THREE ESSAYS ON PRODUCTIVITY AND CROSS-SECTIONAL ASSET PRICING

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Abstract

First essay deals with Productivity shocks. Productivity shocks transmitted from productivity leaders to trailing sectors are systematic sources of risk. Global technology and knowledge diffusion leads to predictable patterns in productivity dynamics across countries and industries. Productivity gaps determine the level of exposure to the systematic leader productivity shocks. Firms in a country-industry with larger productivity gaps relative to the world leader are more dependent on the leader's innovations compared to their own productivity improvements. They thus have higher loadings on the leader productivity shocks and higher average stock returns. For OECD panel data, a country-industry's productivity gap significantly predicts the stock returns of the country-industry: holding the quintile of country- industry portfolios with the largest gaps and shorting the quintile with the smallest gaps generates annual returns of 9.8% (6.7% after risk adjustment with standard factors). A factor associated with the productivity gap explains country-industry portfolio returns substantially better than standard factor models. Loadings on leader-country-productivity shocks are found to have substantial correlation with productivity gaps, and leader productivity shocks are more important for stock returns than idiosyncratic productivity shocks. These findings suggest that the productivity gaps and associated higher average returns are indeed tied to systematic risk.

The second essay deals with Technology shocks. Technology shocks from technological frontier economies are a critical determinant of productivity shocks. These shocks spill over, pervading all lagging economies and are true systematic shocks. A country's aggregate technology gap with the frontier determines the potential for the systematic innovation shocks to affect it, but the country's absorption capacity determines its effective sensitivity to these shocks. We find conforming evidence that the technology gap, R&D intensity, and absorption capacity can explain stock returns. For OECD panel data, a one standard deviation increase in the technology gap increases excess stock returns by 0.578 percent per month. A one standard deviation increase in R&D intensity increases the excess return by 0.637 percent per month. An increase in absorption capacity of one standard deviation increases the excess return by 0.275 percent per month. When global FF

factors are included, the results are diluted, which suggests that the FF factors may alias for the three variables associated with the systematic risk arising from frontier technology shocks.

The third essay deals with Political risk. We find that the differences in Hassan et al. (2019) political Risk proxy derived from text processing of analyst transcripts can price cross-sectional returns after controlling for standard factor risks. A mimicking factor for the political risk measure, when added to the standard Fama French 5 factor model or the Q5 model, explains the test asset returns better than these models. In our limited sample, the changes in PRisk measure captures more information about political risk than the traditional measures from Baker et al. (2016), which suggests that one can start using changes in PRisk characteristic as a political risk proxy.

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Part I

Introduction

The global economy is becoming increasingly integrated causing shocks in one economy to have a ripple effect on every other economy. Simultaneously, the asset management industry in all countries are holding a substantial basket of foreign assets. As such, there is a need for international asset pricing theories. There exist asset pricing theories like ICAPM (Solnik, 1974)& CCAPM (Breeden, 1979). But these theories have not found any empirical support. In such a scenario, one needs to develop an asset pricing model that reflects the global economy's integrated nature and is empirically supported. Such a theory can help understand the differences in stock price returns at a global scale.

In the first paper, Dr. Balvers and I develop an asset pricing model based on productivity shocks of the leading economy. These shocks are combined with the technology and knowledge diffusion process dynamics and modeled in a Production-based asset pricing framework. The production-based asset pricing framework of Cochrane (1991) looks at a firm's investment decision to maximize shareholder's value. Our modeling deviates from Cochrane (1991); Zhang (2005) as it avoids market frictions. The literature on dynamics of the technology diffusion process is well established, where the technology trickles down from the most advanced country to less developed countries (Parente and Prescott, 1994; Comin and Hobijn, 2004, 2010; Comin and Mestieri, 2018). A particular country's productivity has more potential for improvement when there is a big gap in productivity with the leader. This is because there is more potential for productivity improvement from the channels through which the technology diffuses, mainly trade, foreign investment, foreign aid, and espionage. An increase in productivity leads to an increase in investment returns and stock returns. A highly stylized model predicts that the productivity gap is monotonically related to mean stock returns in a cross-section.

We also test the theoretical model for 24 OECD countries using Fama-Macbeth 2 stage cross-section regression. The productivity gap at the country and industry levels are treated as characteristic. After controlling for global CAPM, Fama-French 3 factor, Carhart, Fama-French 5 factor and Fama-French 5 factor risk factors, we find that the country productivity gap is monotonically related to mean stock returns of country-industry portfolios. Besides, when we derive risk factors from the country productivity gap characteristic, we observe that the derived factor is a systematic risk factor. Moreover, the country productivity gap is highly persistent and we find some evidence that the global momentum risk factor can be explained by the country productivity gap.

Production incentives and the general business climate are characterized by the fundamental production infrastructure within a country which is not controllable by individual firms. It depends on human capital, physical and organizational infrastructure, regulation, government influence, etc., which affect a firm's total factor productivity without requiring firm inputs. This productivity component is not transferable across country-industries (or, if so, very slowly as is human capital via migration). One of the important determinants of TFP is the R&D stock. The technology shocks of the technology frontier countries are determinants of the productivity shock.

The second paper, Dr. Balvers and I, includes R&D investment and the R&D stocks in a production-based framework without any market frictions. The R&D stock of the leader is one of the determinants of the TFP. For a lagging country, the TFP is determined by the technology shocks from the leader, the R&D investment, and the technology absorption capacity of the home country. The technology absorption capacity of a home country is determined to some extent by the R&D stock of the home country. A stylized model predicts that the mean expected return will depend upon the technology gap, R&D intensity and the technology absorption capacity. In the empirical finance literature, R&D intensity (Chan et al., 2001; Eberhart et al., 2004; Ho et al., 2004; Hsu, 2009; Lin, 2012) has been observed to be a predictor of the mean returns where the explanation is that R&D creates an option to adopt technology at a higher cost which will pay off only in a strong economy. Hence, the firm with higher R&D intensity is more exposed to regular business cycle risk. Similarly, spillovers from other firms and industries are documented (Hou et al., 2016; Chen et al., 2013; Jiang et al., 2016) to increase mean returns. Our theoretical model incorporates both observations mentioned above.

We test this theoretical model with 24 OECD countries using Fama-Macbeth 2 stage cross-section regression. Our results show that technology gap, R&D intensity can predict mean stock returns at the country level. Our result for absorption capacity is mixed. This could be due to the fact that R&D data availability at country-industry level is sparse compared to productivity data, and the sample time-period is limited. We derive factors from the leader (USA) TFP growth rate and the leader's technology industry (NAICS Sector 54) and show that this factor prices the 24 OECD country-industry portfolios after controlling for standard global risk factors.

Theoretical models of Pastor and Veronesi (2012) and Pástor and Veronesi (2013) show that political risk is priced and there is a risk premium for the political risk factor. Political risk affects the firms' investment and lower employment; thus, Political risk leads to a TFP shock. In the third paper, I and Fangxing empirically show that a recent political risk proxy from Hassan et al. (2019) is monotonically related to firm-level TFP. Moreover, we show that the proxy derived from text processing of analysts' transcript captures systematic political risk and is superior to the commonly used political risk proxy from Baker et al. (2016). We find that political risk premium is negative in a contemporaneous cross-section setting. Brogaard and Detzel (2015) have shown that political risk should have a negative risk premium as political risk leads to a decrease of the opportunity set in Mertons' framework (Merton, 1973).

The first two papers analyze data for 24 OECD countries, whereas the political risk paper only analyzes data for US firms. All three papers use the Fama-Macbeth cross-section regression methodology. They derive risk factors from characteristics using either characteristic mimicking portfolios (Balvers and Luo, 2018) or Fama-French factors (Fama and French, 1992). We test these risk factors using Barillas and Shanken (2017) methodology and show that these risk factors are systematic in nature. Moreover, the first two papers have a theoretical and empirical part. In contrast, the third paper is empirical in nature.

The first two papers are joint work with my Ph.D. supervisor Dr. Balvers. The third paper is in collaboration with another Ph.D. student Fangxing Liu. We both have jointly worked on each part of the paper.

Part II

Productivity Gaps and Global Systematic Risk Exposure: Pricing Country-Industry Portfolios

Productivity Gaps and Global Systematic Risk Exposure: Pricing Country-Industry Portfolios *

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April 29, 2020

Abstract

Productivity shocks transmitted from productivity leaders to trailing sectors are systematic sources of risk. Global technology and knowledge diffusion leads to predictable patterns in productivity dynamics across countries and industries. Productivity gaps determine the level of exposure to the systematic leader productivity shocks. Firms in a country-industry with larger productivity gaps relative to the world leader are more dependent on the leader's innovations compared to their own productivity improvements. They thus have higher loadings on the leader productivity shocks and higher average stock returns. For OECD panel data, a country-industry's productivity gap significantly predicts the stock returns of the country-industry: holding the quintile of country-industry portfolios with the largest gaps and shorting the quintile with the smallest gaps generates annual returns of 9.8% (6.7% after risk adjustment with standard factors). A factor associated with the productivity gap explains country-industry portfolio returns substantially better than standard factor models. Loadings on leader-country-productivity shocks are found to have substantial correlation with productivity gaps, and leader productivity shocks are more important for stock returns than idiosyncratic productivity shocks. These findings suggest that the productivity gaps and associated higher average returns are indeed tied to systematic risk.

Keywords Production-Based Asset Pricing, Productivity Gap, Total Factor Productivity, OECD Countries, International Equity Returns, Technology Diffusion

1 Introduction

We attempt to explain country-wide and industry-wide differences in mean equity returns as originating from differences in exposure to systematic risk. From the production-based asset pricing (PBAP) perspective a true global

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systematic risk must have an important, pervasive, unpredictable, and highly variable impact on supply conditions. We consider productivity shocks with a global impact. Specifically, the technology or knowledge shocks that originate with productivity leaders and eventually spill over to all countries and industries. Even though such shocks do not instantly impact the production levels and net income of trailing producers, their anticipated impact should be capitalized in stock prices rapidly. We develop a simple model which accounts for gradual diffusion of productivity shocks from industry or country technology leaders across the countries and industries trailing in productivity.

The model implies that the productivity gap for any particular industry in a particular country (for short a "country-industry") relative to the productivity of the currently most productive country-industry has important explanatory power for the country-industry's equity returns. We empirically test the model using calculated productivity gaps, and stock return data for firms in OECD countries and demonstrate that total factor productivity gaps explain a significant fraction of the cross-sectional variation in average returns.

Previous studies have proposed plausible theoretical explanations for global differences in equity returns. Solnik (1974) develops an international intertemporal equilibrium model (the ICAPM) that incorporates exchange rate risk to explain the differences in returns across countries. Grauer et al. (1976) use a version of Breeden's consumption-based asset pricing model (Breeden, 1979), the CCAPM, employing the marginal utility of consumption as the pricing kernel to explain cross-country differences in mean returns. Both the ICAPM and CCAPM explanations have been difficult to support empirically. Empirical analysis instead documents the relevance of alternative global (Fama and French, 1998, 2017) and/or local (Hou et al., 2011, and Chaieb, Langlois, and Scaillet, 2020) risk factors for explaining mean returns across countries. Moreover, mean stock returns at the country level show persistence in the short run (Chan et al., 2000, Asness et al., 2013) which reverses in the long run (Balvers et al., 2000, Zaremba et al., 2020). These empirical results cannot easily be explained by consumption-based (i.e., marginal-utility-based) asset pricing models. The discouraging empirical results may be a consequence of time variation in return covariances with global wealth or with consumption or, more generally, indicate a problem in identifying and measuring the appropriate marginal utility components. The recent contribution of Gavazzoni and Santacreu (2020) produces encouraging results in a fully-developed consumption-based general equilibrium model with a non-expected-utility recursive preference formulation (Epstein-Zin). Endogenously developing the international diffusion of technologies, Gavazzoni and Santacreu explain quantitatively the level of the equity premia across countries and predict the correlation in stock returns across country pairs from their shared research and development. They do not address the difference in average returns by country and industry that is our focus.

Production-based asset pricing (PBAP) without frictions along the lines of Brock (1982), Lucas (1978), and Balvers et al. (1990) reasons that aggregate output is proportional to consumption, and that output growth, presumably measured more precisely, may substitute for consumption growth as the pricing kernel. Incorporating the friction of convex adjustment costs to investment, Cochrane (1991, 1996) shows that alternatively investment returns (the return on investment) may be used as a pricing kernel. Since productivity affects output as well as investment returns, both approaches imply that productivity shocks are important for the pricing kernel (in particular, Zhang 2005, Balvers and Huang 2007, Papanikolaou 2011, Lin 2012, Garleanu, Panageas, and Yu 2012, Hirshleifer, Hsu, and Li 2013, Hou, Xue, and Zhang 2014, and Balvers, Gu, and Huang 2017). To this point, PBAP has scarcely been applied in the international asset pricing context to examine and explain stock return differences. Exceptions are Cooper and Priestley (2013), Watanabe et al. (2013), and Titman, Wei, and Xie (2013) who empirically tie returns across countries to local investment-capital ratios and global capital-output ratios.

Productivity in a particular country has more potential for improvement when the country's productivity gap relative to the world's productivity leader (the United States in some instances) is larger. This is the "catch-up" view by which existing advanced technology provides a target for reverse engineering, mimicking, or development that lowers the cost of productivity improvement, making it cheaper to catch up than to invent (see e.g. Comin and Hobijn, 2010 and Wolff, 2014). Hence future investment returns are expected to be higher in countries with lower current levels of productivity. From PBAP, higher investment returns imply higher stock returns, so it is possible to explain and predict future return differences arising from variation in risk exposure between international stock markets (at least within the OECD countries – developed economies with integrated financial and non-financial markets) by current country-wide "gaps" (e.g. Coe et al., 2009) in the levels of productivity.[1]

The literature on productivity elaborates on the dynamics of technology diffusion. The prevailing view of the dynamics of global technological innovation is that technology trickles down from the most advanced economy to less advanced economies (Parente and Prescott, 1994, Comin and Hobijn, 2004, 2010, and Comin and Mestieri, 2018). According to Keller (2004), 90 percent of the productivity growth for most countries can be explained from foreign sources of technology which diffuse through the channels of trade (mainly imports) and foreign direct investment (FDI), and possibly also through foreign aid or corporate espionage. The diffusion is slow as a result of the embodiment effect (Fisher, 2006) which argues that adoption of a new technology requires a series of investments to replace existing vintages of capital. The technology diffusion may well occur in important measure at the industry or firm level but its most important systematic component is likely to be at the country level because the timing of adaptation of new technologies and the associated risk exposure depend crucially on country-wide absorptive capacity which determines how well information about new technology is assimilated to improve productivity and

[1] Our explanation for differences in expected returns is complementary to that based on asset growth or investment as in Cooper and Priestley (2013), Watanabe et al. (2013), and Titman, Wei, and Xie (2013). Projected increases in productivity increase investment returns, leading to higher stock returns, but may also lead to positive net investment and capital deepening (asset growth as considered by Titman et al., 2013, and Watanabe et al., 2013) which, all else equal, will have a negative impact on investment returns, offseting part of the increase in investment returns due to the productivity increase.

efficiency, and depends on factors such as human capital, protection of intellectual property rights, R&D history, and government policies (Hall and Jones 1999, Keller 2004, Mancusi 2008).

Howitt (2000), Griffith et al. (2004), and Coe et al. (2009) argue that country-wide productivity increases are directly related to the technology gap between a country and the technological leader country. The productivity advantage of the leading economy spills over to other economies. The main reason is that mimicking or reverse engineering an existing technology is cheaper than creating it. Thus, lagging economies should ultimately catch up to the leading economy (all else equal) implying, in the process, higher productivity and higher investment returns for the lagging economy.[2] How do productivity differences between individual countries and the leading productivity economy, which we refer to as "productivity gaps", explain cross sectional variation in global stock returns? If a country has a large productivity gap compared to the leading-technology-producing country's productivity, then that country has more potential for improvement in productivity from any channels (such as trade, espionage, foreign investment, and foreign aid). Since enhanced productivity at little extra cost raises investment returns, stock returns rise as well and must be linked to productivity in the PBAP framework.

This paper utilizes the dynamics of technology diffusion in a PBAP framework to explain the cross-sectional variation in stock returns. Variation in systematic risk exposure is linked to productivity gaps which in turn affects mean returns. The implications will be tested using historical data of stock returns by country and industry, productivity levels across industries and countries, and other mediating variables for the group of OECD countries.

2 A Simple Model of Investment with Productivity Spillovers

We present a highly stylized equilibrium model from the production perspective following Brock (1982), Cox et al. (1985), and Berk et al. (1999). These models determine the impact on expected returns of firm-level investment decisions. In the model we avoid market frictions thus deviating from the approach of Cochrane (1991, 1996), Zhang (2005) and others, but following Balvers and Huang (2007), Papanikolaou (2011), and others. Our model adds two elements to a typical PBAP framework: heterogeneity by country and industry in the technologies available to firms; and gradual technology diffusion combined with spillover related to the productivity gap between a particular country-industry and the leading industry.

[2] Because new productivity shocks continue to occur, the process of diffusion will in principle continue indefinitely even if particular gaps are closed over time, with just the composition of the group of leading and lagging economies changing over time. Empirically, it is well known that convergence, although extensively documented for advanced economies, is not apparent between advanced and emerging economies (Galor, 2005). We limit our sample to a group of OECD countries which are advanced economies. Inklaar and Diewert (2016) find empirically that country industries on average did not get closer to the technology frontier over the 1995-2011 period in a sample containing both advanced economies and major emerging economies.

Industries in different countries have access to varying levels of technology and knowledge affecting productivity. We treat industries by country as separate units referred to as "countryindustries" whose investment choices and average stock returns we attempt to explain. The model examines the actions of an individual firm representing a particular country-industry. The firm (i.e., the country-industry) is either the "leader" or one of the "laggards" for its industry worldwide (using the terminology of Bena and Garlappi, 2020)[3]. The leading firm has access to superior technology and is the most advanced of all countries within the same industry. Any other firm in this industry worldwide is lagging, trailing the leading country-industry in terms of technology access. The leaders in the various industries may be likely to operate in the same country, but this is in part an empirical issue. Technology from the leader spills over to lagging producers by various mechanisms (such as trade, direct investment, corporate espionage, information technology, or unilateral aid) which we capture as positively related to the size of the technology gap between the recipient lagging firm and the leading firm. Unlike Bena and Garlappi (2020) we de-emphasize strategic interactions between the firms. For simplicity we assume that the laggards do not expect to take the lead, and that the leader does not expect to lose the lead in its industry worldwide.

Production incentives and the general business climate are characterized by the fundamental production infrastructure within a country which is not controllable by individual firms. It depends on human capital, physical and organizational infrastructure, regulation, government influence, etc. which affect a firm's total factor productivity without requiring firm inputs. This productivity component is not transferable across country-industries (or, if so, very slowly as is human capital via migration). We refer to it as Total Factor Productivity (TFP) or simply as productivity, denoted at time t as z_t. The level of productivity t available imparts a comparative advantage in a particular country-industry. It is affected by i.i.d. productivity shocks η_{t+1} and follows either a random walk or a mean-reverting exogenous process. Production incentives also depends upon the technology diffusion process, which is modelled as the log difference in productivity of the laggard with respect to the productivity of the leaders

A representative firm in a specific country-industry chooses the future capital stock to maximize shareholder value. The decision problem is expressed in the following Bellman equation:

$$V(K_t, z_t, z_t^*) = \max_{K_{t+1}} \left\{ \pi(z_t, K_t, K_{t+1}) + E_t \left[m_{t+1} V(K_{t+1}, z_{t+1}, z_{t+1}^*) \right] \right\} \tag{1}$$

The value function V represents the maximum value of the firm that depends on a vector of state variables, namely: the firm's current capital stock (K_t), the idiosyncratic productivity level (z_t), and the leading country-industry productivity level (z_t^*). The control variable is K_{t+1}, which is implied by the choice of the current gross investment

[3]Bena and Garlappi (2020) provide a specific analysis of the game-theoretical interactions of firms in a market where the ultimate technology leader gains a dominant market share. In this scenario, interestingly, laggard firms face higher systematic risk, as in our model, implying higher average stock returns. Unlike the productivity risk in our model, the systematic risk in Bena and Garlappi derives from a standard market risk factor. Laggard firms have higher market betas because their trailing market position makes them more susceptible to aggregate fluctuations.

level. The stochastic discount factor m_{t+1} rules out the existence of arbitrage. Profit of the firm is represented by π and equals revenue from production less the costs due to investment:

$$\pi(z_t, K_t, K_{t+1}) = Y(K_t, z_t L) - [K_{t+1} - (1-\delta)K_t] \tag{2}$$

The depreciation rate of capital is a constant δ so that the term in square brackets in equation 2 represents investment. We assume that the production function $Y(\,)$ exhibits constant returns to scale in capital and labor. The production function is of the Cobb-Douglas form, labor inputs are assumed fixed for simplicity, and productivity is viewed as labor-saving:

$$Y_t = Y(K_t, z_t L) = A_0 K_t^{\alpha}(z_t L)^{1-\alpha} = A K_t^{\alpha} z_t^{1-\alpha}. \tag{3}$$

By means of a stochastic version of the original formulation in Nelson and Phelps (1966) and based on the dynamics of technology diffusion illustrated by Comin and Hobijn (2004, 2010), we model the productivity state as a geometric random walk. The own country-industry and the lead-country-industry productivity shocks η_{t+1} and η^*_{t+1} are assumed to be uncorrelated accross country-industries. Moreover η_t (as well as η^*_t) is i.i.d and has the log-normal distribution with $\ln(\eta_t) \sim N(-\sigma^2/2\,, \sigma^2)$ and $\ln(\eta^*_t) \sim N(-\sigma^2/2\,, \sigma^2)$ which implies that $E_t(\eta_t) = E_t(\eta^*_t) = 1$.

$$z_{t+1} = \eta_{t+1}(z_t)^{\gamma}(z^*_t)^{1-\gamma} \tag{4}$$

$$z^*_{t+1} = \eta^*_{t+1} z^*_t. \tag{5}$$

The spillover of leader country productivity is captured by $1-\gamma$ which is greater than zero, indicating the existence of positive spillovers, and less than one so that spillovers develop gradually: $0 < \gamma < 1$. Productivity in equation 4 evolves stochastically given the current state which depends partially on home productivity and partly on the productivity of the leading foreign producer. It implies that the leading country industry productivity level z^*_t is a state variable positively affecting the value of the firm since it benefits future productivity of the firm, z_{t+1}, which, in turn, positively affects future profitability from equation 2. The productivity of the leading producer follows an exogenous random walk.[4]

The first order condition for equation 1 generates

[4] Acemoglu et al. (2006), Benhabib et al. (2019), Buera and Oberfield (2020) and Lind and Ramondo (2019) provide a more nuanced view of endogenous productivity growth, considering innovation as well as imitation incentives. Firms closer to the frontier (firms in leader industries or countries in our terminology) have incentives to innovate, whereas firms further from the frontier benefit more from imitation. Given the state of conditioning factors, firms in a particular country end up at an equilibrium distance from the frontier in which, at the margin, imitation and innovation efforts are equally rewarding. Nevertheless, the equilibrium investment returns from either choice are higher when further from the frontier, as follows also from our simpler formulation. Another sophisticated formulation of productivity spillovers, Bloom et al. (2013), considers both positive and negative externalities emerging from a technology gap: increased knowledge and a business-stealing effect. However, they find that the positive spillover dominates, as is maintained in our formulation.

$$E_t\left[m_{t+1}V_K(K_{t+1},z_{t+1},z^*_{t+1})\right]=1, \tag{6}$$

where, following Berk et al. (1999), Zhang (2005), and others the stochastic discount factor (sdf) is specified exogenously based on productivity shocks as below. In our formulation systematic risk is viewed as exclusively related to the productivity shocks of the leading economy η^*_t:[5]

$$m_{t+1}=a(\eta^*_{t+1})^{-\lambda}, \tag{7}$$

where $a=e^{-[r_c+\lambda(1+\lambda)\sigma^2/2]}$. The constant term a normalizes the sdf so that $E_t(m_{t+1})=\frac{1}{1+r}=e^{-r_c}$; r is the risk free rate and r_c is the continuously compounded risk free rate, $r_c\equiv\ln(1+r)$; and λ is an exogenous parameter reflecting aggregate risk aversion.

If we assume that all profits of the firm are paid as dividends, then the total return of the firm can be expressed as follows, where μ_t is the mean continuously compounded stock return, $\mu_t\equiv\ln[E_t(R_{t+1})]$:

$$\mu_t=r_c+g(PG_t). \tag{8}$$

Appendix A derives this result formally.[6] The productivity gap (PG) is defined as the log difference of productivity in a country-industry compared to the productivity of the leading country-industry:

$$PG_t=\ln(\frac{z^*_t}{z_t})=\ln(z^*_t)-\ln(z_t). \tag{9}$$

Using equation 8 we establish the following theoretical properties: (1) the mean stock return varies over time with the productivity gap $PG_t=\ln(\frac{z^*_t}{z_t})$; (2) the mean stock return is always greater than the risk free rate; and (3) the risk premium increases monotonically with the increase in the productivity gap, $g'(PG_t)>0$, which we derive formally in Appendix A for small levels of the risk premium.

Since the sdf specified by the equation 7 is a function of η^*_{t+1} and its distribution and expected value doesn't change over time. As such, we expect the risk premium to be constant and following the Campbell Shiller decomposition (Campbell and Shiller, 1988) there is only cash flow risk and no discount risk in the model.

When a firm/country-industry lags in productivity then it has more potential to catch up and vice versa. From

[5]The sdf in general equilibrium must be a function of the systematic innovation. We choose the functional form for convenience, and for simplicity ignore conditioning variables. It is still possible to solve the model explicitly if we make the constant a in the sdf in the following equation time varying by setting $a_t=az^{*b}_t$. This causes the (global) risk-free rate to vary over time with the leader-country productivity level z^*_t. However, the additional complication detracts from our main objective to analyze variation in the risk premium.

