY | 0,0237 | | (0,568) | 0,0292 | | (0,353) |
| GREECE | -0,025 | ** | (-2,575) | 0,0168 | | (1,23) |
| HONG KONG | 0,0114 | | (0,679) | 0,0022 | | (0,125) |
| INDIA | -0,0021 | | (-0,15) | -0,0194 | | (-0,944) |
| INDONESIA | 0,0006 | | (0,084) | -0,0062 | | (-0,777) |
| IRELAND | 0,0094 | | (0,174) | -0,0079 | | (-0,115) |
| ISRAEL | 0,0194 | | (1,559) | -0,0133 | | (-0,898) |
| ITALY | -0,0121 | | (-0,371) | 0,0863 | ** | (2,076) |
| JAPAN | 0,0111 | | (0,67) | -0,0092 | | (-0,505) |
| KOREA (SOUTH) | -0,0301 | ** | (-2,783) | -0,0415 | ** | (-2,691) |
| MALAYSIA | -0,0068 | | (-1,269) | -0,0055 | ** | (-1,989) |
| MEXICO | 0,0127 | | (1,122) | 0,0251 | | (1,241) |

**Table C.1 continued from previous page**

| | | | | | | |
|---|---|---|---|---|---|---|
| NETHERLANDS | -0,0121 | | (-0,41) | -0,0186 | | (-0,626) |
| NEW ZEALAND | -0,0019 | | (-0,2) | -0,0011 | | (-0,074) |
| NORWAY | -0,0037 | | (-0,334) | 0,0017 | | (0,12) |
| PAKISTAN | -0,0325 | * | (-1,813) | 0,007 | | (0,368) |
| PHILIPPINES | -0,0025 | | (-0,209) | -0,0057 | | (-0,405) |
| POLAND | -0,0242 | | (-0,179) | 0,0764 | | (0,597) |
| RUSSIA | -0,0535 | | (-0,183) | 0,008 | | (0,303) |
| SAUDI ARABIA | 0,1287 | | (1,372) | -0,0064 | | (-0,133) |
| SINGAPORE | 0,0089 | | (1,208) | 0,0252 | | (1,02) |
| SOUTH AFRICA | -0,0196 | | (-1,03) | 0,0307 | | (0,855) |
| SPAIN | -0,0016 | | (-0,407) | -0,0053 | | (-0,878) |
| SRI LANKA | -0,0012 | | (-0,515) | -0,0022 | | (-0,582) |
| SWEDEN | 0,0207 | | (0,608) | -0,0429 | | (-0,963) |
| SWITZERLAND | -0,0025 | | (-0,063) | -0,0286 | | (-0,391) |
| TAIWAN | -0,0239 | ** | (-2,003) | 0,0047 | | (0,226) |
| THAILAND | -0,0083 | | (-0,626) | 0,0108 | | (0,53) |
| TURKEY | 0,0051 | | (0,59) | 0,0047 | | (0,182) |
| UNITED KINGDOM | 0,0191 | | (0,838) | 0,0109 | | (0,216) |
| VIETNAM | -0,0181 | | (-0,23) | 0,026 | | (0,35) |

This table reports estimates of $b_t$ in the regression $R_{t,t+1} = a_t + b_t[AEIG]_y + \varepsilon_{i,t}$ where $R_{t+1,t+h}$ is the future cumulative market returns of the country over h = 1, 6 and 12 months following month t; $[AEIG]_y$ is the y measure of aggregate expected investment plans of the country, where $[\text{AEIG}]_y \in$[AEIG-G, AEIG-M]. The column Growth presents estimates for AEIG-G, which is a measure that aggregates EIG of all growth firms of the market. The column Mature presents estimates for AEIG-M, which is a measure that aggregates EIG of all mature firms of the market. For each country I run one individual time-series regression. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels. All the t-statistic are estimated by using Newey and West (1987) standard errors.

Table C.2 – AEIG conditioned to Life Cycle (h = 3 months)

| | Growth | | | Mature | | |
|---|---|---|---|---|---|---|
| Country | Coeff. | | t statistic | Coeff. | | t statistic |
| AUSTRALIA | 0,0023 | | (0,065) | -0,0394 | | (-0,573) |
| BELGIUM | -0,0375 | * | (-1,791) | 0,038 | | (1,442) |
| BRAZIL | 0,1441 | *** | (3,464) | -0,0783 | * | (-1,74) |
| CANADA | 0,0785 | ** | (2,719) | 0,0211 | | (0,442) |
| CHILE | -0,0047 | | (-0,169) | 0,0562 | | (1,076) |
| CHINA | -0,0103 | | (-0,418) | -0,0079 | | (-0,322) |
| DENMARK | -0,0106 | | (-0,214) | -0,0219 | | (-0,526) |

**Table C.2 continued from previous page**

| | | | | | | |
|---|---|---|---|---|---|---|
| EGYPT | -0,1502 | ** | (-2,103) | 0,0984 | ** | (2,01) |
| FINLAND | -0,0179 | | (-0,179) | -0,1206 | | (-0,744) |
| FRANCE | -0,0522 | | (-1,316) | 0,1363 | ** | (2,118) |
| GERMANY | 0,0497 | | (0,616) | 0,053 | | (0,45) |
| GREECE | -0,0764 | *** | (-3,857) | 0,054 | ** | (2,184) |
| HONG KONG | 0,0296 | | (0,736) | 0,0001 | | (0,004) |
| INDIA | -0,033 | | (-1,024) | -0,0671 | * | (-1,776) |
| INDONESIA | -0,007 | | (-0,46) | -0,0207 | | (-1,449) |
| IRELAND | 0,0615 | | (0,817) | -0,0002 | | (-0,002) |
| ISRAEL | 0,0429 | | (1,568) | -0,0367 | | (-1,46) |
| ITALY | -0,0399 | | (-0,655) | 0,2408 | *** | (4,532) |
| JAPAN | 0,0247 | | (0,64) | -0,0126 | | (-0,358) |
| KOREA (SOUTH) | -0,0903 | *** | (-3,789) | -0,122 | *** | (-4,412) |
| MALAYSIA | -0,0169 | | (-1,509) | -0,0129 | ** | (-2,822) |
| MEXICO | 0,0544 | ** | (2,724) | 0,0644 | * | (1,927) |
| NETHERLANDS | -0,0304 | | (-0,625) | -0,0364 | | (-0,805) |
| NEW ZEALAND | -0,0054 | | (-0,414) | -0,0056 | | (-0,288) |
| NORWAY | 0,0039 | | (0,169) | 0,0038 | | (0,146) |
| PAKISTAN | -0,0348 | | (-1,001) | -0,0217 | | (-0,645) |
| PHILIPPINES | -0,0144 | | (-0,567) | -0,0123 | | (-0,528) |
| POLAND | 0,0923 | | (0,367) | -0,0284 | | (-0,176) |
| RUSSIA | -0,0859 | | (-0,376) | -0,0095 | | (-0,333) |
| SAUDI ARABIA | 0,3901 | ** | (2,577) | 0,024 | | (0,314) |
| SINGAPORE | 0,019 | | (1,121) | 0,0567 | | (1,223) |
| SOUTH AFRICA | -0,062 | | (-1,559) | 0,0663 | | (1,215) |
| SPAIN | 0,0017 | | (0,225) | -0,0162 | | (-1,622) |
| SRI LANKA | -0,0026 | | (-0,626) | -0,0054 | | (-0,752) |
| SWEDEN | 0,1191 | * | (1,876) | -0,1375 | ** | (-2,101) |
| SWITZERLAND | -0,0229 | | (-0,323) | -0,0667 | | (-0,715) |
| TAIWAN | -0,0639 | ** | (-2,495) | 0,0153 | | (0,394) |
| THAILAND | -0,0154 | | (-0,719) | 0,017 | | (0,725) |
| TURKEY | 0,0196 | | (1,122) | -0,0433 | | (-0,992) |
| UNITED KINGDOM | 0,0572 | | (1,233) | 0,022 | | (0,32) |
| VIETNAM | -0,042 | | (-0,287) | -0,0279 | | (-0,302) |

**Table C.2 continued from previous page**

This table reports estimates of $b_t$ in the regression $R_{t,t+1} = a_t + b_t[AEIG]_y + \varepsilon_{i,t}$ where $R_{t+1,t+h}$ is the future cumulative market returns of the country over h = 1, 6 and 12 months following month t; $[AEIG]_y$ is the y measure of aggregate expected investment plans of the country, where $[\text{AEIG}]_y \in$[AEIG-G, AEIG-M]. The column Growth presents estimates for AEIG-G, which is a measure that aggregates EIG of all growth firms of the market. The column Mature presents estimates for AEIG-M, which is a measure that aggregates EIG of all mature firms of the market. For each country I run one individual time-series regression. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels. All the t-statistic are estimated by using Newey and West (1987) standard errors.

Table C.3 – AEIG conditioned to Life Cycle (h = 6 months)

| | Growth | | | Mature | | |
|---|---|---|---|---|---|---|
| Country | Coeff. | | t statistic | Coeff. | | t statistic |
| AUSTRALIA | 0,0191 | | -0,469 | -0,0441 | | (-0,485) |
| BELGIUM | -0,0755 | ** | (-2,558) | 0,0608 | * | -1,681 |
| BRAZIL | 0,2304 | *** | -3,577 | -0,2347 | *** | (-3,408) |
| CANADA | 0,1507 | *** | -3,465 | 0,036 | | -0,516 |
| CHILE | -0,0133 | | (-0,332) | 0,1164 | * | -1,672 |
| CHINA | -0,0241 | | (-0,602) | -0,0454 | | (-1,201) |
| DENMARK | -0,073 | | (-0,938) | -0,0759 | | (-1,228) |
| EGYPT | -0,2761 | ** | (-2,643) | 0,1744 | ** | -2,387 |
| FINLAND | 0,0787 | | -0,656 | -0,1455 | | (-0,649) |
| FRANCE | -0,0872 | * | (-1,769) | 0,2501 | ** | -2,921 |
| GERMANY | 0,0594 | | -0,537 | 0,0551 | | -0,355 |
| GREECE | -0,11 | *** | (-3,379) | 0,1135 | ** | -3,274 |
| HONG KONG | 0,0263 | | -0,416 | 0,0083 | | -0,176 |
| INDIA | -0,0877 | * | (-1,79) | -0,1482 | ** | (-2,666) |
| INDONESIA | -0,016 | | (-0,762) | -0,0564 | ** | (-2,869) |
| IRELAND | 0,1616 | * | -1,83 | 0,0456 | | -0,366 |
| ISRAEL | 0,0445 | | -1,112 | -0,0455 | | (-1,238) |
| ITALY | -0,0708 | | (-0,908) | 0,3592 | *** | -4,688 |
| JAPAN | 0,0537 | | -0,862 | 0,0107 | | -0,202 |
| KOREA (SOUTH) | -0,1404 | *** | (-3,922) | -0,1829 | *** | (-4,36) |
| MALAYSIA | -0,0231 | | (-1,509) | -0,0129 | ** | (-2,071) |
| MEXICO | 0,0944 | ** | -3,154 | -0,0232 | | (-0,46) |
| NETHERLANDS | -0,0664 | | (-1,037) | -0,0815 | | (-1,298) |
| NEW ZEALAND | -0,0077 | | (-0,581) | -0,0096 | | (-0,396) |
| NORWAY | 0,0058 | | -0,173 | -0,0135 | | (-0,38) |
| PAKISTAN | -0,0502 | | (-1,094) | 0,0188 | | -0,406 |
| PHILIPPINES | -0,0194 | | (-0,512) | -0,0251 | | (-0,808) |

**Table C.3 continued from previous page**

| | | | | | | |
|---|---|---|---|---|---|---|
| POLAND | -0,092 | | (-0,286) | -0,2596 | | (-1,478) |
| RUSSIA | 0,291 | | -0,936 | -0,0968 | ** | (-2,299) |
| SAUDI ARABIA | 0,7924 | *** | -3,712 | 0,0666 | | -0,634 |
| SINGAPORE | 0,0446 | | -1,642 | 0,1342 | * | -1,901 |
| SOUTH AFRICA | -0,0944 | | (-1,638) | 0,1595 | ** | -2,438 |
| SPAIN | 0,0063 | | -0,548 | -0,0295 | ** | (-1,983) |
| SRI LANKA | 0,0062 | | -0,977 | -0,0107 | | (-0,987) |
| SWEDEN | 0,1668 | * | -1,937 | -0,2804 | ** | (-3,134) |
| SWITZERLAND | -0,1049 | | (-1,052) | -0,0644 | | (-0,515) |
| TAIWAN | -0,1151 | ** | (-2,966) | -0,0205 | | (-0,35) |
| THAILAND | -0,0124 | | (-0,443) | 0,0292 | | -0,965 |
| TURKEY | 0,0317 | | -1,195 | -0,098 | | (-1,523) |
| UNITED KINGDOM | 0,0815 | | -1,383 | 0,0359 | | -0,36 |
| VIETNAM | -0,1397 | | (-0,79) | -0,1058 | | (-1,013) |

This table reports estimates of $b_t$ in the regression $R_{t,t+1} = a_t + b_t[AEIG]_y + \varepsilon_{i,t}$ where $R_{t+1,t+h}$ is the future cumulative market returns of the country over h = 1, 6 and 12 months following month t; $[AEIG]_y$ is the y measure of aggregate expected investment plans of the country, where $[\text{AEIG}]_y \in$[AEIG-G, AEIG-M]. The column Growth presents estimates for AEIG-G, which is a measure that aggregates EIG of all growth firms of the market. The column Mature presents estimates for AEIG-M, which is a measure that aggregates EIG of all mature firms of the market. For each country I run one individual time-series regression. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels. All the t-statistic are estimated by using Newey and West (1987) standard errors.

Table C.4 – AEIG conditioned to Life Cycle (h = 12 months)

| | Growth | | | Mature | | |
|---|---|---|---|---|---|---|
| Country | Coeff. | | t statistic | Coeff. | | t statistic |
| AUSTRALIA | 0,0156 | | (0,282) | -0,0075 | | (-0,065) |
| BELGIUM | -0,0417 | | (-0,988) | 0,1175 | ** | (2,407) |
| BRAZIL | 0,2465 | ** | (2,508) | -0,4914 | *** | (-5,242) |
| CANADA | 0,2175 | *** | (3,368) | 0,1052 | | (1,056) |
| CHILE | -0,1257 | * | (-1,977) | 0,2535 | ** | (2,798) |
| CHINA | -0,15 | ** | (-2,355) | -0,109 | * | (-1,91) |
| DENMARK | -0,1159 | | (-0,98) | -0,0897 | | (-1,044) |
| EGYPT | -0,4513 | ** | (-2,841) | 0,1726 | | (1,612) |
| FINLAND | 0,3244 | ** | (2,153) | -0,6704 | ** | (-2,218) |
| FRANCE | -0,2169 | ** | (-3,21) | 0,2588 | ** | (2,137) |
| GERMANY | 0,0799 | | (0,523) | -0,0118 | | (-0,053) |
| GREECE | -0,0629 | | (-0,962) | 0,187 | *** | (3,79) |

**Table C.4 continued from previous page**

| | | | | | | |
|---|---|---|---|---|---|---|
| HONG KONG | -0,0456 | | (-0,506) | -0,056 | | (-0,824) |
| INDIA | -0,1284 | * | (-1,699) | -0,253 | ** | (-2,998) |
| INDONESIA | -0,047 | | (-1,492) | -0,0723 | ** | (-2,708) |
| IRELAND | 0,5277 | *** | (5,19) | 0,1931 | | (1,492) |
| ISRAEL | 0,0943 | * | (1,801) | 0,0417 | | (0,716) |
| ITALY | -0,1089 | | (-0,942) | 0,242 | ** | (2,144) |
| JAPAN | 0,1248 | | (1,315) | -0,0402 | | (-0,51) |
| KOREA (SOUTH) | -0,145 | ** | (-2,648) | -0,1409 | ** | (-2,224) |
| MALAYSIA | 0,0136 | | (0,608) | -0,0045 | | (-0,503) |
| MEXICO | 0,106 | ** | (2,177) | -0,2005 | ** | (-2,697) |
| NETHERLANDS | -0,2863 | ** | (-3,205) | -0,3279 | *** | (-3,629) |
| NEW ZEALAND | -0,0212 | | (-1,227) | -0,0246 | | (-0,829) |
| NORWAY | -0,0307 | | (-0,664) | -0,0638 | | (-1,377) |
| PAKISTAN | 0,0254 | | (0,393) | 0,2005 | ** | (2,958) |
| PHILIPPINES | -0,0241 | | (-0,466) | -0,0658 | * | (-1,693) |
| POLAND | 0,4346 | | (1,522) | -0,3538 | * | (-1,795) |
| RUSSIA | 0,9485 | ** | (2,977) | -0,2288 | *** | (-4,597) |
| SAUDI ARABIA | 0,4782 | * | (1,794) | 0,0447 | | (0,392) |
| SINGAPORE | 0,1262 | ** | (2,948) | 0,1599 | | (1,552) |
| SOUTH AFRICA | -0,0094 | | (-0,124) | 0,5203 | *** | (6,543) |
| SPAIN | 0,0309 | * | (1,828) | -0,0782 | *** | (-3,7) |
| SRI LANKA | 0,0349 | *** | (3,616) | -0,0369 | ** | (-2,661) |
| SWEDEN | 0,0189 | | (0,153) | -0,75 | *** | (-5,887) |
| SWITZERLAND | -0,3415 | ** | (-2,643) | -0,1111 | | (-0,661) |
| TAIWAN | -0,1903 | ** | (-3,173) | -0,2066 | ** | (-2,388) |
| THAILAND | 0,038 | | (0,986) | 0,0741 | * | (1,852) |
| TURKEY | 0,0305 | | (0,794) | -0,153 | * | (-1,721) |
| UNITED KINGDOM | 0,0456 | | (0,517) | 0,0244 | | (0,174) |
| VIETNAM | -0,4249 | ** | (-2,159) | -0,3851 | | (-4,075) |

This table reports estimates of $b_t$ in the regression $R_{t,t+1} = a_t + b_t[AEIG]_y + \varepsilon_{i,t}$ where $R_{t+1,t+h}$ is the future cumulative market returns of the country over h = 1, 6 and 12 months following month t; $[AEIG]_y$ is the y measure of aggregate expected investment plans of the country, where $[\text{AEIG}]_y \in$[AEIG-G, AEIG-M]. The column Growth presents estimates for AEIG-G, which is a measure that aggregates EIG of all growth firms of the market. The column Mature presents estimates for AEIG-M, which is a measure that aggregates EIG of all mature firms of the market. For each country I run one individual time-series regression. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels. All the t-statistic are estimated by using Newey and West (1987) standard errors.