[6]The derivation is complex because investment returns no longer exactly equal stock returns due to effectively decreasing returns to scale (although production has constant returns to scale, labor inputs are set exogenously), as in Balvers et al. (2017). The stock returns stochastically exceed investment returns because under decreasing returns to scale the average productivity of capital exceeds the marginal productivity of capital.

the productivity shock point of view, a positive shock lowers the gap for a firm/country which, as a result, becomes less dependent upon technology diffusion from the leading firm/country. This in turn reduces the systematic risk, i.e. the exposure to productivity shocks in the leading economy, and accordingly reduces the expected future return. A productivity gap has a positive effect on the firm's (country-industry's) loading on the aggregate productivity factor, with the latter naturally being represented by the productivity shocks of the leading country-industry. Idiosyncratic productivity shocks may quantitatively be more important in affecting production for individual country-industries than the leader country-industry shocks. However, they are not systematic and are uncorrelated with the leader country-industry shocks; hence sensitivity to these shocks does not affect mean stock returns.

3 Implications of the Model

3.1 Testable hypotheses

The model finds the expected return to be monotonically related to the productivity gap. As the gap increases, the expected return increases. This increase in expected return may be viewed from the PBAP perspective as due to higher average returns on capital, or, from the dual consumption-based perspective as due to the increase in systematic risk: A country with a larger gap stands to gain more from innovations by the leader country and is accordingly more exposed to these foreign productivity shocks, compared to a country with a smaller gap. The consequence of equation 8 is that the productivity gap should explain the cross-sectional disparity of stock returns among a group of countries. Separately, considering the dynamic process of return differences over time, a relatively large productivity gap must be the result of a past accrual of relatively poor realizations of innovation and productivity enhancements, generally accompanied by low stock returns. However, on average, the low returns will be reversed in the future as the larger productivity gap requires higher future stock returns. Since the productivity gap is persistent and disappears only slowly over time, exposure to the productivity in the leader country remains similar for extended periods, inducing a momentum effect. Lastly, the theory also implies that disparities in average stock returns arise from differences in exposure to systematic risk, and that the main source of systematic risk is aggregate shocks to leader productivity.

We propose three hypotheses namely:

Hypothesis 1: Productivity gaps explain country- and industry-wide cross-sectional disparities in mean returns.

Hypothesis 2: Persistence and reversion in productivity gaps generates momentum and mean reversion in equity returns.

Hypothesis 3: Productivity gaps are positively associated with systematic risk exposure.

Hypothesis 1 results from the model where $\partial\mu_t/\partial PG_t > 0$. Hypothesis 2 follows because the productivity gap exhibits positive autocorrelation (from equations 9 and 4) which given Hypothesis 1 could explain momentum in equity returns. Additionally, a high productivity gap over time is systematically reduced, $\partial PG_{t+1}/\partial PG_t < 0$, so that high returns are eventually followed by low returns, suggesting mean reversion. Hypothesis 3 derives from the fact that $\partial\mu_t^{ic}/\partial z_t^* > 0$ for all ic. It follows from the duality between production-based and consumption-based approaches, implying that higher average productivity of capital must be associated with higher systematic risk.

The remainder of the paper empirically considers Hypotheses 1-3 and additional related issues, examining a panel of OECD countries to determine if observed mean return differences are caused by productivity gaps and are consistent with a systematic risk explanation.

3.2 Specification of the productivity gap

Productivity spillovers may arise from various sources of discrepancies between firms. For any firm as presented in the above model we need to specify empirically what is meant by $\ln(z_t^*)$, the leading productivity level that serves as the benchmark from which technologies, approaches, and practices trickle down to individual firms. A particular firm in a particular industry and country may benefit by adopting the best practices of firms in more productive country-industries. These positive spillovers derive often from general "systematic" aspects of productivity that are pervasive at the country-wide level, related to such issues as transportation, infrastructure, or even human resource policies. But additionally a firm may benefit more specifically from observing the technological and managerial processes of firms in its own industry operating in a different country where this industry is currently more productive. In general, we distinguish systematic productivity differences that arise at the country level and, separately, more idiosyncratic differences that are specific to the industry level, between industries in different countries. Distinct productivity spillovers arise from both of these sources of productivity differentials. As the empirical proxy for the first component of the theoretical individual productivity gaps, $\ln(\frac{z_t^*}{z_t})$, we define the aggregate country-wide productivity gap facing an individual firm in industry i and country c at time t as

$$CPG_t^{ic} \equiv \ln(Z_t^{c*}/Z_t^c). \tag{10}$$

CPG is the *country-level* Productivity Gap across countries based on comparing the overall productivity of the leader country c^* to the productivity of the specific country c that is home to the industry grouping of firms i we are considering. Here ic indexes a particular industry in a particular country (a "country-industry"), and a portfolio of all stocks in this country-industry pairing will serve as an individual test asset. The country productivity level is the weighted average within the country, using industry size weights of the productivities of all industries within the country. Z_t^{c*} represents the empirical measure of aggregate productivity level for the most productive country at time t and Z_t^c represents the empirical measure of aggregate productivity level in a specific country c.

As the empirical proxy for the second component of an individual productivity gap we define an industry-based measure. IPG is for each different industry the *industry-specific* Productivity Gap across countries: the difference between the log productivity of the leading-productivity country for industry i, $c^*(i)$, and that in any country c for the same industry i:

$$IPG_t^{ic} \equiv \ln(Z_t^{ic*}/Z_t^{ic}) \tag{11}$$

Z_t^{ic*} is the industry productivity for the country leading in this particular industry at time t, and Z_t^{ic} is the productivity level in this same industry in some country c.

Thus, we can write as a proxy for the concept of productivity gap, $\ln(\frac{z_t^*}{z_t})$, relevant for an individual firm in industry i and country c, that:

$$PG\_Total_t^{ic} = f(CPG_t^{ic}, IPG_t^{ic}) \tag{12}$$

where $f()$ is a function that is increasing in both the country- and industry-specific components of the productivity gap measure. The components of the productivity gap considered separately may have different implications for average returns. If CPG is the dominant component then firms in all industries are subject to similar shocks, and these are then obviously systematic, affecting return fluctuations as well as average returns. If IPG is the dominant component then firms in different industries are affected by different leaders, which are subject to different shocks. The productivity gaps then represent a more idiosyncratic risk exposure. Accordingly, while the productivity gaps then still explain return fluctuations, they should not influence average returns.

4 Data

To test the hypotheses, we employ stock price data for firms in OECD countries as well as macroeconomic data to compute productivity at industry and country levels for OECD countries. We limit our analysis to OECD countries primarily because of the well-established results from the economic growth literature that the economies within the OECD converge over time, whereas this is not generally true for non-OECD countries (in particular not for developing economies). See for instance Dowrick and Nguyen (1989) or Johnson and Papageorgiou (2018).

4.1 Productivity Measures

The Structural Analysis database (STAN) available from the OECD contains macroeconomic data at the industry level. These data can be used to compute productivity at the industry level for OECD countries. STAN has an annual data frequency and uses the International Standard Industry Classification (ISIC) V4 to assign firms to industries, whereas Compustat uses the North American Industry Classification System (NAICS). Mapping of NAICS to ISIC is accomplished with an algorithm detailed in Appendix B. After the mapping only 16 mutually exclusive industry groups/sectors remain. From these we remove the Finance and Insurance and the Real Estate sectors for our analysis as is common practice in the finance literature. Appendix C presents further data particulars.

In comparing data across countries with different currencies and price levels, we adjust productivity for purchasing power parity (PPP) differences. We use the OECD Purchasing Power Parity exchange rate conversion to compute productivity for cross-country comparison. The PPP-adjusted exchange rate can be thought of as the price measure for an economy which is appropriate for comparing labor and capital costs as well as consumption and production value levels across countries in the same units.

Smaller countries tend to display more idiosyncratic variation. For example they may be specialized in just a few concentrated industries. These countries cannot play much of a role as leading economies on the world stage. As such they should be excluded from the group of potential productivity leaders at the aggregate level. To avoid assigning small countries as aggregate productivity leaders in the CPG measure we employ the criterion that a country should contribute at least 0.75% to world GDP to be included in the productivity-leading country group.[7] We use the World Bank (PPP-adjusted) GDP database of all countries to identify the potential productivity-leading countries. The following OECD countries meet the criteria: USA, UK, Germany, France, Canada, Australia, Italy, Japan, South Korea, Netherlands, Spain, Poland, and Mexico. These constitute the group of potential technology-leading countries. The maximum productivity levels for an individual industry and averaged across industries from among this list of countries constitute the components of z_t^* required to compute the CPG productivity gap in equation 9 and equation 12. Our measure for productivity z_t at the country-industry level is total factor productivity (TFP). It adjusts production for the value of the capital inputs ("Net Capital Stock") used and the value of labor inputs ("Employee Hours") used, each in PPP-adjusted USD.[8] STAN does not allow us to compute the TFP at the industry level for all OECD members between 1990 and 2015. In particular, the information to compute TFP for individual industries in Mexico, Spain, and South Korea is not available so that the industry portfolios in

[7]When we change this criterion to consider alternatively 0.5, 1.0 or 2.0 percent our results do not change materially. When the threshold is reduced to 0.5%, Belgium sometimes shows up as productivity leader; when the threshold is increased to 1.0% or 2.0%, the Netherlands drops out as productivity leader and is replaced by either France or the US. In either case the gap numbers change very little and the overall results are not affected.

[8]The labor input data categories in STAN are Employee Hours (hours worked by full-time employees) and Total Hours (hours worked), but the availability varies across countries and industries. Total Hours is available for the USA only from 1998, and for Japan not at all. To allow for inclusion of the USA and Japan as possible productivity leaders in the analysis, the TFP measure we use is based on Employee Hours.

these countries are omitted from analysis.

We compute Productivity Gaps at country and industry levels to account for the potential of various types of technology and knowledge spillovers depending on locality, economic activity, infrastructure, and regulatory environment and organization. At both the country and the industry level, the productivity levels are proxied on an annual basis by the TFP measures relevant for each specific country-industry pairing, as calculated from the STAN data. Proxying the concept of productivity levels by the appropriate TFP measures allows us to compute the two productivity gap component measures for each country-industry ic given in equations 10 and 11.

At each time there are C different values of CPG, where C represents the number of countries, and $C*I$ different values of IPG, where I represents the number of different industries. The two levels of the productivity gap refer to different spillover sources from which productivity improvements can occur. The between-country level "country productivity gap" (CPG) represents an average productivity difference across countries. The within-industry gap "industry productivity gap" (IPG) compares productivity for an industry in a given country among all countries in which this industry operates, to reflect the potential of industry-specific spillovers from highly productive countries to less productive ones. The pooled correlation between CPG and IPG is 0.670 (not tabulated). The reason for the relatively large correlation is that the IPG gap uses the country that is best for the industry as benchmark while the CPG gap uses the country that is best overall as benchmark. For many industries the most productive firms are in the most productive country.

The summary statistics of computed total factor productivity (TFP) at the country level, which is the basis for the CPG measure, are provided in Table 1. An important point to note is that a small country such as Luxembourg may have a very high TFP but is ruled out from the technology-leader group since its productivity advantage is likely narrow (reflecting only a few industry segments) and is unlikely to lead to worldwide spillover effects. The information about the group of potential country leaders in TFP based on the criterion that productivity leaders should at least contribute 0.75% of world economy GDP is listed in the table. Table 1 further contains the descriptive statistics of Z_t^{c*}. For country $c^*(t)$ (the productivity leader country at time t) the value of the productivity gap is by definition equal to zero for time t. The technology leaders vary from year to year.

4.2 Stock Return Data

Stock price data are obtained from Compustat Global. The database provides daily prices, and dividend information to compute total returns at the firm level. All returns are converted to USD using the nominal currency exchange rate that is available from Bloomberg. We use Fama-French global factor data from Kenneth French's website to control for world-wide risk factors. Since this data is available from 1991 onwards, the range of our data is from

1991 to 2015. (STAN updates its macroeconomic data on a lagged but continuous basis; in the most recent update, 2016 data were available for only a few of the countries). The stock price data are available for individual firms with particular industry designations in the various OECD countries. Table 14 in the Data Appendix presents a summary of the stock returns of the available firms by OECD country and by year (from 1992 until 2015) as far as firm returns are available in a country for that year. The average return differences by country and industry are substantial. The monthly average of the mean excess returns for each country-industry portfolio over the 1992-2015 period is 0.144%, quite low in this period (the annualized risk premium is below 2%). The cross-sectional standard deviation of the mean monthly country-industry portfolio excess returns is a relatively high 0.735%. We focus on industries i in countries c and treat equal-weighted portfolios of all available firms for each country-industry with more than one firm as our test assets represented by index ic.[9] To deal with potential data errors, individual stock returns are winsorized at 5%. Table 15 in the Data Appendix C provides an overview of the firms available over the sample period for the set of industries and countries.

4.3 Countries and Industries Included

As the source of the test assets and productivity benchmarks we start with all stocks available from Compustat Global and productivity information of all countries and industries available from STAN, subject to the following criteria:

1. Only countries and industries are included for the periods that have data available to compute Total Factor Productivity (TFP) at the industry level, measuring labor inputs by Employee Hours and capital inputs by Net Capital Stock.

2. Test assets are portfolios of the firms for each country-industry, as long as data for more than one firm are available for a country-industry portfolio during a given month.

Table 13 in the Data Appendix gives a detailed analysis of the countries that are included in the productivity gap computation and the test assets. The following 26 countries are the OECD countries used to compute the various productivity gaps: Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Slovak Republic, Slovenia, Sweden, United Kingdom, and United States.

The remaining 10 OECD countries (Australia, Chile, Iceland, Israel, Mexico, New Zealand, South Korea, Spain, Switzerland, Turkey) are excluded following criterion (1). Based on the Compustat Global data, Table 15 in the Data Appendix contains the number of firms in each country-industry portfolio. The following 14 industries

[9] The number of firms in a portfolio is quite variable across portfolios and across time. However, we find that our main results do not change significantly if we exclude all industry-country portfolios with five or fewer firms. We also find that the results are very similar if we use value-weighted industry portfolios instead of equal-weighted.

are represented: Manufacturing; Electricity, Gas, Steam, and Air Conditioning; Water Supply, Sewage, Waste Management and Remediation Activities; Construction; Wholesale Retail Trade, Repair of Motor Vehicles and Motorcycles; Transportation and Storage; Accommodation and Food Services; Information and Communication; Professional Scientific and Technical Activities; Employment Activities; Education; Human Health Activities; Arts, Entertainment and Recreation; and Other Services. As is typical in the literature we do not include the Finance and Insurance, and the Real Estate industries. Compustat Global does not include U.S. and Canadian stocks so there are no test assets from these countries, even though these countries, in particular the U.S., do show up as leader countries and accordingly affect the productivity gaps for the test assets. It follows that there are test country-industry portfolios from 24 OECD countries ($C = 24$) and 14 Industry groupings ($I = 14$), generating a maximum of 336 test assets at any given time. However, some industries do not occur at all in each of the 24 countries, and many do not have data for all time periods. On average there are around 200 test assets in a given month.

5 Some Ancillary and Illustrative Results

5.1 Productivity Gap Predicting Productivity Growth

The STAN data allow us to identify potential sources of productivity spillovers. We first examine if indeed the productivity gap measures explain future growth in productivity, $\ln(Z^{ic}_{t+d}/Z^{ic}_t)$, for specific industries i in specific countries c, where d is the forecast horizon:

$$\ln(Z^{ic}_{t+d}/Z^{ic}_t) = c_0 + c_1 CPG^{ic}_t + c_2 IPG^{ic}_t + e^{ic}_{t+d}. \tag{13}$$

As a validation of the reasonability of the model assumptions we check to see if, indeed, it is true that productivity gaps predict future increases in productivity. Table 3 shows that each of the two gap measures have a highly significant positive sign in forecasting future productivity. A 1% larger gap implies an additional predicted increase in the growth of the productivity level of roughly 2 basis points (1.6 bps to 2.4 bps for CPG and 1.6 bps to 2.0 bps for IPG as the horizon increases from one to five years). It is equivalent to the 2 percent rate of convergence obtained for total factor productivity of OECD countries by Bernard and Jones (1996) for the 1970-87 period. The result suggests that technology and knowledge spillovers are important and trickle down to technologically less developed economies as previously argued by Comin and Hobijn (2004, 2010) and others. When we consider both gap measures jointly in Panel C, each contributes positively and significantly to the productivity forecasts, with the idiosyncratic gap measure, IPG, quantitatively more than twice as important (1.7 bps per year based on the five year horizon) as the aggregate gap measure, CPG (0.7 bps per year based on the five year horizon). We confirm the growth-literature results for our proxies and data, that the productivity gaps as we measure them are useful predictors for future productivity. Our aim in the following is to examine if the productivity gaps also have the explanatory power for future stock returns that the model suggests.

Whereas both types of spillover effects are expected to forecast and indeed do forecast productivity growth, certain spillovers may have a more significant impact on expected stock returns, namely those that relate to systematic risk exposure. The non-systematic industry gap measure (IPG) may matter because it proxies for sensitivity to risk factors. The systematic country gap measure (CPG) is more clearly relevant in that it directly measures exposure to a presumed systematic risk. We view the CPG gap measure as exposure to systematic risk as it is pervasive; whereas the IPG gap measure is industry specific and not directly tied to a systematic source of risk.

5.2 Productivity Shocks and Realized Returns

The prediction is not that all changes in productivity affect asset returns. They are likely important determinants of profitability and net cash flows, but they may be neither unexpected nor systematic. We examine if there is a direct connection between the excess returns of each country-industry portfolio and the systematic risk measured by the productivity shocks of the leader countries or industries. In doing so we control for idiosyncratic productivity risk which is represented by the (equal-weighted) productivity shock of each country-industry's own portfolio of firms. It is important to include this control because (notwithstanding our simplifying theoretical assumption of zero correlation between z_t^* and z_t), leader country-industry productivity shocks may be positively correlated with the productivity changes attributed to shocks of trailing country-industries with, in that case, the latter spuriously reflecting the importance of the former. Table 4 presents the result of a pooled regression of the cross-section and annual time series of all country-industry returns explained by the contemporaneous change in the leader country productivity level, $\Delta \ln Z_t^{c*}$, and the change in the industry-specific leader country productivity level, $\Delta \ln Z_t^{ic*}$, over the same period as each annual return, and controlling also for the specific country-industry's own productivity shock over that period, $\Delta \ln Z_t^{ic}$:

$$r_t^{ic} - r_t^f = \alpha_0 + \alpha_{ic} \Delta \ln \left(Z_t^{ic} \right) + \alpha_{ic}^* \Delta \ln \left(Z_t^{ic*} \right) + \alpha_c^* \Delta \ln \left(Z_t^{c*} \right) + \epsilon_t^{ic}. \tag{14}$$

We find in Table 4 that the idiosyncratic own productivity shocks ($\Delta \ln Z_t^{ic}$), by themselves, positively and significantly explain the individual returns contemporaneously. The industry-specific leading country shocks ($\Delta \ln Z_t^{ic*}$), also positively and significantly impact excess returns, either in isolation or together with the idiosyncratic productivity shocks. However, when the leader country productivity shocks are included ($\Delta \ln Z_t^{c*}$), the own country-industry productivity shock loadings are no longer significant. The leader country productivity shocks are by far the most important and have a significant positive contemporaneous effect on all stock returns. The leading country productivity shocks also dominate industry-specific leading country shocks ($\Delta \ln Z_t^{ic*}$) in their impact on contemporaneous stock returns, even though the industry-leading shocks predict future productivity better (as shown in Table 3). The results in Table 4 thus suggest strongly that it is systematic productivity shocks rather than idiosyncratic and predictable industry-specific productivity shocks that affect returns. It supports our view that leading-country productivity shocks, rather than just any productivity changes, are good candidates for systematic risk factors.

5.3 Productivity Gaps and Average Returns

It is necessary for a systematic risk factor to explain common time-series variation in realized returns but it is also necessary for it to explain cross-sectional variation in mean returns. We take an initial time for which most countries have productivity data available in our sample, 2000, as year zero and then obtain the average subsequent country returns, for the 15 years from then until the end of our sample, 2001-2015. Estimating the link between the country productivity gap measure and average returns at the country level yields

$$\hat{\mu}^c_{2001-2015} = 0.069 + \underset{(4.328)}{0.637}\, CPG_{2000} \tag{15}$$

with t-stat in parentheses and $R^2 = 0.50$. The slope coefficient is positive and significant so that a larger country productivity gap implies higher future average stock returns. This holds in addition to the result, familiar from the growth literature, in equation 13 that a larger gap implies higher future productivity growth. Figure 1 shows the results for the mean returns predicted by the initial productivity gap. Adding the industry productivity gap IPG_{2000} as an explanatory variable makes virtually no difference: the variable is insignificant and the R-squared and predicted mean returns do not change (result not shown). This is consistent with CPG_{2000} representing systematic risk exposure and IPG_{2000} representing idiosyncratic risk exposure. The data involve a single cross-sectional regression for 22 of the 24 countries in the sample (Portugal and Slovakia still drop out for the year 2000 productivity data, and 2001-2015 period return, providing sufficient productivity data only later in the sample). Given the cross-sectional standard deviation of CPG equal to 0.470 and the slope coefficient equal to 0.637, a one-standard deviation difference in a country's country productivity gap increases the average country-index stock return by 0.30% monthly, about 3.66% annualized. We provide more reliable and comprehensive results in the following by predicting country-industry as well as country returns based on the productivity gaps one month at a time, which allows us to use considerably more data.

6 Empirical Results

6.1 Productivity Gaps and Stock Returns

To test Hypothesis 1 with our panel data set we perform a standard Fama-MacBeth two-stage regression procedure on the industry portfolios in each of the different countries, at a monthly frequency. Equally-weighted industry portfolio are constructed from the Compustat data, where the portfolios consist of all firms in a particular industry of a particular country.

In the first stage, a time series regression is performed for each country-industry portfolio (denoted by ic, representing the industry index i and country index c) as in equation 16 to obtain the loadings of the portfolio returns on a set of standard systematic risk factors:

$$r_t^{ic} - r_t^f = \alpha^{ic} + \boldsymbol{\beta_t^{ic}}(\boldsymbol{F_t}) + \epsilon_t^{ic} \tag{16}$$

Here$\boldsymbol{F_t}$ is the vector of risk factors $\begin{bmatrix} F_{1t} \\ F_{2t} \\ \vdots \\ F_{nt} \end{bmatrix}$, and $\boldsymbol{\beta_t^{ic}}$ is the vector of estimated factor loadings $\begin{bmatrix} \beta_{1t}^{ic} \\ \beta_{2t}^{ic} \\ \vdots \\ \beta_{nt}^{ic} \end{bmatrix}$.

The risk factors represent those of the standard models: CAPM, Fama-French global three-factor (FF3), Fama-French global four-factor, including also the global Carhart momentum factor (FF3+MOM), Fama-French global five-factor (FF5), and Fama-French global five-factor including the global momentum factor (FF5+MOM). The excess annual returns of the industry portfolio are regressed on the different sets of factors. These factors act as controls for known factor risk.

In the second stage cross-sectional regressions are performed for each (monthly) time period in which the excess monthly returns for every country-industry portfolio are regressed on the productivity gap and the beta coefficients of the risk factors determined in the first stage:

$$r_{t+1}^{ic} - r_{t+1}^f = a_{t+1} + \boldsymbol{b_{t+1}}(\boldsymbol{\beta_t^{ic}}) + \boldsymbol{c_{t+1}}(\boldsymbol{PG_t^{ic}}) + \eta_{t+1}^{ic} \tag{17}$$

In equation 17 $\boldsymbol{PG_t^{ic}}$ is the vector of productivity gaps $[CPG_t^{ic}\ IPG_t^{ic}]'$ associated with each individual country-industry portfolio ic, $\boldsymbol{\beta_t^{ic}}$ is the vector of factor loadings for each country-industry portfolio obtained from the first stage. In the first stage a rolling regression is used to determine the set of betas for each model, with a window of at least 24 months expanding to a maximum of 60 months (following Fama and MacBeth, 1973). The coefficient (row) vectors $a_t, \boldsymbol{b_t}$, and $\boldsymbol{c_t}$ are estimated separately for each time period based on betas determined purely from prior data. Our productivity data start in January 1970 (for some countries). However, we use the global Fama-French risk factors which start in July 1990. Losing a minimum of 24 months for beta estimation, our effective sample period starts in July 1992. Thus, we employ monthly data from July 1992 until December 2015. This amounts to 282 monthly sample observations.

Since there are two productivity gap measures in equation 17, there are two $\boldsymbol{c_t}$ coefficients in the second stage of standard Fama-MacBeth regressions. The mean of 282 monthly cross-sectional regressions, $[c_1\ c_2] = \frac{1}{282} \sum_{t=1992,7}^{2015,12} \boldsymbol{c_t}$, represents the estimated mean of the cross-sectional coefficients and the standard deviation of each element of $\boldsymbol{c}$ represents its standard error. The null hypothesis is that coefficients are 0, and a standard t-test is performed separately for each coefficient to check for statistical significance. Rejecting the null hypothesis in favor of the alternative hypothesis that $c_1 > 0$ and $c_2 = 0$ confirms Hypothesis 1.

The cross-sectional mean coefficients and its standard error for equation 17 are presented for the augmented versions of the CAPM, the FF3+Mom (Carhart), and the FF5+Mom versions (for brevity and because the differences are inconsequential the results for the FF3 and FF5 models are omitted) in Tables 5, 6, and 7. We observe that in each model the coefficient on the aggregate country productivity gap CPG is positive and significant, for most specifications at the 1% level, after controlling for market, Carhart, and FF5+Mom factors. The result clearly suggests that in a panel of OECD countries, the country productivity gap as an indicator of systematic productivity risk explains important variation in cross-sectional returns. The coefficient on the country productivity gap CPG across the different risk models varies within the range 0.577-0.917 (and larger in the formulations that also include the industry productivity gap IPG). Given the CPG average time-series standard deviation of 0.53, a country productivity gap that is larger by one standard deviation implies a monthly return that is between 0.306 percent and 0.486 percent higher, or, annualized, between 3.7% and 6.0% higher, a quantitatively significant result. These results support Hypothesis 1. Moreover, as expected when only systematic risk is priced, the idiosyncratic industry productivity gap measure IPG is insignificant when it is included, without also including CPG. When both IPG and CPG are included, the marginal impact of IPG is negative, whereas the impact of CPG becomes larger. The net impact of both is very similar to when only the CPG measure is included, suggesting a collinearity issue. Thus, the idiosyncratic gap measure, while forecasting future productivity changes, does not on net affect average future stock returns.

If the country gap is very high then sensitivity to respond to the shock could be slow due to a) the embodiment effect and b) local factors (legal system, corruption, trade and technology barriers, political instability etc.) In such cases, future expected cash flow is not going to improve and the country gap will keep on increasing. Since we are dealing with OECD countries we don't see this effect in the empirical data. Nevertheless, if other undeveloped and developing countries are included then our results may not hold.

Sorting results

To present the above results alternatively in a non-parametric way we sort all country-industry portfolios by prior CPG gap into quintiles. Quintile 1 includes the country-industries with the 20% smallest gaps at each time and Quintile 5 includes the country-industries with the 20% largest gaps at each time. The subsequent monthly returns are recorded for each quintile. In Table 8, Panel A the difference between the fifth quintile and first quintile mean returns is 7.92% annually (monthly return difference equal 0.637%) and significant at the 1% level. In Panel B we sort in the same way but now measure returns by the alphas from the Fama-French five-factor model plus momentum. In this case the difference is 5.07% annually (monthly difference is 0.413%) and significant at the 1% level. If we instead sort by the IPG gap the returns still increase with the quintiles but the difference is smaller and not statistically significant. In addition, for an independent double sort into quintiles based on both gaps, the mean return difference attributable to the IPG gap is negligible. These IPG-sorting results are consistent with the parametric results in Tables 5, 6, and 7 and are not reported.

6.2 Connection to Momentum and Mean Reversion in International Stock Returns

To test the momentum part of Hypothesis 2 and see if the model can explain the results of international momentum in Chan et al., 2000, Asness et al., 2013, we concentrate on the factor sensitivities for each country-industry portfolio, β^{ic}_{WML}, obtained in the first stage for the systematic momentum factor. The WML factor loadings for each country-industry averaged over the sample period are regressed cross-sectionally on the average productivity gap values pertaining to each country-industry, $\boldsymbol{PG^{ic} = \frac{1}{282} \sum_{t=1992,7}^{2015,12} PG^{ic}_t}$ in a cross-sectional regression as in equation 18 below. The momentum part of Hypothesis 2 is supported if the null hypothesis that a slope coefficient $h = 0$ can be rejected in favor of the alternative hypothesis that a slope coefficient is significantly positive, $h > 0$, (in which case the momentum effect, at least in part, aliases for the actual productivity gap effect on risk loadings):

$$\beta^{ic}_{WML} = g + \boldsymbol{hPG^{ic}} + \omega^{ic}. \tag{18}$$

In addition, we check directly how much the risk premium on β^{ic}_{WML} is attenuated when $\boldsymbol{PG^{ic}}$ is added in the cross-sectional regressions, equation 17.

Table 9 presents the mean coefficients of the 282 monthly cross-sectional regressions between the factor loadings of the systematic momentum factor and the productivity gaps. Results are similar when the momentum betas are those of the Carhart model (in Panel A) or the momentum betas of the Fama-French five-factor model plus momentum (in Panel B). We clearly see that the cross-sectional variation of the factor loadings on the systematic momentum factor can be explained by either one of the productivity gaps. Similar to what we find for the explanatory power of productivity gaps for the portfolio returns tested in Hypothesis 1, we also find in testing Hypothesis 2 that the aggregate country productivity gap is the most important gap measure (although the standard deviation of the industry gap is slightly higher than that of the country gap, 0.70 versus 0.53, the country gap coefficient is up to six times as large as the industry gap coefficient, 0.217 versus 0.037). Dummy variables for the leader country and industry momentum betas are significantly negative, indicating that, all else equal, a leader country or industry has a smaller momentum beta. The reason is that the productivity levels of the leading countries and industries depend on their own discoveries and improvements which are more likely to follow a random pattern. We further discuss the importance of the dummy variables for leader countries or industries in Section 6.5.

Additional evidence concerning the momentum explanation in Hypothesis 2 may be obtained from Tables 6 and 7 by comparing the estimated momentum risk premium with and without the aggregated country gap measure. In both cases the momentum risk premium decreases, by around one-third (from 0.24 to 0.16 in Table 6) for the Carhart model, and by almost half (from 0.24 to 0.13 in Table 7) for the FF5+Mom model. While the decrease in the momentum risk premium is as predicted when the aggregate productivity gap is included, the effect is partial. The momentum risk premium is not significant when the aggregate productivity gap is incorporated in the regression, but, in our sample, it is not significant even before the country productivity gap is added to the regression.

Because the length of our sample is limited to less than 25 years we do not look to directly confirm the finding of mean reversion in international country-wide returns (Balvers et al., 2000, Zaremba et al., 2020). However, we can test the mechanism responsible for mean reversion in the model. It requires that initial low country-wide productivity levels indicative of low previous returns are followed by relatively high country-wide returns. Currently-large productivity gaps suggest a previous series of low productivity realizations and low returns. Mean reversion would imply subsequent high returns. If the mechanism implied by the model is feasible we predict that the size of the productivity gap at the beginning of the sample is directly related to the subsequent average returns:

$$\mu_T^c = a + \boldsymbol{b}\boldsymbol{PG_0^c} + \upsilon_T^c, \tag{19}$$

where we would expect to find $\boldsymbol{b} > \boldsymbol{0}$ for the country gap CPG but not for the country average industry gap IPG to confirm the mechanism leading to mean reversion. We already showed the results for this regression in equation 15 which confirm the hypothesis regarding the mechanism for mean reversion.

The evidence we provide here that productivity gaps and systematic productivity risk are responsible for the momentum and mean reversion patterns observed in international stock returns should be termed “circumstantial”. We do not provide direct evidence and can only conclude that, as far as we can tell, the momentum and mean reversion observations are consistent with the systematic productivity risk perspective.

6.3 Systematic Risk and Productivity Gaps

Even though Hypothesis 1 may tell us if the productivity gaps contribute to average returns, it is not clear in how far the return premia may be viewed as compensation for systematic risk. We have shown theoretically from the perspective of production-based asset pricing that a larger productivity gap leads to a higher average return on capital which must imply higher stock returns. From the dual consumption-based perspective, the higher stock returns must be tied to increased exposure to systematic risk. Hypothesis 3 relates the return premia directly to systematic risk measures. To evaluate the hypothesis we check whether the productivity gaps relate to direct measures of loadings on systematic productivity risk, ν_t^{ic}:

$$CPG_t^{ic} = c + d\nu_t^{ic} \tag{20}$$

Hypothesis 3 is confirmed if the null hypothesis that a slope coefficient $d = 0$ can be rejected in favor of the alternative hypothesis that a slope coefficient is significantly positive, $d > 0$.

While we find that both the potential for aggregate and for industry-specific spillover effects increase future productivity, only the potential for aggregate spillover effects theoretically increases average stock returns. The industries in countries with larger aggregate productivity gaps subsequently generate persistently higher stock returns. Our model suggests as the reason that firms in lagging countries will be more affected by the productivity shocks in the leading economy. These lead-country productivity shocks represent a systematic risk factor because they disperse widely across all lagging-country firms. The firms with the larger productivity gaps will be more sensitive to these shocks and, accordingly, have larger loadings on this systematic risk (the leading economy productivity shocks). These firms should have higher mean returns on average as compensation for the systematic risk.

To confirm explicitly the key element in our systematic risk explanation, that systematic risk exposure of firms in a country-industry is directly linked to its productivity gap, we first generate standard empirical estimates for the systematic risk exposure by running time-series regressions for the returns of all country-industry portfolios against both of the leader country productivity measures: the aggregate leader country productivity shocks $\Delta \ln Z_t^{c*}$ and the industry-specific leader country productivity shocks $\Delta \ln Z_t^{ic*}$. Second, we then examine (with standard Fama-MacBeth regressions) if the obtained exposures β_{ic}^{c*} and β_{ic}^{ic*} are indeed related to the country productivity gap measure (a special case of equation 20):

$$CPG_t^{ic} = a_{0t} + a_t^{c*}(\beta_{ic}^{c*}) + a_t^{ic*}(\beta_{ic}^{ic*}) + \epsilon_t^{ic}.$$

Using the full-sample leader productivity betas for each country-industry portfolio, we find from the Fama-

MacBeth regressions in Table 11, showing the time-averages of a_t^{c*} and a_t^{ic*}, that the leader-country-productivity beta β_{ic}^{c*} for the country-industries is positively and significantly correlated with the aggregate country productivity gaps for the country-industries, either by itself or when the industry-specific beta β_{ic}^{ic*} is included. The industry-specific beta β_{ic}^{ic*} by itself is statistically significant, but quantitatively small. When added to β_{ic}^{c*} it has significant marginal explanatory power for the CPG_t^{ic}, although the effect of the leader-country productivity beta, 0.12, is quantitatively larger than the effect of the leading-industry beta, 0.07. The link between leader-country-productivity betas and country productivity gaps explicitly support the supposed mechanism by which returns are affected by productivity gaps, providing support for the systematic risk explanation.

6.4 Behavioral or Systematic Risk Explanation

A straightforward alternative explanation for the importance of productivity gaps on future returns, not previously explored to our knowledge, similarly rests on the idea of productivity spillovers. However, it presumes a very different mechanism: spillovers arising from larger gaps generate higher future productivity and profitability. Cashflows to stockholders are expected to increase and directly lead to higher returns. While a straightforward explanation, it rests on investor behavioral biases: observable larger productivity gaps generate higher future windfall profits due to spillovers, but this potential is ignored at least in part by current investors who do not bid up stock prices until the anticipated windfall profits become fully discounted in the stock prices. The information about productivity gaps is disseminated slowly, as in Hong and Stein (1999), for instance. If investors would fully bid up stock prices earlier, and in absence of a systematic risk explanation, stock returns would not be higher when the anticipated windfall spillovers from the productivity gap are realized. Thus, the cashflow-based explanation relies on an underreaction perspective.

The earlier regression results presented in Table 3 allow us to distinguish the systematic risk explanation from the cashflow explanation with underreaction. Here systematic shocks in the form of leader country productivity shocks, $\Delta \ln (Z_t^{c*})$, have an important impact on returns. This by itself does not rule out the behavioral explanation. However, the fact that the idiosyncratic shocks, $\Delta \ln Z_t^{ic}$, are unimportant for stock returns, in spite of representing presumably similar windfall gains for cashflows as the leader-country shocks, argues against the cashflow explanation.

6.5 Systematic Risk of the Leader Countries

So far we have not considered one further specific implication of the theory concerning the source of systematic risk. As the productivity gap decreases, industries becomes less dependent on the worldwide advances originating in the leading country, and their exposure to systematic risk diminishes. However, at the extreme, when the productivity gap decreases to zero, the industry now is in the leading country. At that point, risk exposure actually increases rather than decreases because the industry is by definition fully exposed to its own productivity shocks which are to a large extent country-wide and thus, in the leader country, are systematic. I.e., as the industry is no longer catching up it increasingly sets the standard for worldwide productivity improvements and its idiosyncratic productivity shocks are now worldwide systematic productivity shocks. In practice, the transition is probably not as stark as presented here, mostly because the "leader" country position is really a continuous concept which, in spite of our discrete proxy for it, may be shared to different degrees by several economies. Nevertheless, relying on the imperfect proxy, the systematic risk measure for the leader industries should be determined differently from that of the other industries. To deal with this empirically we distinguish the leading industries in the leader country from the other test assets, using dummy variables.

In the parametric tests shown in Tables 5, 6, and 7 we insert dummy variables $CPG0_t^{ic}$ and $IPG0_t^{ic}$ equal to 1 at times when the (country or industry, respectively) productivity gap is equal to 0. In these cases, the country-industry is located in the leader country or in the leader country for its industry, respectively. Rather than facing no systematic risk because it cannot mimic the innovations in the leader country, it operates in the leader country itself and its innovations actually become systematic. Their returns therefore should be substantially higher than the productivity gap predicts – we expect the coefficient on the dummy variable to be positive. As shown in Tables 5, 6, and 7 the dummy coefficients representing the subsample with $CPG_t^{ic} = 0$, indeed are everywhere positive. However, they are not statistically significant and quantitatively quite small, varying from 0.090 (expanded CAPM) to 0.263 (expanded Carhart). This amounts to between 1.1% to 3.2% annualized difference between the mean return for a leader country compared to that of a non-leader country exhibiting an (almost) zero productivity gap. These numbers are lower than anticipated. Possible explanations are that the zero-one leadership assignation is not a very accurate representation of the transmission of productivity innovations, or that the insignificance of the results is a data problem resulting from the number of leaders being only a small fraction (four to five percent) of the data, together maybe with the risk premium in actuality being quite small.

For the non-parametric sorting case we cannot use dummy variables. Rather, we exclude all country industries in months when they are in the leader country (when they have a productivity gap of zero, $CPG_t^{ic} = 0$). We then sort the remaining country industries into quintiles. The results are in Table 8, Panels C and D. As predicted, the difference between the returns of Quintile 5 (large productivity gaps) and Quintile 1 (small productivity gaps) is now larger, equal to 9.82% annualized (0.784% monthly). When we include the risk correction based on the FF5+momentum factor model the annualized return is 6.65% as shown in Panel D (0.583% monthly), again larger than when we include the country-industries with zero gaps. Both are significantly positive at the 1% level. The reason that excluding the industries with zero gaps makes a difference is that these industries are included in Quintile 1 (or Quintile 2 since there are industries from productive small countries with negative gap values) because they have small (zero) gaps. However, they should have high systematic risk and, accordingly, high expected returns and are now rightly excluded from Quintile 1 (or Quintile 2) which is the quintile shorted in the sorting strategy and, in this case, ends up with comparatively lower returns (compare in particular Panels B and D). The difference compared to the case where we included the mis-assigned assets with zero gaps is 1.76% percent for raw return differences and 1.5% for differences in alphas. Since only a small fraction of the assets is mis-assigned (only a small fraction, about four to five percent, of the country-industries are in the leader country) the return difference here is quite substantial.

6.6 Productivity Gap Mimicking Factor

The connection to systematic risk of the productivity gap measured by CPG suggests that a mimicking factor may be generated that contributes to pricing assets. We utilize the method of Balvers and Luo (2018) and Balduzzi and Robotti (2008) to generate a "characteristic mimicking factor" with the property that the loadings of each test asset ic on this factor equals the asset characteristic – in this case, the country-specific productivity gap, CPG_t^{ic}, at each time t. For monthly return data, the loading estimate on this factor for a particular month therefore is at the same time an estimate of the productivity gap (observable only at the annual frequency) for the month. The mimicking factor allows a more comprehensive look at the systematic risk represented by the productivity gap.

The mimicking factor is obtained as

$$r_t^{PG} = (\boldsymbol{r_t^{ic}})' \left(\boldsymbol{\hat{\Sigma}_{t-1}^{ic}}\right)^{-\mathbf{1}} \boldsymbol{CPG_{t-1}^{ic}},$$

where $\boldsymbol{r_t^{ic}}$ is the vector of returns in month t for the country-industries. $\boldsymbol{\hat{\Sigma}_{t-1}^{ic}}$is the estimated covariance matrix for the country-industry returns using information prior to month t. We use 24 prior months to estimate this covariance matrix on a rolling basis. $\boldsymbol{CPG_{t-1}^{ic}}$ is the vector of the aggregate country production gaps for each country-industry using the most recent annual observation preceding month t. In view of the difficulty of pricing leader country-industries (zero-gap country-industries) based on the productivity gaps discussed in section 6.5, we exclude all periods in which a country-industry is in the leader country (has a gap of zero) from both the determination of the mimicking factor and from the test assets.

To see how well the productivity gap factor explains the country-industry portfolios, given that the factor loadings evolve as the production gaps change over time, we perform again a standard Fama-MacBeth procedure. The loadings on the production gap factor (as well as on the other factors we consider) of all country industry portfolios are estimated on a rolling basis using up to 60 prior monthly observations with a minimum of 24 observations (as in Fama and MacBeth, 1973). The predicted return is the loading for each factor times the realized factor return for the month. For each country-industry portfolio we then compare the predicted return against the realized monthly return, and average over all sample months. The result is show in Figure 2(a). The country and industry are identified by the first three letters and last three letters, respectively, of the labels in Figure 2. See Appendix C, Table 15 for the legend. The solid line indicates the regression of realized mean returns on predicted mean returns. The R-squared for this regression is 27.1 percent. The dotted line is the 45-degree line, indicating that the estimated risk premium approximately tracks the true risk premium. The slope of the regression line is not significantly different from one.

The absolute value of the alphas (the differences between the average realized and the average predicted returns) for the country-industry assets is a relatively large 0.466%. This is typical for models explaining industry portfolios. It is exacerbated by the relatively short sample size which causes realized mean returns to deviate stochastically by more from true mean returns.[10] Figure 2(a) illustrates that our model works less well for explaining the country-industry portfolios with negative mean returns. However, it is for these assets that the misestimation error of portfolio mean returns resulting from the relatively short time series of the sample may be most prominent, as negative risk premia for primary assets are generally not observed in samples with long time series. Generally, the country industries deviating most from their predicted values are smaller industries in smaller countries. The misestimation error is more severe for less diversified portfolios. More diversified portfolios should have reduced measurement error of the mean returns and hence should provide a better fit. To check this we aggregate all industries within a country and consider the model fit at the national level (for all countries with on average by industry at least 24 months of data). Figure 3(a) shows indeed a closer fit for the 21 countries that meet the data criteria, with an R-squared of 56.5 percent.

The remaining results in Table 10 and in Figures 2 and 3 display the model fit for the competing models. Each of these models perform substantially worse than the productivity gap factor model. The figures show the CAPM (panel b), the Carhart model (panel c), and the Fama-French 5-factor model with momentum (panel d). The FF3 and FF5 model performances are listed in Table 10 but are not displayed in the figures. The fit for the 187 country-industries in Figure 2 is conveyed by R-squares of 0.7%, 8.4%, 12.0%, 8.3%, and 7.0%, for CAPM, FF3, Carhart, FF5, and FF5Mom, respectively. For the 21 countries in Figure 3, the R-squares for CAPM, FF3, Carhart, FF5, and FF5Mom are, respectively, 33.8%, 8.0%, 1.0%, 17.7%, and 9.8%. The absolute alphas for these same models are 0.553%, 0.577%, 0.543%, 0.604%, and 0.574%, respectively. The relatively good fit for the CAPM in explaining country returns is misleading since the "tracking" coefficient is negative, meaning that higher predicted returns are associated with lower realized returns. Of the competing models the Carhart model performs best. Its tracking coefficient is 0.879 which is not significantly different from 1.0 and it explains 12.0% of the variation in mean country-industry asset returns.[11]

[10]To appreciate the numerical importance of the relatively short sample consider that the standard deviation of an industry portfolio return, averaged across all country-industries we use as test assets, is 7.29 percent for monthly returns. With 282 monthly returns this implies an average standard deviation of 0.43 percent for estimated monthly return means. This number is already close to the absolute alpha values generated by the model. When we consider country average returns as the test assets, the average standard deviation for these more diversified portfolios is 4.87 percent for monthly returns. With 282 monthly returns this generates an average standard deviation of 0.29 percent for the estimated monthly country-index return means. Our model applied to the country-index portfolios (as displayed in Figure 2a) generates accordingly a larger R-squared and smaller alphas: the average absolute alpha for the country-index portfolios is 0.22. Another indication of the imprecision of monthly mean return estimates is that, among the country-industry test assets for our sample period, 75 of 182 have a negative estimated equity premium. For mainstream asset pricing views the majority of these negative mean excess return estimates cannot reflect actual risk premia.

[11]Part of the better fit for the Production-Gap Factor model is due to a few outliers, mostly industries from the Czech Republic (which have relatively few time series data points). When we remove all Czech data points, the R-squared for the Production-Gap

Barillas-Shanken Tests

The above model comparison is relevant for the country industry portfolios as test assets and for the conditional model versions when factor loadings vary over time. Based on Barillas and Shanken (2017) we can make a nested unconditional (assuming constant factor loadings over the full sample) model comparison that is valid for any group of test assets. Essentially, any group of factors that has a larger maximum Sharpe ratio than a competing group of factors, will explain any group of test assets better (as long as this group of test assets includes both groups of factors). A model that consists of the union of the factors from two contesting models is the "large" model. We can test if the large model explains assets significantly better than either one of the "small" component models. The test is equivalent to the GRS test but with the small model serving as the factor model and the large model serving as the test assets. The test finds whether the maximum Sharpe Ratio of the large model is significantly larger than the Sharpe Ratio of the small model; or, equivalently, whether the factors excluded from the small model have significantly positive alphas as a group when explained by the factors from the small model. If they have significantly larger alphas, it follows that the large model when set to explain any group of test assets will have smaller alphas than the small model (when weighted by the inverse return covariance matrix).

The results of the Barillas-Shanken tests are shown in Table 12. As summary statistics for all factors considered, note that the Sharpe ratios vary from 0.070 (for the size factor) to 0.289 (for the productivity-gap factor). Only the profit factor has a Sharpe ratio of 0.239 close to the productivity-gap factor. This is interesting because both factors may be related conceptually in the sense that high productivity gaps may be associated with high profitability (due to the ability to cheaply mimic existing technology and knowledge). However, a large productivity gap also implies a low level of current productivity which is detrimental to profitability. As it is, the correlation between the two factors in our data is equal to -0.007 which is not significantly different from zero.

Applying the Barillas-Shanken test to compare one-factor models we find that, for all FF5 model factors plus the momentum factor, viewed individually as a factor model, the productivity gap factor has a significantly positive alpha, meaning that it contributes significantly to the explanation of any group of asset returns when added to one of the six factors. On the other hand, when the market factor or the size factor is added to the productivity gap factor either factor does not contribute to the explanation of any group of asset returns – the alpha of either factor is not significantly positive at the 5% level – meaning that the productivity gap factor explains this factor and that this factor is not marginally useful in explaining other asset returns. The alphas of the value and investment growth factors also are not significantly positive at the 1% level. The remaining FF5 factors, the profitability factor as well as the momentum factor, have significantly positive alphas (even at the 1% level) so that they are not subsumed by the productivity gap factor. The profit and momentum factors, thus, neither subsume nor are subsumed by the productivity gap factor.

The multi-factor models (FF3, Carhart, FF5, and FF5+Momentum) also cannot outperform the productivity

based model decreases somewhat to 20.8% (not tabulated), but still remains substantially higher than for the other models in Table 10.

gap factor model. The three FF3 factors jointly do not subsume the productivity gap factor, but the productivity gap factor subsumes the FF3 factors in the sense that the alphas of these three factors jointly are not significantly positive at the 1% level. Similarly, the Carhart, FF5, and FF5+Mom models do not subsume the productivity gap factor at any reasonable level of significance. On the other hand, the productivity gap factor by itself also does not subsume the Carhart, FF5, and FF5+Mom models at any reasonable level of significance. A further positive indication of the importance of the productivity gap factor is that its factor alphas generate higher GRS statistics than do the factor alphas of the multi-factor models the other way around (which is, of course, not a statistically significant difference). Furthermore, likely the factor model comparison results are affected by the unconditional nature of the test which (in this form) does not allow for time variation in factor loadings, an essential element of the productivity gap factor model. Lastly, the Barillas-Shanken results require that the test assets include all of the factors under consideration. This is automatically the case for the productivity gap factor for our test assets, but not for the FF5+Momentum factors (with the exception of the market factor). Thus, these factors should be expected to perform less well for the country-industry test assets we consider than would be expected based on the Barillas-Shanken tests.

7 Conclusion

There is broad consensus in the finance field that systematic risk is the suitable concept of risk for explaining average asset returns. But, curiously, there are few specific theories of what determines systematic risk. The APT and Merton Model merely provide a structure of how we can process systematic risk once it has been identified. With well-developed and integrated international markets, a systematic risk must be pervasive worldwide, as well as fundamentally important and persistent. In the current paper we propose that a strong candidate for a systematic risk is the fundamental uncertainty in how well resources may be combined to generate desired products. The uncertainty is a result of fundamental randomness in how technology and know-how develop to stimulate production. Discoveries (managerial, technological, procedural, etc.) are the random realizations that, when useful, spread worldwide. These realizations are the risk that generally originates with productivity leaders and spreads globally. The cause of systematic risk thus is the variation in productivity of leading producers that are in the best position to develop and discover new techniques and practices.