# APPENDIX D

# AEIG predictive ability in all countries (Emerging versus Developed Markets)

Table D.1 – All firms based AEIG in Emerging and Developed Markets (h = 1 month)

| Country | EM/DM | Coeff. | | t Statistic | Adj. R2 | N |
|---|---|---|---|---|---|---|
| AUSTRALIA | DM | 0,003 | | (0,049) | -0,004 | 259 |
| BELGIUM | DM | 0,013 | | (0,81) | -0,001 | 259 |
| BRAZIL | EM | -0,017 | ** | (-2,549) | 0,027 | 199 |
| CANADA | DM | 0,044 | | (1,621) | 0,006 | 259 |
| CHILE | EM | 0,031 | | (1,493) | 0,005 | 235 |
| CHINA | EM | 0,008 | | (0,327) | -0,003 | 258 |
| DENMARK | DM | 0,004 | | (0,227) | -0,004 | 259 |
| EGYPT | EM | -0,013 | | (-0,9) | -0,001 | 204 |
| FINLAND | DM | -0,180 | * | (-1,72) | 0,008 | 258 |
| FRANCE | DM | 0,031 | | (0,692) | -0,002 | 259 |
| GERMANY | DM | 0,029 | | (0,317) | -0,003 | 259 |
| GREECE | EM | -0,009 | | (-0,416) | -0,004 | 216 |
| HONG KONG | DM | 0,013 | | (0,416) | -0,003 | 259 |
| INDIA | EM | -0,020 | | (-0,741) | -0,002 | 247 |
| INDONESIA | EM | 0,004 | | (0,764) | -0,002 | 185 |
| IRELAND | DM | -0,007 | | (-0,06) | -0,004 | 259 |
| ISRAEL | DM | -0,008 | | (-0,686) | -0,002 | 258 |
| ITALY | DM | -0,001 | | (-0,018) | -0,004 | 259 |
| JAPAN | DM | -0,015 | | (-0,754) | -0,002 | 258 |
| KOREA (SOUTH) | EM | -0,038 | ** | (-2,73) | 0,026 | 247 |
| MALAYSIA | EM | -0,005 | ** | (-2,126) | 0,014 | 258 |

**Table D.1 continued from previous page**

| | | | | | | |
|---|---|---|---|---|---|---|
| MEXICO | EM | 0,022 | | (0,474) | -0,003 | 258 |
| NETHERLANDS | DM | 0,022 | | (0,849) | -0,001 | 259 |
| NEW ZEALAND | DM | 0,001 | | (0,114) | -0,004 | 259 |
| NORWAY | DM | 0,021 | | (0,726) | -0,002 | 259 |
| PAKISTAN | EM | -0,013 | | (-0,579) | -0,003 | 258 |
| PHILIPPINES | EM | -0,006 | | (-0,424) | -0,003 | 247 |
| POLAND | EM | -0,067 | | (-0,539) | -0,003 | 247 |
| RUSSIA | EM | 0,016 | | (1,141) | 0,001 | 216 |
| SAUDI ARABIA | EM | 0,007 | | (0,071) | -0,007 | 139 |
| SINGAPORE | DM | 0,020 | | (0,961) | 0,000 | 258 |
| SOUTH AFRICA | EM | 0,034 | | (0,819) | -0,001 | 259 |
| SPAIN | DM | -0,005 | | (-0,627) | -0,003 | 192 |
| SRI LANKA | EM | -0,002 | | (-0,646) | -0,002 | 247 |
| SWEDEN | DM | -0,024 | | (-0,401) | -0,003 | 258 |
| SWITZERLAND | DM | 0,024 | | (0,206) | -0,004 | 259 |
| TAIWAN | EM | -0,042 | | (-1,633) | 0,007 | 247 |
| THAILAND | EM | 0,010 | | (0,457) | -0,003 | 258 |
| TURKEY | EM | -0,003 | | (-0,861) | -0,001 | 258 |
| UNITED KINGDOM | DM | 0,027 | | (0,51) | -0,003 | 259 |
| VIETNAM | EM | -0,029 | | (-0,192) | -0,011 | 91 |

This table reports estimates of $b_t$ in the regression $R_{t,t+1} = a_t + b_t AEIG_t + \varepsilon_{i,t}$ where $R_{t+1,t+h}$ is the future cumulative market returns of the country over h = 1, 6 and 12 months following month t; $AEIG_t$ is the measure of aggregate expected investment growth of all firms in the market as Li, Wang and Yu (2020). For each country I run one individual time-series regression. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels. All the t-statistic are estimated by using Newey and West (1987) standard errors.

Table D.2 – All firms based AEIG in Emerging and Developed Markets (h = 3 months)

| Country | EM/DM | Coeff. | | t Statistic | Adj. R2 | N |
|---|---|---|---|---|---|---|
| AUSTRALIA | DM | 0,031 | | (0,464) | -0,003 | 257 |
| BELGIUM | DM | 0,036 | | (1,365) | 0,003 | 257 |
| BRAZIL | EM | -0,059 | ** | (2,517) | 0,092 | 197 |
| CANADA | DM | 0,121 | | (0,209) | 0,020 | 257 |
| CHILE | EM | 0,088 | *** | (-3,516) | 0,019 | 233 |
| CHINA | EM | 0,023 | | (1,51) | -0,003 | 256 |
| DENMARK | DM | 0,006 | | (0,461) | -0,004 | 257 |
| EGYPT | EM | -0,047 | | (0,512) | 0,013 | 202 |
| FINLAND | DM | -0,485 | | (-0,214) | 0,043 | 256 |

**Table D.2 continued from previous page**

| | | | | | | |
|---|---|---|---|---|---|---|
| FRANCE | DM | 0,086 | | (-1,608) | 0,005 | 257 |
| GERMANY | DM | 0,059 | | (0,25) | -0,003 | 257 |
| GREECE | EM | -0,040 | | (-0,842) | 0,000 | 214 |
| HONG KONG | DM | 0,032 | | (1,566) | -0,003 | 257 |
| INDIA | EM | -0,087 | | (0,16) | 0,008 | 245 |
| INDONESIA | EM | 0,013 | | (0,796) | 0,003 | 183 |
| IRELAND | DM | -0,034 | | (1,191) | -0,004 | 257 |
| ISRAEL | DM | -0,031 | | (-1,477) | 0,006 | 256 |
| ITALY | DM | 0,026 | | (-1,125) | -0,004 | 257 |
| JAPAN | DM | -0,032 | | (0,186) | -0,001 | 256 |
| KOREA (SOUTH) | EM | -0,116 | | (0,906) | 0,077 | 245 |
| MALAYSIA | EM | -0,011 | *** | (-4,556) | 0,029 | 256 |
| MEXICO | EM | 0,106 | ** | (2,354) | 0,003 | 256 |
| NETHERLANDS | DM | 0,060 | | (0,493) | 0,006 | 257 |
| NEW ZEALAND | DM | 0,003 | * | (-1,89) | -0,004 | 257 |
| NORWAY | DM | 0,042 | | (-1,016) | -0,001 | 257 |
| PAKISTAN | EM | -0,041 | * | (-1,757) | 0,001 | 256 |
| PHILIPPINES | EM | -0,011 | | (1,228) | -0,003 | 245 |
| POLAND | EM | -0,563 | *** | (-4,61) | 0,049 | 245 |
| RUSSIA | EM | 0,056 | ** | (-2,93) | 0,053 | 214 |
| SAUDI ARABIA | EM | 0,061 | | (1,366) | -0,006 | 137 |
| SINGAPORE | DM | 0,046 | | (-1,103) | 0,002 | 256 |
| SOUTH AFRICA | EM | 0,101 | | (-0,444) | 0,006 | 257 |
| SPAIN | DM | -0,019 | *** | (-3,69) | 0,006 | 190 |
| SRI LANKA | EM | -0,005 | *** | (3,586) | 0,001 | 245 |
| SWEDEN | DM | -0,101 | | (0,395) | 0,001 | 256 |
| SWITZERLAND | DM | 0,028 | | (1,617) | -0,004 | 257 |
| TAIWAN | EM | -0,127 | | (-1,101) | 0,025 | 245 |
| THAILAND | EM | 0,017 | ** | (-2,7) | -0,002 | 256 |
| TURKEY | EM | -0,010 | | (0,67) | 0,006 | 256 |
| UNITED KINGDOM | DM | 0,066 | | (-1,632) | -0,001 | 257 |
| VIETNAM | EM | -0,153 | | (-0,804) | -0,004 | 89 |

This table reports estimates of $b_t$ in the regression $R_{t,t+1} = a_t + b_t AEIG_t + \varepsilon_{i,t}$ where $R_{t+1,t+h}$ is the future cumulative market returns of the country over h = 1, 6 and 12 months following month t; $AEIG_t$ is the measure of aggregate expected investment growth of all firms in the market as Li, Wang and Yu (2020). For each country I run one individual time-series regression. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels. All the t-statistic are estimated by using Newey and West (1987) standard errors.

Table D.3 – All firms based AEIG in Emerging and Developed Markets (h = 6 month)

| Country | EM/DM | Coeff. | | t Statistic | Adj. R2 | N |
|---|---|---|---|---|---|---|
| AUSTRALIA | DM | 0,042 | | (0,474) | -0,003 | 254 |
| BELGIUM | DM | 0,061 | * | (1,659) | 0,007 | 254 |
| BRAZIL | EM | -0,120 | ** | (2,923) | 0,166 | 194 |
| CANADA | DM | 0,206 | | (0,2) | 0,029 | 254 |
| CHILE | EM | 0,115 | *** | (-5,901) | 0,018 | 230 |
| CHINA | EM | -0,010 | ** | (2,123) | -0,004 | 253 |
| DENMARK | DM | 0,009 | | (0,334) | -0,004 | 254 |
| EGYPT | EM | -0,097 | | (-0,324) | 0,028 | 199 |
| FINLAND | DM | -1,076 | | (-0,248) | 0,118 | 253 |
| FRANCE | DM | 0,160 | ** | (-2,793) | 0,014 | 254 |
| GERMANY | DM | 0,056 | | (0,043) | -0,004 | 254 |
| GREECE | EM | -0,061 | | (-0,686) | 0,001 | 211 |
| HONG KONG | DM | -0,028 | ** | (2,11) | -0,004 | 254 |
| INDIA | EM | -0,181 | | (0,031) | 0,021 | 242 |
| INDONESIA | EM | 0,021 | | (0,744) | 0,004 | 180 |
| IRELAND | DM | -0,049 | | (0,975) | -0,004 | 254 |
| ISRAEL | DM | -0,078 | * | (-1,816) | 0,026 | 253 |
| ITALY | DM | 0,006 | ** | (-2,452) | -0,004 | 254 |
| JAPAN | DM | -0,039 | | (0,046) | -0,002 | 253 |
| KOREA (SOUTH) | EM | -0,208 | | (0,787) | 0,111 | 242 |
| MALAYSIA | EM | -0,011 | *** | (-6,276) | 0,015 | 253 |
| MEXICO | EM | -0,045 | ** | (2,298) | -0,003 | 253 |
| NETHERLANDS | DM | 0,111 | | (-0,138) | 0,013 | 254 |
| NEW ZEALAND | DM | 0,001 | ** | (-2,587) | -0,004 | 254 |
| NORWAY | DM | 0,053 | | (-1,079) | -0,002 | 254 |
| PAKISTAN | EM | -0,135 | ** | (-2,49) | 0,025 | 253 |
| PHILIPPINES | EM | -0,025 | | (1,294) | -0,002 | 242 |
| POLAND | EM | -1,135 | *** | (-5,568) | 0,179 | 242 |
| RUSSIA | EM | 0,102 | ** | (-2,211) | 0,077 | 211 |
| SAUDI ARABIA | EM | 0,189 | | (-0,39) | -0,002 | 134 |
| SINGAPORE | DM | 0,058 | ** | (-2,726) | 0,000 | 253 |
| SOUTH AFRICA | EM | 0,210 | | (-0,746) | 0,026 | 254 |
| SPAIN | DM | -0,034 | *** | (-7,308) | 0,012 | 187 |
| SRI LANKA | EM | -0,011 | *** | (4,31) | 0,006 | 242 |
| SWEDEN | DM | -0,303 | | (0,889) | 0,019 | 253 |
| SWITZERLAND | DM | 0,009 | ** | (2,792) | -0,004 | 254 |
| TAIWAN | EM | -0,242 | | (-1,532) | 0,043 | 242 |

**Table D.3 continued from previous page**

| | | | | | | |
|---|---|---|---|---|---|---|
| THAILAND | EM | 0,043 | *** | (-3,456) | 0,003 | 253 |
| TURKEY | EM | -0,023 | | (1,339) | 0,024 | 253 |
| UNITED KINGDOM | DM | 0,083 | ** | (-2,696) | -0,002 | 254 |
| VIETNAM | EM | -0,283 | | (-1,269) | 0,007 | 86 |

This table reports estimates of $b_t$ in the regression $R_{t,t+1} = a_t + b_t AEIG_t + \varepsilon_{i,t}$ where $R_{t+1,t+h}$ is the future cumulative market returns of the country over h = 1, 6 and 12 months following month t; $AEIG_t$ is the measure of aggregate expected investment growth of all firms in the market as Li, Wang and Yu (2020). For each country I run one individual time-series regression. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels. All the t-statistic are estimated by using Newey and West (1987) standard errors.

Table D.4 – All firms based AEIG in Emerging and Developed Markets (h = 12 months)

| Country | EM/DM | Coeff. | | t Statistic | Adj. R2 | N |
|---|---|---|---|---|---|---|
| AUSTRALIA | DM | -0,095 | | (-0,834) | -0,001 | 248 |
| BELGIUM | DM | 0,060 | | (1,216) | 0,002 | 248 |
| BRAZIL | EM | -0,235 | ** | (2,606) | 0,300 | 188 |
| CANADA | DM | 0,267 | | (0,751) | 0,023 | 248 |
| CHILE | EM | 0,138 | *** | (-11,533) | 0,015 | 224 |
| CHINA | EM | -0,260 | ** | (2,073) | 0,020 | 247 |
| DENMARK | DM | 0,047 | | (0,283) | -0,002 | 248 |
| EGYPT | EM | -0,215 | ** | (-3,056) | 0,071 | 193 |
| FINLAND | DM | -2,459 | | (0,596) | 0,349 | 247 |
| FRANCE | DM | 0,217 | *** | (-5,687) | 0,013 | 248 |
| GERMANY | DM | 0,068 | | (-0,754) | -0,004 | 248 |
| GREECE | EM | -0,063 | * | (-1,909) | -0,002 | 205 |
| HONG KONG | DM | -0,382 | ** | (2,007) | 0,033 | 248 |
| INDIA | EM | -0,330 | | (-0,096) | 0,033 | 236 |
| INDONESIA | EM | 0,036 | | (-0,674) | 0,007 | 174 |
| IRELAND | DM | 0,123 | | (0,204) | -0,003 | 248 |
| ISRAEL | DM | -0,241 | ** | (-2,371) | 0,113 | 247 |
| ITALY | DM | -0,160 | *** | (-5,057) | -0,002 | 248 |
| JAPAN | DM | -0,162 | | (-1,247) | 0,011 | 247 |
| KOREA (SOUTH) | EM | -0,270 | | (-0,577) | 0,087 | 236 |
| MALAYSIA | EM | -0,007 | *** | (-9,005) | -0,001 | 247 |
| MEXICO | EM | -0,287 | ** | (2,087) | 0,008 | 247 |
| NETHERLANDS | DM | 0,152 | ** | (-2,463) | 0,012 | 248 |
| NEW ZEALAND | DM | -0,002 | *** | (-3,952) | -0,004 | 248 |
| NORWAY | DM | -0,062 | | (-0,751) | -0,002 | 248 |

**Table D.4 continued from previous page**

| | | | | | | |
|---|---|---|---|---|---|---|
| PAKISTAN | EM | -0,196 | ** | (-2,992) | 0,027 | 247 |
| PHILIPPINES | EM | -0,070 | | (1,464) | 0,007 | 236 |
| POLAND | EM | -1,347 | *** | (-4,844) | 0,204 | 236 |
| RUSSIA | EM | 0,188 | | (-0,926) | 0,166 | 205 |
| SAUDI ARABIA | EM | 0,425 | * | (-1,737) | 0,019 | 128 |
| SINGAPORE | DM | 0,019 | ** | (-2,792) | -0,004 | 247 |
| SOUTH AFRICA | EM | 0,446 | | (-1,63) | 0,077 | 248 |
| SPAIN | DM | -0,066 | *** | (-7,835) | 0,025 | 181 |
| SRI LANKA | EM | -0,029 | *** | (6,444) | 0,032 | 236 |
| SWEDEN | DM | -0,902 | * | (1,859) | 0,091 | 247 |
| SWITZERLAND | DM | -0,334 | *** | (4,653) | 0,002 | 248 |
| TAIWAN | EM | -0,401 | ** | (-2,943) | 0,055 | 236 |
| THAILAND | EM | 0,111 | *** | (-3,848) | 0,024 | 247 |
| TURKEY | EM | -0,077 | ** | (2,661) | 0,160 | 247 |
| UNITED KINGDOM | DM | -0,085 | *** | (-6,924) | -0,003 | 248 |
| VIETNAM | EM | -0,665 | ** | (-2,8) | 0,080 | 80 |

This table reports estimates of $b_t$ in the regression $R_{t,t+1} = a_t + b_t AEIG_t + \varepsilon_{i,t}$ where $R_{t+1,t+h}$ is the future cumulative market returns of the country over h = 1, 6 and 12 months following month t; $AEIG_t$ is the measure of aggregate expected investment growth of all firms in the market as Li, Wang and Yu (2020). For each country I run one individual time-series regression. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels. All the t-statistic are estimated by using Newey and West (1987) standard errors.

# APPENDIX E

# Ability of AEIG to Predict Future Return Controlled by others Predictors

Table E.1 – AEIG based on all firms of the country to predict future return (h=1) controlled by opthers predictors

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| AUSTRALIA | 0.033 | 0.021 | -0.016 | 0.068 | -0.002 | -0.005 |
| | ( 1.198) | ( 0.282) | (-0.723) | ( 0.528) | (-0.186) | (-0.690) |
| BELGIUM | -0.007 | 0.018 | 0.012 | 0.000 | -0.003 | -0.010 |
| | (-0.230) | ( 0.806) | ( 0.753) | (-0.236) | (-1.073) | (-1.770) |
| BRAZIL | 0.012 | -0.015 | -0.009 | 0.001 | 0.006 * | -0.006 |
| | ( 0.570) | (-1.377) | (-1.820) | ( 0.582) | ( 2.291) | (-1.759) |
| CANADA | 0.042 ** | 0.029 | -0.011 * | -0.113 * | 0.007 | -0.005 |
| | ( 2.973) | ( 0.740) | (-2.181) | (-2.106) | ( 1.700) | (-1.104) |
| CHILE | 0.012 | 0.016 | 0.000 | 0.000 | -0.003 | -0.003 |
| | ( 0.427) | ( 0.521) | (-0.017) | ( 0.733) | (-1.030) | (-1.000) |
| CHINA | 0.057 * | 0.051 | -0.049 * | 0.004 | 0.010 | -0.011 ** |
| | ( 2.052) | ( 1.412) | (-2.281) | ( 0.199) | ( 1.421) | (-3.194) |
| DENMARK | 0.023 | 0.023 | 0.005 | -0.033 | 0.001 | -0.002 |
| | ( 1.282) | ( 1.031) | ( 0.675) | (-1.328) | ( 0.281) | (-0.360) |
| FINLAND | 0.017 | -0.169 | -0.001 | 0.028 | 0.002 | -0.014 |
| | ( 0.299) | (-1.494) | (-0.026) | ( 0.093) | ( 0.157) | (-1.372) |
| FRANCE | 0.049 | -0.027 | -0.021 | 0.018 | 0.000 | -0.008 |
| | ( 1.314) | (-0.326) | (-1.102) | ( 0.121) | ( 0.020) | (-0.824) |
| GERMANY | 0.069 | 0.101 | -0.030 | -0.007 | 0.006 | -0.016 |
| | ( 1.680) | ( 0.960) | (-1.257) | (-0.076) | ( 1.003) | (-1.227) |
| GREECE | 0.026 | 0.040 | -0.016 | 0.065 | 0.002 | -0.003 |
| | ( 1.214) | ( 1.234) | (-1.505) | ( 0.629) | ( 0.373) | (-0.841) |
| INDIA | -0.046 | -0.124 ** | 0.005 | 0.012 *** | -0.007 | -0.002 |
| | (-1.323) | (-2.642) | ( 1.103) | ( 4.246) | (-1.631) | (-1.305) |