We develop a simple international production-based asset pricing model that accounts for technology spillover effects across countries and across industries. Firms, in countries and industries that lag behind the leading technology country or industry, face what we call "productivity gaps". Systematic productivity risks are driven mostly by the stochastic progress made in the leading-technology countries or industries, which spills over gradually to lagging-technology countries or industries. Larger productivity gaps in particular countries and industries mean that the firms in these country-industries stand to gain more from technology spillovers over time and, accordingly, are more exposed to the productivity shocks that occur in the leading-technology economies and industries. The latter factor is responsible for higher average stock returns for firms in the countries and industries with larger productivity gaps; these firms depend more on leader-country productivity gains and thus have higher loadings on the global systematic productivity risk. Because of the dynamics of the technology spillovers, productivity levels in lagging economies and industries are likely to catch up over time, but do so slowly. The high systematic productivity risk exposure of lagging firms, therefore, only diminishes slowly over time. In the overall picture, low returns accompanying a slide to a large productivity gap, are eventually reversed through subsequent persistently higher average returns, a process that shows aspects of both mean reversion and momentum in international returns.

The implications of the theory that technologically lagging firms (1) have higher average returns, that (2) display momentum and eventual mean reversion, and (3) display higher systematic risk, are examined here using detailed annual industry- and country-specific productivity data for OECD countries, and monthly stock return data for firms in these countries. The technology spillovers may occur through a multitude of different channels. We empirically examine two measures of productivity gaps that capture spillovers relevant to individual firms. In particular, we assess two contributory components to the productivity deficit, and the potential spillovers, faced by a particular firm: (a) gaps in the firm's country productivity relative to the most productive country; and (b) gaps at the industry level in the firm's country relative to the country which is the most productive for this particular industry. The total spillovers that benefit a firm may be a combination of these two different (but partially correlated) sources.

Both the aggregate country productivity gap and the industry-specific country productivity gap have significant explanatory power for future productivity in individual country-industries. Nevertheless, only the aggregate country productivity gap has forecast power for future stock returns. Firms in countries with a larger aggregate country productivity gap have significantly higher average returns, irrespective of the set of global risk factor exposures we use as controls. The reason is that a larger country productivity gap generates more exposure for the country's firms (industries) to the leader country productivity shocks, which by nature have a pervasive global impact and are indicators of systematic risk. The higher loadings on systematic risk emanating from the country productivity gaps imply higher average returns for the firms in countries with larger productivity gaps. In contrast, larger industry productivity gaps present a risk that is not systematic and has no detectable impact on average returns. As the country productivity gaps are persistent, the higher mean returns in countries with larger productivity gaps are also persistent. We find that a firm's exposure to systematic productivity risk is positively linked to the firm's exposure to the Carhart momentum factor, so that the model is consistent with the (systematic) momentum effect across countries. Further, after experiencing periods of relative decline which manifest in low returns and increasing country productivity gaps, the increased exposure to systematic risk generates a subsequent period of higher returns (with momentum) that reverses the negative earlier returns and resembles mean reversion.

A straightforward alternative explanation for our empirical result of a positive link between country productivity gaps and subsequent stock returns for the country's firms is that larger positive spillovers simply generate windfall gains in productivity and profit for these firms, which are responsible for higher stock returns. This explanation is inherently different from what our model suggests, especially because it requires the stock market to be inefficient in that the anticipated benefits of future productivity spillovers are at best partially incorporated in current stock prices, a scenario referred to as underreaction in the behavioral finance literature. In juxtaposition, our explanation assumes that anticipated positive spillovers are fully incorporated in stock prices but tie a firm more strongly to the systematic productivity risk emanating from the productivity-leading country, generating higher average returns as compensation for the increased systematic risk exposure.

Our results convey that a larger country productivity gap implies that firms in the lagging country exhibit higher future productivity growth. However, while these findings support our basic model, they are consistent also with the behavioral explanation. To decide among the competing explanations we check specifically if we can tie productivity gaps to systematic risk exposure. We investigate if it is possible to identify the positive link between productivity gaps and productivity betas as required for the systematic risk explanation. Estimating full-sample leader productivity betas for each country-industry portfolio, we find in Fama-MacBeth regressions that leader-country-productivity betas are positively and significantly correlated with country-industry productivity gaps. Indeed, changes in the stock prices of firms in countries with larger productivity gaps are significantly more positively correlated with the productivity shocks measured for the productivity leader country. Further, own-country-industry productivity shocks are far less important which argues against the cash flow explanation because, in this view, any productivity windfall (including in particular own-country-industry productivity shocks) should increase cash flows and, accordingly, given the inefficient markets perspective, increase stock returns.

It appears that productivity spillover effects are important on a global scale and generate significant predictability in stock returns as well as important differences in mean stock returns across countries and industries and over time, that are related to time-varying loadings on systematic productivity risk. We find some support for the view that the dynamics across countries between productivity shocks, productivity gaps, and stock returns may be partly responsible for empirical findings of momentum and mean reversion in international returns.

References

Acemoglu, D., Aghion, P., and Zilibotti, F. (2006). Distance to frontier, selection, and economic growth. *Journal of the European Economic Association*, 4(1):37–74.

Asness, C. S., Moskowitz, T. J., and Pedersen, L. H. (2013). Value and momentum everywhere. *Journal of Finance*, 68(3):929–985.

Balduzzi, P. and Robotti, C. (2008). Mimicking portfolios, economic risk premia, and tests of multi-beta models. *Journal of Business & Economic Statistics*, 26(3):354–368.

Balvers, R. and Luo, A. H. (2018). Distinguishing factors and characteristics with characteristic-mimicking portfolios.

Balvers, R., Wu, Y., and Gilliland, E. (2000). Mean reversion across national stock markets and parametric contrarian investment strategies. *Journal of Finance*, 55(2):745–772.

Balvers, R. J., Cosimano, T. F., and McDonald, B. (1990). Predicting stock returns in an efficient market. *Journal of Finance*, 45:1109–1128.

Balvers, R. J., Gu, L., and Huang, D. (2017). Profitability, value, and stock returns in production-based asset pricing without frictions. *Journal of Money, Credit and Banking*, 49(7):1621–1651.

Balvers, R. J. and Huang, D. (2007). Productivity-based asset pricing: Theory and evidence. *Journal of Financial Economics*, 86(2):405–445.

Barillas, F. and Shanken, J. (2017). Which alpha? *The Review of Financial Studies*, 30(4):1316–1338.

Bena, J. and Garlappi, L. (2020). Corporate innovation and returns. *The Review of Corporate Finance Studies*, 9(2):340–383.

Benhabib, J., Perla, J., and Tonetti, C. (2019). Reconciling models of diffusion and innovation: A theory of the productivity distribution and technology frontier.

Berk, J. B., Green, R. C., and Naik, V. (1999). Optimal investment, growth options, and security returns. *The Journal of Finance*, 54(5):1553–1607.

Bernard, A. B. and Jones, C. I. (1996). Productivity across industries and countries: Time series theory and evidence. *Review of Economics and Statistics*, 78(1):135–146.

Bloom, N., Schankerman, M., and Van Reenen, J. (2013). Identifying technology spillovers and product market rivalry. *Econometrica*, 81(4):1347–1393.

Breeden, D. (1979). An intertemporal asset pricing model with stochastic consumption and investment opportunities. *Journal of Financial Economics*, 7(3):265–296.

Brock, W. A. (1982). Asset prices in a production economy. In *The economics of information and uncertainty*, pages 1–46. University of Chicago Press.

Buera, F. J. and Oberfield, E. (2020). The global diffusion of ideas. *Econometrica*, 88(1):83–114.

Campbell, J. Y. and Shiller, R. J. (1988). The dividend-price ratio and expectations of future dividends and discount factors. *The Review of Financial Studies*, 1(3):195–228.

Chaieb, I., Langlois, H., and Scaillet, O. (2020). Factors and risk premia in individual international stock returns.

Chan, K., Hameed, A., and Tong, W. (2000). Profitability of momentum stragegies in the international equity markets. *Journal of Financial and Quantitative Analysis*, 35(2):153–172.

Cochrane, J. H. (1991). Production-based asset pricing and the link between stock returns and economic fluctuations. *Journal of Finance*, 46(1):209–237.

Cochrane, J. H. (1996). A cross-sectional test of an investment-based asset pricing model. *Journal of Political Economy*, 104(3):572–621.

Coe, D. T., Helpman, E., and Hoffmaister, A. W. (2009). International r&d spillovers and institutions. *European Economic Review*, 53(7):723–741.

Comin, D. and Hobijn, B. (2004). Cross-country technology adoption: making the theories face the facts. *Journal of Monetary Economics*, 51(1):39–83.

Comin, D. and Hobijn, B. (2010). An exploration of technology diffusion. *American Economic Review*, 100(5):2031–59.

Comin, D. and Mestieri, M. (2018). If technology has arrived everywhere, why has income diverged? *American Economic Journal: Macroeconomics*, 10(3):137–78.

Cooper, I. and Priestley, R. (2013). The world business cycle and expected returns. *Review of Finance*, 17(3):1029–1064.

Cox, J., Ingersoll, J., and Ross, S. (1985). An intertemporal general equilibrium model of asset prices. *Econometrica*, 53(2):363–384.

Dowrick, S. and Nguyen, D.-T. (1989). Oecd comparative economic growth 1950-85: Catch-up and convergence. *The American Economic Review*, 79(5):1010–1030.

Fama, E. F. and French, K. R. (1998). Value versus growth: The international evidence. *Journal of Finance*, 53(6):1975–1999.

Fama, E. F. and French, K. R. (2017). International tests of a five-factor asset pricing model. *Journal of Financial Economics*, 123(3):441 – 463.

Fama, E. F. and MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3):607–636.

Fisher, J. D. M. (2006). The dynamic effects of neutral and investment-specific technology shocks. *Journal of Political Economy*, 114(3):413–451.

Galor, O. (2005). Chapter 4 from stagnation to growth: Unified growth theory. volume 1 of *Handbook of Economic Growth*, pages 171 – 293. Elsevier.

Garleanu, N., Panageas, S., and Yu, J. (2012). Technological growth and asset pricing. *The Journal of Finance*, 67(4):1265–1292.

Gavazzoni, F. and Santacreu, A. M. (2020). International r&d spillovers and asset prices. *Journal of Financial Economics*, 136(2):330 – 354.

Grauer, F. L., Litzenberger, R. H., and Stehle, R. E. (1976). Sharing rules and equilibrium in an international capital market under uncertainty. *Journal of Financial Economics*, 3(3):233–256.

Griffith, R., Redding, S., and van Reenen, J. (2004). Mapping the two faces of r&d: Productivity growth in a panel of oecd industries. *Review of Economics and Statistics*, 86:883–895.

Hall, R. E. and Jones, C. I. (1999). Why do some countries produce so much more output per worker than others? *Quarterly Journal of Economics*, 114:83–116.

Hirshleifer, D., Hsu, P.-H., and Li, D. (2013). Innovative efficiency and stock returns. *Journal of Financial Economics*, 107(3):632–654.

Hong, H. and Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance*, 54(6):2143–2184.

Hou, K., Karolyi, G. A., and Kho, B. C. (2011). What factors drive global stock returns? *Review of Financial Studies*, 24(8):2527–2574.

Hou, K., Xue, C., and Zhang, L. (2014). Digesting Anomalies: An Investment Approach. *The Review of Financial Studies*, 28(3):650–705.

Howitt, P. (2000). Endogenous growth and cross-country income differences. *American Economic Review*, 90(4):829–846.

Inklaar, R. and Diewert, W. E. (2016). Measuring industry productivity and cross-country convergence. *Journal of Econometrics*, 191(2):426 – 433. Innovations in Measurement in Economics and Econometrics.

Johnson, P. and Papageorgiou, C. (2018). What remains of cross-country convergence? MPRA working paper 89355.

Keller, W. (2004). International technology diffusion. *Journal of Economic Literature*, 42:752–782.

Lin, X. (2012). Endogenous technological progress and the cross-section of stock returns. *Journal of Financial Economics*, 103(2):411–427.

Lind, N. and Ramondo, N. (2019). *Oxford Research Encyclopedia of Economics and Finance*, chapter The Economics of Innovation, Knowledge Diffusion, and Globalization.

Lucas, R. E. (1978). Asset prices in an exchange economy. *Econometrica*, 46(6):1429–1445.

Mancusi, M. L. (2008). International spillovers and absorptive capacity: A cross-country cross-sector analysis based on patents and citations. *Journal of International Economics*, 76:155–165.

Nelson, R. R. and Phelps, E. S. (1966). Investment in humans, technological diffusion, and economic growth. *American Economic Review*, 56(1/2):69–75.

OECD (2001). *Measurement of Aggregate and Industry-level Productivity Growth - OECD Manual*. OECD Publishing.

Papanikolaou, D. (2011). Investment shocks and asset prices. *Journal of Political Economy*, 119(4):639–685.

Parente, S. L. and Prescott, E. C. (1994). Barriers to technology adoption and development. *Journal of Political Economy*, 102(2):298–321.

Solnik, B. (1974). An equilibrium model of the international capital market. *Journal of Economic Theory*, 8(4):500–524.

Titman, S., John Wei, K. C., and Xie, F. (2013). Market development and the asset growth effect: International evidence. *Journal of Financial and Quantitative Analysis*, 48(5):1405–1432.

Watanabe, A., Xu, Y., Yao, T., and Yu, T. (2013). The asset growth effect: Insights from international equity markets. *Journal of Financial Economics*, 108(2):529–563.

Wolff, E. N. (2014). *Productivity Convergence*. Cambridge Books. Cambridge University Press.

Zaremba, A., Kizys, R., and Raza, M. W. (2020). The long-run reversal in the long run: Insights from two centuries of international equity returns. *Journal of Empirical Finance*, 55:177 – 199.

Zhang, L. (2005). The value premium. *The Journal of Finance*, 60(1):67–103.

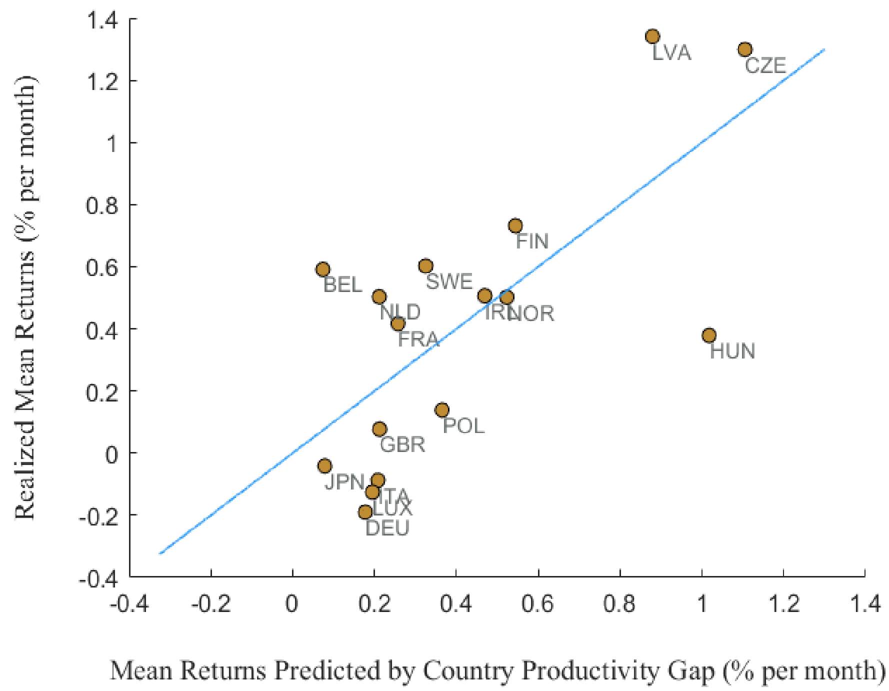
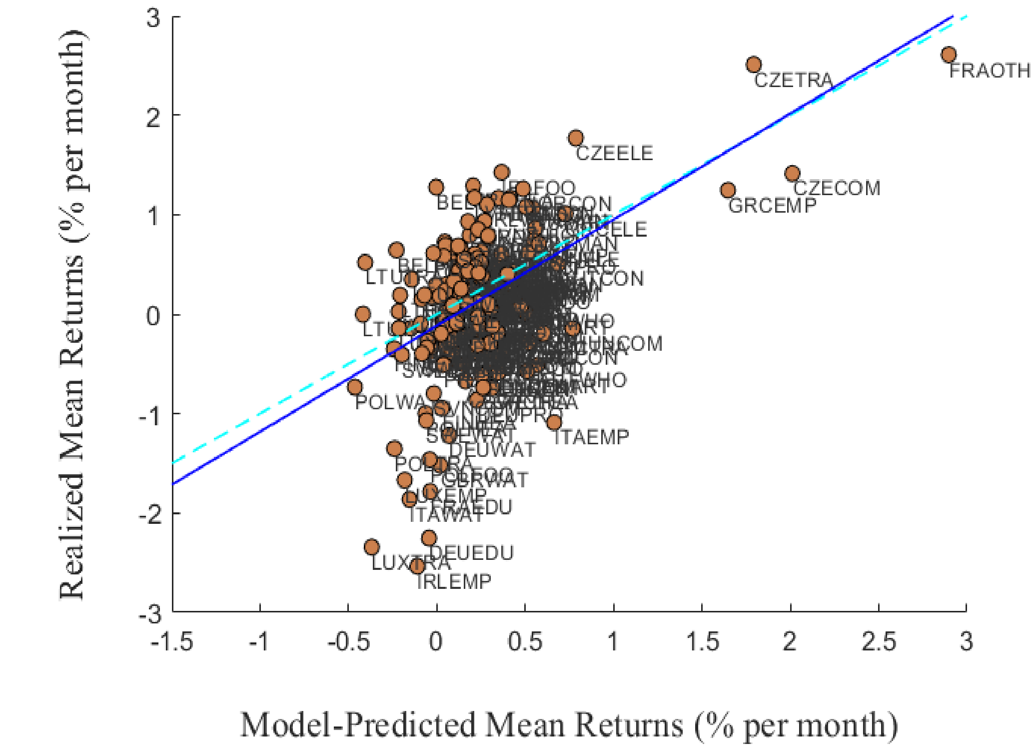
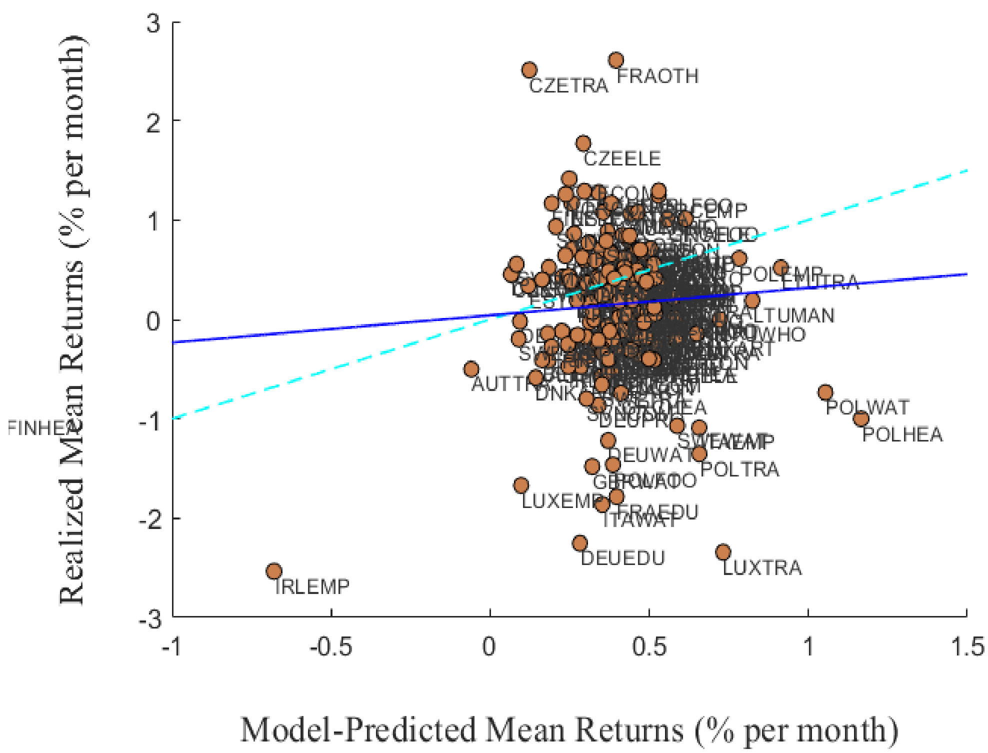


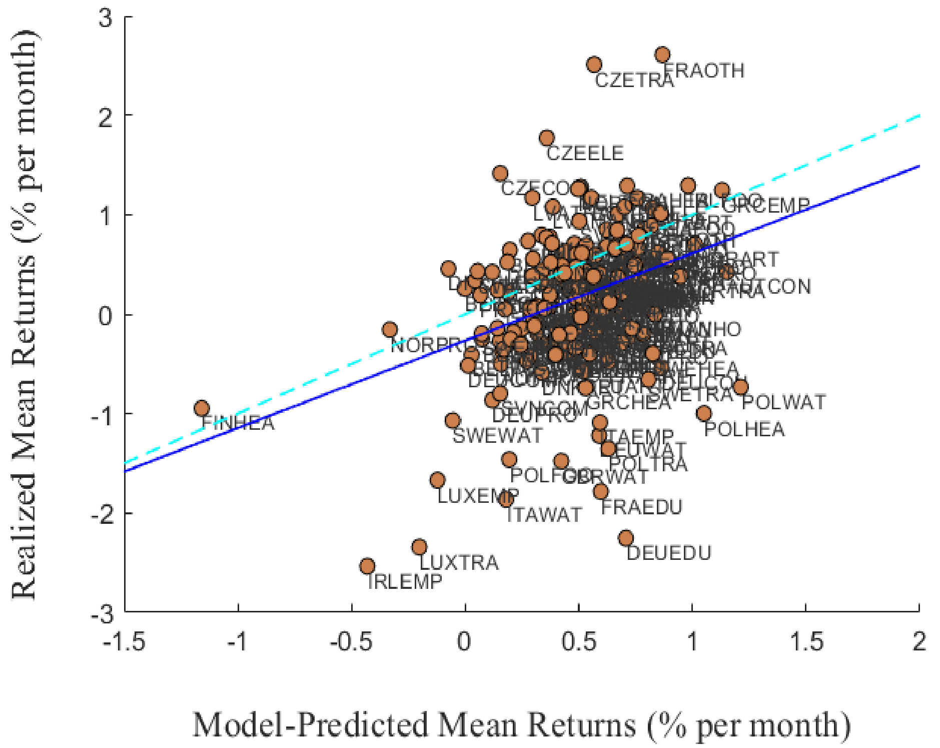
Figure 1: Initial Productivity Gaps and Average Country Returns



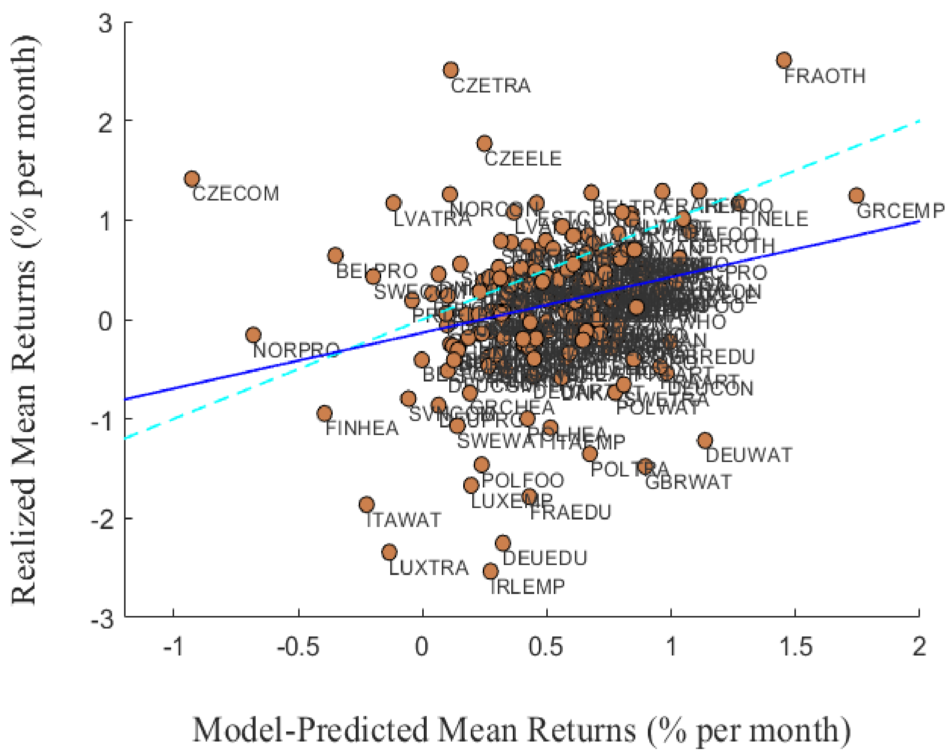
(a) Production-Gap Mimicking Factor Model