*Continued*

Table E.1 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| INDONESIA | 0.100 * | 0.006 | -0.012 | 0.000 | -0.003 | 0.004 |
| | ( 2.343) | ( 0.743) | (-0.487) | (-1.772) | (-0.465) | ( 1.190) |
| IRELAND | 0.016 | -0.001 | -0.005 | -0.164 | 0.003 | -0.002 |
| | ( 0.239) | (-0.008) | (-0.118) | (-0.703) | ( 0.225) | (-0.204) |
| ISRAEL | 0.009 | -0.010 | 0.000 | 0.000 | 0.001 | -0.004 |
| | ( 0.502) | (-0.513) | (-0.070) | (-0.006) | ( 1.050) | (-1.324) |
| ITALY | 0.070 | 0.071 | -0.029 | -0.205 | -0.002 | 0.005 |
| | ( 1.070) | ( 0.558) | (-0.849) | (-0.725) | (-0.184) | ( 0.425) |
| JAPAN | 0.012 | 0.006 | -0.008 | -0.001 | 0.011 | -0.003 |
| | ( 0.469) | ( 0.148) | (-0.781) | (-0.561) | ( 0.778) | (-0.792) |
| MALAYSIA | 0.111 | 0.002 | -0.028 | -0.104 | -0.008 | 0.003 |
| | ( 1.863) | ( 0.262) | (-1.813) | (-1.250) | (-0.791) | ( 0.604) |
| MEXICO | 0.049 | 0.032 | -0.011 | -0.014 * | -0.003 | 0.002 |
| | ( 1.723) | ( 0.672) | (-0.863) | (-2.544) | (-0.793) | ( 0.618) |
| NETHERLANDS | 0.055 * | 0.018 | -0.017 | 0.018 | -0.003 | -0.002 |
| | ( 2.563) | ( 0.555) | (-1.913) | ( 0.338) | (-0.437) | (-0.479) |
| NEW ZEALAND | 0.000 | -0.018 | 0.003 | 0.009 | 0.003 | -0.013 |
| | ( 0.010) | (-0.755) | ( 0.431) | ( 0.116) | ( 0.322) | (-1.201) |
| NORWAY | 0.080 | 0.073 | -0.016 | -0.018 | -0.001 | -0.005 |
| | ( 1.884) | ( 1.442) | (-1.105) | (-1.742) | (-0.414) | (-0.608) |
| PAKISTAN | 0.024 | -0.002 | -0.002 | -0.001 | 0.002 | 0.000 |
| | ( 1.083) | (-0.057) | (-1.117) | (-0.890) | ( 0.617) | (-0.309) |
| PHILIPPINES | 0.040 | -0.011 | -0.005 | -0.004 | 0.001 | -0.002 |
| | ( 1.326) | (-0.505) | (-0.605) | (-0.893) | ( 0.163) | (-0.400) |
| POLAND | 0.111 | -0.094 | 0.011 | -0.277 | 0.007 | -0.021 |
| | ( 0.843) | (-0.699) | ( 0.198) | (-0.805) | ( 0.448) | (-0.736) |
| RUSSIA | 0.003 | 0.032 | 0.001 | -0.001 | 0.006 | -0.003 |
| | ( 0.032) | ( 1.087) | ( 0.199) | (-0.214) | ( 0.444) | (-0.530) |
| SAUDI ARABIA | 0.185 | -0.106 | -0.061 | -0.058 | -0.005 | 0.001 |
| | ( 1.237) | (-0.887) | (-1.739) | (-0.394) | (-0.078) | ( 0.110) |
| SINGAPORE | 0.102 ** | 0.031 | -0.003 | -0.462 ** | 0.010 | -0.007 * |
| | ( 2.980) | ( 1.044) | (-0.268) | (-2.645) | ( 1.327) | (-2.515) |
| SOUTH AFRICA | -0.022 | 0.031 | 0.005 | 0.010 | -0.001 | 0.000 |
| | (-0.623) | ( 0.607) | ( 0.506) | ( 0.481) | (-0.768) | ( 0.150) |
| SPAIN | 0.051 * | 0.004 | -0.032 * | 0.062 | -0.004 | 0.003 |
| | ( 2.078) | ( 0.423) | (-2.413) | ( 1.646) | (-0.936) | ( 0.667) |
| SRI LANKA | 0.014 | -0.001 | 0.003 | 0.001 | -0.001 | -0.002 |
| | ( 0.353) | (-0.387) | ( 1.007) | ( 0.518) | (-0.432) | (-1.482) |
| SWEDEN | 0.093 | -0.017 | -0.030 | -0.012 | 0.003 | -0.008 |
| | ( 1.842) | (-0.257) | (-1.482) | (-0.653) | ( 0.492) | (-1.396) |
| SWITZERLAND | 0.045 | 0.093 | -0.020 | -0.044 | 0.005 | -0.017 |
| | ( 1.014) | ( 0.459) | (-0.952) | (-0.321) | ( 0.337) | (-1.392) |
| THAILAND | 0.019 | 0.012 | -0.002 | -0.001 | 0.000 | -0.003 |
| | ( 0.427) | ( 0.434) | (-0.153) | (-0.098) | ( 0.031) | (-0.454) |
| TURKEY | 0.008 | 0.000 | -0.010 * | -0.022 | 0.002 | -0.001 |

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*T*able E.1 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| | ( 0.302) | (-0.052) | (-2.522) | (-0.604) | ( 1.724) | (-0.834) |
| UNITED KINGDOM | 0.041 | 0.052 | -0.018 | 0.108 | -0.001 | -0.004 |
| | ( 1.537) | ( 0.597) | (-1.057) | ( 0.248) | (-0.328) | (-0.667) |
| VIETNAM | 0.532 | 0.250 | -0.002 | 0.000 | -0.038 | 0.009 |
| | ( 0.692) | ( 0.594) | (-0.009) | (-0.864) | (-0.385) | ( 0.192) |

This table reports estimates of $b_t$, $c_t$, $d_t$, $e_t$ and $f_t$ in the regression $R_{t,t+1} = a_t + b_t AEIG_{i,t} + c_t DY_{i,t} + d_t I/K_{i,t} + e_t Interest_{i,t} + f_t INFL_{i,t} + \varepsilon_{i,t}$ where $R_{t+1,t+h}$ is the future cumulative market returns of the country over h = 1, 6 and 12 months following month t; $[AEIG]_y$ is the y measure of aggregate expected investment plans of the country, where $AEIG_{i,t}$ is the aggregate expected investment growth for the country $i$. $DY_{i,t}$, $I/K_{i,t}$, $Interest_{i,t}$ and $INFL_{i,t}$, are respectively dividend yield, investiment-to-capital, interest rate and inflation for the country $i$ in month $t$. For each country I run one individual time-series regression. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels. All the t-statistic are estimated by using Newey and West (1987) standard errors.

Table E.2 – AEIG predicitive regression controlled by opthers predictors (h = 3 months)

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| AUSTRALIA | 0.085 ** | 0.073 | -0.033 | 0.078 | -0.002 | -0.015 |
| | ( 2.659) | ( 0.864) | (-1.314) | ( 0.525) | (-0.195) | (-1.785) |
| BELGIUM | 0.032 | 0.027 | -0.003 | -0.001 | -0.008 | -0.015 |
| | ( 0.664) | ( 0.742) | (-0.128) | (-0.385) | (-1.627) | (-1.650) |
| BRAZIL | 0.016 | -0.038 * | -0.031 *** | 0.006 | 0.019 *** | -0.016 ** |
| | ( 0.401) | (-1.990) | (-3.598) | ( 1.458) | ( 4.282) | (-2.625) |
| CANADA | 0.125 *** | 0.111 | -0.035 *** | -0.338 *** | 0.017 * | -0.010 |
| | ( 5.099) | ( 1.647) | (-4.284) | (-3.663) | ( 2.377) | (-1.268) |
| CHILE | 0.037 | 0.064 | 0.003 | 0.000 | -0.009 | -0.004 |
| | ( 0.752) | ( 1.149) | ( 0.233) | ( 0.544) | (-1.669) | (-0.695) |
| CHINA | 0.136 * | 0.177 * | -0.103 * | 0.002 | 0.028 * | -0.033 *** |
| | ( 2.585) | ( 2.578) | (-2.502) | ( 0.058) | ( 2.147) | (-5.113) |
| DENMARK | 0.061 * | 0.063 | 0.016 | -0.094 * | 0.001 | -0.001 |
| | ( 2.047) | ( 1.727) | ( 1.189) | (-2.276) | ( 0.147) | (-0.131) |
| FINLAND | -0.007 | -0.401 ** | 0.009 | 0.391 | -0.005 | -0.039 ** |
| | (-0.094) | (-2.749) | ( 0.333) | ( 1.031) | (-0.410) | (-2.879) |
| FRANCE | 0.109 * | -0.112 | -0.044 | 0.182 | -0.003 | -0.025 * |
| | ( 2.302) | (-1.112) | (-1.853) | ( 1.010) | (-0.323) | (-2.017) |
| GERMANY | 0.194 *** | 0.245 | -0.072 * | -0.053 | 0.019 * | -0.060 ** |
| | ( 3.390) | ( 1.688) | (-2.169) | (-0.423) | ( 2.271) | (-3.293) |
| GREECE | 0.042 | 0.056 | -0.035 | 0.232 | -0.001 | -0.001 |
| | ( 1.073) | ( 0.968) | (-1.892) | ( 1.247) | (-0.109) | (-0.093) |
| INDIA | -0.130 * | -0.483 *** | 0.012 | 0.038 *** | -0.029 *** | -0.004 |
| | (-2.237) | (-6.152) | ( 1.628) | ( 8.319) | (-3.861) | (-1.310) |
| INDONESIA | 0.300 *** | 0.016 | -0.042 | 0.000 ** | -0.008 | 0.013 * |
| | ( 4.217) | ( 1.302) | (-1.040) | (-3.101) | (-0.863) | ( 2.387) |

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*T*able E.2 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| IRELAND | -0.052 | -0.056 | 0.030 | 0.058 | -0.008 | 0.001 |
| | (-0.511) | (-0.287) | ( 0.501) | ( 0.168) | (-0.344) | ( 0.064) |
| ISRAEL | -0.005 | -0.035 | 0.013 | -0.015 | 0.005 * | -0.012 * |
| | (-0.178) | (-1.099) | ( 1.222) | (-0.451) | ( 1.985) | (-2.383) |
| ITALY | 0.137 | 0.364 * | -0.049 | -0.495 | -0.016 | 0.021 |
| | ( 1.696) | ( 2.319) | (-1.148) | (-1.423) | (-1.587) | ( 1.420) |
| JAPAN | 0.006 | 0.000 | -0.011 | -0.001 | 0.027 | -0.007 |
| | ( 0.122) | (-0.005) | (-0.558) | (-0.350) | ( 0.926) | (-0.929) |
| MALAYSIA | 0.200 * | -0.005 | -0.067 ** | -0.049 | -0.015 | 0.006 |
| | ( 2.021) | (-0.388) | (-2.650) | (-0.358) | (-0.843) | ( 0.737) |
| MEXICO | 0.187 *** | 0.143 | -0.046 * | -0.050 *** | -0.005 | 0.002 |
| | ( 4.179) | ( 1.891) | (-2.351) | (-5.741) | (-0.828) | ( 0.429) |
| NETHERLANDS | 0.156 *** | 0.075 | -0.037 ** | -0.008 | -0.013 | -0.010 |
| | ( 4.937) | ( 1.627) | (-2.793) | (-0.100) | (-1.274) | (-1.575) |
| NEW ZEALAND | 0.010 | -0.040 | 0.010 | 0.055 | -0.003 | -0.023 |
| | ( 0.197) | (-1.346) | ( 1.188) | ( 0.586) | (-0.356) | (-1.716) |
| NORWAY | 0.188 * | 0.253 ** | -0.034 | -0.066 *** | -0.003 | 0.007 |
| | ( 2.484) | ( 2.822) | (-1.342) | (-3.637) | (-0.702) | ( 0.532) |
| PAKISTAN | 0.077 * | -0.022 | -0.006 * | -0.003 | 0.003 | 0.000 |
| | ( 2.067) | (-0.458) | (-2.255) | (-1.467) | ( 0.648) | (-0.127) |
| PHILIPPINES | 0.078 | -0.026 | -0.012 | -0.007 | 0.002 | -0.002 |
| | ( 1.552) | (-0.719) | (-0.953) | (-0.972) | ( 0.293) | (-0.347) |
| POLAND | 0.244 | -0.668 *** | -0.003 | -0.380 | 0.007 | -0.047 |
| | ( 1.531) | (-4.117) | (-0.049) | (-0.905) | ( 0.386) | (-1.351) |
| RUSSIA | 0.034 | 0.105 ** | 0.003 | -0.005 | 0.021 | -0.012 |
| | ( 0.318) | ( 3.152) | ( 0.454) | (-0.997) | ( 1.270) | (-1.631) |
| SAUDI ARABIA | 0.582 ** | -0.312 | -0.172 ** | -0.333 | -0.006 | 0.008 |
| | ( 2.653) | (-1.725) | (-3.302) | (-1.553) | (-0.063) | ( 0.734) |
| SINGAPORE | 0.285 *** | 0.070 | -0.007 | -1.330 *** | 0.031 * | -0.017 *** |
| | ( 4.695) | ( 1.339) | (-0.347) | (-4.306) | ( 2.348) | (-3.683) |
| SOUTH AFRICA | -0.075 | 0.093 | 0.019 | 0.031 | -0.004 | 0.001 |
| | (-1.443) | ( 1.247) | ( 1.330) | ( 1.049) | (-1.763) | ( 0.165) |
| SPAIN | 0.121 ** | -0.002 | -0.079 *** | 0.220 *** | -0.010 | 0.004 |
| | ( 3.254) | (-0.130) | (-3.872) | ( 3.804) | (-1.489) | ( 0.469) |
| SRI LANKA | 0.037 | -0.003 | 0.008 | 0.002 | -0.004 | -0.005 * |
| | ( 0.517) | (-0.596) | ( 1.700) | ( 1.004) | (-0.718) | (-2.475) |
| SWEDEN | 0.216 ** | -0.095 | -0.065 * | -0.027 | 0.004 | -0.024 ** |
| | ( 2.857) | (-1.007) | (-2.084) | (-1.018) | ( 0.351) | (-2.761) |
| SWITZERLAND | 0.108 | 0.139 | -0.047 | -0.122 | 0.022 | -0.055 *** |
| | ( 1.916) | ( 0.536) | (-1.734) | (-0.696) | ( 1.206) | (-3.568) |
| THAILAND | 0.047 | 0.029 | -0.012 | 0.006 | -0.001 | -0.006 |
| | ( 0.921) | ( 0.927) | (-0.893) | ( 0.833) | (-0.148) | (-0.888) |
| TURKEY | 0.036 | -0.002 | -0.028 *** | -0.077 | 0.006 ** | -0.003 |
| | ( 0.861) | (-0.328) | (-4.556) | (-1.347) | ( 2.912) | (-1.342) |
| UNITED KINGDOM | 0.097 ** | 0.134 | -0.031 | -0.009 | -0.002 | -0.011 |

*Continued*

Table E.2 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| | ( 2.974) | ( 1.270) | (-1.526) | (-0.016) | (-0.821) | (-1.388) |
| VIETNAM | 0.157 | 0.001 | 0.280 | 0.000 | -0.165 | 0.013 |
| | ( 0.157) | ( 0.002) | ( 0.952) | (-1.382) | (-1.312) | ( 0.236) |

This table reports estimates of $b_t$, $c_t$, $d_t$, $e_t$ and $f_t$ in the regression $R_{t,t+1} = a_t + b_t AEIG_{i,t} + c_t DY_{i,t} + d_t I/K_{i,t} + e_t Interest_{i,t} + f_t INFL_{i,t} + \varepsilon_{i,t}$ where $R_{t+1,t+h}$ is the future cumulative market returns of the country over h = 1, 6 and 12 months following month t; $[AEIG]_y$ is the y measure of aggregate expected investment plans of the country, where $AEIG_{i,t}$ is the aggregate expected investment growth for the country $i$. $DY_{i,t}$, $I/K_{i,t}$, $Interest_{i,t}$ and $INFL_{i,t}$, are respectively dividend yield, investment-to-capital, interest rate and inflation for the country $i$ in month $t$. For each country I run one individual time-series regression. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels. All the t-statistic are estimated by using Newey and West (1987) standard errors.

Table E.3 – AEIG predicitive regression controlled by opthers predictors (h = 6 months)

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| AUSTRALIA | 0.162 *** | 0.081 | -0.061 | 0.246 | -0.005 | -0.033 ** |
| | ( 3.929) | ( 0.756) | (-1.913) | ( 1.301) | (-0.324) | (-3.139) |
| BELGIUM | 0.066 | 0.048 | -0.012 | 0.001 | -0.014 * | -0.026 * |
| | ( 1.002) | ( 0.970) | (-0.335) | ( 0.305) | (-2.037) | (-2.143) |
| BRAZIL | 0.023 | -0.085 ** | -0.055 *** | 0.005 | 0.038 *** | -0.036 *** |
| | ( 0.421) | (-3.128) | (-4.563) | ( 0.955) | ( 6.078) | (-4.087) |
| CANADA | 0.202 *** | 0.173 | -0.060 *** | -0.511 *** | 0.027 * | -0.018 |
| | ( 5.749) | ( 1.800) | (-5.079) | (-3.842) | ( 2.589) | (-1.557) |
| CHILE | 0.079 | -0.005 | -0.018 | 0.002 * | -0.012 | -0.017 * |
| | ( 1.214) | (-0.064) | (-1.010) | ( 2.165) | (-1.716) | (-2.150) |
| CHINA | 0.170 * | 0.270 * | -0.129 * | 0.009 | 0.055 ** | -0.055 *** |
| | ( 2.100) | ( 2.542) | (-1.988) | ( 0.145) | ( 2.728) | (-5.586) |
| DENMARK | 0.117 ** | 0.101 | 0.024 | -0.133 * | -0.003 | -0.009 |
| | ( 2.696) | ( 1.908) | ( 1.268) | (-2.218) | (-0.315) | (-0.568) |
| FINLAND | -0.052 | -0.885 *** | 0.033 | 0.772 | -0.017 | -0.082 *** |
| | (-0.556) | (-4.762) | ( 0.965) | ( 1.621) | (-0.964) | (-4.849) |
| FRANCE | 0.212 *** | -0.305 * | -0.090 ** | 0.474 * | 0.000 | -0.058 *** |
| | ( 3.641) | (-2.449) | (-3.093) | ( 2.123) | ( 0.020) | (-3.664) |
| GERMANY | 0.323 *** | 0.358 * | -0.113 ** | -0.106 | 0.036 ** | -0.111 *** |
| | ( 4.509) | ( 1.973) | (-2.721) | (-0.681) | ( 3.316) | (-4.842) |
| GREECE | 0.094 | 0.076 | -0.046 | 0.047 | -0.001 | -0.001 |
| | ( 1.597) | ( 0.894) | (-1.759) | ( 0.168) | (-0.054) | (-0.064) |
| INDIA | -0.179 * | -0.938 *** | 0.020 * | 0.066 *** | -0.062 *** | -0.003 |
| | (-2.296) | (-8.955) | ( 2.095) | (10.990) | (-6.096) | (-0.737) |
| INDONESIA | 0.541 *** | 0.030 | -0.039 | 0.000 *** | -0.024 | 0.027 *** |
| | ( 5.350) | ( 1.687) | (-0.673) | (-3.788) | (-1.839) | ( 3.496) |
| IRELAND | -0.209 | -0.147 | 0.112 | 0.421 | -0.037 | 0.020 |
| | (-1.655) | (-0.607) | ( 1.527) | ( 0.986) | (-1.296) | ( 1.103) |
| ISRAEL | -0.004 | -0.058 | 0.029 * | -0.073 | 0.008 * | -0.014 |