(b) CAPM

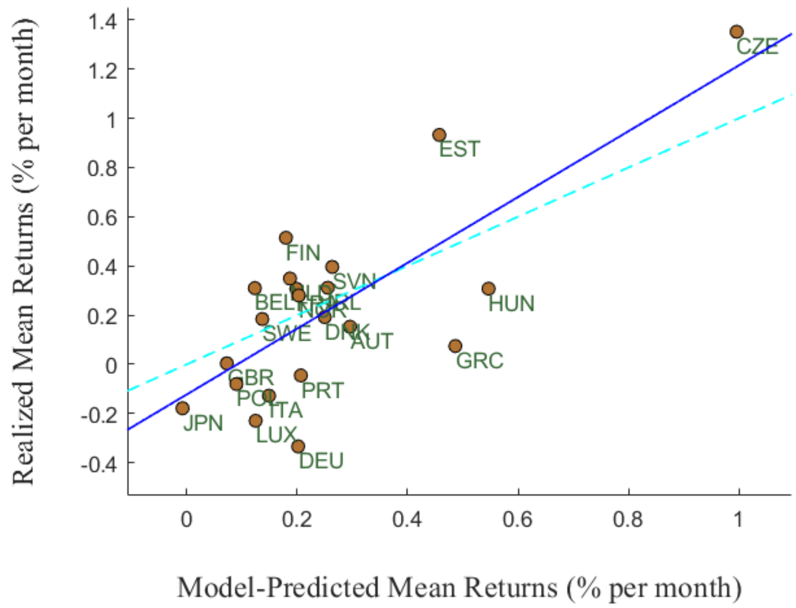


(c) Fama-French 3-Factor Model

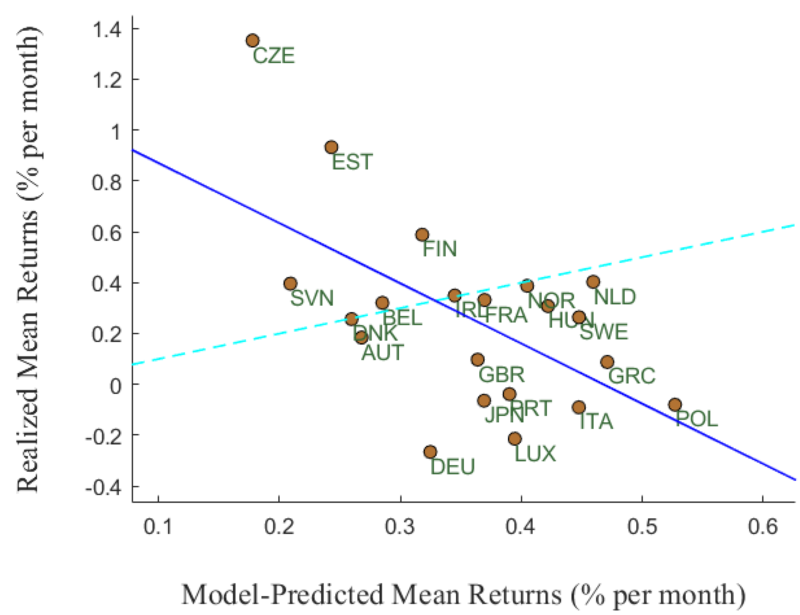


(d) Fama-French 5-Factor Model

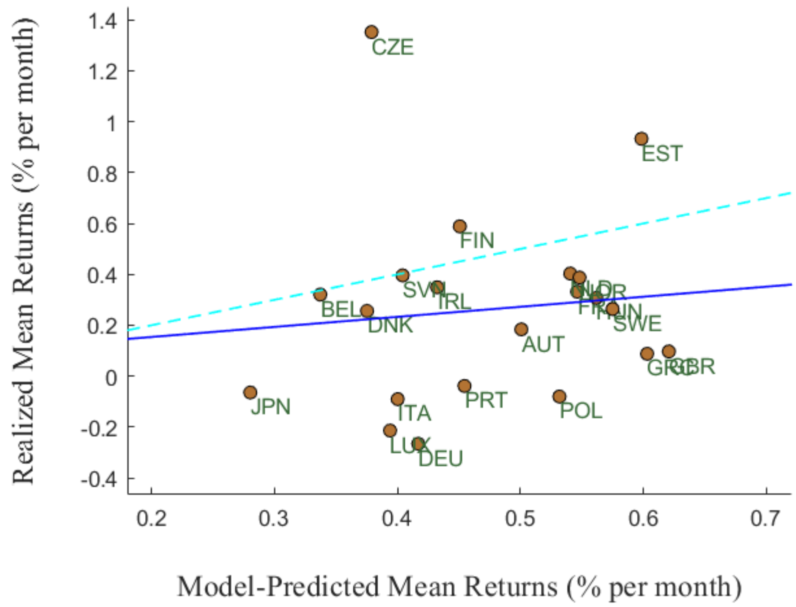
Figure 2: Performance of Factor Models in Explaining Country-Industry Portfolio Returns



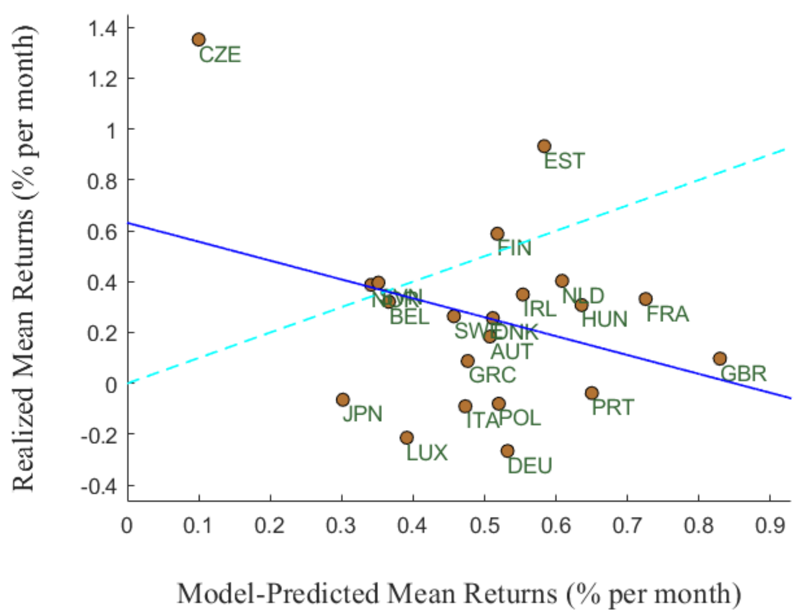
(a) Production-Gap Mimicking Factor Model



(b) CAPM



(c) Fama-French 3-Factor Model



(d) Fama-French 5-Factor Model

Figure 3: Performance of Factor Models in Explaining Country Portfolio Returns

Table 1: Country Level Total Factor Productivity

This Table presents the Mean, Standard Deviation (SD), Maximum, and Minimum of the Total Factor Productivity measure (TFP) for each country. In calculating TFP, capital is measured as the Net Capital Stock in PPP-adjusted USD and labor is measured in Employee Hours (hours worked by full time employees). Count is the number of years for which the country has the appropriate data in the 1990-2015 sample period. The countries are Austria (AUT), Belgium (BEL), Canada (CAN), the Czech Republic (CZE), Germany (DEU), Denmark (DMK), Estonia (EST), Finland (FIN), France (FRA), Great Britain (GBR), Greece (GRC), Hungary (HUN), Ireland (IRL), Italy (ITA), Japan (JPN), Lithuania (LTU), Luxemburg (LUX), Latvia (LVA), the Netherlands (NLD), Norway (NOR), Poland (POL), Portugal (PRT), the Slovak Republic (SVK), Slovenia (SVN), Sweden (SWE), and the United States of America (USA).

Country Level Total Factor Productivity					
Country	Mean	SD	Max	Min	Count
AUT	6.77	0.61	8.12	6.14	21
BEL	11.53	1.60	14.38	8.96	20
CAN	8.33	0.27	8.65	7.91	7
CZE	1.94	0.63	2.75	1.11	21
DEU	7.20	0.81	8.82	6.03	24
DNK	7.03	1.49	9.66	5.38	26
EST	3.41	0.78	4.56	2.38	15
FIN	6.23	1.09	8.34	5.14	26
FRA	8.85	1.41	11.78	6.70	26
GBR	8.12	1.67	10.03	5.31	21
GRC	5.00	0.76	6.10	3.64	19
HUN	2.33	0.57	2.99	1.46	19
IRL	5.42	0.89	7.32	4.12	20
ITA	6.78	0.67	8.04	5.96	26
JPN	8.31	1.26	11.14	6.49	22
LTU	2.23	0.50	2.99	1.36	16
LUX	8.00	1.31	10.06	5.99	20
LVA	2.17	0.51	3.02	1.38	15
NLD	9.58	1.35	12.27	7.43	26
NOR	5.98	0.86	7.55	4.64	26
POL	5.21	0.37	5.77	4.59	15
PRT	4.64	0.04	4.67	4.61	2
SVK	2.36	0.39	2.86	1.78	12
SVN	7.01	1.42	8.96	4.57	16
SWE	7.05	1.29	9.63	5.48	21
USA	7.88	0.74	8.73	6.31	26

Table 2: Country Level TFP Leaders

Total Factor Productivity (TFP) leader countries by year among the countries that contribute morer than 0.75% of world GDP and have TFP data available at the industry level: USA, UK, Germany, France, Canada, Australia, Italy, Japan, South Korea, Netherlands, Spain, Poland, and Mexico. TFP is calculated based on Employee Hours (hours worked by full time employees) and Net Capital Stock. The leader countries include France (FRA), the Netherlands (NLD), Japan (JPN), and the United States (USA).

Year	Maximum TFP	Max TFP Country
1990	7.811	FRA
1991	8.676	NLD
1992	8.711	NLD
1993	8.834	NLD
1994	10.350	JPN
1995	11.140	JPN
1996	9.881	JPN
1997	9.256	JPN
1998	8.912	JPN
1999	9.601	JPN
2000	9.526	JPN
2001	8.506	USA
2002	8.544	NLD
2003	9.980	NLD
2004	10.495	NLD
2005	9.309	NLD
2006	9.610	NLD
2007	10.196	NLD
2008	10.142	NLD
2009	11.091	NLD
2010	11.146	NLD
2011	10.667	NLD
2012	11.383	NLD
2013	12.271	NLD
2014	11.073	FRA
2015	10.183	FRA

Table 3: Forecastability of Productivity Changes from Productivity Gaps

Future changes in empirical measures of the productivity levels Z_t^{ic} for country-industry portfolios ic are regressed on current values of the relevant productivity gaps for the country-industry portfolio. We consider five different intervals d for the period of the future changes:

$$\ln(Z_{t+d}^{ic}) - \ln(Z_t^{ic}) = \alpha_0^d + \boldsymbol{\alpha_{PG}^d PG_t^{ic}} + \epsilon^d,$$

where $PG^{ic} = [CPG^{ic}, IPG^{ic}]$. Panel A presents the results with the relevant country level gap CPG as the forecast variable; Panel B presents the results with the relevant industry gap IPG as the independent variable; Panel C presents the results with both country level gap CPG and industry gap IPG as the independent variables. The coefficients and standard errors are for the pooled regression with White standard errors.

	$\ln Z_{t+1}^{ic} - \ln Z_t^{ic}$	$\ln Z_{t+2}^{ic} - \ln Z_t^{ic}$	$\ln Z_{t+3}^{ic} - \ln Z_t^{ic}$	$\ln Z_{t+4}^{ic} - \ln Z_t^{ic}$	$\ln Z_{t+5}^{ic} - \ln Z_t^{ic}$
Panel A: CPG					
α_{CPG}	0.016	0.037	0.066	0.090	0.118
t-stat	(5.75)***	(8.64)***	(11.88)***	(13.65)***	(16.03)***
p-value	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R^2	0.01	0.01	0.03	0.04	0.05
N	7,221	6,792	6,379	5,983	5,588
Panel B: IPG					
α_{IPG}	0.016	0.037	0.059	0.079	0.099
t-stat	(7.76)***	(11.36)***	(14.11)***	(15.77)***	(17.41)***
p-value	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R^2	0.01	0.03	0.04	0.06	0.07
N	7,413	6,984	6,571	6,159	5,748
Panel C: CPG and IPG					
α_{CPG}	0.000	0.002	0.014	0.022	0.036
t-stat	(0.08)	(0.28)	(1.82)*	(2.45)**	(3.45)***
p-value	[0.94]	[0.78]	[0.07]	[0.01]	[0.00]
α_{IPG}	0.017	0.037	0.054	0.071	0.086
t-stat	(5.73)***	(8.00)***	(9.22)***	(10.16)***	(10.54)***
p-value	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R^2	0.01	0.03	0.05	0.06	0.08
N	7,221	6,792	6,379	5,983	5,588

* p<0.10; ** p<0.05; *** p<0.01

Table 4: Returns with respect to Leading Productivity Shocks

Excess Returns of country-industry portfolio r_t^{ic} are regressed on its own productivity level shock, the productivity shock of the leader country for the industry, and the productivity shock of the leader country, in a pooled regression across time periods and country-industry portfolios. For the firm's own productivity level shock we use the change in $\Delta \ln(Z_t^{ic})$ which is industry productivity at the country-industry portfolio level; for the productivity shock of the industry leader country we use the change in leader industry productivity $\Delta \ln\left(Z_t^{ic*}\right)$; and for the productivity shock of the leader country we take leader country productivity $\Delta \ln\left(Z_t^{c*}\right)$.

$$r_t^{ic} - r_t^f = \alpha^0 + \alpha^{ic}\Delta \ln\left(Z_t^{ic}\right) + \alpha^{ic*}\Delta \ln\left(Z_t^{ic*}\right) + \alpha^{c*}\Delta \ln\left(Z_t^{c*}\right) + \epsilon_t^{ic}.$$

where $\Delta \ln\left(Z_t^{ic}\right) = \ln\left(Z_t^{ic}\right) - \ln\left(Z_{t-1}^{ic}\right)$, $\Delta \ln\left(Z_t^{ic*}\right) = \ln\left(Z_t^{ic*}\right) - \ln\left(Z_{t-1}^{ic*}\right)$, $\Delta \ln\left(Z_t^{c*}\right) = \ln\left(Z_t^{c*}\right) - \ln\left(Z_{t-1}^{c*}\right)$.

Coefficients	$r_t^{ic} - r_t^f$						
α_{ic}	0.219			0.183	-0.086		-0.067
t-stat	(3.57)***			(2.94)***	(-1.46)		(-1.14)
p-value	[0.00]			[0.00]	[0.14]		[0.26]
α_{ic}^*		0.194		0.169		-0.168	-0.163
t-stat		(3.95)***		(3.39)***		(-3.47)***	(-3.34)***
p-value		[0.00]		[0.00]		[0.00]	[0.00]
α_c^*			1.535		1.561	1.627	1.645
t-stat			(21.40)***		(21.11)***	(21.30)***	(21.10)***
p-value			[0.00]		[0.00]	[0.00]	[0.00]
R^2	0.00	0.01	0.14	0.01	0.14	0.15	0.15
N	2,730	2,730	2,730	2,730	2,730	2,730	2,730

* p<0.10; ** p<0.05; *** p<0.01

Table 5: Second Stage Fama-MacBeth Regressions with Productivity Gaps and the Global CAPM Risk Factor

The returns of the equal-weighted country-industry portfolios are regressed at a monthly frequency for the period July 1992-December 2015 on the various productivity gaps relevant for each country-industry portfolio and controlling for the global CAPM beta of the country-industry portfolio. The computation of the productivity gap measures uses TFP based on capital measured as the Net Capital Stock in current PPP terms and labor measured in Employee Hours. The global market factor is taken from Kenneth French's website. The cross-sectional regression is a specific case of equation 17:

$$r_{t+1}^{ic} - r_{t+1}^{f} = a_t + b_t^{MKT} \beta_{MKT}^{ic} + \boldsymbol{c_t}\,(\boldsymbol{PG_t^{ic}}) + \eta_t^{ic}$$

Here $\boldsymbol{PG_t^{ic}} = [CPG_t^{ic}\, CPG0_t^{ic}\, IPG_t^{ic}\, IPC0_t^{ic}]'$,with $CPG_t^{ic}$and $IPG_t^{ic}$the country and the industry productivity gap, respectively, and $CPG0_t^{ic}$ ($IPC0_t^{ic}$) a dummy variable that is equal to one when $CPG_t^{ic} = 0$ ($IPG_t^{ic} = 0$), the productivity gap equals zero. The coefficients and the standard errors in this table are the means and standard deviations of a_t, $b_t^{MKT}$and elements of $\boldsymbol{c_t} = [c_t^{CPG}, c_t^{CPG0}, c_t^{IPG}, c_t^{IPG0}]$ based on the 282 monthly regression from July 1992 until December 2015.

Coef			PG				CAPM		CAPM + PG				
c^{CPG}	0.902		1.167	0.892		1.350		0.917		1.166	0.916		1.386
T-STAT	(3.23)***		(4.35)***	(3.09)***		(4.09)***		(3.31)***		(4.40)***	(3.19)***		(4.20)***
P-VALUE	[0.00]		[0.00]	[0.00]		[0.00]		[0.00]		[0.00]	[0.00]		[0.00]
c^{IPG}		0.073	-0.252		0.107	-0.197			0.074	-0.244		0.113	-0.190
T-STAT		(0.77)	(-3.00)***		(1.13)	(-2.31)**			(0.80)	(-2.93)***		(1.24)	(-2.27)**
P-VALUE		[0.44]	[0.00]		[0.26]	[0.02]			[0.43]	[0.00]		[0.22]	[0.02]
c^{CPG0}				0.149		0.158					0.090		0.107
T-STAT				(0.68)		(0.72)					(0.38)		(0.45)
P-VALUE				[0.49]		[0.47]					[0.71]		[0.65]
c^{IPG0}					0.137	0.162						0.120	0.141
T-STAT					(1.29)	(1.44)						(1.17)	(1.28)
P-VALUE					[0.20]	[0.15]						[0.24]	[0.20]
b^{MKT}							-0.510	-0.458	-0.476	-0.435	-0.417	-0.512	-0.444
T-STAT							(-1.74)	(-1.57)	(-1.63)	(-1.49)	(-1.42)	(-1.77)*	(-1.53)
P-VALUE							[0.08]	[0.12]	[0.10]	[0.14]	[0.71]	[0.08]	[0.13]
R^2							0.06	0.10	0.08	0.11	0.12	0.09	0.14
N	34,321	34,321	34,321	34,321	34,321	34,321	34,321	34,321	34,321	34,321	34,321	34,321	34,321

* $p<0.10$; ** $p<0.05$; *** $p<0.01$

Table 6: Second Stage Fama-MacBeth Regressions with Productivity Gaps and the Global Carhart Model

The returns of the equal-weighted country-industry portfolios are regressed at a monthly frequency for the period July 1992-December 2015 on the various productivity gaps relevant for each country-industry portfolio and controlling for exposure to systematic risk factors. The computation of the productivity gap measures uses TFP based on capital measured as the Net Capital Stock in current PPP terms and labor measured in Employee Hours. The global risk factors are from Kenneth French's website. The cross-sectional regression is a specific case of 17:

$$r_{t+1}^{ic} - r_{t+1}^{f} = a_t + b_t^{MKT}\beta_{MKT}^{ic} + b_t^{SMB}\beta_{SMB}^{ic} + b_t^{HML}\beta_{HML}^{ic} + b_t^{WML}\beta_{WML}^{ic} \boldsymbol{+c_t}\left(\boldsymbol{PG_t^{ic}}\right) + \eta_t^{ic}$$

Here $\boldsymbol{PG_t^{ic}} = [CPG_t^{ic}\, CPG0_t^{ic}\, IPG_t^{ic}\, IPC0_t^{ic}]'$,with $CPG_t^{ic}$and $IPG_t^{ic}$the country and the industry productivity gap, respectively, and $CPG0_t^{ic}$ ($IPC0_t^{ic}$) a dummy variable that is equal to one when $CPG_t^{ic} = 0$ ($IPG_t^{ic} = 0$), the productivity gap equals zero. The coefficients and the standard errors in this table are the means and standard deviations of a_t, $b_t^{MKT}, b_t^{SMB}, b_t^{HML}, b_t^{WML}$and elements of $\boldsymbol{c_t} = [c_t^{CPG}, c_t^{CPG0}, c_t^{IPG}, c_t^{IPG0}]$ based on the 282 monthly regression from July 1992 until December 2015.

Coef	CARHART	CARHART + PG					
c^{CPG}		0.830		1.061	0.821		1.326
T-STAT		(2.96)***		(3.64)***	(2.83)***		(4.17)***
P-VALUE		[0.00]		[0.00]	[0.00]		[0.00]
c^{IPG}			0.035	-0.240		0.052	-0.196
T-STAT			(0.45)	(-3.48)***		(0.66)	(-2.60)***
P-VALUE			[0.65]	[0.00]		[0.51]	[0.01]
c^{CPG0}					0.237		0.263
T-STAT					(0.87)		(0.94)
P-VALUE					[0.39]		[0.35]
c^{IPG0}						0.061	0.074
T-STAT						(0.61)	(0.76)
P-VALUE						[0.54]	[0.45]
b^{MKT}	-0.244	-0.245	-0.240	-0.228	-0.232	-0.262	-0.255
T-STAT	(-0.93)	(-0.93)	(-0.92)	(-0.87)	(-0.85)	(-1.00)	(-0.94)
P-VALUE	[0.36]	[0.35]	[0.36]	[0.39]	[0.39]	[0.32]	[0.35]
b^{SMB}	-0.064	-0.137	-0.074	-0.142	-0.116	-0.074	-0.115
T-STAT	(-0.57)	(-1.27)	(-.68)	(-1.32)	(-1.09)	(-0.69)	(-1.07)
P-VALUE	[0.57]	[0.20]	[0.50]	[0.19]	[0.28]	[0.50]	[0.29]
b^{HML}	0.315	0.304	0.339	0.311	0.295	0.341	0.309
T-STAT	(2.39)**	(2.30)**	(2.56)**	(2.35)**	(2.21)**	(2.55)**	(2.31)**
P-VALUE	[0.02]	[0.02]	[0.01]	[0.02]	[0.03]	[0.01]	[0.02]
b^{WML}	0.236	0.161	0.193	0.146	0.218	0.196	0.175
T-STAT	(1.17)	(0.79)	(0.95)	(0.71)	(1.05)	(0.97)	(0.85)
P-VALUE	[0.24]	[0.43]	[0.34]	[0.48]	[0.29]	[0.33]	[0.40]
R^2	0.14	0.17	0.16	0.18	0.20	0.17	0.21
N	34,218	34,218	34,218	34,218	34,218	34,218	34,218

* p<0.10; ** p<0.05; *** p<0.01

Table 7: Second Stage Fama-MacBeth Regressions with Productivity Gaps and the Global Fama-French Five-Factor Model plus Momentum

The returns of the equal-weighted and value-weighted country-industry portfolios are regressed at a monthly frequency for the period July 1992-December 2015 on the various productivity gaps relevant for each country-industry portfolio and controlling for exposure to systematic risk factors. The computation of the productivity gap measures uses TFP based on capital measured as the Net Capital Stock in current PPP terms and labor measured in Employee Hours. The global risk factors are from Kenneth French's website. The cross-section regression is a specific case of equation (17):

$$r_{t+1}^{ic}-r_{t+1}^{f}=a_t+b_t^{MKT}\beta_{MKT}^{ic}+b_t^{SMB}\beta_{SMB}^{ic}+b_t^{HML}\beta_{HML}^{ic}+b_t^{RMW}\beta_{RMW}^{ic}+b_t^{CMA}\beta_{CMA}^{ic}+b_t^{WML}\beta_{WML}^{ic}\boldsymbol{+c_t(PG_t^{ic})}+\eta_t^{ic}$$

Here $\boldsymbol{PG_t^{ic}}=[CPG_t^{ic}\ CPG0_t^{ic}\ IPG_t^{ic}\ IPC0_t^{ic}]'$,with $CPG_t^{ic}$and $IPG_t^{ic}$the country and the industry productivity gap, respectively, and $CPG0_t^{ic}$ ($IPC0_t^{ic}$) a dummy variable that is equal to one when $CPG_t^{ic}=0$ ($IPG_t^{ic}=0$), the productivity gap equals zero. The coefficients and the standard errors in this table are the means and standard deviations of a_t, $b_t^{MKT}, b_t^{SMB}, b_t^{HML}, b_t^{RMW}, b_t^{CMA}, b_t^{WML}$and subsets of $\boldsymbol{c_t}=[c_t^{CPG}, c_t^{CPG0}, c_t^{IPG}, c_t^{IPG0}]$ based on the 282 monthly regression from July 1992 until December 2015. We eliminate the finance and insurance, and real estate industry groups.

Coef	FF5 + Mom			FF5 + Mom+PG			
c^{CPG}		0.577		0.808	0.610		1.122
T-STAT		(2.30)**		(3.20)***	(2.34)**		(4.06)***
P-VALUE		[0.02]		[0.00]	[0.02]		[0.00]
c^{IPG}			-0.048	-0.243		-0.028	-0.207
T-STAT			(-0.61)	(-3.30)***		(-0.33)	(2.60)***
P-VALUE			[0.54]	[0.00]		[0.74]	[0.01]
c^{CPG0}					0.160		0.177
T-STAT					(0.56)		(0.60)
P-VALUE					[0.57]		[0.55]
c^{IPG0}						0.063	0.094
T-STAT						(0.64)	(0.94)
P-VALUE						[0.52]	[0.35]
b^{MKT}	-0.283	-0.214	-0.247	-0.215	-0.211	-0.289	-0.249
T-STAT	(-1.06)	(-0.80)	(-0.92)	(-0.80)	(-0.77)	(-1.08)	(-0.90
P-VALUE	[0.29]	[0.42]	[0.36]	[0.42]	[0.44]	[0.28]	[0.37]
b^{SMB}	0.006	-0.072	-0.007	-0.081	-0.061	-0.004	-0.062
T-STAT	(0.06)	(-0.65)	(-0.07)	(-0.74)	(-0.56)	(-0.04)	(-0.55)
P-VALUE	[0.96]	[0.51]	[0.95]	[0.46]	[0.57]	[0.97]	[0.58]
b^{HML}	0.340	0.325	0.364	0.337	0.309	0.371	0.328
T-STAT	(2.56)**	(2.43)**	(2.73)***	(2.52)**	(2.30)**	(2.74)***	(2.41)**
P-VALUE	[0.01]	[0.02]	[0.01]	[0.01]	[0.02]	[0.01]	[0.02]
b^{RMW}	-0.025	0.050	-0.013	0.039	0.035	-0.000	0.032
T-STAT	(-0.30)	(0.61)	(-0.16)	(0.48)	(0.41)	(-0.00	(0.37)
P-VALUE	[0.76]	[0.54]	[0.87]	[0.63]	[0.68]	[1.00]	[0.71]
b^{CMA}	0.105	0.127	0.117	0.131	0.177	0.110	0.176
T-STAT	(0.83)	(1.02)	(0.92)	(1.03)	(1.43)	(0.86)	(1.40)
P-VALUE	[0.11]	[0.31]	[0.36]	[0.30]	[0.15]	[0.39]	[0.16]
b^{WML}	0.244	0.131	0.205	0.133	0.198	0.205	0.169
T-STAT	(1.22)	(0.65)	(1.02)	(0.65)	(0.97)	(1.02)	(0.83)
P-VALUE	[0.22]	[0.52]	[0.31]	[0.52]	[0.33]	[0.31]	[0.41]
R^2	0.20	0.22	0.21	0.23	0.24	0.23	0.25
N	34,126	34,126	34,126	34,126	34,126	34,126	34,126

* $p<0.10$; ** $p<0.05$; *** $p<0.01$

Table 8: Portfolio Sort: unisort on CPG

The equally weighted country industry portfolios are sorted into quintiles using the previous year CPG value. The portfolios are formed in June and are held for a year without rebalancing. Quintile 1 holds the country-industry portfolios with the smallest productivity gaps and, Quintile 5 holds the portfolios with the largest productivity gaps. Panels A and C present the excess return for the quintiles and the difference between the fifth and first quintile.

Panels B and D presents the alpha for the quintiles based on Fama French five-factor model with the systematic momentum factor. In Panels C and D we present the results only for country industries with $CPG \neq 0$ so that the leader country industries at each time are excluded because the leader country has high systematic risk even though it has a zero productivity gap.

Panel A (mean returns and includes $CPG = 0$)						
	1	**2**	**3**	**4**	**5**	**5-1**
$\mu^{ic} - r^f$	0.204	-0.181	0.063	0.494	0.841	0.637
T-STAT	(0.886)	(-0.697)	(0.259)	(1.818)*	(2.522)**	(2.966)***
P-VALUE	[0.376]	[0.486]	[0.796]	[0.070]	[0.012]	[0.003]
Panel B (alphas and includes $CPG = 0$)						
α^{ic}	-0.506	-0.598	-0.357	-0.103	-0.092	0.413
T-STAT	(-4.931)***	(-3.982)***	(-3.204)***	(-0.723)	(-0.484)	(2.397)**
P-VALUE	[0.000]	[0.000]	[0.002]	[0.470]	[0.629]	[0.017]
Panel C (mean returns and includes only $CPG \neq 0$)						
$\mu^{ic} - r^f$	0.209	-0.330	0.151	0.400	0.939	0.784
T-STAT	(0.918)	(-1.319)	(0.595)	(1.409)	(2.756)***	(3.548)***
P-VALUE	[0.359]	[0.188]	[0.552]	[0.160]	[0.006]	[0.000]
Panel D (alphas and includes only $CPG \neq 0$)						
α^{ic}	-0.576	-0.529	-0.248	-0.130	-0.038	0.538
T-STAT	(-5.223)***	(-3.836)***	(-2.207)**	(-0.836)	(-0.193)	(2.996)***
P-VALUE	[0.000]	[0.000]	[0.028]	[0.404]	[0.847]	[0.003]

* p<0.10; ** p<0.05; *** p<0.01

Table 9: Cross-Sectional Regression of Momentum Factor Loadings from the Five-Factor plus Momentum Model on the Productivity Gap Measures

The momentum betas based on the Fama-French Three-Factor Model plus Momentum (Panel A) and the largest risk model we used, the Fama-French Five-Factor Model plus Momentum (Panel B) of each country-industry portfolio are regressed at a monthly frequency for the period July 1992-December 2015 on the various productivity gaps relevant for each country-industry portfolio. The computation of the productivity gap measures uses TFP based on capital measured as the Net Capital Stock in current PPP terms and labor measured in Employee Hours. The global risk factors are from Kenneth French's website.

$$\beta^{ic}_{WML_t} = a_t + \boldsymbol{c_t}(\boldsymbol{PG^{ic}_t}) + \eta^{ic}_t$$

Here $\boldsymbol{PG^{ic}_t} = \begin{bmatrix} CPG^{ic}_t \\ IPG^{ic}_t \end{bmatrix}$. The coefficients and the standard errors in this table are the means and standard deviations of the elements of $\boldsymbol{c_t} = [c^{CPG}_t, c^{IPG}_t]$ based on the 282 monthly regressions from July 1992 until December 2015.

Coefficients			**BetaWML**			
			Panel A: Carhart Model Momentum Betas			
c^{CPG}	0.250		0.217	0.203		0.202
t-stat	(8.07)***		(6.59)***	(6.53)***		(4.40)***
p-value	[0.00]		[0.00]	[0.00]		[0.00]
c^{IPG}		0.093	0.037		0.093	0.055
t-stat		(11.68)***	(4.96)***		(9.91)***	(6.77)***
p-value		[0.00]	[0.00]		[0.00]	[0.00]
c^{CPG0}				-0.227		-0.239
t-stat				(-7.80)***		(-8.12)***
p-value				[0.00]		[0.00]
c^{IPG0}					-0.024	0.016
t-stat					(-3.54)***	(1.75)*
p-value					[0.00]	[0.08]
R^2	0.05	0.03	0.06	0.12	0.03	0.14
N	34,343	34,343	34,343	34,343	34,343	34,343
			Panel B: FF5+Mom Model Momentum Betas			
c^{CPG}	0.255		0.197	0.215		0.183
t-stat	(8.33)***		(6.11)***	(6.88)***		(4.01)***
p-value	[0.00]		[0.00]	[0.00]		[0.00]
c^{IPG}		0.106	0.062		0.106	0.079
t-stat		(13.03)***	(7.82)***		(11.16)***	(8.75)***
p-value		[0.00]	[0.00]		[0.00]	[0.00]
c^{CPG0}				-0.172		-0.190
t-stat				(-8.04)***		(-8.51)***
p-value				[0.00]		[0.00]
c^{IPG0}					-0.103	0.016
t-stat					(-12.29)***	(1.68)*
p-value					[0.00]	[0.09]
R^2	0.04	0.03	0.06	0.08	0.04	0.11
N	34,343	34,343	34,343	34,343	34,343	34,343

* p<0.10; ** p<0.05; *** p<0.01

Table 10: Model Comparisons for Explaining the Mean Country-Industry Portfolio Returns

The returns of the country-industry portfolios (all permutations from 24 countries and 14 industries included if data for more than one firm are available for at least 24 months) are regressed at a monthly frequency for the period July 1992-December 2015 on the risk factors of various models to estimate factor loadings based on 60 months with at least 24 months being available. The factor loadings estimated from past data are used to predict returns of a months later:

$$\hat{E}_{t-1}(r_t^{ic} - r_t^f) = \boldsymbol{(\hat{\beta}_{t-1}^{ic})' F_t}$$

$$Avg(r_t^{ic} - r_t^f) = \hat{a} + \hat{b} Avg[\hat{E}_{t-1}(r_t^{ic} - r_t^f)] + \hat{\varepsilon}^{ic}$$

The productivity gap model (PGM) consists of the productivity gap characteristic mimicking portfolio, $r_t^{PG:}$ The global risk factors are from Kenneth French's website: the market factor r_t^{MMF},the size factor r_t^{SMB},the value factor r_t^{HML},the profitability factor r_t^{RMW},the investment growth factor r_t^{CMA},and the momentum factor r_t^{WML}. The alternative models are the Fama-French 3-factor (FF3) model (r_t^{MMF},r_t^{SMB}, r_t^{HML}), the Carhart model (r_t^{MMF},r_t^{SMB}, r_t^{HML}, r_t^{WML}), the Fama-French 5-factor (FF5) model (r_t^{MMF}, r_t^{SMB}, r_t^{HML}, r_t^{RMW}, r_t^{CMA}) and the FF5Mom (FF5+momentum) model (r_t^{MMF}, r_t^{SMB}, r_t^{HML}, r_t^{RMW}, r_t^{CMA}, r_t^{WML}).

	PG	CAPM	FF3	Carhart	FF5	FF5+Mom
$\hat{a}$	-0.115	1.106	-0.207	-0.266	-0.206	-0.134
T-STAT	(-2.157)**	(3.960)***	(-2.078)**	(-2.766)**	(-2.063)*	(-1.475)
$\hat{b}$	1.066	-2.365	0.698	0.879	0.633	0.561
T-STAT	(8.282)***	(-3.117)***	(4.123)***	(5.012)***	(4.097)***	(3.732)***
R^2	0.271	0.007	0.084	0.120	0.083	0.070
$\lvert\alpha\rvert$	0.466	0.553	0.577	0.543	0.604	0.574
N	46,996	46,996	46,996	46,996	46,996	46,996

* p<0.10; ** p<0.05; *** p<0.01

Table 11: Productivity Gaps and Systematic Risk Exposure

Employing the Black-Jensen-Scholes Procedure (estimating betas for the full sample period) we first obtain full-sample betas for each country-industry portfolio. The time series of annual excess returns of each country-industry portfolio is regressed against the productivity shocks of the leader country and the productivity shocks of the specific industry's leader country to compute risk exposures (betas).

$$r_t^{ic} - r_t^f = \beta_0 + \beta^{c*}\Delta\ln\left(Z_t^{c*}\right) + \beta^{ic*}\Delta\ln\left(Z_t^{ic*}\right) + \epsilon_t^{ic},$$

where $\Delta\ln\left(Z_t^{c*}\right) = \ln\left(Z_t^{c*}\right) - \ln\left(Z_{t-1}^{c*}\right)$, and $\Delta\ln\left(Z_t^{ic*}\right) = \ln\left(Z_t^{ic*}\right) - \ln\left(Z_{t-1}^{ic*}\right)$. Second, cross-sectional regressions of the Country Productivity Gap for each country-industry at each time period against the estimated betas:

$$CPG_t^{ic} = a_t^0 + a_t^{c*}(\beta^{c*}) + a_t^{ic*}(\beta^{ic*}) + \eta_t^{ic}.$$

The mean coefficients and t-stats of the time series for the 24 annual regressions ($a^{c*} = \sum_{t=1}^{24} a_t^{c*}/24$ and $a^{ic*} = \sum_{t=1}^{24} a_t^{ic*}/24$) are presented below.

Coefficients		CPG^{ic}	
a^{c*}	0.153		0.119
t-stat	(10.08)***		(10.55)***
p-value	[0.00]		[0.00]
a^{ic*}		0.041	0.074
t-stat		(7.61)***	(9.05)***
p-value		[0.00]	[0.00]
R^2	0.13	0.02	0.11
N	3,104	3,104	3,104

* p<0.10; ** p<0.05; *** p<0.01

Table 12: Model Comparisons for Explaining any Group of Test Assets

The productivity gap model (PGF) consists of the productivity gap characteristic mimicking portfolio, $r_t^{PG:}$ The global risk factors are from Kenneth French's website: the market factor r_t^{MMF},the size factor r_t^{SMB},the value factor r_t^{HML},the profitability factor r_t^{RMW},the investment growth factor r_t^{CMA},and the momentum factor r_t^{WML}. The alternative models are the Fama-French 3-factor (FF3) model (r_t^{MMF},r_t^{SMB}, r_t^{HML}), the Carhart model (r_t^{MMF},r_t^{SMB}, r_t^{HML}, r_t^{WML}), the Fama-French 5-factor (FF5) model (r_t^{MMF}, r_t^{SMB}, r_t^{HML}, r_t^{RMW},r_t^{CMA}) and the FF5Mom (FF5+momentum) model (r_t^{MMF}, r_t^{SMB}, r_t^{HML}, r_t^{RMW},r_t^{CMA}, r_t^{WML}).

Panel A: Test whether PGF is a significant addition to alternative factor models

	PG $\Longrightarrow$	MMF	SMB	HML	RMW	CMA	WML	FF3	Carhart	FF5	FF5Mom
SR	0.289	0.110	0.070	0.142	0.239	0.121	0.163	0.209	0.319	0.435	0.466
GRS	N.A.	22.99	24.30	23.81	15.14	25.57	24.66	20.23	18.16	14.073	13.22
F-CRIT	N.A.	3.873	3.873	3.873	3.873	3.873	3.873	3.873	3.873	3.873	3.873
P-VALUE	N.A.	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]

Panel B: Test whether the alternative factors are a significant addition to PGF

	PG $\Longleftarrow$	MMF	SMB	HML	RMW	CMA	WML	FF3	Carhart	FF5	FF5Mom
GRS	N.A.	1.750	0.798	4.885	22.96	4.899	7.625	2.859	5.863	8.878	8.550
F-CRIT	N.A.	3.873	3.873	3.873	3.873	3.873	3.873	2.635	2.402	2.245	2.129
P-VALUE	N.A.	[0.19]	[0.37]	[0.03]	[0.00]	[0.03]	[0.01]	[0.04]	[0.00]	[0.00]	[0.00]

* $p<0.10$; ** $p<0.05$; *** $p<0.01$

Appendix A: Derivations

Expression for Equilibrium Stock Returns

From equation (1), (2)and (3) we obtain:

$$V_K(K_{t+1}, z_{t+1}, z^*_{t+1}) = \alpha \frac{Y_{t+1}}{K_{t+1}} + (1-\delta) \tag{A.1}$$

$$K_{t+1} = G\ z^*_t(\frac{z_t}{z^*_t})^{\gamma}, \text{where } G = e^{\frac{-\alpha\sigma^2}{2}} \left(\frac{\alpha A}{r+\delta}\right)^{\frac{1}{1-\alpha}} \tag{A.2}$$

Given that $\ln(\eta_t) \sim N(-\sigma^2/2\,, \sigma^2)$ it holds that $E_t(\eta^b_{t+1}) = e^{\frac{-\sigma^2}{2}b(1-b)}$for any parameter b, which we use repeatedly in the derivations. Stock prices P are ex-dividend firm values, $P_t = V(K_t, z_t, z^*_t) - \pi(z_t, K_t, K_{t+1})$, so that

$$P_t = V(K_t, z_t, z^*_t) - [F(K_t, z_t L) + (1-\delta)K_t - K_{t+1}] = E_t\left[m_{t+1} V(K_{t+1}, z_{t+1}, z^*_{t+1})\right] \tag{A.3}$$

It is convenient to derive stock price net of the capital stock, which represents the firm's growth options:

$$P_t - K_{t+1} = E_t\left[m_{t+1}\left(Y_{t+1} + (1-\delta)K_{t+1}\right)\right] - K_{t+1} + E_t\left[m_{t+1}(P_{t+1} - K_{t+2})\right] \tag{A.4}$$

In deriving equation (A.4), equation (1) is moved one time period ahead and equation (A.3) is used.

$$E_t\left[m_{t+1}\left(Y_{t+1} + (1-\delta)K_{t+1}\right)\right] - K_{t+1} = \frac{E_t(Y_{t+1}) - (r+\delta)K_{t+1}}{1+r} \tag{A.5}$$

Equation (A.5) is derived from the equation (6) and equation (A.1). It also follows from these equation that

$$E_t(Y_{t+1}) = \frac{r+\delta}{\alpha} K_{t+1} \tag{A.6}$$

Thus, from equations (A.5) and (A.6):

$$E_t\left[m_{t+1}\left(Y_{t+1} + (1-\delta)K_{t+1}\right)\right] - K_{t+1} = FK_{t+1},\ F = \frac{(1-\alpha)(r+\delta)}{\alpha(1+r)} \tag{A.7}$$

$$P_t - K_{t+1} = FK_{t+1} + E_t\left[m_{t+1}(P_{t+1} - K_{t+2})\right] \tag{A.8}$$

$$P_t - K_{t+1} = Hz^*_t(\frac{z^*_t}{z_t})^{-\gamma} + E_t\left[m_{t+1}(P_{t+1} - K_{t+2})\right],\ H = FG = e^{\frac{-\alpha\sigma^2}{2}} \left(\frac{(1-\alpha)A}{1+r}\right)\left(\frac{\alpha A}{r+\delta}\right)^{\frac{\alpha}{1-\alpha}} \tag{A.9}$$

Equation (A.9) can be solved forward to find the stock price (the growth options part). The future discounted dividend components may be found based on the following:

$$E_t\left[m_{t+1}z^*_{t+1}(\frac{z_{t+1}}{z^*_{t+1}})^{\gamma}\right] = \frac{e^{-\sigma^2(1-\gamma)(\gamma+\lambda)}}{1+r} z^*_t(\frac{z_t}{z^*_t})^{\gamma 2} \tag{A.10}$$

$$\begin{aligned} E_t\left\{m_{t+1}E_{t+1}\left[m_{t+1}z^*_{t+2}(\frac{z_{t+2}}{z^*_{t+2}})^{\gamma}\right]\right\} &= e^{-\sigma^2(1-\gamma)(\gamma+\lambda)}E_t\left[m_{t+1}z^*_{t+1}(\frac{z_{t+1}}{z^*_{t+1}})^{\gamma^2}\right] \\ &= \left(e^{-\sigma^2[(1-\gamma)(\gamma+\lambda)+(1-\gamma^2)(\gamma^2+\lambda)]}\right) z^*_t(\frac{z_t}{z^*_t})^{\gamma^3} \end{aligned} \tag{A.11}$$

By induction the formula for the stock price is obtained as

$$P_t - K_{t+1} = Hz^*_t\left[\sum_{i=1}^{\infty} e^{-\sum_{j=0}^{i-1}\rho_j}(\frac{z_t}{z^*_t})^{\gamma^i}\right], \;\; \rho_j = \sigma^2(1-\gamma^j)(\gamma^j+\lambda) + \ln(1+r), \;\; \rho_0 = 0 \tag{A.12}$$

$$P_{t+1} - K_{t+2} = Hz^*_{t+1}\left[\sum_{i=1}^{\infty} e^{-\sum_{j=0}^{i-1}\rho_j}(\frac{z_{t+1}}{z^*_{t+1}})^{\gamma^i}\right] \tag{A.13}$$

$$E_t(P_{t+1} - K_{t+2}) = Hz^*_t\left[e^{-[\rho_0+\sigma^2(1-\gamma)\gamma]}(\frac{z^*_t}{z_t})^{-\gamma^2} + e^{-[\rho_1+\sigma^2(1-\gamma^2)\gamma^2]}(\frac{z^*_t}{z_t})^{-\gamma^3 + \,\cdots}\right] \tag{A.14}$$

$$E_t(P_{t+1} - K_{t+2}) = Hz^*_t e^{\sigma^2\lambda+\ln(1+r]}\left\{e^{-\rho_1}\left[(\frac{z^*_t}{z_t})^{\gamma}e^{\sigma^2\lambda}\right]^{-\gamma} + e^{-(\rho_1+\rho_2)}\left[(\frac{z^*_t}{z_t})^{\gamma}e^{\sigma^2\lambda}\right]^{-\gamma^2} + \;\cdots\right\} \tag{A.15}$$

We can write gross stock returns as

$$E_t(R_{t+1}) = \frac{E_t(P_{t+1} - K_{t+2}) + \{[(r+\delta)/\alpha] + (1-\delta)\}K_{t+1}}{(P_t - K_{t+1}) + K_{t+1}} \tag{A.16}$$

$$E_t(R_{t+1}) = \frac{Fe^{\ln(1+r]}\left\{e^{-\rho_1}\left[(\frac{z^*_t}{z_t})^{\gamma}e^{\sigma^2\lambda}\right]^{1-\gamma} + e^{-(\rho_1+\rho_2)}\left[(\frac{z^*_t}{z_t})^{\gamma}e^{\sigma^2\lambda}\right]^{1-\gamma^2} + \;\cdots\right\} + [(r+\delta)/\alpha] + (1-\delta)}{1 + F\left\{1 + e^{-\rho_1}\left[(\frac{z^*_t}{z_t})^{\gamma}\right]^{\gamma-\gamma^2} + e^{-(\rho_1+\rho_2)}\left[(\frac{z^*_t}{z_t})^{\gamma}\right]^{\gamma-\gamma^3} + \;\cdots\right\}} \tag{A.17}$$

$$E_t(R_{t+1}) = \frac{Fe^{\ln(1+r]}\left\{e^{-\rho_1}\left[(\frac{z^*_t}{z_t})^{\gamma}e^{\sigma^2\lambda}\right]^{1-\gamma} + e^{-(\rho_1+\rho_2)}\left[(\frac{z^*_t}{z_t})^{\gamma}e^{\sigma^2\lambda}\right]^{1-\gamma^2} + \;\cdots\right\} + [(r+\delta)/\alpha] + (1-\delta)}{1 + F\left\{1 + e^{-\rho_1}\left[(\frac{z^*_t}{z_t})^{\gamma}\right]^{1-\gamma} + e^{-(\rho_1+\rho_2)}\left[(\frac{z^*_t}{z_t})^{\gamma}\right]^{1-\gamma^2} + \;\cdots\right\}} \tag{A.18}$$

$$\frac{E_t(R_{t+1})}{1+r} = \frac{\left\{e^{-\rho_1}\left[(\frac{z_t^*}{z_t})^\gamma e^{\sigma^2\lambda}\right]^{1-\gamma} + e^{-(\rho_1+\rho_2)}\left[(\frac{z_t^*}{z_t})^\gamma e^{\sigma^2\lambda}\right]^{1-\gamma^2} + \cdots\right\} + \frac{\alpha(1+r)}{(r+\delta)(1-\alpha)]} + 1}{\left\{e^{-\rho_1}\left[(\frac{z_t^*}{z_t})^\gamma\right]^{1-\gamma} + e^{-(\rho_1+\rho_2)}\left[(\frac{z_t^*}{z_t})^\gamma\right]^{1-\gamma^2} + \cdots\right\} + \frac{\alpha(1+r)}{(r+\delta)(1-\alpha)]} + 1} \tag{A.19}$$

$$\frac{E_t(R_{t+1})}{1+r} = \frac{f(cx_t)+b}{f(x_t)+b},$$

$$x_t = (\frac{z_t^*}{z_t})^\gamma, c = e^{\sigma^2\lambda}, b = \frac{\alpha(1+r)}{(r+\delta)(1-\alpha)]} + 1, f(x) = e^{-\rho_1}x^{1-\gamma} + e^{-(\rho_1+\rho_2)}x^{1-\gamma^2} + \cdots \tag{A.20}$$

Now we can find the sign of the effect of $(\frac{z_t^*}{z_t})$ on expected returns by focusing on x in equation (A.20) which is monotonically related to it. For $dE_t(R_{t+1})/dx$:

$$\frac{dE_t(R_{t+1})}{(1+r)dx} = \frac{cf'(cx)[f(x)+b] - f'(x)[f(cx)+b]}{[f(x)+b]^2} \tag{A.21}$$

It is dicult to sign the result analytically in general terms. We show instead that the sign is always positive at least for small risk premium $c-1>0$: First, $dE_t(R_{t+1})/dx|_{c=1} = 0$ as follows easily from (A.21). So it is sufficient to show that $d\{dE_t(R_{t+1})/dx\}/dc|_{c=1} > 0$: Since the denominator in equation (A.21) is always positive and does not depend on c we can ignore it.

$$sgn\{\frac{d[dE_t(R_{t+1})/dx]}{dc}\} = sgn\{[f'(cx) + cxf"(cx)][f(x)+b] - xf'(x)f'(cx)\} > 0 \tag{A.22}$$

Multiply by x (which is always positive) and evaluate at $c=1$ to determine if the sign is positive:

$$sgn\{\frac{d[dE_t(R_{t+1})/dx]}{dc}|_{c=1}\} = sgn\{[xf'(x) + x^2f"(x)][f(x)+b] - [xf'(x)]^2\} > 0 \tag{A.23}$$

To show this, define for convenience $f_n = e^{-(\rho_1+\rho_2+\ldots\rho_n)}x^{1-\gamma^n}$. Then

$$f(x) = f_1 + f_2 + \ldots, \quad xf'(x) = (1-\gamma)f_1 + (1-\gamma^2)f_2 + \ldots$$

$$x^2f"(x) = -\gamma(1-\gamma)f_1 - \gamma^2(1-\gamma^2)f_2 + \ldots \tag{A.24}$$

It follows that $xf'(x) + x^2f"(x) = (1-\gamma)^2f_1 + (1-\gamma^2)^2f_2 + \ldots > 0$. We can then ignore$b>0$ in (A.23) since it only reinforces the positive sign. Then comparing $[xf'(x)+x^2f"(x)]f(x)$ against $-[xf'(x)]^2$ the terms that are not in common are of the form: $[(1-\gamma^i)^2 + (1-\gamma^i)^2]f_if_j$ and $-2(1-\gamma^i)(1-\gamma^j)f_if_j$which are positive in sum since $[(1-\gamma^i)+(1-\gamma^j)]^2 > 0$. This proves the sign in equation (A.23).

Hence, there are three results: (1) The mean stock return varies over time with $x_t = (z_t^*/z_t)^\gamma$ only; (2) The net mean stock return always exceeds the risk free rate; and (3) For small risk premium, the mean stock return always increases in the productivity gap. To obtain equation (8) in the text we define in equation (A.20): $r_c \equiv \ln(1+r)$, $\mu_t \equiv E_t[\ln(R_{t+1})]$, and $g(x) \equiv [f(cx)+b]/f(x)+b]$.

Appendix B: Productivity Measures

Compustat Global Database

Return are computed in local currency using the following Compustat fields: prccd, trfd and ajexdi. The returns are computed as $prccd * trfd/ajexdi$ and converted to USD using exchange rates from Bloomberg.