*Continued*

*T*able E.3 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| | (-0.103) | (-1.285) | ( 1.974) | (-1.561) | ( 2.245) | (-1.958) |
| ITALY | 0.169 | 0.638 ** | -0.050 | -0.676 | -0.033 * | 0.033 |
| | ( 1.483) | ( 2.869) | (-0.826) | (-1.381) | (-2.250) | ( 1.607) |
| JAPAN | -0.030 | -0.028 | -0.001 | 0.000 | 0.039 | -0.002 |
| | (-0.395) | (-0.235) | (-0.047) | (-0.054) | ( 0.851) | (-0.168) |
| MALAYSIA | 0.238 | -0.006 | -0.091 ** | 0.200 | -0.028 | 0.002 |
| | ( 1.778) | (-0.362) | (-2.648) | ( 1.074) | (-1.172) | ( 0.188) |
| MEXICO | 0.458 *** | 0.010 | -0.124 *** | -0.094 *** | 0.011 | -0.013 |
| | ( 7.065) | ( 0.096) | (-4.419) | (-7.374) | ( 1.260) | (-1.675) |
| NETHERLANDS | 0.314 *** | 0.161 ** | -0.071 *** | -0.087 | -0.026 | -0.019 * |
| | ( 7.706) | ( 2.715) | (-4.067) | (-0.869) | (-1.946) | (-2.389) |
| NEW ZEALAND | 0.045 | -0.068 | 0.022 * | 0.096 | -0.017 | -0.031 * |
| | ( 0.740) | (-1.920) | ( 2.092) | ( 0.851) | (-1.512) | (-1.978) |
| NORWAY | 0.364 *** | 0.425 *** | -0.076 * | -0.132 *** | -0.008 | 0.033 |
| | ( 3.738) | ( 3.666) | (-2.351) | (-5.557) | (-1.438) | ( 1.910) |
| PAKISTAN | 0.123 * | -0.179 ** | -0.013 *** | -0.002 | -0.004 | 0.004 |
| | ( 2.523) | (-2.852) | (-3.535) | (-0.947) | (-0.744) | ( 1.761) |
| PHILIPPINES | 0.086 | -0.073 | -0.030 | -0.005 | 0.007 | -0.001 |
| | ( 1.279) | (-1.529) | (-1.807) | (-0.494) | ( 0.863) | (-0.159) |
| POLAND | 0.168 | -1.348 *** | -0.030 | 0.197 | -0.011 | -0.053 |
| | ( 1.056) | (-8.313) | (-0.451) | ( 0.469) | (-0.558) | (-1.532) |
| RUSSIA | 0.096 | 0.149 *** | -0.008 | -0.004 | 0.017 | -0.011 |
| | ( 0.705) | ( 3.497) | (-1.088) | (-0.532) | ( 0.818) | (-1.176) |
| SAUDI ARABIA | 1.268 *** | -0.670 ** | -0.342 *** | -1.044 *** | 0.032 | 0.032 * |
| | ( 4.937) | (-3.119) | (-5.550) | (-4.115) | ( 0.277) | ( 2.523) |
| SINGAPORE | 0.401 *** | 0.050 | 0.030 | -2.404 *** | 0.068 *** | -0.033 *** |
| | ( 4.437) | ( 0.622) | ( 0.975) | (-5.219) | ( 3.450) | (-4.764) |
| SOUTH AFRICA | -0.092 | 0.229 ** | 0.016 | 0.069 * | -0.005 | -0.005 |
| | (-1.557) | ( 2.681) | ( 0.951) | ( 2.067) | (-1.929) | (-1.283) |
| SPAIN | 0.196 *** | -0.016 | -0.127 *** | 0.388 *** | -0.011 | -0.004 |
| | ( 3.773) | (-0.886) | (-4.448) | ( 4.861) | (-1.127) | (-0.343) |
| SRI LANKA | 0.061 | -0.007 | 0.019 ** | 0.004 | -0.008 | -0.010 ** |
| | ( 0.597) | (-0.882) | ( 2.716) | ( 1.372) | (-1.031) | (-3.050) |
| SWEDEN | 0.455 *** | -0.307 * | -0.142 *** | -0.041 | 0.001 | -0.039 *** |
| | ( 4.665) | (-2.534) | (-3.553) | (-1.214) | ( 0.048) | (-3.469) |
| SWITZERLAND | 0.224 ** | 0.454 | -0.097 ** | -0.285 | 0.017 | -0.074 *** |
| | ( 2.898) | ( 1.279) | (-2.611) | (-1.192) | ( 0.648) | (-3.451) |
| THAILAND | 0.036 | 0.075 | -0.014 | 0.017 | -0.002 | -0.009 |
| | ( 0.537) | ( 1.843) | (-0.789) | ( 1.753) | (-0.264) | (-1.085) |
| TURKEY | 0.067 | -0.011 | -0.037 *** | -0.166 | 0.011 *** | -0.006 |
| | ( 1.098) | (-1.489) | (-4.259) | (-1.924) | ( 3.547) | (-1.870) |
| UNITED KINGDOM | 0.184 *** | 0.216 | -0.058 * | 0.101 | -0.006 | -0.022 * |
| | ( 4.401) | ( 1.583) | (-2.204) | ( 0.149) | (-1.847) | (-2.237) |
| VIETNAM | 0.848 | -0.249 | 0.371 | 0.000 * | -0.303 * | 0.096 |

*Continued*

Table E.3 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| | ( 0.746) | (-0.411) | ( 1.056) | (-2.157) | (-2.025) | ( 1.515) |

This table reports estimates of $b_t$, $c_t$, $d_t$, $e_t$ and $f_t$ in the regression $R_{t,t+1} = a_t + b_t AEIG_{i,t} + c_t DY_{i,t} + d_t I/K_{i,t} + e_t Interest_{i,t} + f_t INFL_{i,t} + \varepsilon_{i,t}$ where $R_{t+1,t+h}$ is the future cumulative market returns of the country over h = 1, 6 and 12 months following month t; $[AEIG]_y$ is the y measure of aggregate expected investment plans of the country, where $AEIG_{i,t}$ is the aggregate expected investment growth for the country $i$. $DY_{i,t}$, $I/K_{i,t}$, $Interest_{i,t}$ and $INFL_{i,t}$, are respectively dividend yield, investiment-to-capital, interest rate and inflation for the country $i$ in month $t$. For each country I run one individual time-series regression. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels. All the t-statistic are estimated by using Newey and West (1987) standard errors.

Table E.4 – AEIG predicitive regression controlled by opthers predictors (h = 12 months)

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| AUSTRALIA | 0.286 *** | -0.172 | -0.038 | 0.517 * | -0.042 * | -0.052 *** |
| | ( 5.699) | ( -1.356) | ( -1.015) | ( 2.295) | ( -2.235) | ( -4.236) |
| BELGIUM | 0.131 | 0.055 | -0.050 | 0.010 | -0.023 * | -0.026 |
| | ( 1.499) | ( 0.834) | ( -1.046) | ( 1.805) | ( -2.390) | ( -1.605) |
| BRAZIL | -0.114 | -0.159 *** | -0.032 | -0.003 | 0.054 *** | -0.049 *** |
| | ( -1.449) | ( -4.297) | ( -1.963) | ( -0.433) | ( 6.442) | ( -4.130) |
| CANADA | 0.333 *** | 0.045 | -0.071 *** | -0.760 *** | 0.056 *** | -0.056 *** |
| | ( 6.463) | ( 0.323) | ( -4.216) | ( -3.919) | ( 3.588) | ( -3.423) |
| CHILE | 0.196 * | -0.255 ** | -0.082 *** | 0.006 *** | -0.022 * | -0.035 *** |
| | ( 2.428) | ( -2.896) | ( -3.678) | ( 5.089) | ( -2.503) | ( -3.663) |
| CHINA | 0.090 | 0.156 | 0.064 | 0.075 | 0.024 | -0.073 *** |
| | ( 0.715) | ( 0.922) | ( 0.595) | ( 0.742) | ( 0.770) | ( -4.696) |
| DENMARK | 0.222 *** | 0.185 * | 0.019 | -0.144 | -0.026 | -0.010 |
| | ( 3.799) | ( 2.587) | ( 0.720) | ( -1.782) | ( -1.799) | ( -0.480) |
| FINLAND | -0.016 | -2.213 *** | 0.038 | 0.689 | -0.007 | -0.139 *** |
| | ( -0.157) | (-10.727) | ( 1.055) | ( 1.353) | ( -0.365) | ( -7.781) |
| FRANCE | 0.298 *** | -0.568 *** | -0.127 ** | 0.571 | 0.033 | -0.116 *** |
| | ( 3.881) | ( -3.439) | ( -3.271) | ( 1.926) | ( 1.811) | ( -5.345) |
| GERMANY | 0.434 *** | 0.546 * | -0.098 | -0.596 ** | 0.087 *** | -0.227 *** |
| | ( 4.513) | ( 2.248) | ( -1.749) | ( -2.808) | ( 5.657) | ( -7.190) |
| GREECE | 0.024 | -0.058 | 0.033 | -0.197 | -0.031 | 0.004 |
| | ( 0.246) | ( -0.451) | ( 0.858) | ( -0.400) | ( -1.410) | ( 0.282) |
| INDIA | -0.011 | -1.573 *** | 0.019 | 0.089 *** | -0.122 *** | 0.009 |
| | ( -0.090) | ( -9.900) | ( 1.273) | ( 9.656) | ( -7.927) | ( 1.534) |
| INDONESIA | 0.956 *** | 0.062 * | 0.100 | 0.000 *** | -0.077 *** | 0.063 *** |
| | ( 6.756) | ( 2.517) | ( 1.232) | ( -5.293) | ( -4.207) | ( 5.890) |
| IRELAND | -0.334 * | -0.086 | 0.168 * | 0.667 | -0.044 | 0.030 |
| | ( -2.528) | ( -0.337) | ( 2.181) | ( 1.494) | ( -1.438) | ( 1.597) |
| ISRAEL | -0.061 | -0.163 * | 0.083 *** | -0.213 ** | 0.010 * | -0.007 |
| | ( -0.939) | ( -2.494) | ( 3.906) | ( -3.155) | ( 2.029) | ( -0.710) |
| ITALY | -0.249 | 0.895 ** | 0.135 | 0.743 | -0.086 *** | 0.044 |

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*T*able E.4 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| | ( -1.575) | ( 2.913) | ( 1.603) | ( 1.098) | ( -4.117) | ( 1.542) |
| JAPAN | -0.052 | -0.142 | 0.023 | -0.001 | -0.019 | 0.025 |
| | ( -0.450) | ( -0.794) | ( 0.537) | ( -0.309) | ( -0.252) | ( 1.426) |
| MALAYSIA | 0.161 | -0.028 | -0.103 * | 0.068 | 0.020 | 0.009 |
| | ( 0.823) | ( -1.152) | ( -2.035) | ( 0.249) | ( 0.584) | ( 0.537) |
| MEXICO | 0.988 *** | -0.272 | -0.299 *** | -0.150 *** | 0.058 *** | -0.057 *** |
| | ( 10.840) | ( -1.845) | ( -7.645) | ( -8.329) | ( 4.801) | ( -5.188) |
| NETHERLANDS | 0.461 *** | 0.253 ** | -0.063 * | -0.101 | -0.061 ** | -0.046 *** |
| | ( 8.145) | ( 3.076) | ( -2.453) | ( -0.728) | ( -3.196) | ( -4.230) |
| NEW ZEALAND | 0.212 ** | 0.010 | 0.021 | 0.099 | -0.073 *** | 0.024 |
| | ( 2.838) | ( 0.242) | ( 1.695) | ( 0.732) | ( -5.208) | ( 1.249) |
| NORWAY | 0.542 *** | 0.416 ** | -0.110 ** | -0.180 *** | -0.013 | 0.037 |
| | ( 4.454) | ( 2.808) | ( -2.736) | ( -5.819) | ( -1.705) | ( 1.737) |
| PAKISTAN | 0.141 * | -0.274 ** | -0.017 ** | -0.003 | -0.005 | 0.010 ** |
| | ( 1.987) | ( -3.149) | ( -3.243) | ( -0.683) | ( -0.685) | ( 2.982) |
| PHILIPPINES | 0.131 | -0.128 * | -0.034 | -0.012 | 0.000 | 0.012 |
| | ( 1.581) | ( -2.147) | ( -1.640) | ( -0.960) | ( 0.001) | ( 1.097) |
| POLAND | 0.061 | -1.692 *** | -0.129 | 1.282 ** | -0.056 ** | -0.014 |
| | ( 0.359) | ( -9.698) | ( -1.796) | ( 2.836) | ( -2.682) | ( -0.378) |
| RUSSIA | 0.080 | 0.205 *** | -0.021 * | 0.013 | -0.006 | 0.001 |
| | ( 0.503) | ( 4.069) | ( -2.422) | ( 1.389) | ( -0.252) | ( 0.085) |
| SAUDI ARABIA | 0.708 * | -0.924 *** | -0.173 * | -1.160 *** | 0.320 * | 0.006 |
| | ( 2.312) | ( -3.614) | ( -2.305) | ( -3.726) | ( 2.364) | ( 0.382) |
| SINGAPORE | 0.215 | -0.303 * | 0.239 *** | -4.355 *** | 0.168 *** | -0.059 *** |
| | ( 1.695) | ( -2.458) | ( 5.493) | ( -6.671) | ( 6.040) | ( -6.100) |
| SOUTH AFRICA | -0.307 *** | 0.344 *** | 0.040 * | 0.174 *** | -0.005 | -0.009 |
| | ( -4.381) | ( 3.356) | ( 2.079) | ( 4.325) | ( -1.387) | ( -1.911) |
| SPAIN | 0.212 ** | -0.068 * | -0.143 ** | 0.583 *** | -0.007 | -0.020 |
| | ( 2.653) | ( -2.550) | ( -3.263) | ( 4.890) | ( -0.511) | ( -1.327) |
| SRI LANKA | -0.091 | -0.034 ** | 0.035 *** | 0.006 | 0.013 | -0.014 ** |
| | ( -0.624) | ( -2.961) | ( 3.433) | ( 1.387) | ( 1.074) | ( -2.983) |
| SWEDEN | 0.456 ** | -1.069 *** | -0.097 | -0.051 | -0.039 * | -0.045 ** |
| | ( 3.280) | ( -6.184) | ( -1.697) | ( -1.043) | ( -1.991) | ( -2.716) |
| SWITZERLAND | 0.250 * | 0.426 | -0.109 * | -0.217 | -0.005 | -0.075 * |
| | ( 2.465) | ( 0.917) | ( -2.240) | ( -0.698) | ( -0.147) | ( -2.541) |
| THAILAND | -0.075 | 0.147 ** | 0.037 | 0.005 | 0.003 | -0.008 |
| | ( -0.853) | ( 2.761) | ( 1.647) | ( 0.408) | ( 0.265) | ( -0.708) |
| TURKEY | -0.021 | -0.066 *** | -0.005 | -0.163 | 0.021 *** | -0.016 *** |
| | ( -0.248) | ( -6.472) | ( -0.427) | ( -1.219) | ( 5.243) | ( -3.864) |
| UNITED KINGDOM | 0.269 *** | 0.132 | -0.059 | -0.102 | -0.014 ** | -0.035 ** |
| | ( 4.779) | ( 0.712) | ( -1.637) | ( -0.112) | ( -3.328) | ( -2.669) |
| VIETNAM | 2.505 * | -0.629 | 0.575 | -0.001 *** | -0.582 ** | 0.231 *** |
| | ( 2.327) | ( -1.093) | ( 1.414) | ( -4.051) | ( -3.412) | ( 4.041) |

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Table E.4 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|

This table reports estimates of $b_t$, $c_t$, $d_t$, $e_t$ and $f_t$ in the regression $R_{t,t+1} = a_t + b_t AEIG_{i,t} + c_t DY_{i,t} + d_t I/K_{i,t} + e_t Interest_{i,t} + f_t INFL_{i,t} + \varepsilon_{i,t}$ where $R_{t+1,t+h}$ is the future cumulative market returns of the country over h = 1, 6 and 12 months following month t; $[AEIG]_y$ is the y measure of aggregate expected investment plans of the country, where $AEIG_{i,t}$ is the aggregate expected investment growth for the country $i$. $DY_{i,t}$, $I/K_{i,t}$, $Interest_{i,t}$ and $INFL_{i,t}$, are respectively dividend yield, investiment-to-capital, interest rate and inflation for the country $i$ in month $t$. For each country I run one individual time-series regression. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels. All the t-statistic are estimated by using Newey and West (1987) standard errors.

Table E.5 – AEIG predictive regression controlled by opthers predictors (h = 1 month / AEIG based only on growth firms)

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| AUSTRALIA | 0.031 | -0.016 | -0.014 | 0.087 | -0.002 | -0.005 |
| | ( 1.121) | (-0.192) | (-0.644) | ( 0.612) | (-0.227) | (-0.763) |
| BELGIUM | -0.009 | 0.024 | 0.013 | 0.000 | -0.003 | -0.010 |
| | (-0.313) | ( 1.122) | ( 0.864) | ( 0.010) | (-1.124) | (-1.785) |
| BRAZIL | 0.013 | -0.058 | -0.009 | 0.001 | 0.006 ** | -0.008 * |
| | ( 0.635) | (-1.673) | (-1.831) | ( 0.555) | ( 2.714) | (-2.016) |
| CANADA | 0.043 ** | 0.026 | -0.011 * | -0.114 * | 0.007 | -0.005 |
| | ( 3.019) | ( 0.756) | (-2.199) | (-2.116) | ( 1.734) | (-1.049) |
| CHILE | 0.014 | -0.001 | -0.003 | 0.000 | -0.003 | -0.004 |
| | ( 0.510) | (-0.043) | (-0.352) | ( 1.004) | (-1.011) | (-1.120) |
| CHINA | 0.072 ** | -0.020 | -0.069 *** | 0.016 | 0.005 | -0.007 * |
| | ( 2.785) | (-0.493) | (-3.629) | ( 0.802) | ( 0.814) | (-2.122) |
| DENMARK | 0.025 | 0.053 | 0.006 | -0.041 | 0.000 | -0.001 |
| | ( 1.392) | ( 1.596) | ( 0.786) | (-1.596) | ( 0.078) | (-0.090) |
| EGYPT | 0.087 | -0.046 | -0.013 | -0.012 | NA | NA |
| | ( 1.399) | (-1.531) | (-1.258) | (-0.573) | ( NA) | ( NA) |
| FINLAND | -0.005 | -0.220 | 0.003 | 0.131 | -0.004 | -0.015 |
| | (-0.080) | (-1.333) | ( 0.126) | ( 0.465) | (-0.435) | (-1.382) |
| FRANCE | 0.050 | -0.013 | -0.021 | 0.004 | 0.000 | -0.007 |
| | ( 1.309) | (-0.179) | (-1.119) | ( 0.027) | (-0.030) | (-0.739) |
| GERMANY | 0.074 | 0.112 | -0.031 | -0.011 | 0.007 | -0.017 |
| | ( 1.751) | ( 1.076) | (-1.302) | (-0.120) | ( 1.052) | (-1.299) |
| GREECE | 0.027 | 0.027 | -0.012 | 0.016 | 0.003 | -0.003 |
| | ( 1.237) | ( 1.264) | (-1.334) | ( 0.147) | ( 0.444) | (-0.904) |
| HONG KONG | 0.049 * | 0.008 | -0.017 | -0.009 | NA | NA |
| | ( 2.073) | ( 0.295) | (-1.783) | (-0.303) | ( NA) | ( NA) |
| INDIA | -0.056 | -0.121 ** | 0.005 | 0.012 *** | -0.008 | -0.002 |
| | (-1.650) | (-2.769) | ( 1.228) | ( 4.343) | (-1.720) | (-1.403) |
| INDONESIA | 0.112 * | 0.009 | -0.008 | 0.000 | -0.004 | 0.005 |
| | ( 2.484) | ( 1.104) | (-0.310) | (-1.939) | (-0.688) | ( 1.378) |
| IRELAND | 0.017 | -0.024 | -0.004 | -0.156 | 0.003 | -0.002 |

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Table E.5 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| | ( 0.245) | (-0.232) | (-0.107) | (-0.672) | ( 0.234) | (-0.168) |
| ISRAEL | 0.007 | -0.018 | 0.000 | 0.003 | 0.001 | -0.004 |
| | ( 0.405) | (-0.936) | (-0.020) | ( 0.134) | ( 0.900) | (-1.475) |
| ITALY | 0.064 | 0.083 | -0.028 | -0.154 | -0.001 | 0.004 |
| | ( 0.976) | ( 0.866) | (-0.823) | (-0.566) | (-0.098) | ( 0.313) |
| JAPAN | 0.007 | -0.007 | -0.007 | 0.000 | 0.013 | -0.003 |
| | ( 0.270) | (-0.188) | (-0.681) | (-0.285) | ( 0.872) | (-0.653) |
| KOREA (SOUTH) | 0.044 ** | -0.042 *** | -0.003 | 0.000 | NA | NA |
| | ( 3.123) | (-4.432) | (-0.325) | (-1.954) | ( NA) | ( NA) |
| MALAYSIA | 0.133 * | 0.005 | -0.029 | -0.119 | -0.013 | 0.003 |
| | ( 2.185) | ( 0.716) | (-1.913) | (-1.527) | (-1.140) | ( 0.673) |
| MEXICO | 0.049 | 0.020 | -0.009 | -0.015 * | -0.003 | 0.003 |
| | ( 1.698) | ( 0.563) | (-0.727) | (-2.554) | (-0.842) | ( 0.699) |
| NETHERLANDS | 0.057 ** | 0.021 | -0.016 | 0.014 | -0.004 | -0.003 |
| | ( 2.611) | ( 0.674) | (-1.820) | ( 0.249) | (-0.499) | (-0.571) |
| NEW ZEALAND | 0.021 | -0.007 | -0.001 | 0.006 | 0.000 | -0.009 |
| | ( 0.577) | (-0.233) | (-0.173) | ( 0.078) | ( 0.029) | (-0.975) |
| NORWAY | 0.082 | 0.081 | -0.015 | -0.018 | -0.002 | -0.004 |
| | ( 1.947) | ( 1.692) | (-1.057) | (-1.820) | (-0.766) | (-0.531) |
| PAKISTAN | 0.020 | -0.011 | -0.002 | -0.001 | 0.001 | 0.000 |
| | ( 0.877) | (-0.632) | (-1.037) | (-0.727) | ( 0.666) | (-0.211) |
| PHILIPPINES | 0.040 | -0.008 | -0.004 | -0.004 | 0.000 | -0.001 |
| | ( 1.314) | (-0.460) | (-0.555) | (-0.908) | ( 0.088) | (-0.385) |
| POLAND | 0.150 | -0.179 | -0.002 | -0.272 | 0.000 | -0.015 |
| | ( 1.114) | (-1.377) | (-0.033) | (-0.804) | ( 0.014) | (-0.520) |
| RUSSIA | 0.004 | 0.019 | 0.001 | -0.001 | 0.005 | -0.002 |
| | ( 0.038) | ( 0.871) | ( 0.165) | (-0.160) | ( 0.323) | (-0.345) |
| SAUDI ARABIA | 0.193 | -0.042 | -0.059 | -0.063 | -0.010 | 0.002 |
| | ( 1.237) | (-0.465) | (-1.644) | (-0.429) | (-0.142) | ( 0.275) |
| SINGAPORE | 0.092 * | -0.010 | 0.006 | -0.558 ** | 0.014 | -0.006 * |
| | ( 2.432) | (-0.232) | ( 0.416) | (-3.111) | ( 1.742) | (-2.374) |
| SOUTH AFRICA | -0.025 | 0.018 | 0.006 | 0.011 | -0.001 | 0.001 |
| | (-0.668) | ( 0.292) | ( 0.571) | ( 0.486) | (-0.701) | ( 0.225) |
| SPAIN | 0.049 | 0.002 | -0.031 * | 0.063 | -0.004 | 0.003 |
| | ( 1.882) | ( 0.126) | (-2.250) | ( 1.593) | (-0.720) | ( 0.552) |
| SRI LANKA | 0.013 | -0.001 | 0.003 | 0.001 | -0.001 | -0.002 |
| | ( 0.327) | (-0.294) | ( 1.033) | ( 0.570) | (-0.449) | (-1.486) |
| SWEDEN | 0.093 | -0.003 | -0.031 | -0.012 | 0.004 | -0.009 |
| | ( 1.827) | (-0.045) | (-1.486) | (-0.631) | ( 0.533) | (-1.437) |
| SWITZERLAND | 0.020 | -0.131 | -0.011 | 0.001 | 0.015 | -0.020 |
| | ( 0.448) | (-0.787) | (-0.510) | ( 0.005) | ( 1.135) | (-1.648) |
| TAIWAN | 0.068 * | -0.014 | -0.013 * | -0.010 | NA | NA |
| | ( 2.548) | (-0.529) | (-2.333) | (-1.934) | ( NA) | ( NA) |
| THAILAND | 0.014 | 0.025 | 0.000 | -0.001 | 0.002 | -0.004 |
| | ( 0.283) | ( 0.565) | (-0.014) | (-0.100) | ( 0.298) | (-0.573) |

*Continued*

*T*able E.5 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| TURKEY | 0.009 | -0.001 | -0.010 * | -0.022 | 0.002 | -0.001 |
| | ( 0.314) | (-0.344) | (-2.461) | (-0.621) | ( 1.713) | (-0.839) |
| UNITED KINGDOM | 0.039 | 0.023 | -0.020 | 0.171 | -0.001 | -0.003 |
| | ( 1.441) | ( 0.285) | (-1.140) | ( 0.386) | (-0.260) | (-0.541) |
| VIETNAM | 0.253 | 0.056 | 0.061 | 0.000 | -0.043 | 0.013 |
| | ( 0.423) | ( 0.150) | ( 0.305) | (-0.825) | (-0.434) | ( 0.214) |

This table reports estimates of $b_t$, $c_t$, $d_t$, $e_t$ and $f_t$ in the regression $R_{t,t+1} = a_t + b_t[AEIG]_{i,t,y} + c_tDY_{i,t} + d_tI/K_{i,t} + e_tInterest_{i,t} + f_tINFL_{i,t} + \varepsilon_{i,t}$ where $R_{t+1,t+h}$ is the future cumulative market returns of the country over h = 1, 6 and 12 months following month t; $[AEIG]_{i,t,y}$ is the y measure of aggregate expected investment plans of the country i for the month t, where $[AEIG]_y$ in [AEIG-B, AEIG-G, AEIG-M]. AEIG-B is the aggregate EIG measure base on all firms of the market, AEIG-G is the aggregate EIG measure base only on growth firms of the market, and AEIG-M based only on mature firms. $DY_{i,t}$, $I/K_{i,t}$, $Interest_{i,t}$ and $INFL_{i,t}$, are respectively dividend yield, investiment-to-capital, interest rate and inflation for the country $i$ in month $t$. For each country I run one individual time-series regression. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels. All the t-statistic are estimated by using Newey and West (1987) standard errors.

Table E.6 – AEIG predictive regression controlled by opthers predictors (h = 3 month / AEIG based only on growth firms)

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| AUSTRALIA | 0.081 * | -0.020 | -0.026 | 0.117 | -0.003 | -0.016 |
| | ( 2.493) | (-0.218) | (-1.082) | ( 0.717) | (-0.278) | (-1.942) |
| BELGIUM | 0.019 | 0.050 | 0.004 | 0.000 | -0.009 | -0.015 |
| | ( 0.410) | ( 1.477) | ( 0.153) | ( 0.002) | (-1.831) | (-1.674) |
| BRAZIL | 0.023 | -0.170 ** | -0.031 *** | 0.005 | 0.021 *** | -0.021 ** |
| | ( 0.640) | (-2.703) | (-3.659) | ( 1.361) | ( 4.959) | (-3.150) |
| CANADA | 0.126 *** | 0.099 | -0.036 *** | -0.341 *** | 0.017 * | -0.010 |
| | ( 5.199) | ( 1.658) | (-4.325) | (-3.685) | ( 2.450) | (-1.183) |
| CHILE | 0.043 | 0.013 | -0.004 | 0.001 | -0.009 | -0.005 |
| | ( 0.877) | ( 0.300) | (-0.265) | ( 0.948) | (-1.539) | (-0.901) |
| CHINA | 0.188 *** | -0.039 | -0.169 *** | 0.042 | 0.010 | -0.020 ** |
| | ( 3.778) | (-0.503) | (-4.583) | ( 1.134) | ( 0.922) | (-3.305) |
| DENMARK | 0.066 * | 0.156 ** | 0.018 | -0.117 ** | -0.002 | 0.004 |
| | ( 2.252) | ( 2.867) | ( 1.437) | (-2.821) | (-0.219) | ( 0.348) |
| EGYPT | 0.314 ** | -0.173 *** | -0.048 ** | -0.053 | NA | NA |
| | ( 2.974) | (-3.400) | (-2.737) | (-1.412) | ( NA) | ( NA) |
| FINLAND | -0.067 | -0.587 ** | 0.018 | 0.627 | -0.021 | -0.039 ** |
| | (-0.862) | (-2.745) | ( 0.661) | ( 1.736) | (-1.565) | (-2.916) |
| FRANCE | 0.109 * | -0.066 | -0.045 | 0.141 | -0.004 | -0.022 |
| | ( 2.277) | (-0.749) | (-1.887) | ( 0.778) | (-0.460) | (-1.793) |
| GERMANY | 0.211 *** | 0.296 * | -0.077 * | -0.067 | 0.021 * | -0.062 *** |
| | ( 3.590) | ( 2.086) | (-2.333) | (-0.537) | ( 2.414) | (-3.429) |

*Continued*

Table E.6 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| GREECE | 0.043 | 0.040 | -0.030 | 0.169 | 0.000 | -0.001 |
| | ( 1.123) | ( 1.051) | (-1.871) | ( 0.839) | (-0.045) | (-0.163) |
| HONG KONG | 0.153 *** | 0.014 | -0.042 * | -0.068 | NA | NA |
| | ( 3.333) | ( 0.268) | (-2.299) | (-1.130) | ( NA) | ( NA) |
| INDIA | -0.172 ** | -0.443 *** | 0.014 * | 0.040 *** | -0.029 *** | -0.005 |
| | (-2.993) | (-6.057) | ( 2.033) | ( 8.370) | (-3.841) | (-1.594) |
| INDONESIA | 0.329 *** | 0.024 | -0.032 | 0.000 *** | -0.011 | 0.015 ** |
| | ( 4.422) | ( 1.820) | (-0.770) | (-3.352) | (-1.201) | ( 2.660) |
| IRELAND | -0.049 | -0.063 | 0.029 | 0.062 | -0.009 | 0.001 |
| | (-0.483) | (-0.420) | ( 0.491) | ( 0.182) | (-0.393) | ( 0.094) |
| ISRAEL | -0.005 | -0.036 | 0.012 | -0.014 | 0.005 * | -0.012 * |
| | (-0.162) | (-1.116) | ( 1.163) | (-0.410) | ( 2.035) | (-2.382) |
| ITALY | 0.120 | 0.317 ** | -0.051 | -0.247 | -0.011 | 0.013 |
| | ( 1.483) | ( 2.727) | (-1.215) | (-0.738) | (-1.134) | ( 0.941) |
| JAPAN | -0.011 | -0.043 | -0.008 | 0.000 | 0.032 | -0.005 |
| | (-0.215) | (-0.571) | (-0.393) | ( 0.119) | ( 1.090) | (-0.702) |
| KOREA (SOUTH) | 0.113 *** | -0.120 *** | -0.002 | -0.001 ** | NA | NA |
| | ( 4.609) | (-7.389) | (-0.164) | (-3.067) | ( NA) | ( NA) |
| MALAYSIA | 0.210 * | -0.003 | -0.068 ** | -0.065 | -0.016 | 0.006 |
| | ( 2.083) | (-0.239) | (-2.686) | (-0.509) | (-0.836) | ( 0.766) |
| MEXICO | 0.187 *** | 0.079 | -0.041 * | -0.052 *** | -0.006 | 0.004 |
| | ( 4.131) | ( 1.401) | (-2.022) | (-5.737) | (-0.951) | ( 0.640) |
| NETHERLANDS | 0.162 *** | 0.087 | -0.034 * | -0.027 | -0.015 | -0.012 |
| | ( 5.097) | ( 1.967) | (-2.551) | (-0.338) | (-1.463) | (-1.840) |
| NEW ZEALAND | 0.055 | -0.016 | 0.001 | 0.050 | -0.009 | -0.015 |
| | ( 1.247) | (-0.447) | ( 0.151) | ( 0.517) | (-0.963) | (-1.256) |
| NORWAY | 0.197 ** | 0.256 ** | -0.033 | -0.063 *** | -0.006 | 0.008 |
| | ( 2.634) | ( 3.038) | (-1.344) | (-3.666) | (-1.386) | ( 0.615) |
| PAKISTAN | 0.061 | -0.043 | -0.005 * | -0.002 | 0.003 | 0.000 |
| | ( 1.592) | (-1.491) | (-1.971) | (-1.180) | ( 0.831) | (-0.007) |
| PHILIPPINES | 0.076 | -0.015 | -0.010 | -0.007 | 0.001 | -0.002 |
| | ( 1.515) | (-0.545) | (-0.836) | (-0.982) | ( 0.138) | (-0.329) |
| POLAND | 0.419 ** | -0.805 *** | -0.049 | -0.484 | -0.020 | -0.015 |
| | ( 2.622) | (-5.210) | (-0.741) | (-1.192) | (-0.976) | (-0.440) |
| RUSSIA | 0.037 | 0.067 ** | 0.002 | -0.005 | 0.016 | -0.009 |
| | ( 0.346) | ( 2.663) | ( 0.382) | (-0.892) | ( 0.981) | (-1.205) |
| SAUDI ARABIA | 0.597 * | -0.124 | -0.164 ** | -0.345 | -0.020 | 0.011 |
| | ( 2.586) | (-0.935) | (-3.064) | (-1.594) | (-0.188) | ( 1.059) |
| SINGAPORE | 0.267 *** | -0.006 | 0.010 | -1.514 *** | 0.038 ** | -0.016 *** |
| | ( 3.999) | (-0.076) | ( 0.356) | (-4.756) | ( 2.738) | (-3.417) |
| SOUTH AFRICA | -0.064 | 0.126 | 0.021 | 0.021 | -0.005 | 0.002 |
| | (-1.188) | ( 1.414) | ( 1.436) | ( 0.639) | (-1.963) | ( 0.472) |
| SPAIN | 0.112 ** | -0.016 | -0.075 *** | 0.230 *** | -0.007 | 0.002 |
| | ( 2.851) | (-0.706) | (-3.557) | ( 3.784) | (-0.916) | ( 0.225) |
| SRI LANKA | 0.034 | -0.003 | 0.009 | 0.002 | -0.004 | -0.005 * |

*Continued*

Table E.6 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| | ( 0.484) | (-0.476) | ( 1.737) | ( 1.076) | (-0.741) | (-2.479) |
| SWEDEN | 0.214 ** | -0.040 | -0.066 * | -0.024 | 0.005 | -0.025 ** |
| | ( 2.801) | (-0.421) | (-2.093) | (-0.931) | ( 0.468) | (-2.862) |
| SWITZERLAND | 0.049 | -0.380 | -0.025 | -0.006 | 0.047 ** | -0.062 *** |
| | ( 0.839) | (-1.794) | (-0.941) | (-0.033) | ( 2.719) | (-4.082) |
| TAIWAN | 0.223 *** | -0.028 | -0.043 *** | -0.031 *** | NA | NA |
| | ( 4.656) | (-0.610) | (-4.409) | (-3.375) | ( NA) | ( NA) |
| THAILAND | 0.031 | 0.064 | -0.007 | 0.006 | 0.003 | -0.008 |
| | ( 0.580) | ( 1.283) | (-0.532) | ( 0.910) | ( 0.433) | (-1.185) |
| TURKEY | 0.037 | -0.004 | -0.027 *** | -0.078 | 0.006 ** | -0.003 |
| | ( 0.872) | (-0.686) | (-4.470) | (-1.368) | ( 2.907) | (-1.357) |
| UNITED KINGDOM | 0.086 ** | 0.013 | -0.038 | 0.280 | -0.001 | -0.007 |
| | ( 2.605) | ( 0.133) | (-1.847) | ( 0.522) | (-0.619) | (-0.926) |
| VIETNAM | -0.026 | -0.734 | 0.404 | 0.000 | -0.140 | -0.065 |
| | (-0.035) | (-1.608) | ( 1.600) | (-1.895) | (-1.130) | (-0.879) |

This table reports estimates of $b_t$, $c_t$, $d_t$, $e_t$ and $f_t$ in the regression $R_{t,t+1} = a_t + b_t[AEIG]_{i,t,y} + c_t DY_{i,t} + d_t I/K_{i,t} + e_t Interest_{i,t} + f_t INFL_{i,t} + \varepsilon_{i,t}$ where $R_{t+1,t+h}$ is the future cumulative market returns of the country over h = 1, 6 and 12 months following month t; $[AEIG]_{i,t,y}$ is the y measure of aggregate expected investment plans of the country i for the month t, where $[AEIG]_y$ in [AEIG-B, AEIG-G, AEIG-M]. AEIG-B is the aggregate EIG measure base on all firms of the market, AEIG-G is the aggregate EIG measure base only on growth firms of the market, and AEIG-M based only on mature firms. $DY_{i,t}$, $I/K_{i,t}$, $Interest_{i,t}$ and $INFL_{i,t}$, are respectively dividend yield, investiment-to-capital, interest rate and inflation for the country $i$ in month $t$. For each country I run one individual time-series regression. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels. All the t-statistic are estimated by using Newey and West (1987) standard errors.

Table E.7 – AEIG predictive regression controlled by opthers predictors (h = 6 month / AEIG based only on growth firms)

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| AUSTRALIA | 0.152 *** | -0.093 | -0.051 | 0.345 | -0.007 | -0.035 *** |
| | ( 3.672) | (-0.790) | (-1.666) | ( 1.661) | (-0.463) | (-3.377) |
| BELGIUM | 0.032 | 0.101 * | 0.006 | 0.004 | -0.016 * | -0.027 * |
| | ( 0.527) | ( 2.220) | ( 0.162) | ( 0.880) | (-2.381) | (-2.194) |
| BRAZIL | 0.052 | -0.407 *** | -0.056 *** | 0.004 | 0.043 *** | -0.048 *** |
| | ( 1.010) | (-4.626) | (-4.765) | ( 0.715) | ( 7.267) | (-5.171) |
| CANADA | 0.206 *** | 0.145 | -0.060 *** | -0.514 *** | 0.028 ** | -0.018 |
| | ( 5.889) | ( 1.699) | (-5.107) | (-3.853) | ( 2.729) | (-1.523) |
| CHILE | 0.091 | -0.067 | -0.032 | 0.003 ** | -0.015 * | -0.018 * |
| | ( 1.409) | (-1.215) | (-1.721) | ( 2.775) | (-1.980) | (-2.295) |
| CHINA | 0.251 ** | -0.115 | -0.243 *** | 0.073 | 0.029 | -0.033 *** |
| | ( 3.292) | (-0.965) | (-4.205) | ( 1.274) | ( 1.690) | (-3.578) |
| DENMARK | 0.125 ** | 0.268 *** | 0.030 | -0.175 ** | -0.008 | 0.000 |
| | ( 2.955) | ( 3.396) | ( 1.626) | (-2.933) | (-0.764) | ( 0.000) |

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*T*able E.7 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| EGYPT | 0.614 *** | -0.324 *** | -0.091 *** | -0.110 | NA | NA |
| | ( 3.880) | (-4.263) | (-3.452) | (-1.915) | ( NA) | ( NA) |
| FINLAND | -0.201 * | -1.464 *** | 0.055 | 1.259 ** | -0.051 ** | -0.084 *** |
| | (-2.077) | (-5.380) | ( 1.627) | ( 2.816) | (-3.086) | (-5.010) |
| FRANCE | 0.209 *** | -0.212 | -0.092 ** | 0.402 | -0.002 | -0.052 ** |
| | ( 3.531) | (-1.924) | (-3.110) | ( 1.791) | (-0.189) | (-3.319) |
| GERMANY | 0.342 *** | 0.401 * | -0.118 ** | -0.121 | 0.037 *** | -0.114 *** |
| | ( 4.653) | ( 2.260) | (-2.840) | (-0.773) | ( 3.422) | (-4.993) |
| GREECE | 0.071 | 0.020 | -0.036 | 0.050 | -0.002 | 0.001 |
| | ( 1.263) | ( 0.368) | (-1.553) | ( 0.167) | (-0.156) | ( 0.094) |
| HONG KONG | 0.219 *** | -0.011 | -0.064 * | -0.066 | NA | NA |
| | ( 3.433) | (-0.157) | (-2.532) | (-0.790) | ( NA) | ( NA) |
| INDIA | -0.262 *** | -0.828 *** | 0.027 ** | 0.070 *** | -0.060 *** | -0.005 |
| | (-3.352) | (-8.359) | ( 2.770) | (10.766) | (-5.784) | (-1.194) |
| INDONESIA | 0.590 *** | 0.041 * | -0.022 | 0.000 *** | -0.030 * | 0.030 *** |
| | ( 5.573) | ( 2.228) | (-0.375) | (-4.073) | (-2.194) | ( 3.784) |
| IRELAND | -0.202 | -0.123 | 0.109 | 0.418 | -0.040 | 0.020 |
| | (-1.603) | (-0.658) | ( 1.499) | ( 0.982) | (-1.426) | ( 1.128) |
| ISRAEL | -0.001 | -0.050 | 0.027 | -0.074 | 0.008 * | -0.013 |
| | (-0.020) | (-1.085) | ( 1.863) | (-1.572) | ( 2.385) | (-1.864) |
| ITALY | 0.149 | 0.493 ** | -0.059 | -0.256 | -0.022 | 0.020 |
| | ( 1.299) | ( 3.006) | (-0.996) | (-0.542) | (-1.628) | ( 1.001) |
| JAPAN | -0.066 | -0.117 | 0.005 | 0.002 | 0.050 | 0.002 |
| | (-0.872) | (-1.025) | ( 0.182) | ( 0.606) | ( 1.098) | ( 0.161) |
| KOREA (SOUTH) | 0.174 *** | -0.194 *** | -0.022 | -0.001 * | NA | NA |
| | ( 4.713) | (-8.014) | (-1.050) | (-2.121) | ( NA) | ( NA) |
| MALAYSIA | 0.313 * | 0.005 | -0.097 ** | 0.130 | -0.043 | 0.003 |
| | ( 2.292) | ( 0.361) | (-2.807) | ( 0.751) | (-1.641) | ( 0.306) |
| MEXICO | 0.457 *** | 0.014 | -0.122 *** | -0.094 *** | 0.011 | -0.013 |
| | ( 6.980) | ( 0.175) | (-4.171) | (-7.237) | ( 1.224) | (-1.637) |
| NETHERLANDS | 0.326 *** | 0.178 ** | -0.066 *** | -0.118 | -0.030 * | -0.023 ** |
| | ( 7.974) | ( 3.121) | (-3.724) | (-1.163) | (-2.263) | (-2.771) |
| NEW ZEALAND | 0.126 * | -0.033 | 0.005 | 0.089 | -0.026 * | -0.018 |
| | ( 2.355) | (-0.779) | ( 0.594) | ( 0.776) | (-2.473) | (-1.272) |
| NORWAY | 0.377 *** | 0.449 *** | -0.073 * | -0.128 *** | -0.013 * | 0.035 * |
| | ( 3.935) | ( 4.145) | (-2.309) | (-5.764) | (-2.364) | ( 2.070) |
| PAKISTAN | 0.078 | -0.132 *** | -0.009 * | -0.002 | 0.002 | 0.003 |
| | ( 1.555) | (-3.539) | (-2.443) | (-0.917) | ( 0.456) | ( 1.303) |
| PHILIPPINES | 0.082 | -0.050 | -0.025 | -0.005 | 0.005 | -0.001 |
| | ( 1.223) | (-1.351) | (-1.631) | (-0.546) | ( 0.639) | (-0.122) |
| POLAND | 0.478 ** | -1.423 *** | -0.103 | -0.077 | -0.056 ** | 0.006 |
| | ( 3.017) | (-9.283) | (-1.553) | (-0.190) | (-2.807) | ( 0.175) |
| RUSSIA | 0.101 | 0.096 ** | -0.009 | -0.003 | 0.011 | -0.006 |
| | ( 0.736) | ( 2.982) | (-1.148) | (-0.449) | ( 0.509) | (-0.712) |
| SAUDI ARABIA | 1.293 *** | -0.240 | -0.320 *** | -1.047 *** | -0.009 | 0.038 ** |