STAN

The following STAN's fields are used to compute TFP: Hours worked-total engaged (HRSN), Hours worked employee (HRSE), Net Capital Stock at current replacement cost (CAPN), Value added at current price (VALU), Labor cost (LABR), Total Employment (EMPN), Self-employed (SELF), Number of Employees (EMPE), Full time equivalents – total engaged (FTEN), Full time equivalents – employees (FTEE), Other taxes less subsidy in production (OTXS) and Gross Operating Surplus and mixed income (GOPS). The OECD Productivity OECD (2001, pp 112-114) elaborates on the procedure for computing TFP. Labor inputs are in hours. The capital input $CAPN_{PPP}$ is CAPN (Net Capital Stock at current replacement cost) adjusted for PPP by converting to USD using the OECD PPP exchange rate. The value-added TFP measure is used where the $VALU_{PPP}$is VALU adjusted for PPP by converting to USD using OECD PPP exchange rate. The VALU field is analogous to GDP per industry/country.

$$log(TFP) = log(VALU_{PPP}) - ((labshare * log(HRSE)) + (capshare * log(CAPN_{PPP})) \tag{B.1}$$

OECD assumes $labshare + capshare = 1$, then the definitions of TFP given in equation B.1 are the same as the weighted average of labor and capital productivity and are given by equation B.2:

$$log(TFP) = \left(labshare * log(\frac{VALU_{PPP}}{HRSE})\right) + \left(capshare * log(\frac{VALU_{PPP}}{CAPN_{PPP}})\right) \tag{B.2}$$

The Labor share (labshare) and capital share (capshare) are determined by estimating the proportion of value-add to labor and capital factors. Intuitively, the value added has contributions from labor and capital factors that determines the labor share and capital share. This disaggregation is not simple because there is a mixed income part which is combined with the Gross operating surplus of firms (GOPS). STAN database expresses Value added (at current price) relationship as in equation B.3

$$VALU = LABR + GOPS + OTXS \tag{B.3}$$

If mixed income were not included in GOPS, then it would have been part of capital income. The proportion of mixed-income attributed to labor is extrapolated with the assumption that self-employed have the same compensation as full-time employees. The self-employment is measured in hours (HRSE-HRSN) or numbers (EMPN-EMPE, FTEN-FTEE) depending upon the availability of data. The labor component of mixed-income $LABR_{MIXED}$ is given by equation B.4

$$LABR_{MIXED} = \frac{LABR}{HRSN} * (HRSE - HRSN) = \frac{LABR}{EMPN} * (EMPN - EMPE) = \frac{LABR}{FTEN} * (FTEN - FTEE) \tag{B.4}$$

Once we disaggregate the labor income component from the mixed income part, we can determine the tax share of the labor factor

$$TAX\_Share_{Labor} = \frac{LABR + LABR_{MIXED}}{VALK} \tag{B.5}$$

Finally, *labshare* is given by:

$$labshare = \frac{LABR + LABR_{MIXED} + (TAX\_Share_{Labor} * OTXS)}{VALK} \tag{B.6}$$

The capital share is determined residually and given by:

$$capshare = 1 - labshare \tag{B.7}$$

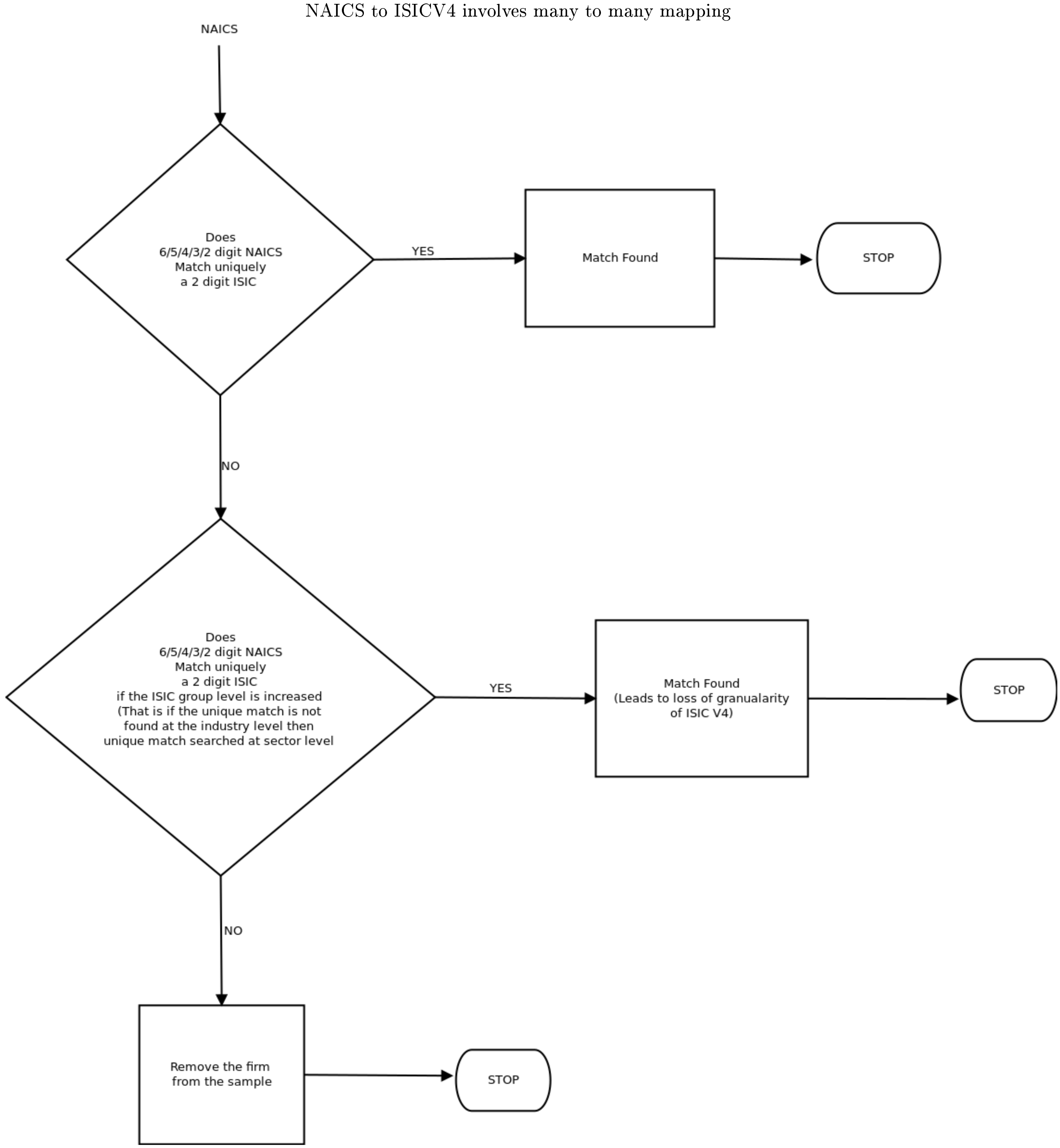
In keeping with the OECD convention *labshare* and *capshare* are averaged across two time periods (t & $t-1$).

Mapping NAICS with ISICV4.0

One important point to note is that Compustat uses North American Industry classification system (NAICS) whereas STAN uses the version 4.0 of the International Standard Industrial Classification (ISIC). The standard correspondence table is utilized to map NAICS into ISIC V4. In the Compustat data, we observe that classification of all firms is not available in 6 digits of NAICS. There are firms with 2,3,4,5 or 6-digit NAICS which implies that classification is available at the sector, subsector, industry groups or industry level. We use a simple algorithm to map NAICS (2,3,4,5 or 6 digits) code to ISIC V4.0. Since the mapping of NACIS to ISICV4.0 is many to many mapping, we keep on expanding the ISIC matching industry so that the NAICS can map into a logical unit.

The flowchart of the algorithm used to map NAICS to ISICV4 is in figure 4. In the process of mapping we loose 10% of the firms as they map to multiple sectors.

Figure 4: Mapping NAICS To ISICV4
NAICS to ISICV4 involves many to many mapping



Appendix C: Details of Included Data

Table 13 gives a detailed analysis of countries that are included in the productivity gap computation and the test assets. Table 15 contains details of the test assets which are the country industry portfolios. Table 14 presents a summary of the stock returns of the available firms by OECD country and by year (from 1992 until 2015) as far as firm returns are available in a country for that year.

Table 13: Intersection of STAN and the Compustat Global Database to compute TFP based on Employee Hours

	OECD - STAN			COMPUSTAT GLOBAL
Country	**Name**	**TFP using EH**	**Used in computing Productivity Gap**	**Country Industry Test Assets**
AUS	Australia	NO HRSE		
AUT	Austria		✓	✓
BEL	Belgium		✓	✓
CAN	Canada		✓	
CHL	Chile	NO CAPN HRSE		
CRI	Costa Rica	NO HRSE		
CHE	Switzerland	NO CAPN HRSE		
CZE	Czech Republic		✓	✓
DEU	Germany		✓	✓
DNK	Denmark		✓	✓
ESP	Spain	NO CAPN		
EST	Estonia		✓	✓
FIN	Finland		✓	✓
FRA	France		✓	✓
GBR	United Kingdom		✓	✓
GRC	Greece		✓	✓
HUN	Hungary		✓	✓
ISL	Iceland	NO CAPN HRSE		
IRL	Ireland		✓	✓
ISR	Israel	No α		
ITA	Italy		✓	✓
JPN	Japan		✓	✓
KOR	Korea	NO HRSE		
LTU	Lithuania		✓	✓
LUX	Luxembourg		✓	✓
LVA	Latvia		✓	✓
MEX	Mexico	NO HRSE		
NLD	Netherlands		✓	✓
NOR	Norway		✓	✓
POL	Poland		✓	✓
PRT	Portugal		✓	✓
SVK	Slovak Republic		✓	✓
SVN	Slovenia		✓	✓
SWE	Sweden		✓	✓
TUR	Turkey	NO HRSE		
USA	United States		✓	

Table 14: Excess Returns of Equally Weighted Country Portfolios by Year

Equal-weighted portfolio returns for the OECD countries available in Compustat Global by Country and Year for the period 1992-2015. The excess returns are monthly means (aritmetic) and are in USD percentage terms obtained after local prices are converted to USD. The risk free rate used to compute the excess return is the USA risk free rate.The countries include Austria (AUT), Belgium (BEL), the Czech Republic (CZE), Germany (DEU), Denmark (DMK), Estonia (EST), Finland (FIN), France (FRA), Great Britain (GBR), Greece (GRC), Hungary (HUN), Ireland (IRL), Italy (ITA), Japan (JPN), Lithuania (LTU), Luxembourg (LUX), Latvia (LVA), Netherlands (NLD), Norway (NOR), Poland (POL), Portugal (PRT), Slovak Republic(SVK), Slovenia (SVN), Sweden (SWE), and the United States of America (USA).

Year	AUT	BEL	CZE	DEU	DMK	EST	FIN	FRA	GBR	GRC	HUN	IRL	ITA	JPN	LTU	LUX	LVA	NLD	NOR	POL	PRT	SVK	SVN	SWE	USA
1992	-2.24	-0.61		-1.56	-2.40		-0.75	-0.94	-1.58	-2.77	-11.99		-3.55	-2.48		-2.93		-0.29	-3.72					-3.35	0.51
1993	1.25	1.53		1.99	1.15		3.12	1.86	2.33	3.71	1.63		-0.64	1.48		2.73		1.84	4.60					3.85	0.66
1994	-0.05	0.47		0.80	1.05		0.77	-0.02	-0.08	0.53	0.89		0.01	0.51		2.06		1.47	0.82					0.94	-0.30
1995	-1.07	0.82	-0.29	0.01	0.25		-0.29	-0.24	0.59	-0.31	-2.17	-0.07	-1.14	-1.24		0.11		1.04	1.67	0.22	-1.23	-1.32	1.11	1.68	2.20
1996	-1.60	0.31	2.57	-1.32	1.71	7.62	3.12	0.62	1.51	-0.90	2.08	2.36	-0.41	-1.68		0.97		2.17	2.36	3.09	1.24	5.46	-0.01	2.22	1.24
1997	-0.74	0.25	-2.39	0.22	-0.40	0.44	0.23	-0.53	0.24	2.23	0.89	0.47	1.19	-4.45		-0.55	1.70	0.28	0.22	-0.18	0.60	-3.69	-0.03	0.28	1.95
1998	0.90	1.84	0.24	0.83	-0.98	-4.20	0.42	1.49	-0.33	4.66	-1.70	-0.04	2.10	0.06		0.09	-3.36	0.76	-3.25	-0.05	1.55	-2.84	1.61	-0.20	1.65
1999	-2.60	-1.49	0.63	-1.33	-0.09	1.81	0.30	0.36	1.38	8.88	-0.52	-0.51	0.38	3.06		1.96	0.47	-0.93	2.21	0.96	-1.02	-1.92	-0.69	1.39	1.59
2000	-3.02	-1.63	-1.31	-2.48	-0.89	2.31	-2.35	-0.57	-1.31	-7.03	-2.31	-0.63	-0.88	-2.34		-1.39	1.17	-0.89	-2.21	-0.57	-1.14	-2.83	-0.80	-0.92	-1.37
2001	-1.37	-0.75	1.13	-2.81	-1.44	-0.20	-0.28	-1.06	-1.01	-1.04	-0.87	-1.63	-2.53	-1.12		-1.30	0.27	-1.50	-1.67	-2.29	-1.75	3.28	0.64	-1.34	-1.14
2002	0.72	0.76	5.21	-1.97	0.47	3.61	0.63	0.51	-1.09	-1.36	1.91	1.17	-0.56	-0.26		-1.87	0.31	-0.73	0.02	-1.62	0.31	1.33	4.78	-0.20	-1.94
2003	2.52	3.00	6.29	2.74	4.06	4.58	4.49	2.66	2.87	3.76	1.48	4.78	2.66	2.60		4.57	7.41	3.23	3.42	3.47	2.52	5.83	2.97	4.16	2.29
2004	2.29	2.63	5.99	0.84	2.37	3.00	2.39	1.60	1.65	-0.51	3.84	2.40	1.31	1.61		3.32	3.68	2.31	3.18	3.82	2.09	4.34	2.62	3.09	0.87
2005	0.34	0.93	1.50	0.65	2.21	3.07	1.21	0.71	-0.20	0.95	0.78	1.23	0.52	1.45		1.52	5.68	1.84	2.52	0.92	0.00	-1.03	-1.92	1.44	0.28
2006	1.77	1.68	3.02	0.61	1.65	3.52	2.67	1.83	1.65	3.30	3.88	2.40	1.72	-2.11		2.42	0.81	2.68	2.86	5.15	2.41	3.05	2.18	1.62	0.83
2007	0.75	0.77	3.55	-0.06	0.63	-0.31	1.07	0.99	-1.05	1.92	2.19	-1.29	-0.26	-1.48		0.17	0.67	0.47	1.36	1.24	1.24	0.86	4.64	-0.51	0.12
2008	-3.81	-2.02	-1.64	-2.94	-4.72	-6.09	-3.76	-3.24	-5.65	-4.94	-3.99	-6.07	-3.67	-1.29		-4.04	-4.93	-4.25	-6.54	-5.34	-2.72	-3.20	-5.92	-5.12	-3.68
2009	2.13	1.71	2.63	0.80	0.44	1.53	3.29	2.05	2.51	1.25	2.47	1.72	1.01	0.65		1.95	3.05	2.91	3.36	3.04	1.92	0.57	0.10	3.72	2.28
2010	0.86	0.02	0.78	0.31	-0.88	3.37	0.94	-0.03	0.27	-3.52	-0.33	-0.93	-0.69	1.44	1.57	-0.12	2.92	0.85	0.97	0.56	-1.74	-1.21	-1.44	1.28	1.49
2011	-2.09	-0.99	0.50	-0.93	-1.73	-2.66	-2.36	-1.47	-1.38	-3.62	-2.39	-1.96	-2.43	0.26	-2.41	-2.08	-0.91	-1.97	-1.55	-4.78	-2.67	-1.11	-3.88	-2.19	0.14
2012	0.82	0.63	0.64	0.18	0.05	2.00	0.50	0.74	1.18	3.35	0.76	1.13	-0.11	0.60	1.05	-0.09	0.75	1.18	1.12	-0.12	-0.17	0.65	0.42	0.73	1.31
2013	1.30	1.57	-0.27	0.99	1.54	0.96	1.96	1.51	1.58	1.86	0.93	2.83	2.07	1.33	1.21	0.02	0.23	1.98	0.21	0.63	2.40	1.17	-0.36	1.30	2.57
2014	-0.46	-0.43	-0.18	-0.76	-1.14	-1.90	-1.20	-0.33	-0.56	-2.00	-1.14	-0.97	-1.35	-0.40	-0.67	-2.33	0.32	-1.06	-1.69	-2.00	-0.89	-0.90	1.95	-1.26	0.96
2015	0.09	0.51	0.97	-0.46	0.19	0.76	1.31	-0.11	-0.29	-1.00	0.93	0.75	-0.61	0.66	-0.56	-1.25	0.14	0.03	-1.00	-0.64	-0.80	0.69	-2.02	0.49	0.07
Mean	-0.14	0.48	1.41	-0.24	0.13	1.16	0.73	0.35	0.13	0.31	-0.12	0.34	-0.24	-0.13	0.03	0.16	1.07	0.56	0.39	0.26	0.10	0.34	0.28	0.55	0.61

Table 15: Country/Industry Portfolios (Test Assets) Time Series Description

This table provides information about the available firm-level data by industry for each country. *Months* is the number of months for which the country industry portfilio data is available between July 1992 to December 2015. *Start Year* and the *End Year* is the data availability in years. *Firms* is the mean number of firms in the country industry portfilio; *Min* is the minimum number of firms in the portfolio and *Max* is the maximum number of firms in the portfolio. The Industry Portfolios are represented by MAN for Manufacturing, ELE for Electricity, Gas, Steam, and Air Conditioning, WAT is Water Supply, Sewage, Waste Management and Remediation Activities, CON is Construction, WHO is Wholesale Retail Trade, Repair of Motor Vehicles and Motorcycles, TRA is Transportation and Storage, FOO is Accomodation and Food Services, COM is Information and Communication, PRO is Professional Scientific and Technical Activities, EMP is Employment Activities, EDU is Education, HEA is Human Health Activities, ART is Arts, Entertainment and Recreation, and OTH is Other Services. The countries include Austria (AUT), Belgium (BEL), the Czech Republic (CZE), Germany (DEU), Denmark (DMK), Estonia (EST), Finland (FIN), France (FRA), Great Britain (GBR), Greece (GRC), Hungary (HUN), Ireland (IRL), Italy (ITA), Japan (JPN), Lithuania (LTU), Luxembourg (LUX), Latvia (LVA), and Netherlands (NLD), Norway (NOR), Poland (POL), Portugal (PRT), Slovak Republic(SVK), Slovenia (SVN), and Sweden (SWE).

	Industry	MAN	ELE	WAT	CON	WHO	TRA	FOO	COM	PRO	EMP	EDU	HEA	ART	OTH
Country															
AUT	Start Year	1992	1992		1992	1992	1992	1999	1998	2001	1994			2000	
	End Year	2015	2015		2015	2015	2015	2015	2015	2007	2001			2015	
	Months	282	282		277	269	272	193	205	62	51			179	
	Firms	47.4	4.0		2.8	2.1	1.5	2.3	8.7	1.0	1.0			2.2	
	Min	25	3		1	1	1	1	1	1	1			1	
	Max	57	5		5	4	2	4	13	1	1			4	
BEL	Start Year	1992	1992		1992	1992	1992	1992	1995	2005	1992			1997	
	End Year	2015	2015		2015	2015	2015	2007	2015	2015	2007			2015	
	Months	282	282		282	282	281	175	241	108	175			205	
	Firms	48.2	4.4		3.4	11.8	3.0	2.4	15.0	1.5	1.0			1.6	
	Min	16	2		2	8	2	1	1	1	1			1	
	Max	64	11		4	15	4	3	23	3	1			2	
CZE	Start Year	1995	1995	1997	1995		1995	1997	1995					1997	
	End Year	2015	2015	2015	2001		2013	2008	2015					2015	
	Months	251	251	94	78		175	55	241					94	
	Firms	8.7	6.5	1.0	1.0		1.9	1.0	2.2					1.0	
	Min	4	2	1	1		1	1	1					1	
	Max	18	12	1	1		3	1	3					1	
DEU	Start Year	1992	1992	1995	1992	1992	1992	1992	1992	1992	1992	2001	1992	1999	2001
	End Year	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2014
	Months	282	282	242	282	282	282	282	282	282	282	148	280	202	149
	Firms	270.1	22.3	3.4	14.7	39.5	9.1	1.8	116.0	15.0	12.8	1.3	8.2	7.4	1.4

	Industry	MAN	ELE	WAT	CON	WHO	TRA	FOO	COM	PRO	EMP	EDU	HEA	ART	OTH
	Min	113	16	1	8	12	2	1	4	1	4	1	1	1	1
	Max	337	30	5	19	50	14	2	183	27	22	2	12	11	2
DNK	Start Year	1992	1993	1993	1992	1992	1992		1993	1992	1992			1995	
	End Year	2015	2015	2007	2015	2015	2015		2015	2006	2005			2015	
	Months	282	239	130	281	282	282		267	159	150			241	
	Firms	59.3	1.4	1.0	7.0	11.2	8.6		13.2	1.0	1.6			5.4	
	Min	16	1	1	1	2	6		1	1	1			1	
	Max	75	2	1	8	17	13		25	1	2			8	
EST	Start Year	1997			1997	1997	2006		1999					2006	
	End Year	2015			2015	2015	2015		2015					2015	
	Months	227			218	211	111		192					98	
	Firms	5.8			3.1	1.0	1.0		1.4					1.2	
	Min	3			1	1	1		1					1	
	Max	8			6	1	1		3					2	
FIN	Start Year	1992	1994	1992	1992	1992	1993	2013	1992	1996	1996		1999		
	End Year	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015		2015		
	Months	282	254	273	251	282	268	25	280	240	224		163		
	Firms	59.7	2.6	1.0	2.6	7.5	6.7	1.2	22.6	3.3	2.5		1.1		
	Min	26	1	1	1	3	5	1	1	1	1		1		
	Max	74	4	1	4	10	9	2	37	5	3		2		
FRA	Start Year	1992	1992	1992	1992	1992	1992	1992	1992	1992	1992	2000	1994	1992	2000
	End Year	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015
	Months	282	282	282	282	282	282	282	282	282	282	168	253	280	156
	Firms	247.7	9.3	4.6	16.3	45.3	8.9	11.7	101.4	29.9	11.3	1.5	4.1	6.8	2.0
	Min	82	3	1	6	19	5	4	12	5	2	1	1	1	1
	Max	313	19	8	24	64	16	18	160	46	18	2	6	10	3
GBR	Start Year	1992	1992	1992	1992	1992	1992	1992	1992	1992	1992	1992	1992	1992	1992
	End Year	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015
	Months	282	282	282	282	282	282	282	282	282	282	282	282	282	282
	Firms	403.3	13.0	6.2	47.8	117.4	31.9	37.5	197.6	94.2	47.1	4.7	7.9	35.1	3.2
	Min	329	10	3	33	67	14	19	69	39	31	2	3	11	2
	Max	503	22	9	64	187	41	56	290	151	64	9	12	51	4
GRC	Start Year	1992	1998	2013	1994	1992	1996	1992	1995	1996	1992		1996	2000	

	Industry	MAN	ELE	WAT	CON	WHO	TRA	FOO	COM	PRO	EMP	EDU	HEA	ART	OTH
	End Year	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015		2015	2015	
	Months	282	204	32	257	281	229	278	243	232	272		228	182	
	Firms	67.2	1.9	1.0	15.3	17.9	6.8	4.0	22.0	2.3	1.3		4.2	3.5	
	Min	6	1	1	1	1	2	1	1	1	1		1	1	
	Max	98	3	1	21	31	9	6	32	3	2		5	4	
HUN	Start Year	1993	1995			1992		1993	1997	2012	1993				
	End Year	2015	2015			2015		2015	2015	2015	2015				
	Months	269	239			269		261	215	38	117				
	Firms	16.4	2.7			2.4		1.9	5.4	1.0	1.0				
	Min	1	1			1		1	1	1	1				
	Max	24	4			3		2	8	1	1				
IRL	Start Year	1992	2008		1992	1992	1992	1992	1992	1992	1998			1992	
	End Year	2015	2015		2015	2015	2015	2015	2015	2015	2015			2015	
	Months	282	64		281	281	281	184	282	281	199			269	
	Firms	25.1	1.0		3.9	6.4	4.2	3.8	7.1	5.6	2.3			3.5	
	Min	13	1		1	4	2	1	1	1	1			1	
	Max	31	1		6	9	7	6	15	9	4			6	
ITA	Start Year	1992	1992	1999	1992	1992	1992	1992	1992	1999	2001	1992	2006	1992	2007
	End Year	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015
	Months	282	282	187	282	282	282	272	282	193	179	245	87	282	99
	Firms	94.0	16.0	1.5	8.2	7.6	5.8	1.8	27.0	2.9	3.5	1.0	1.0	4.6	1.0
	Min	58	8	1	6	3	3	1	8	1	1	1	1	2	1
	Max	128	26	2	10	13	10	3	51	8	5	1	1	7	1
JPN	Start Year	1992	1992	1995	1992	1992	1992	1992	1992	1992	1992	1992	1992	1992	1992
	End Year	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015
	Months	282	282	236	282	282	282	282	282	282	282	274	280	282	282
	Firms	1480.9	22.2	3.6	208.0	492.7	99.0	86.5	244.9	82.0	55.7	22.4	10.5	13.6	7.9
	Min	961	16	1	126	158	61	20	27	17	5	1	1	2	1
	Max	1628	26	8	248	601	111	116	403	121	83	33	22	18	12
LTU	Start Year	2010	2010		2010	2010	2010		2010		2013				
	End Year	2015	2015		2015	2015	2015		2015		2015				
	Months	61	61		56	61	60		61		29				
	Firms	15.0	5.7		1.0	2.0	3.1		1.0		1.0				