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*T*able E.7 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| | ( 4.682) | (-1.524) | (-4.987) | (-4.006) | (-0.072) | ( 2.969) |
| SINGAPORE | 0.345 *** | -0.111 | 0.072 | -2.752 *** | 0.082 *** | -0.034 *** |
| | ( 3.475) | (-1.027) | ( 1.798) | (-5.822) | ( 3.962) | (-4.827) |
| SOUTH AFRICA | -0.090 | 0.212 * | 0.020 | 0.062 | -0.006 * | -0.003 |
| | (-1.460) | ( 2.080) | ( 1.196) | ( 1.681) | (-2.065) | (-0.769) |
| SPAIN | 0.180 ** | -0.049 | -0.120 *** | 0.413 *** | -0.004 | -0.007 |
| | ( 3.260) | (-1.602) | (-4.075) | ( 4.889) | (-0.368) | (-0.618) |
| SRI LANKA | 0.055 | -0.006 | 0.020 ** | 0.004 | -0.009 | -0.010 ** |
| | ( 0.546) | (-0.696) | ( 2.772) | ( 1.477) | (-1.066) | (-3.053) |
| SWEDEN | 0.444 *** | -0.167 | -0.143 *** | -0.034 | 0.003 | -0.041 *** |
| | ( 4.474) | (-1.354) | (-3.510) | (-0.988) | ( 0.235) | (-3.636) |
| SWITZERLAND | 0.142 | -0.365 | -0.063 | -0.143 | 0.056 * | -0.086 *** |
| | ( 1.773) | (-1.250) | (-1.741) | (-0.576) | ( 2.319) | (-4.018) |
| TAIWAN | 0.439 *** | -0.029 | -0.088 *** | -0.057 *** | NA | NA |
| | ( 6.410) | (-0.436) | (-6.281) | (-4.345) | ( NA) | ( NA) |
| THAILAND | 0.011 | 0.135 * | -0.006 | 0.016 | 0.007 | -0.014 |
| | ( 0.151) | ( 2.103) | (-0.319) | ( 1.737) | ( 0.793) | (-1.522) |
| TURKEY | 0.066 | -0.014 | -0.036 *** | -0.167 | 0.011 *** | -0.006 |
| | ( 1.088) | (-1.773) | (-4.161) | (-1.939) | ( 3.577) | (-1.925) |
| UNITED KINGDOM | 0.163 *** | -0.012 | -0.072 ** | 0.659 | -0.005 | -0.015 |
| | ( 3.820) | (-0.091) | (-2.676) | ( 0.948) | (-1.548) | (-1.546) |
| VIETNAM | 0.883 | -1.129 * | 0.471 | -0.001 ** | -0.253 | -0.022 |
| | ( 1.051) | (-2.222) | ( 1.602) | (-2.796) | (-1.738) | (-0.267) |

This table reports estimates of $b_t$, $c_t$, $d_t$, $e_t$ and $f_t$ in the regression $R_{t,t+1} = a_t + b_t[AEIG]_{i,t,y} + c_t DY_{i,t} + d_t I/K_{i,t} + e_t Interest_{i,t} + f_t INFL_{i,t} + \varepsilon_{i,t}$ where $R_{t+1,t+h}$ is the future cumulative market returns of the country over h = 1, 6 and 12 months following month t; $[AEIG]_{i,t,y}$ is the y measure of aggregate expected investment plans of the country i for the month t, where $[AEIG]_y$ in [AEIG-B, AEIG-G, AEIG-M]. AEIG-B is the aggregate EIG measure base on all firms of the market, AEIG-G is the aggregate EIG measure base only on growth firms of the market, and AEIG-M based only on mature firms. $DY_{i,t}$, $I/K_{i,t}$, $Interest_{i,t}$ and $INFL_{i,t}$, are respectively dividend yield, investiment-to-capital, interest rate and inflation for the country $i$ in month $t$. For each country I run one individual time-series regression. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels. All the t-statistic are estimated by using Newey and West (1987) standard errors.

Table E.8 – AEIG predictive regression controlled by opthers predictors (h = 12 month / AEIG based only on growth firms)

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| AUSTRALIA | 0.273 *** | -0.346 * | -0.042 | 0.735 ** | -0.045 * | -0.055 *** |
| | ( 5.445) | ( -2.490) | ( -1.158) | ( 2.996) | ( -2.429) | ( -4.483) |
| BELGIUM | 0.097 | 0.109 | -0.032 | 0.013 * | -0.024 ** | -0.027 |
| | ( 1.178) | ( 1.784) | ( -0.698) | ( 2.197) | ( -2.653) | ( -1.655) |
| BRAZIL | -0.074 | -0.713 *** | -0.033 * | -0.005 | 0.063 *** | -0.069 *** |
| | ( -1.037) | ( -6.013) | ( -2.113) | ( -0.717) | ( 8.071) | ( -5.564) |

*Continued*

Table E.8 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| CANADA | 0.331 *** | 0.060 | -0.071 *** | -0.764 *** | 0.055 *** | -0.054 ** |
| | ( 6.515) | ( 0.488) | ( -4.233) | ( -3.935) | ( 3.586) | ( -3.255) |
| CHILE | 0.208 ** | -0.242 *** | -0.094 *** | 0.007 *** | -0.030 *** | -0.033 *** |
| | ( 2.601) | ( -3.607) | ( -4.174) | ( 5.541) | ( -3.359) | ( -3.524) |
| CHINA | 0.152 | -0.403 * | -0.078 | 0.128 | 0.017 | -0.045 ** |
| | ( 1.296) | ( -2.159) | ( -0.825) | ( 1.409) | ( 0.623) | ( -3.200) |
| DENMARK | 0.238 *** | 0.248 * | 0.010 | -0.139 | -0.031 * | -0.004 |
| | ( 4.089) | ( 2.262) | ( 0.406) | ( -1.692) | ( -2.129) | ( -0.163) |
| EGYPT | 0.722 ** | -0.458 *** | -0.103 ** | -0.079 | NA | NA |
| | ( 3.076) | ( -4.077) | ( -2.654) | ( -0.878) | ( NA) | ( NA) |
| FINLAND | -0.345 ** | -3.341 *** | 0.083 * | 1.933 *** | -0.084 *** | -0.143 *** |
| | ( -3.305) | (-10.352) | ( 2.273) | ( 3.980) | ( -4.641) | ( -7.920) |
| FRANCE | 0.286 *** | -0.464 ** | -0.127 ** | 0.519 | 0.031 | -0.112 *** |
| | ( 3.660) | ( -3.161) | ( -3.243) | ( 1.750) | ( 1.704) | ( -5.154) |
| GERMANY | 0.464 *** | 0.623 ** | -0.105 | -0.618 ** | 0.089 *** | -0.232 *** |
| | ( 4.715) | ( 2.620) | ( -1.898) | ( -2.916) | ( 5.785) | ( -7.361) |
| GREECE | -0.070 | -0.196 * | 0.051 | 0.060 | -0.041 | 0.012 |
| | ( -0.862) | ( -2.523) | ( 1.507) | ( 0.126) | ( -1.894) | ( 0.970) |
| HONG KONG | 0.134 | -0.274 ** | -0.014 | -0.044 | NA | NA |
| | ( 1.439) | ( -2.643) | ( -0.380) | ( -0.366) | ( NA) | ( NA) |
| INDIA | -0.150 | -1.416 *** | 0.029 | 0.095 *** | -0.120 *** | 0.006 |
| | ( -1.247) | ( -9.447) | ( 1.927) | ( 9.719) | ( -7.683) | ( 1.056) |
| INDONESIA | 1.013 *** | 0.067 * | 0.114 | 0.000 *** | -0.083 *** | 0.066 *** |
| | ( 6.792) | ( 2.570) | ( 1.377) | ( -5.391) | ( -4.305) | ( 5.943) |
| IRELAND | -0.330 * | -0.107 | 0.167 * | 0.679 | -0.046 | 0.031 |
| | ( -2.499) | ( -0.550) | ( 2.184) | ( 1.526) | ( -1.527) | ( 1.636) |
| ISRAEL | -0.048 | -0.135 * | 0.076 *** | -0.219 ** | 0.011 * | -0.005 |
| | ( -0.738) | ( -2.028) | ( 3.657) | ( -3.205) | ( 2.269) | ( -0.452) |
| ITALY | -0.272 | 0.684 ** | 0.118 | 1.313 * | -0.068 *** | 0.026 |
| | ( -1.706) | ( 3.028) | ( 1.434) | ( 2.003) | ( -3.666) | ( 0.927) |
| JAPAN | -0.116 | -0.293 | 0.033 | 0.002 | 0.005 | 0.030 |
| | ( -1.021) | ( -1.712) | ( 0.792) | ( 0.444) | ( 0.072) | ( 1.788) |
| KOREA (SOUTH) | 0.161 ** | -0.184 *** | -0.059 | 0.000 | NA | NA |
| | ( 2.742) | ( -4.859) | ( -1.817) | ( 0.695) | ( NA) | ( NA) |
| MALAYSIA | 0.334 | 0.000 | -0.115 * | -0.114 | -0.014 | 0.012 |
| | ( 1.665) | ( 0.010) | ( -2.283) | ( -0.446) | ( -0.360) | ( 0.735) |
| MEXICO | 0.991 *** | -0.160 | -0.310 *** | -0.147 *** | 0.060 *** | -0.059 *** |
| | ( 10.731) | ( -1.466) | ( -7.509) | ( -8.005) | ( 4.885) | ( -5.356) |
| NETHERLANDS | 0.479 *** | 0.278 *** | -0.055 * | -0.148 | -0.067 *** | -0.052 *** |
| | ( 8.467) | ( 3.530) | ( -2.137) | ( -1.057) | ( -3.540) | ( -4.598) |
| NEW ZEALAND | 0.228 *** | -0.059 | 0.017 | 0.136 | -0.072 *** | 0.018 |
| | ( 3.512) | ( -1.174) | ( 1.560) | ( 0.999) | ( -5.628) | ( 1.121) |
| NORWAY | 0.552 *** | 0.454 ** | -0.106 ** | -0.178 *** | -0.017 * | 0.040 |
| | ( 4.611) | ( 3.307) | ( -2.676) | ( -6.170) | ( -2.458) | ( 1.890) |
| PAKISTAN | 0.021 | -0.314 *** | -0.008 | 0.001 | 0.001 | 0.009 ** |

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Table E.8 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| | ( 0.300) | ( -6.382) | ( -1.714) | ( 0.217) | ( 0.255) | ( 3.291) |
| PHILIPPINES | 0.121 | -0.081 | -0.024 | -0.012 | -0.004 | 0.012 |
| | ( 1.472) | ( -1.768) | ( -1.246) | ( -1.014) | ( -0.438) | ( 1.116) |
| POLAND | 0.351 | -1.319 *** | -0.174 * | 0.789 | -0.092 *** | 0.048 |
| | ( 1.871) | ( -7.271) | ( -2.215) | ( 1.656) | ( -3.844) | ( 1.196) |
| RUSSIA | 0.094 | 0.145 *** | -0.021 * | 0.012 | -0.011 | 0.004 |
| | ( 0.582) | ( 3.856) | ( -2.417) | ( 1.312) | ( -0.450) | ( 0.385) |
| SAUDI ARABIA | 0.599 | -0.407 * | -0.116 | -1.053 ** | 0.284 | 0.007 |
| | ( 1.816) | ( -2.255) | ( -1.500) | ( -3.290) | ( 1.943) | ( 0.459) |
| SINGAPORE | 0.035 | -0.570 *** | 0.342 *** | -4.829 *** | 0.193 *** | -0.072 *** |
| | ( 0.256) | ( -3.788) | ( 6.135) | ( -7.365) | ( 6.726) | ( -7.294) |
| SOUTH AFRICA | -0.346 *** | 0.159 | 0.047 * | 0.194 *** | -0.004 | -0.007 |
| | ( -4.647) | ( 1.277) | ( 2.409) | ( 4.324) | ( -1.058) | ( -1.507) |
| SPAIN | 0.186 * | -0.147 *** | -0.136 ** | 0.642 *** | 0.009 | -0.026 |
| | ( 2.245) | ( -3.366) | ( -3.066) | ( 5.162) | ( 0.586) | ( -1.645) |
| SRI LANKA | -0.102 | -0.032 ** | 0.036 *** | 0.006 | 0.012 | -0.014 ** |
| | ( -0.704) | ( -2.755) | ( 3.535) | ( 1.537) | ( 1.010) | ( -2.984) |
| SWEDEN | 0.390 ** | -0.835 *** | -0.085 | -0.027 | -0.042 * | -0.048 ** |
| | ( 2.698) | ( -4.653) | ( -1.425) | ( -0.532) | ( -1.988) | ( -2.838) |
| SWITZERLAND | 0.180 | -0.322 | -0.081 | -0.095 | 0.032 | -0.088 ** |
| | ( 1.714) | ( -0.840) | ( -1.694) | ( -0.293) | ( 0.980) | ( -2.981) |
| TAIWAN | 0.762 *** | 0.054 | -0.162 *** | -0.087 *** | NA | NA |
| | ( 7.709) | ( 0.565) | ( -7.864) | ( -4.598) | ( NA) | ( NA) |
| THAILAND | -0.109 | 0.234 ** | 0.049 * | 0.002 | 0.019 | -0.015 |
| | ( -1.163) | ( 2.797) | ( 2.034) | ( 0.135) | ( 1.784) | ( -1.272) |
| TURKEY | -0.029 | -0.075 *** | -0.002 | -0.163 | 0.022 *** | -0.016 *** |
| | ( -0.346) | ( -7.069) | ( -0.165) | ( -1.232) | ( 5.447) | ( -4.137) |
| UNITED KINGDOM | 0.227 *** | -0.259 | -0.085 * | 0.975 | -0.012 ** | -0.023 |
| | ( 3.940) | ( -1.421) | ( -2.337) | ( 1.024) | ( -2.932) | ( -1.751) |
| VIETNAM | 2.923 *** | -1.808 *** | 0.522 | -0.001 *** | -0.426 ** | 0.041 |
| | ( 4.139) | ( -4.241) | ( 1.777) | ( -5.218) | ( -2.847) | ( 0.591) |

This table reports estimates of $b_t$, $c_t$, $d_t$, $e_t$ and $f_t$ in the regression $R_{t,t+1} = a_t + b_t[AEIG]_{i,t,y} + c_t DY_{i,t} + d_t I/K_{i,t} + e_t Interest_{i,t} + f_t INFL_{i,t} + \varepsilon_{i,t}$ where $R_{t+1,t+h}$ is the future cumulative market returns of the country over h = 1, 6 and 12 months following month t; $[AEIG]_{i,t,y}$ is the y measure of aggregate expected investment plans of the country i for the month t, where $[AEIG]_y$ in [AEIG-B, AEIG-G, AEIG-M]. AEIG-B is the aggregate EIG measure base on all firms of the market, AEIG-G is the aggregate EIG measure base only on growth firms of the market, and AEIG-M based only on mature firms. $DY_{i,t}$, $I/K_{i,t}$, $Interest_{i,t}$ and $INFL_{i,t}$, are respectively dividend yield, investiment-to-capital, interest rate and inflation for the country $i$ in month $t$. For each country I run one individual time-series regression. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels. All the t-statistic are estimated by using Newey and West (1987) standard errors.

Table E.9 – AEIG predictive regression controlled by opthers predictors (h = 1 month / AEIG based only on mature firms)

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| AUSTRALIA | 0.033 | 0.022 | -0.016 | 0.070 | -0.002 | -0.005 |
| | ( 1.205) | ( 0.349) | (-0.745) | ( 0.546) | (-0.182) | (-0.686) |
| BELGIUM | -0.003 | 0.012 | 0.010 | -0.001 | -0.003 | -0.010 |
| | (-0.101) | ( 0.623) | ( 0.646) | (-0.418) | (-1.004) | (-1.756) |
| BRAZIL | 0.014 | -0.014 | -0.009 | 0.001 | 0.005 * | -0.006 |
| | ( 0.641) | (-1.431) | (-1.827) | ( 0.547) | ( 2.250) | (-1.787) |
| CANADA | 0.043 ** | 0.022 | -0.010 * | -0.111 * | 0.008 | -0.006 |
| | ( 3.002) | ( 0.609) | (-2.165) | (-2.078) | ( 1.919) | (-1.255) |
| CHILE | 0.011 | 0.017 | -0.001 | 0.000 | -0.004 | -0.003 |
| | ( 0.409) | ( 0.544) | (-0.075) | ( 0.918) | (-1.130) | (-0.971) |
| CHINA | 0.049 | 0.035 * | -0.050 * | 0.002 | 0.014 | -0.010 *** |
| | ( 1.757) | ( 2.124) | (-2.566) | ( 0.113) | ( 1.915) | (-3.717) |
| DENMARK | 0.024 | 0.011 | 0.004 | -0.029 | 0.001 | -0.003 |
| | ( 1.296) | ( 0.726) | ( 0.546) | (-1.181) | ( 0.293) | (-0.402) |
| EGYPT | 0.067 | -0.031 | -0.009 | -0.008 | NA | NA |
| | ( 1.280) | (-1.627) | (-1.144) | (-0.385) | ( NA) | ( NA) |
| FINLAND | 0.017 | -0.162 | -0.001 | 0.036 | 0.001 | -0.013 |
| | ( 0.292) | (-1.534) | (-0.035) | ( 0.121) | ( 0.108) | (-1.212) |
| FRANCE | 0.049 | -0.032 | -0.020 | 0.026 | 0.000 | -0.009 |
| | ( 1.306) | (-0.412) | (-1.090) | ( 0.178) | ( 0.023) | (-0.888) |
| GERMANY | 0.067 | 0.086 | -0.029 | -0.006 | 0.006 | -0.016 |
| | ( 1.631) | ( 0.856) | (-1.209) | (-0.065) | ( 0.973) | (-1.219) |
| GREECE | 0.010 | 0.008 | -0.010 | 0.082 | 0.001 | -0.002 |
| | ( 0.593) | ( 0.302) | (-1.029) | ( 0.772) | ( 0.139) | (-0.535) |
| HONG KONG | 0.045 | -0.015 | -0.017 | -0.001 | NA | NA |
| | ( 1.957) | (-0.568) | (-1.793) | (-0.040) | ( NA) | ( NA) |
| INDIA | -0.046 | -0.111 * | 0.006 | 0.011 *** | -0.006 | -0.002 |
| | (-1.334) | (-2.430) | ( 1.413) | ( 4.100) | (-1.402) | (-1.307) |
| INDONESIA | 0.092 * | 0.001 | -0.017 | 0.000 | -0.001 | 0.003 |
| | ( 2.216) | ( 0.143) | (-0.698) | (-1.622) | (-0.226) | ( 1.008) |
| IRELAND | 0.018 | 0.015 | -0.005 | -0.171 | 0.003 | -0.002 |
| | ( 0.253) | ( 0.117) | (-0.136) | (-0.724) | ( 0.194) | (-0.216) |
| ISRAEL | 0.010 | -0.006 | -0.001 | -0.001 | 0.002 | -0.004 |
| | ( 0.558) | (-0.337) | (-0.106) | (-0.075) | ( 1.101) | (-1.257) |
| ITALY | 0.071 | 0.038 | -0.031 | -0.190 | -0.001 | 0.005 |
| | ( 1.087) | ( 0.288) | (-0.892) | (-0.659) | (-0.105) | ( 0.383) |
| JAPAN | 0.012 | 0.006 | -0.008 | -0.001 | 0.011 | -0.003 |
| | ( 0.472) | ( 0.153) | (-0.780) | (-0.561) | ( 0.779) | (-0.793) |
| KOREA (SOUTH) | 0.051 ** | -0.055 * | 0.007 | 0.000 * | NA | NA |
| | ( 2.909) | (-2.071) | ( 0.750) | (-2.130) | ( NA) | ( NA) |
| MALAYSIA | 0.118 * | 0.004 | -0.028 | -0.118 | -0.009 | 0.003 |
| | ( 2.209) | ( 0.494) | (-1.838) | (-1.365) | (-1.069) | ( 0.609) |
| MEXICO | 0.052 | -0.007 | -0.012 | -0.014 * | -0.003 | 0.002 |

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*T*able E.9 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| | ( 1.850) | (-0.135) | (-0.957) | (-2.465) | (-0.769) | ( 0.640) |
| NETHERLANDS | 0.054 * | 0.019 | -0.017 | 0.017 | -0.003 | -0.002 |
| | ( 2.533) | ( 0.609) | (-1.878) | ( 0.313) | (-0.435) | (-0.465) |
| NEW ZEALAND | -0.013 | -0.011 | 0.006 | 0.013 | 0.002 | -0.012 |
| | (-0.234) | (-0.724) | ( 0.574) | ( 0.171) | ( 0.286) | (-1.166) |
| NORWAY | 0.088 * | 0.055 | -0.018 | -0.018 | -0.001 | -0.005 |
| | ( 2.096) | ( 1.242) | (-1.354) | (-1.648) | (-0.536) | (-0.673) |
| PAKISTAN | 0.024 | 0.003 | -0.002 | -0.001 | 0.002 | 0.000 |
| | ( 1.087) | ( 0.091) | (-1.061) | (-0.945) | ( 0.671) | (-0.366) |
| PHILIPPINES | 0.041 | -0.012 | -0.005 | -0.004 | 0.000 | -0.001 |
| | ( 1.332) | (-0.473) | (-0.597) | (-0.885) | ( 0.128) | (-0.383) |
| POLAND | 0.205 | 0.305 | 0.001 | -0.488 | 0.002 | -0.013 |
| | ( 1.401) | ( 1.464) | ( 0.014) | (-1.381) | ( 0.142) | (-0.452) |
| RUSSIA | -0.013 | 0.029 | 0.001 | 0.000 | 0.004 | -0.001 |
| | (-0.141) | ( 1.032) | ( 0.108) | ( 0.066) | ( 0.284) | (-0.176) |
| SAUDI ARABIA | 0.207 | -0.112 | -0.069 | -0.046 | -0.014 | 0.000 |
| | ( 1.434) | (-0.896) | (-1.916) | (-0.312) | (-0.209) | ( 0.052) |
| SINGAPORE | 0.102 ** | 0.021 | -0.001 | -0.495 ** | 0.012 | -0.006 * |
| | ( 2.944) | ( 0.842) | (-0.119) | (-2.967) | ( 1.664) | (-2.363) |
| SOUTH AFRICA | -0.023 | 0.029 | 0.005 | 0.010 | -0.001 | 0.000 |
| | (-0.644) | ( 0.627) | ( 0.513) | ( 0.503) | (-0.765) | ( 0.139) |
| SPAIN | 0.049 * | 0.002 | -0.032 * | 0.062 | -0.004 | 0.003 |
| | ( 2.020) | ( 0.316) | (-2.348) | ( 1.632) | (-0.874) | ( 0.606) |
| SRI LANKA | 0.011 | 0.000 | 0.003 | 0.001 | -0.002 | -0.002 |
| | ( 0.278) | (-0.077) | ( 0.987) | ( 0.627) | (-0.482) | (-1.464) |
| SWEDEN | 0.094 | -0.032 | -0.030 | -0.014 | 0.003 | -0.008 |
| | ( 1.851) | (-0.477) | (-1.454) | (-0.727) | ( 0.440) | (-1.354) |
| SWITZERLAND | 0.045 | 0.113 | -0.021 | -0.043 | 0.004 | -0.016 |
| | ( 1.050) | ( 0.582) | (-0.997) | (-0.313) | ( 0.266) | (-1.340) |
| TAIWAN | 0.086 ** | 0.028 | -0.018 ** | -0.011 * | NA | NA |
| | ( 3.002) | ( 0.777) | (-2.770) | (-2.151) | ( NA) | ( NA) |
| THAILAND | 0.028 | -0.001 | -0.003 | -0.002 | 0.001 | -0.002 |
| | ( 0.618) | (-0.055) | (-0.281) | (-0.338) | ( 0.180) | (-0.282) |
| TURKEY | 0.018 | -0.017 | -0.014 ** | -0.011 | 0.003 * | -0.003 |
| | ( 0.652) | (-1.869) | (-3.161) | (-0.320) | ( 2.269) | (-1.726) |
| UNITED KINGDOM | 0.041 | 0.049 | -0.018 | 0.121 | -0.001 | -0.004 |
| | ( 1.517) | ( 0.527) | (-1.073) | ( 0.276) | (-0.334) | (-0.642) |
| VIETNAM | 0.240 | 0.007 | 0.071 | 0.000 | -0.042 | 0.007 |
| | ( 0.405) | ( 0.038) | ( 0.369) | (-0.935) | (-0.410) | ( 0.140) |

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*T*able E.9 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|

This table reports estimates of $b_t$, $c_t$, $d_t$, $e_t$ and $f_t$ in the regression $R_{t,t+1} = a_t + b_t[AEIG]_{i,t,y} + c_t DY_{i,t} + d_t I/K_{i,t} + e_t Interest_{i,t} + f_t INFL_{i,t} + \varepsilon_{i,t}$ where $R_{t+1,t+h}$ is the future cumulative market returns of the country over h = 1, 6 and 12 months following month t; $[AEIG]_{i,t,y}$ is the y measure of aggregate expected investment plans of the country i for the month t, where $[AEIG]_y$ in [AEIG-B, AEIG-G, AEIG-M]. AEIG-B is the aggregate EIG measure base on all firms of the market, AEIG-G is the aggregate EIG measure base only on growth firms of the market, and AEIG-M based only on mature firms. $DY_{i,t}$, $I/K_{i,t}$, $Interest_{i,t}$ and $INFL_{i,t}$, are respectively dividend yield, investiment-to-capital, interest rate and inflation for the country $i$ in month $t$. For each country I run one individual time-series regression. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels. All the t-statistic are estimated by using Newey and West (1987) standard errors.

Table E.10 – AEIG predictive regression controlled by opthers predictors (h = 3 months / AEIG based only on mature firms)

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| AUSTRALIA | 0.085 ** | 0.069 | -0.034 | 0.086 | -0.002 | -0.015 |
| | ( 2.669) | ( 0.969) | (-1.355) | ( 0.583) | (-0.192) | (-1.784) |
| BELGIUM | 0.035 | 0.022 | -0.005 | -0.002 | -0.008 | -0.015 |
| | ( 0.740) | ( 0.681) | (-0.186) | (-0.558) | (-1.603) | (-1.633) |
| BRAZIL | 0.019 | -0.036 * | -0.031 *** | 0.005 | 0.019 *** | -0.017 ** |
| | ( 0.483) | (-2.023) | (-3.605) | ( 1.421) | ( 4.227) | (-2.648) |
| CANADA | 0.127 *** | 0.083 | -0.035 *** | -0.331 *** | 0.019 ** | -0.012 |
| | ( 5.171) | ( 1.319) | (-4.240) | (-3.594) | ( 2.813) | (-1.580) |
| CHILE | 0.038 | 0.050 | 0.000 | 0.001 | -0.010 | -0.004 |
| | ( 0.768) | ( 0.899) | (-0.034) | ( 0.956) | (-1.835) | (-0.710) |
| CHINA | 0.139 ** | 0.074 * | -0.128 *** | 0.014 | 0.029 * | -0.027 *** |
| | ( 2.611) | ( 2.329) | (-3.443) | ( 0.371) | ( 2.124) | (-5.140) |
| DENMARK | 0.060 * | 0.039 | 0.015 | -0.087 * | 0.001 | -0.002 |
| | ( 2.022) | ( 1.567) | ( 1.110) | (-2.159) | ( 0.196) | (-0.193) |
| EGYPT | 0.219 * | -0.103 ** | -0.030 * | -0.032 | NA | NA |
| | ( 2.431) | (-3.166) | (-2.153) | (-0.901) | ( NA) | ( NA) |
| FINLAND | -0.008 | -0.379 ** | 0.008 | 0.415 | -0.007 | -0.035 * |
| | (-0.106) | (-2.782) | ( 0.315) | ( 1.104) | (-0.519) | (-2.585) |
| FRANCE | 0.108 * | -0.114 | -0.043 | 0.194 | -0.003 | -0.025 * |
| | ( 2.300) | (-1.196) | (-1.842) | ( 1.069) | (-0.368) | (-2.079) |
| GERMANY | 0.185 ** | 0.192 | -0.068 * | -0.048 | 0.019 * | -0.060 ** |
| | ( 3.270) | ( 1.401) | (-2.039) | (-0.386) | ( 2.189) | (-3.286) |
| GREECE | 0.013 | -0.012 | -0.023 | 0.241 | -0.003 | 0.001 |
| | ( 0.396) | (-0.267) | (-1.362) | ( 1.273) | (-0.307) | ( 0.255) |
| HONG KONG | 0.149 ** | -0.009 | -0.042 * | -0.060 | NA | NA |
| | ( 3.309) | (-0.178) | (-2.295) | (-0.991) | ( NA) | ( NA) |
| INDIA | -0.132 * | -0.434 *** | 0.016 * | 0.034 *** | -0.025 ** | -0.004 |
| | (-2.244) | (-5.628) | ( 2.291) | ( 7.854) | (-3.310) | (-1.309) |

*Continued*

Table E.10 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| INDONESIA | 0.276 *** | 0.003 | -0.057 | 0.000 ** | -0.004 | 0.011 * |
| | ( 3.981) | ( 0.222) | (-1.419) | (-2.824) | (-0.436) | ( 2.066) |
| IRELAND | -0.051 | -0.007 | 0.028 | 0.043 | -0.009 | 0.000 |
| | (-0.493) | (-0.038) | ( 0.469) | ( 0.123) | (-0.385) | ( 0.033) |
| ISRAEL | -0.008 | -0.044 | 0.015 | -0.014 | 0.004 | -0.013 * |
| | (-0.276) | (-1.535) | ( 1.400) | (-0.441) | ( 1.718) | (-2.554) |
| ITALY | 0.139 | 0.275 | -0.052 | -0.478 | -0.017 | 0.022 |
| | ( 1.706) | ( 1.685) | (-1.204) | (-1.340) | (-1.473) | ( 1.423) |
| JAPAN | 0.003 | -0.009 | -0.010 | 0.000 | 0.028 | -0.007 |
| | ( 0.055) | (-0.116) | (-0.515) | (-0.252) | ( 0.960) | (-0.868) |
| KOREA (SOUTH) | 0.135 *** | -0.164 *** | 0.025 | -0.001 ** | NA | NA |
| | ( 4.229) | (-3.390) | ( 1.556) | (-3.327) | ( NA) | ( NA) |
| MALAYSIA | 0.258 ** | 0.006 | -0.071 ** | -0.122 | -0.026 | 0.007 |
| | ( 2.934) | ( 0.478) | (-2.837) | (-0.858) | (-1.789) | ( 0.851) |
| MEXICO | 0.199 *** | 0.032 | -0.051 ** | -0.049 *** | -0.005 | 0.002 |
| | ( 4.462) | ( 0.386) | (-2.635) | (-5.553) | (-0.730) | ( 0.420) |
| NETHERLANDS | 0.153 *** | 0.076 | -0.036 ** | -0.008 | -0.013 | -0.009 |
| | ( 4.843) | ( 1.643) | (-2.722) | (-0.102) | (-1.281) | (-1.499) |
| NEW ZEALAND | -0.024 | -0.027 | 0.017 | 0.067 | -0.004 | -0.021 |
| | (-0.358) | (-1.387) | ( 1.398) | ( 0.700) | (-0.396) | (-1.676) |
| NORWAY | 0.215 ** | 0.193 * | -0.043 | -0.066 *** | -0.004 | 0.005 |
| | ( 2.878) | ( 2.452) | (-1.795) | (-3.447) | (-0.940) | ( 0.413) |
| PAKISTAN | 0.077 * | -0.010 | -0.006 * | -0.003 | 0.003 | 0.000 |
| | ( 2.080) | (-0.187) | (-2.173) | (-1.559) | ( 0.743) | (-0.214) |
| PHILIPPINES | 0.081 | -0.034 | -0.013 | -0.007 | 0.002 | -0.002 |
| | ( 1.591) | (-0.788) | (-1.010) | (-0.966) | ( 0.304) | (-0.321) |
| POLAND | 0.327 | 0.262 | 0.016 | -0.880 * | 0.013 | -0.031 |
| | ( 1.789) | ( 1.005) | ( 0.232) | (-1.978) | ( 0.634) | (-0.853) |
| RUSSIA | -0.015 | 0.082 * | 0.001 | -0.001 | 0.010 | -0.002 |
| | (-0.144) | ( 2.507) | ( 0.136) | (-0.186) | ( 0.650) | (-0.380) |
| SAUDI ARABIA | 0.643 ** | -0.398 * | -0.200 *** | -0.287 | -0.023 | 0.005 |
| | ( 3.041) | (-2.098) | (-3.736) | (-1.327) | (-0.242) | ( 0.463) |
| SINGAPORE | 0.283 *** | 0.045 | -0.002 | -1.411 *** | 0.035 ** | -0.016 *** |
| | ( 4.628) | ( 1.013) | (-0.122) | (-4.781) | ( 2.821) | (-3.490) |
| SOUTH AFRICA | -0.077 | 0.085 | 0.019 | 0.032 | -0.004 | 0.000 |
| | (-1.494) | ( 1.276) | ( 1.347) | ( 1.099) | (-1.754) | ( 0.143) |
| SPAIN | 0.121 ** | -0.001 | -0.079 *** | 0.220 *** | -0.010 | 0.004 |
| | ( 3.222) | (-0.140) | (-3.849) | ( 3.809) | (-1.656) | ( 0.490) |
| SRI LANKA | 0.026 | 0.000 | 0.009 | 0.002 | -0.005 | -0.005 * |
| | ( 0.361) | ( 0.012) | ( 1.708) | ( 1.226) | (-0.807) | (-2.461) |
| SWEDEN | 0.217 ** | -0.113 | -0.063 * | -0.032 | 0.003 | -0.024 ** |
| | ( 2.879) | (-1.190) | (-2.043) | (-1.182) | ( 0.329) | (-2.732) |
| SWITZERLAND | 0.112 * | 0.203 | -0.049 | -0.122 | 0.019 | -0.053 *** |
| | ( 2.023) | ( 0.819) | (-1.847) | (-0.703) | ( 1.041) | (-3.461) |
| TAIWAN | 0.277 *** | 0.097 | -0.058 *** | -0.036 *** | NA | NA |

*Continued*

*T*able E.10 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| | ( 5.429) | ( 1.547) | (-5.127) | (-3.785) | ( NA) | ( NA) |
| THAILAND | 0.064 | 0.002 | -0.015 | 0.003 | 0.001 | -0.004 |
| | ( 1.262) | ( 0.062) | (-1.103) | ( 0.427) | ( 0.145) | (-0.614) |
| TURKEY | 0.069 | -0.055 *** | -0.041 *** | -0.048 | 0.009 *** | -0.007 ** |
| | ( 1.620) | (-3.883) | (-5.930) | (-0.864) | ( 3.915) | (-3.003) |
| UNITED KINGDOM | 0.095 ** | 0.123 | -0.032 | 0.029 | -0.002 | -0.010 |
| | ( 2.924) | ( 1.102) | (-1.565) | ( 0.055) | (-0.828) | (-1.325) |
| VIETNAM | 0.139 | 0.205 | 0.308 | 0.000 | -0.202 | 0.000 |
| | ( 0.184) | ( 0.959) | ( 1.259) | (-1.292) | (-1.552) | ( 0.000) |

This table reports estimates of $b_t$, $c_t$, $d_t$, $e_t$ and $f_t$ in the regression $R_{t,t+1} = a_t + b_t[AEIG]_{i,t,y} + c_t DY_{i,t} + d_t I/K_{i,t} + e_t Interest_{i,t} + f_t INFL_{i,t} + \varepsilon_{i,t}$ where $R_{t+1,t+h}$ is the future cumulative market returns of the country over h = 1, 6 and 12 months following month t; $[AEIG]_{i,t,y}$ is the y measure of aggregate expected investment plans of the country i for the month t, where $[AEIG]_y$ in [AEIG-B, AEIG-G, AEIG-M]. AEIG-B is the aggregate EIG measure base on all firms of the market, AEIG-G is the aggregate EIG measure base only on growth firms of the market, and AEIG-M based only on mature firms. $DY_{i,t}$, $I/K_{i,t}$, $Interest_{i,t}$ and $INFL_{i,t}$, are respectively dividend yield, investiment-to-capital, interest rate and inflation for the country $i$ in month $t$. For each country I run one individual time-series regression. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels. All the t-statistic are estimated by using Newey and West (1987) standard errors.

Table E.11 – AEIG predictive regression controlled by opthers predictors (h = 6 months / AEIG based only on mature firms)

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| AUSTRALIA | 0.162 *** | 0.073 | -0.062 | 0.255 | -0.005 | -0.033 ** |
| | ( 3.935) | ( 0.809) | (-1.933) | ( 1.366) | (-0.326) | (-3.146) |
| BELGIUM | 0.078 | 0.030 | -0.018 | 0.000 | -0.014 | -0.026 * |
| | ( 1.217) | ( 0.692) | (-0.515) | ( 0.099) | (-1.925) | (-2.125) |
| BRAZIL | 0.031 | -0.079 ** | -0.055 *** | 0.005 | 0.037 *** | -0.036 *** |
| | ( 0.533) | (-3.143) | (-4.570) | ( 0.912) | ( 5.998) | (-4.109) |
| CANADA | 0.205 *** | 0.143 | -0.059 *** | -0.504 *** | 0.030 ** | -0.020 |
| | ( 5.809) | ( 1.600) | (-5.053) | (-3.794) | ( 3.019) | (-1.824) |
| CHILE | 0.077 | 0.007 | -0.017 | 0.002 * | -0.012 | -0.017 * |
| | ( 1.181) | ( 0.103) | (-0.992) | ( 2.316) | (-1.697) | (-2.100) |
| CHINA | 0.178 * | 0.106 * | -0.172 ** | 0.032 | 0.055 * | -0.046 *** |
| | ( 2.181) | ( 2.161) | (-2.968) | ( 0.530) | ( 2.592) | (-5.649) |
| DENMARK | 0.115 ** | 0.067 | 0.023 | -0.124 * | -0.003 | -0.010 |
| | ( 2.651) | ( 1.849) | ( 1.227) | (-2.125) | (-0.250) | (-0.632) |
| EGYPT | 0.478 *** | -0.221 *** | -0.066 ** | -0.076 | NA | NA |
| | ( 3.583) | (-4.598) | (-3.174) | (-1.386) | ( NA) | ( NA) |
| FINLAND | -0.055 | -0.824 *** | 0.032 | 0.837 | -0.020 | -0.073 *** |
| | (-0.583) | (-4.771) | ( 0.939) | ( 1.773) | (-1.189) | (-4.333) |
| FRANCE | 0.211 *** | -0.311 ** | -0.090 ** | 0.505 * | -0.001 | -0.057 *** |
| | ( 3.639) | (-2.633) | (-3.074) | ( 2.251) | (-0.065) | (-3.771) |

*Continued*

*T*able E.11 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| GERMANY | 0.313 *** | 0.305 | -0.109 ** | -0.105 | 0.036 ** | -0.111 *** |
| | ( 4.423) | ( 1.777) | (-2.626) | (-0.670) | ( 3.263) | (-4.828) |
| GREECE | 0.057 | -0.001 | -0.034 | 0.089 | -0.004 | 0.002 |
| | ( 1.180) | (-0.016) | (-1.368) | ( 0.318) | (-0.251) | ( 0.234) |
| HONG KONG | 0.214 *** | -0.062 | -0.065 * | -0.047 | NA | NA |
| | ( 3.419) | (-0.876) | (-2.580) | (-0.564) | ( NA) | ( NA) |
| INDIA | -0.181 * | -0.850 *** | 0.029 ** | 0.060 *** | -0.053 *** | -0.003 |
| | (-2.276) | (-8.162) | ( 2.976) | (10.195) | (-5.280) | (-0.733) |
| INDONESIA | 0.496 *** | 0.005 | -0.066 | 0.000 *** | -0.016 | 0.023 ** |
| | ( 5.018) | ( 0.259) | (-1.160) | (-3.405) | (-1.299) | ( 3.077) |
| IRELAND | -0.208 | -0.053 | 0.109 | 0.398 | -0.039 | 0.019 |
| | (-1.633) | (-0.227) | ( 1.482) | ( 0.918) | (-1.342) | ( 1.055) |
| ISRAEL | -0.010 | -0.072 | 0.032 * | -0.072 | 0.007 | -0.015 * |
| | (-0.221) | (-1.778) | ( 2.175) | (-1.566) | ( 1.954) | (-2.151) |
| ITALY | 0.169 | 0.523 * | -0.051 | -0.673 | -0.036 * | 0.036 |
| | ( 1.465) | ( 2.243) | (-0.836) | (-1.341) | (-2.176) | ( 1.675) |
| JAPAN | -0.044 | -0.066 | 0.002 | 0.001 | 0.043 | 0.000 |
| | (-0.580) | (-0.538) | ( 0.063) | ( 0.208) | ( 0.945) | (-0.012) |
| KOREA (SOUTH) | 0.241 *** | -0.338 *** | 0.029 | -0.002 *** | NA | NA |
| | ( 4.984) | (-4.671) | ( 1.241) | (-3.493) | ( NA) | ( NA) |
| MALAYSIA | 0.291 * | 0.003 | -0.094 ** | 0.137 | -0.038 | 0.003 |
| | ( 2.444) | ( 0.200) | (-2.801) | ( 0.711) | (-1.946) | ( 0.269) |
| MEXICO | 0.461 *** | -0.159 | -0.121 *** | -0.092 *** | 0.011 | -0.012 |
| | ( 7.203) | (-1.365) | (-4.371) | (-7.215) | ( 1.213) | (-1.535) |
| NETHERLANDS | 0.308 *** | 0.170 ** | -0.070 *** | -0.093 | -0.026 | -0.018 * |
| | ( 7.565) | ( 2.848) | (-3.982) | (-0.928) | (-1.926) | (-2.285) |
| NEW ZEALAND | -0.017 | -0.047 * | 0.035 * | 0.117 | -0.018 | -0.029 |
| | (-0.205) | (-2.032) | ( 2.316) | ( 1.027) | (-1.554) | (-1.923) |
| NORWAY | 0.408 *** | 0.339 ** | -0.091 ** | -0.133 *** | -0.010 | 0.030 |
| | ( 4.245) | ( 3.326) | (-2.919) | (-5.349) | (-1.737) | ( 1.784) |
| PAKISTAN | 0.125 * | -0.174 ** | -0.013 *** | -0.002 | -0.004 | 0.005 |
| | ( 2.562) | (-2.627) | (-3.589) | (-0.972) | (-0.824) | ( 1.899) |
| PHILIPPINES | 0.093 | -0.094 | -0.034 | -0.005 | 0.007 | -0.001 |
| | ( 1.377) | (-1.628) | (-1.912) | (-0.479) | ( 0.866) | (-0.096) |
| POLAND | 0.041 | -0.438 | 0.055 | -0.310 | 0.020 | -0.042 |
| | ( 0.207) | (-1.531) | ( 0.728) | (-0.636) | ( 0.910) | (-1.055) |
| RUSSIA | 0.029 | 0.106 * | -0.011 | 0.002 | 0.001 | 0.004 |
| | ( 0.207) | ( 2.543) | (-1.464) | ( 0.360) | ( 0.028) | ( 0.509) |
| SAUDI ARABIA | 1.412 *** | -0.911 *** | -0.409 *** | -0.951 *** | 0.004 | 0.025 * |
| | ( 5.774) | (-4.090) | (-6.521) | (-3.816) | ( 0.039) | ( 2.036) |
| SINGAPORE | 0.394 *** | 0.012 | 0.037 | -2.500 *** | 0.072 *** | -0.032 *** |
| | ( 4.336) | ( 0.183) | ( 1.259) | (-5.690) | ( 3.835) | (-4.701) |
| SOUTH AFRICA | -0.094 | 0.218 ** | 0.016 | 0.071 * | -0.005 | -0.005 |
| | (-1.616) | ( 2.866) | ( 0.974) | ( 2.137) | (-1.931) | (-1.337) |
| SPAIN | 0.195 *** | -0.012 | -0.127 *** | 0.389 *** | -0.013 | -0.003 |

*Continued*

*T*able E.11 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| | ( 3.710) | (-0.881) | (-4.397) | ( 4.885) | (-1.494) | (-0.295) |
| SRI LANKA | 0.037 | 0.001 | 0.021 ** | 0.005 | -0.010 | -0.010 ** |
| | ( 0.351) | ( 0.085) | ( 2.738) | ( 1.728) | (-1.170) | (-3.037) |
| SWEDEN | 0.460 *** | -0.304 * | -0.140 *** | -0.054 | 0.002 | -0.039 *** |
| | ( 4.719) | (-2.492) | (-3.513) | (-1.532) | ( 0.125) | (-3.479) |
| SWITZERLAND | 0.225 ** | 0.522 | -0.099 ** | -0.276 | 0.013 | -0.072 ** |
| | ( 2.972) | ( 1.539) | (-2.703) | (-1.163) | ( 0.505) | (-3.329) |
| TAIWAN | 0.520 *** | 0.157 | -0.110 *** | -0.064 *** | NA | NA |
| | ( 7.107) | ( 1.731) | (-6.796) | (-4.760) | ( NA) | ( NA) |
| THAILAND | 0.044 | 0.057 | -0.014 | 0.015 | 0.002 | -0.012 |
| | ( 0.667) | ( 1.584) | (-0.781) | ( 1.572) | ( 0.217) | (-1.306) |
| TURKEY | 0.125 * | -0.089 *** | -0.061 *** | -0.117 | 0.014 *** | -0.012 *** |
| | ( 2.039) | (-4.470) | (-6.300) | (-1.387) | ( 4.629) | (-3.593) |
| UNITED KINGDOM | 0.181 *** | 0.202 | -0.059 * | 0.151 | -0.006 | -0.021 * |
| | ( 4.348) | ( 1.412) | (-2.243) | ( 0.222) | (-1.852) | (-2.171) |
| VIETNAM | 1.135 | 0.289 | 0.324 | 0.000 | -0.346 * | 0.080 |
| | ( 1.339) | ( 1.202) | ( 1.119) | (-1.987) | (-2.258) | ( 1.225) |

This table reports estimates of $b_t$, $c_t$, $d_t$, $e_t$ and $f_t$ in the regression $R_{t,t+1} = a_t + b_t[AEIG]_{i,t,y} + c_t DY_{i,t} + d_t I/K_{i,t} + e_t Interest_{i,t} + f_t INFL_{i,t} + \varepsilon_{i,t}$ where $R_{t+1,t+h}$ is the future cumulative market returns of the country over h = 1, 6 and 12 months following month t; $[AEIG]_{i,t,y}$ is the y measure of aggregate expected investment plans of the country i for the month t, where $[AEIG]_y$ in [AEIG-B, AEIG-G, AEIG-M]. AEIG-B is the aggregate EIG measure base on all firms of the market, AEIG-G is the aggregate EIG measure base only on growth firms of the market, and AEIG-M based only on mature firms. $DY_{i,t}$, $I/K_{i,t}$, $Interest_{i,t}$ and $INFL_{i,t}$, are respectively dividend yield, investiment-to-capital, interest rate and inflation for the country $i$ in month $t$. For each country I run one individual time-series regression. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels. All the t-statistic are estimated by using Newey and West (1987) standard errors.

Table E.12 – AEIG predictive regression controlled by opthers predictors (h = 12 months / AEIG based only on mature firms)

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| AUSTRALIA | 0.288 *** | -0.124 | -0.040 | 0.489 * | -0.041 * | -0.052 *** |
| | ( 5.718) | ( -1.155) | ( -1.039) | ( 2.194) | ( -2.212) | ( -4.196) |
| BELGIUM | 0.144 | 0.036 | -0.056 | 0.009 | -0.022 * | -0.026 |
| | ( 1.679) | ( 0.625) | ( -1.199) | ( 1.656) | ( -2.303) | ( -1.589) |
| BRAZIL | -0.100 | -0.147 *** | -0.032 * | -0.004 | 0.054 *** | -0.050 *** |
| | ( -1.239) | ( -4.308) | ( -1.973) | ( -0.484) | ( 6.329) | ( -4.164) |
| CANADA | 0.328 *** | 0.087 | -0.071 *** | -0.763 *** | 0.054 *** | -0.054 *** |
| | ( 6.407) | ( 0.675) | ( -4.244) | ( -3.939) | ( 3.705) | ( -3.390) |
| CHILE | 0.187 * | -0.180 * | -0.064 ** | 0.005 *** | -0.017 | -0.035 *** |
| | ( 2.283) | ( -2.030) | ( -3.093) | ( 4.604) | ( -1.940) | ( -3.513) |
| CHINA | 0.003 | 0.205 ** | 0.106 | 0.034 | 0.062 | -0.079 *** |
| | ( 0.028) | ( 2.721) | ( 1.139) | ( 0.360) | ( 1.899) | ( -6.239) |

*Continued*

Table E.12 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| DENMARK | 0.214 *** | 0.156 ** | 0.024 | -0.146 | -0.024 | -0.012 |
| | ( 3.677) | ( 3.184) | ( 0.922) | ( -1.875) | ( -1.672) | ( -0.558) |
| EGYPT | 0.618 ** | -0.372 *** | -0.088 ** | -0.034 | NA | NA |
| | ( 3.209) | ( -5.377) | ( -2.903) | ( -0.403) | ( NA) | ( NA) |
| FINLAND | -0.026 | -2.014 *** | 0.037 | 0.903 | -0.019 | -0.117 *** |
| | ( -0.262) | (-10.569) | ( 1.038) | ( 1.785) | ( -1.017) | ( -6.540) |
| FRANCE | 0.297 *** | -0.572 *** | -0.126 ** | 0.620 * | 0.031 | -0.114 *** |
| | ( 3.885) | ( -3.661) | ( -3.251) | ( 2.084) | ( 1.721) | ( -5.488) |
| GERMANY | 0.419 *** | 0.465 * | -0.091 | -0.596 ** | 0.086 *** | -0.228 *** |
| | ( 4.405) | ( 2.020) | ( -1.632) | ( -2.790) | ( 5.591) | ( -7.183) |
| GREECE | 0.095 | 0.081 | 0.013 | -0.343 | -0.027 | -0.001 |
| | ( 1.099) | ( 0.686) | ( 0.378) | ( -0.717) | ( -1.258) | ( -0.073) |
| HONG KONG | 0.136 | -0.447 *** | -0.025 | 0.024 | NA | NA |
| | ( 1.524) | ( -4.448) | ( -0.695) | ( 0.205) | ( NA) | ( NA) |
| INDIA | -0.005 | -1.495 *** | 0.031 * | 0.081 *** | -0.110 *** | 0.010 |
| | ( -0.041) | ( -9.587) | ( 2.059) | ( 9.051) | ( -7.368) | ( 1.616) |
| INDONESIA | 0.868 *** | 0.021 | 0.049 | 0.000 *** | -0.062 *** | 0.055 *** |
| | ( 6.232) | ( 0.774) | ( 0.613) | ( -4.730) | ( -3.520) | ( 5.313) |
| IRELAND | -0.328 * | 0.049 | 0.163 * | 0.619 | -0.048 | 0.029 |
| | ( -2.464) | ( 0.203) | ( 2.112) | ( 1.368) | ( -1.543) | ( 1.555) |
| ISRAEL | -0.064 | -0.157 ** | 0.087 *** | -0.220 ** | 0.009 | -0.008 |
| | ( -0.991) | ( -2.665) | ( 4.033) | ( -3.308) | ( 1.874) | ( -0.784) |
| ITALY | -0.255 | 0.741 * | 0.135 | 0.758 | -0.091 *** | 0.048 |
| | ( -1.585) | ( 2.264) | ( 1.557) | ( 1.094) | ( -3.815) | ( 1.617) |
| JAPAN | -0.086 | -0.233 | 0.031 | 0.001 | -0.006 | 0.029 |
| | ( -0.752) | ( -1.269) | ( 0.715) | ( 0.111) | ( -0.087) | ( 1.652) |
| KOREA (SOUTH) | 0.361 *** | -0.645 *** | 0.023 | -0.002 ** | NA | NA |
| | ( 5.174) | ( -6.267) | ( 0.687) | ( -3.078) | ( NA) | ( NA) |
| MALAYSIA | 0.299 | -0.007 | -0.114 * | -0.064 | -0.007 | 0.011 |
| | ( 1.707) | ( -0.280) | ( -2.301) | ( -0.226) | ( -0.261) | ( 0.714) |
| MEXICO | 0.967 *** | -0.463 ** | -0.281 *** | -0.146 *** | 0.056 *** | -0.054 *** |
| | ( 10.845) | ( -2.952) | ( -7.295) | ( -8.199) | ( 4.645) | ( -4.947) |
| NETHERLANDS | 0.454 *** | 0.253 ** | -0.064 * | -0.097 | -0.060 ** | -0.044 *** |
| | ( 8.009) | ( 3.068) | ( -2.514) | ( -0.702) | ( -3.102) | ( -4.085) |
| NEW ZEALAND | 0.204 * | 0.001 | 0.023 | 0.102 | -0.072 *** | 0.021 |
| | ( 2.050) | ( 0.027) | ( 1.257) | ( 0.744) | ( -5.165) | ( 1.190) |
| NORWAY | 0.583 *** | 0.369 ** | -0.122 ** | -0.188 *** | -0.014 | 0.036 |
| | ( 4.870) | ( 2.855) | ( -3.140) | ( -5.792) | ( -1.905) | ( 1.712) |
| PAKISTAN | 0.149 * | -0.185 * | -0.016 ** | -0.004 | -0.002 | 0.009 * |
| | ( 2.068) | ( -2.002) | ( -3.066) | ( -1.075) | ( -0.210) | ( 2.502) |
| PHILIPPINES | 0.144 | -0.165 * | -0.041 | -0.011 | 0.000 | 0.013 |
| | ( 1.728) | ( -2.277) | ( -1.845) | ( -0.941) | ( -0.036) | ( 1.208) |
| POLAND | -0.510 * | -1.904 *** | 0.041 | 1.346 ** | 0.012 | -0.030 |
| | ( -2.448) | ( -6.391) | ( 0.512) | ( 2.653) | ( 0.508) | ( -0.731) |
| RUSSIA | -0.004 | 0.117 * | -0.025 ** | 0.021 * | -0.033 | 0.024 ** |

*Continued*

*T*able E.12 continued from previous page

| | (Intercept) | AEIG | DY | I/K | Interest | INFL |
|---|---|---|---|---|---|---|
| | ( -0.022) | ( 2.331) | ( -2.884) | ( 2.286) | ( -1.378) | ( 2.723) |
| SAUDI ARABIA | 0.977 ** | -1.220 *** | -0.277 *** | -1.110 *** | 0.282 * | 0.002 |
| | ( 3.267) | ( -4.466) | ( -3.507) | ( -3.664) | ( 2.241) | ( 0.133) |
| SINGAPORE | 0.219 | -0.209 * | 0.224 *** | -4.048 *** | 0.151 *** | -0.063 *** |
| | ( 1.706) | ( -2.037) | ( 5.289) | ( -6.524) | ( 5.691) | ( -6.504) |
| SOUTH AFRICA | -0.311 *** | 0.327 *** | 0.041 * | 0.176 *** | -0.005 | -0.009 * |
| | ( -4.498) | ( 3.582) | ( 2.116) | ( 4.450) | ( -1.380) | ( -1.980) |
| SPAIN | 0.237 ** | -0.032 | -0.161 *** | 0.601 *** | -0.019 | -0.011 |
| | ( 2.879) | ( -1.633) | ( -3.557) | ( 5.003) | ( -1.437) | ( -0.711) |
| SRI LANKA | -0.142 | -0.012 | 0.036 ** | 0.009 * | 0.008 | -0.013 ** |
| | ( -0.940) | ( -0.968) | ( 3.312) | ( 2.029) | ( 0.706) | ( -2.776) |
| SWEDEN | 0.475 *** | -0.954 *** | -0.096 | -0.086 | -0.033 | -0.047 ** |
| | ( 3.357) | ( -5.395) | ( -1.659) | ( -1.675) | ( -1.671) | ( -2.772) |
| SWITZERLAND | 0.249 * | 0.469 | -0.110 * | -0.207 | -0.008 | -0.073 * |
| | ( 2.502) | ( 1.055) | ( -2.285) | ( -0.669) | ( -0.226) | ( -2.460) |
| TAIWAN | 0.770 *** | 0.072 | -0.165 *** | -0.089 *** | NA | NA |
| | ( 7.229) | ( 0.544) | ( -6.817) | ( -4.548) | ( NA) | ( NA) |
| THAILAND | -0.100 | 0.170 *** | 0.046 * | 0.008 | 0.010 | -0.021 |
| | ( -1.159) | ( 3.725) | ( 2.042) | ( 0.636) | ( 0.939) | ( -1.774) |
| TURKEY | 0.084 | -0.167 *** | -0.050 *** | -0.093 | 0.026 *** | -0.023 *** |
| | ( 1.004) | ( -6.433) | ( -3.925) | ( -0.714) | ( 6.294) | ( -5.311) |
| UNITED KINGDOM | 0.269 *** | 0.143 | -0.058 | -0.116 | -0.014 *** | -0.036 ** |
| | ( 4.789) | ( 0.738) | ( -1.627) | ( -0.127) | ( -3.334) | ( -2.677) |
| VIETNAM | 3.307 *** | 0.766 *** | 0.322 | -0.001 *** | -0.626 *** | 0.183 ** |
| | ( 4.630) | ( 3.794) | ( 1.090) | ( -3.610) | ( -4.100) | ( 3.374) |

This table reports estimates of $b_t$, $c_t$, $d_t$, $e_t$ and $f_t$ in the regression $R_{t,t+1} = a_t + b_t[AEIG]_{i,t,y} + c_t DY_{i,t} + d_t I/K_{i,t} + e_t Interest_{i,t} + f_t INFL_{i,t} + \varepsilon_{i,t}$ where $R_{t+1,t+h}$ is the future cumulative market returns of the country over h = 1, 6 and 12 months following month t; $[AEIG]_{i,t,y}$ is the y measure of aggregate expected investment plans of the country i for the month t, where $[AEIG]_y$ in [AEIG-B, AEIG-G, AEIG-M]. AEIG-B is the aggregate EIG measure base on all firms of the market, AEIG-G is the aggregate EIG measure base only on growth firms of the market, and AEIG-M based only on mature firms. $DY_{i,t}$, $I/K_{i,t}$, $Interest_{i,t}$ and $INFL_{i,t}$, are respectively dividend yield, investiment-to-capital, interest rate and inflation for the country $i$ in month $t$. For each country I run one individual time-series regression. The subscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels. All the t-statistic are estimated by using Newey and West (1987) standard errors.