	Industry	MAN	ELE	WAT	CON	WHO	TRA	FOO	COM	PRO	EMP	EDU	HEA	ART	OTH
	Min	14	4		1	2	2		1		1				
	Max	17	6		1	2	4		1		1				
LUX	Start Year	1992	1992		1998	1992	2007		1992	2000	2001			1992	
	End Year	2015	2015		2015	2015	2015		2015	2015	2015			2015	
	Months	282	248		175	144	100		282	146	158			216	
	Firms	14.8	1.3		1.5	1.5	2.1		4.8	1.0	2.6			1.3	
	Min	3	1		1	1	1		1	1	1			1	
	Max	31	2		3	2	3		7	1	4			3	
LVA	Start Year	1997			1998		2000						2007		
	End Year	2015			2015		2015						2015		
	Months	219			123		185						85		
	Firms	11.7			1.0		3.9						1.0		
	Min	1			1		1						1		
	Max	18			1		5						1		
NLD	Start Year	1992			1992	1992	1992	1992	1992	1992	1992			1992	
	End Year	2015			2015	2015	2015	2015	2015	2015	2015			2015	
	Months	282			282	282	282	203	282	282	282			282	
	Firms	68.6			7.8	17.9	4.2	1.0	26.3	8.5	5.3			4.5	
	Min	48			6	6	3	1	10	6	3			1	
	Max	83			9	29	6	1	49	11	7			9	
NOR	Start Year	1992	1992	2014	1992	1992	1992	1998	1992	1992	1998			1992	
	End Year	2015	2015	2015	2015	2015	2015	2006	2015	2015	2015			2015	
	Months	282	282	20	282	277	282	100	282	282	202			282	
	Firms	49.1	4.3	1.6	4.5	3.3	18.3	1.6	18.5	7.3	1.0			14.3	
	Min	20	3	1	1	1	10	1	2	3	1			3	
	Max	76	7	2	7	5	24	2	31	12	1			33	
POL	Start Year	1995	1995	2008	1995	1995	2004	1998	1996	1995	2003	2010	2006	2012	
	End Year	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	
	Months	251	247	95	251	243	132	204	238	244	145	52	115	41	
	Firms	97.4	6.6	3.9	17.5	22.2	3.5	3.9	39.8	9.8	5.9	1.6	4.9	1.5	
	Min	9	1	1	1	1	1	1	1	1	1	1	1	1	
	Max	236	19	7	48	68	10	8	134	37	13	3	12	2	
PRT	Start Year	1992	1997		1992	1992	1992	1992	1994	1998			2014	1992	

	Industry	MAN	ELE	WAT	CON	WHO	TRA	FOO	COM	PRO	EMP	EDU	HEA	ART	OTH
	End Year	2015	2015		2015	2015	2015	2015	2015	2001			2015	2015	
	Months	282	222		273	281	55	282	256	45			22	280	
	Firms	17.8	1.5		3.2	5.5	1.0	2.7	8.3	1.0			1.0	2.9	
	Min	12	1		1	2	1	2	1	1			1	1	
	Max	29	3		5	8	1	5	12	1			1	5	
SVK	Start Year	1995			1995		2005	2011	2007						
	End Year	2015			2011		2010	2015	2015						
	Months	244			73		42	54	104						
	Firms	4.7			1.0		1.8	1.0	1.0						
	Min	2			1		1	1	1						
	Max	6			1		2	1	1						
SVN	Start Year	1995				1995	1998	1995	2005	1999					
	End Year	2015				2015	2015	2015	2015	2015					
	Months	241				238	196	224	124	170					
	Firms	8.5				2.9	1.0	1.0	2.1	1.0					
	Min	1				1	1	1	1	1					
	Max	12				4	1	1	3	1					
SWE	Start Year	1992	1992	2001	1992	1992	1992	1997	1992	1992	1993	2001	2000	2001	
	End Year	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	
	Months	282	282	171	282	282	282	227	282	282	268	150	181	163	
	Firms	137.9	3.2	1.7	9.4	20.2	9.1	2.5	48.8	12.2	8.3	1.0	2.8	5.8	
	Min	40	1	1	6	7	5	1	2	1	1	1	1	1	
	Max	281	6	5	16	34	15	4	81	23	17	1	5	10	

Part III

Stock Prices and Research & Development with Technology Gaps and Spillovers.

Stock Prices and Research & Development with Technology Gaps and Spillovers.

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Abstract

Technology shocks from technological frontier economies are a critical determinant of productivity shocks. These shocks spill over, pervading all lagging economies and are true systematic shocks. A country's aggregate technology gap with the frontier, the absorption capacity related to R&D and spillover determines the potential for the systematic innovation shocks to affect it. We find conforming evidence that the technology gap, R&D intensity, and absorption capacity can explain stock returns. For OECD panel data, a one standard deviation increase in the technology gap increases excess stock returns by 0.58 percent per month. A one standard deviation increase in the R&D intensity increases the excess return by 0.55 percent per month. When global FF factors are included, the results are diluted, which suggests that the FF factors may alias for the three variables associated with the systematic risk arising from frontier technology shocks.

Keywords Production-Based Asset Pricing, Technology Shocks, Technology Gap, R&D Stocks, R&D Intensity, Absorption Capacity, Import Share, OECD Countries, Global Differences in Equity Returns, Technology Diffusion

1 Introduction

Anand and Balvers (2020) showed that productivity shocks of leading economies are sources of systematic risk. This is supported by the technology diffusion literature, which postulates that technology is produced by a handful of countries and trickles down to less developed countries. Thus, countries with lower productivity have more potential to improve, and their future investment returns are expected to be larger. The productivity gap of a country, defined as the log difference between the productivity of the leader and the productivity of the given country, represents systematic risk and predicts returns. The return explanation and empirical investigation takes frontier productivity

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shocks as exogenous and ignores the role of Research and Development (R&D).

In the present paper, we include R&D investment and the resulting R&D stocks in the model. The choice of R&D stock of the leader country determines its total factor productivity. For lagging countries, the R&D stock may not lead to frontier innovation but does affect their capacity to absorb new technology. Absorption of frontier technology is further aided by trade between lagging economies and frontier economies. We develop a theoretical model from production-based asset pricing that shows that stock returns are predicted by technology gaps, R&D intensity, and technology absorption capacity, and empirically test it for OECD country-industry portfolios.

Viewing leader country technology shocks as the systematic risk factor implies that average stock returns depend positively on the technology gap (a firm with lower productivity benefits more from mimicking a new technology, increasing its sensitivity to leader innovations). The R&D intensity is also monotonically related to future stock returns as firms with higher R&D intensity have a higher sensitivity to technology leaders' innovations and increase systematic risk domestically. Moreover, higher R&D intensity signifies a larger proportion of investment in R&D relative to capital investment, which enhances the capacity to absorb new technology. Technology flows through various channels (mainly imports) from the technology leaders and absorption capacity determines the extend to which the technology can be absorbed.

We find that a one standard deviation increase in the technology gap increases the excess return by 0.58 percent per month. Additionally, a one standard deviation increase in R&D intensity causes an increase in excess return by 0.55 percent per month.

Gavazzoni and Santacreu (2020) view international diffusion of technology shocks as affecting systematic risk and average stock returns. This view produces encouraging results in a fully developed symmetric two-country general equilibrium model with a non-expected-utility recursive preference formulation. Endogenously developing the international diffusion of technologies, Gavazzoni and Santacreu explain quantitatively the level of the equity premium and predict the correlation in stock returns across the two symmetric countries from their shared R&D. They don't address the cross-sectional differences in average returns that is our focus.

Many researchers like Chan et al. (2001), Eberhart et al. (2004), Ho et al. (2004), Hsu (2009), Lin (2012), and Gu (2016) find for U.S. firms that higher R&D intensity predicts higher future stock returns. The explanation, as in Garleanu et al. 2009, and Kung and Schmid 2015), is that R&D, when successful, creates an option to adopt a new technology at a cost, which will pay off only in a strong economy. Hence, the firm with higher R&D intensity is more exposed to regular business cycle risk, which implies more systematic risk and higher average returns. An alternative explanation is that R&D investments imply a higher fixed cost, which implies more operational leverage. A strong economy is required for the revenue to compensate for the fixed cost. Both explanations are based on the conventional market or consumption risk to serve as the systematic risk factor. The consequence is that empirical results for explaining cross-sectional differences in average returns are not strong.

Hou et al. (2016) confirm the same result of higher R&D intensity implying higher stock returns at the international level. Chen et al. (2013) and Jiang et al. (2016) obtain a similar effect for R&D spillovers: U.S. firms receiving more positive technology benefits (spillovers) from the inventions of other firms are found to have higher future returns. The explanation here is that, while clearly free external benefits lead to positive stock returns, the fact that these returns are predictable means that the market underreacts initially to the observation of these spillovers. Tseng (2020) obtains a comparable empirical result, but his alternative rational explanation is that firms that are more sensitive to spillovers will benefit from them mostly when the economy is strong. It follows that their stock pays off most (least) when the economy is strong (weak), implying more systematic risk so that the investors require a higher average return.

2 Theoretical Model:

We present a highly stylized equilibrium model from the production perspective following Brock (1982), Cox et al. (1985), and Berk et al. (1999). These models determine the impact on expected returns of firm-level investment decisions. In the model, we avoid market frictions, thus deviating from the approach of Cochrane (1991, 1996), Zhang (2005) and others, but following Balvers and Huang (2007), Papanikolaou (2011), and others.

A representative firm in a specific country-industry chooses the future capital stock to maximize shareholder value. The decision problem is expressed in the following Bellman equation:

$$V_t = \max_{i_t, h_t} \{Y_t - i_t - h_t + E_t\left[m_{t+1} V_{t+1}\right]\} \tag{1}$$

The value function V represents the maximum value of the firm that depends on a vector of state variables, namely: the firm's current capital stock (K_t), the idiosyncratic R&D Stock level (z_t), and the leading country-industry R&D Stock level (z_t^*). The control variables are i_t and h_t, which are the current gross investment level and R&D expenditure. The stochastic discount factor m_{t+1}, being uniformly positive, rules out the existence of arbitrage.

$$K_{t+1} = (1 - \delta)K_t + i_t \tag{2}$$

The depreciation rate of capital is a constant δ in equation (2) . We assume that the production function $Y(\,)$ exhibits constant returns to scale in capital and labor. The production function is of the Cobb-Douglas form, labor inputs are assumed fixed for simplicity, and productivity is viewed as labor-saving. Since we are only concerned with cross-sectional implication we assume that θ (representing tfp) does not vary with time. Here z_t is the R&D stock

$$Y_t = Y(K_t, z_t L) = A^0 K_t^{\alpha}(z_t L)^{1-\alpha} = \theta K_t^{\alpha} z_t^{1-\alpha} \tag{3}$$

The R&D stock is a state variable and its equation of motion is:

$$z_{t+1} = \eta_{t+1}\left\{z_t + h_t + (\gamma + \lambda z_t)(z_t^* - z_t)\right\} \tag{4}$$

$$z_{t+1}^* = \eta_{t+1}^*\left\{z_t^* + h_t^*\right\} \tag{5}$$

The R&D stock in equation 4 evolves stochastically given the current state which depends partially on the home and partly on the leading foreign producer R&D stock, and the R&D investment and the technology absorption capacity of the home country. It implies that the R&D stock level of the leading country industry z_t^* is a state variable positively affecting the value of the firm since it benefits the future R&D stock level of the firm, z_{t+1}, The total absorption capacity $((\gamma + \lambda z_t))$ is dependent upon the current R&D stock. It has two components namely: a) γ which is spillover independent of R&D and b) λz_t which is the absorption capacity dependent on R&D. The realized spillover is also dependent on the difference between the R&D stock of the leading foreign producer and the current R&D stock. The new R&D stock of the leading producer depends stochastically on the previous-period stock and current R&D.

The stochastic discount factor need not be specified specifically. General assumptions concerning the sdf are that $E_t\left[m_{t+1}\right] = \frac{1}{1+r}$, that the sdf is independent of idiosyncratic shocks, in particular η_{t+1}, and is always positive (ruling out arbitrage). Lastly, the sdf depends on η_{t+1}^* without time variation.

Defining:

$$E_t\left[\eta_{t+1}^{\beta}\right] \equiv \widehat{\eta}_{\beta} \tag{6}$$

$$E_t\left[\eta_{t+1}\right] \equiv \widehat{\eta}_1 = 1 \tag{7}$$

$$E_t\left[\eta^*_{t+1}m_{t+1}\right] = \frac{1}{1+\kappa} \tag{8}$$

$$z_{t+1} = \eta_{t+1}\widehat{z}_{t+1} \equiv \eta_{t+1}\left[z_t + h_t + (\gamma+\lambda z_t)(z^*_t - z_t)\right] \tag{9}$$

$$z^*_{t+1} = \eta^*_{t+1}\widehat{z}^*_{t+1} \equiv \eta^*_{t+1}\left\{z^*_t + h^*_t\right\} \tag{10}$$

The first order condition for equation 1 generates

$$E_t\left[m_{t+1}V_K(t+1)\right] = 1, \tag{11}$$

$$E_t\left[\eta_{t+1}m_{t+1}V_{\boldsymbol{Z}}(t+1)\right] = 1 \tag{12}$$

Envelop Conditions are:

$$V_K(t) = \alpha\frac{Y(t)}{K_t} + (1-\delta) \tag{13}$$

$$V_Z(t) = (1-\alpha)\frac{Y(t)}{z_t} + 1 - \gamma + \lambda(z^*_t - 2z_t) \tag{14}$$

With these we can show that

$$E_t(r^s_{t+1} - r) = \frac{\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}(\kappa - r)}{\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}} + \frac{1}{r}\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}} + \frac{1+\kappa}{r}\left[\left(\frac{r+\delta}{\alpha} - \delta\right)\frac{x}{\widehat{\gamma}_t} - 1 + (1-\widehat{\eta}_2)\lambda\frac{\widehat{z}_{t+1}}{\widehat{\gamma}_t}\right]} \tag{15}$$

where $\gamma + \lambda\widehat{z}_{t+1} = \widehat{\gamma}_t$, $x = \frac{K_{t+1}}{\widehat{z}_{t+1}} = \left(\frac{\alpha\theta\widehat{\eta}_\beta}{r+\delta}\right)^{\frac{1}{\beta}}$. R&D Intensity is defined as $R\&D_{intensity} = \frac{\widehat{z}_{t+1}}{K_{t+1}} = \frac{1}{x} = constant$ in this model. Appendix A formally derives the model.

We can modify equation 15[1] as :

$$E_t(r^s_{t+1} - r) = \frac{\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}(\kappa - r)}{\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}} + \frac{1}{r}\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}} + \frac{1+\kappa}{r}\left[\left(\frac{r+\delta}{\alpha} - \delta\right)\frac{x}{\widehat{\gamma}_t} - \widehat{\eta}_2 - (1-\widehat{\eta}_2)\frac{\gamma}{\widehat{\gamma}_t}\right]} \tag{16}$$

[1] $\because \gamma + \lambda\widehat{z}_{t+1} = \widehat{\gamma}_t$ & $\widehat{\eta}_2 > 1$ follows from $E[X1^2] = Var(X1) + E[X1]^2$
$(1-\widehat{\eta}_2)\lambda\frac{\widehat{z}_{t+1}}{\widehat{\gamma}_t} = (1-\widehat{\eta}_2) - (1-\widehat{\eta}_2)\frac{\gamma}{\widehat{\gamma}_t}$; let $-(1-\widehat{\eta}_2) = \zeta > 0$

3 Implications of the Model

Equation 8 defines the sdf, which in turn give rise to a constant risk premium of $\kappa - r$. Equation 16 can be interpreted as $E_t(r^s_{t+1} - r) = \beta_t(\kappa - r)$ which is similar to a conditional CAPM, where β_t is given as:

$$\beta_t = \frac{\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}}{\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}} + \frac{1}{r}\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}} + \frac{1+\kappa}{r}\left[\left(\frac{r+\delta}{\alpha} - \delta\right)\frac{x}{\widehat{\gamma}_t} - \widehat{\eta}_2 - (1-\widehat{\eta}_2)\frac{\gamma}{\widehat{\gamma}_t}\right]} \tag{17}$$

In equation 17 the right hand side reflects the expectations in time t. We see that the condition beta is a function of variables $\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}$, x and $\widehat{\gamma}_t$. $\widehat{\gamma}_t$ itself is a function of γ and λ. Let us define:

1. The technology gap as $log(\frac{\hat{z}^*_{t+1}}{\widehat{z}_{t+1}})$,
2. R&D intensity as $\frac{\widehat{z}_{t+1}}{K_{t+1}} = \frac{1}{x} = \left(\frac{r+\delta}{\alpha\theta\widehat{\eta}_\beta}\right)^{\frac{1}{\beta}}$,
3. Spillover independent of R&D as γ
4. Absorption capacity which is dependent on R&D as $\lambda\hat{z}^*_{t+1}$

From equation 17 we can find the relationship with the aforementioned variables. If we assume that $\left[\left(\frac{r+\delta}{\alpha} - \delta\right)\frac{x}{\widehat{\gamma}_t} - \widehat{\eta}_2 - (1-\widehat{\eta}_2)\frac{\gamma}{\widehat{\gamma}_t}\right]$ is positive, then we can comment on the relationship with β_t:

- If $log(\frac{\hat{z}^*_{t+1}}{\widehat{z}_{t+1}})$ increases then β_t increases [2].
- If $\frac{\widehat{z}_{t+1}}{K_{t+1}}$ increases then β_t increases [3].
- If γ increases then its effect on β_t is indeterminate.
- If $\lambda\widehat{z}_{t+1}$ increases then β_t increases [4].

The intuition of these effects is as follows. As the Technology gap increases, so does the potential to improve the productivity through the various channels (trade, espionage, foreign investment, and foreign aid). Since enhanced productivity at little extra cost (small technology change) raises investment returns, stock returns rise in the PBAP framework. Alternatively, when the gap increases, the expected return increases. A country with a larger gap stands to gain more from innovations by the leader country and is accordingly more exposed to these foreign productivity

[2] $\beta_t = \frac{1}{1+\frac{1}{r}+\frac{\frac{1+\kappa}{r}(A)}{\frac{\hat{z}^*_{t+1}}{\widehat{z}_{t+1}}}}$, where $A = \left[\left(\frac{r+\delta}{\alpha} - \delta\right)\frac{x}{\widehat{\gamma}_t} - \widehat{\eta}_2 - (1-\widehat{\eta}_2)\frac{\gamma}{\widehat{\gamma}_t}\right]$ assumed to be greater than 0.

[3] $\beta_t = \frac{\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}}{\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}(1+\frac{1}{r})+\frac{1+\kappa}{r}\left[\left(\frac{r+\delta}{\alpha}-\delta\right)\frac{x}{\widehat{\gamma}_t}\right]+\frac{1+\kappa}{r}\left[-\widehat{\eta}_2-(1-\widehat{\eta}_2)\frac{\gamma}{\widehat{\gamma}_t}\right])}$. Since $\frac{1+\kappa}{r} > 0$, $\left(\frac{r+\delta}{\alpha} - \delta\right) > 0$, and $\widehat{\gamma}_t > 0$. As x increases, $\frac{1}{x} = \frac{\widehat{z}_{t+1}}{K_{t+1}}$ decreases and β_t decreases.

[4] $\beta_t = \frac{\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}}{\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}(1+\frac{1}{r})+\frac{1+\kappa}{r}\frac{1}{\gamma+\lambda\widehat{z}_{t+1}}\left[\left(\frac{r+\delta}{\alpha}-\delta\right)x-(1-\widehat{\eta}_2)\gamma\right]-\frac{1+\kappa}{r}\widehat{\eta}_2)}$. Since $\frac{1+\kappa}{r} > 0$, $\left(\frac{r+\delta}{\alpha} - \delta\right)x > 0$, $\gamma > 0$, $\widehat{z}_{t+1} > 0$, and $\widehat{\eta}_2 > 1$. As λ increases so does β_t.

shocks, compared to a country with a smaller gap.

Similarly, intuitively If R&D intensity increases, so does the potential to adopt technology. Increased R&D improves absorption of new technology. Both reasons will increase the expected return when R&D intensity increases. With the higher R&D intensity then countries can respond more easily to leader-country productivity shocks raising the β_t.

Intuitively if the technology absorption capacity increases, so does the expected return. This happens as the sensitivity to the spillover of the technology shocks increases with increased absorption. An increase in γ means a higher spillover effect which directly makes a country more sensitive to leader-country productivity improvements. However a secondary effect is that the free-rider effect of the spillover implies less incentive for R&D which lowers sensitivity to the leader-country shocks, causing the net effect of γ to be ambiguous

Moreover we observe that the risk premium is constant in the model as such from the Campbell Shiller decomposition(Campbell and Shiller, 1988) there is only a cash flow impact and no discount rate impact.

3.1 Testable Hypotheses

- Hypothesis 1: The country-wide technology gap explains country and industry wide cross-sectional disparities in mean returns.

- Hypothesis 2: R&D intensity explains country and industry wide cross-sectional disparities in mean returns.
- Hypothesis 3: The effect of γ represented by imports, is ambiguous.
- Hypothesis 4: λz_t, represented by the present R&D stock, is positively related to mean stock return.

4 Data

We use the OECD Anberd Database for industry-level R&D expenditure data. For macro data, we use the OECD STAN database and convert the values to PPP USD terms by using the OECD purchasing power parity exchange rate data. Stock returns are converted to nominal USD with Bloomberg Exchange rate data. Additionally, we use the BTDIxE database from OECD to obtain import-related data. Moreover, as controls for possible omitted risk factors we use the Fama-French global risk factors from Kenneth French's Website.

4.1 Measuring the R&D stock

To capitalize R&D investments, the depreciation/amortization rate of R&D assets is required. Estimating depreciation rates of intangibles such as R&D assets is difficult. Amortization Models aim to find returns on R&D capital and are based on questionable numbers such as the relationship between amortization and earnings. Lev and Sougiannis (1996) use the "amortization approach" to determine the R&D depreciation rate. They find for US data that the R&D depreciation rate varies by industry: Scientific Instruments 20%, Electrical Equipment 13% and Chemicals 11%.

Others use a production function to model the R&D depreciation rate based on simplistic assumptions. Bernstein and Mamuneas (2006) estimate that the US Chemical industry has an 18% R&D depreciation rate, and Electrical Equipment has a 29% depreciation rate.

The BEA (Bureau of Economic Analysis) has established R&DSA, an R&D satellite account. Before 2007 BEA used a 15% depreciation rate. In 2007, BEA adopted an industry-specific depreciation rate: transportation equipment 18%, computer equipment 16.5%, chemicals 11%, and all other industries 15% ((Mead et al., 2007)).

Chan et al. (2001) defines the R&D stock as : $z_t = h_t + 0.8h_{t-1} + 0.6h_{t-2} + 0.4h_{t-3} + 0.2h_{t-4}$ which represents a 20% straight line depreciation of nominal R&D expenditures. Coe and Helpman (1995) uses a depreciation rate of 5% but performs robustness checks for 10% and 15% as well. Chan further assumes that half of h_t is a result of labor cost and is not included in estimation the R&D stock. Braconier et al. (2001) uses a perpetual inventory method.

The R&D stock can be computed as $z_t = (1-\vartheta)z_{t-1} + h_t$ where ϑ is the depreciation rate, z_t is the R&D stock & h_t is the R&D investment. Recursively, the R&D Stock equation will lead to

$$z_t = h_t + (1-\vartheta)h_{t-1} + (1-\vartheta)^2 h_{t-2} \ldots + (1-\vartheta)^{n-2} h_{t-(n-2)} + (1+\frac{1}{\vartheta})(1-\vartheta)^{n-1} h_{t-(n-1)} \tag{18}$$

In equation $18 z_{t-(n-1)}$ is approximated by a perpetuity of $h_{t-(n-1)}$with the depreciation rate of ϑ. The depreciation rate ϑ for each industry is that used by BEA.

Table 1 details the statistical properties of the R&D stock at the country level. R&D stock data are available on an annual basis, and the sample analysis is from 1990 to 2015. Table 2 contains the R&D stock leaders at the country level between 1990 to 2015. It is not surprising that the USA is the leader in all years of that time period.

The Anberd database available from the OECD contains R&D expenditure data at the industry level. This data can be used to compute the R&D stock at the industry level for OECD countries. Anberd has an annual data frequency and uses the International Standard Industry Classification (ISIC) V4 to assign firms to industries, whereas Compustat uses the North American Industry Classification System (NAICS). Mapping of NAICS to ISIC is accomplished with an algorithm enumerated in Appendix B. After the mapping, only 16 mutually exclusive industry groups/sectors remain. From these we remove the Finance and Insurance and the Real Estate sectors for our analysis as is common practice in the finance literature. Appendix C presents further data details.

The BTDIxE (Bilateral Trade by Industry and End-use) database from OECD contains the trade level data between partner countries. This data is used to help capture the technology absorption capacity of the entity.

In comparing data across countries with different currencies and price levels, we adjust productivity for purchasing power parity (PPP) differences. We use the OECD Purchasing Power Parity exchange rate conversion to compute productivity for cross-country comparison. The PPP-adjusted exchange rate can be thought of as a mean rate for an economy, which is appropriate for comparing labor and capital costs as well as consumption and production levels across countries.

We employ the BEA depreciation rates ((Mead et al., 2007)) and equation (18) with $n >= 3$ (i.e., for all cases with a minimum of 3 consecutive annual R&D investment data points, and in those cases taking n as large as the data allow) to compute the R&D stock. Since we lose industry classification granularity while mapping ISIC V4 to NAICS the depreciation rate is set to 15%.

4.2 Stock Return Data

The stock price data are from Compustat Global. The database provides daily prices and dividend information to compute total returns at the firm level. The returns are converted to USD using the nominal currency exchange rate available from Bloomberg. We use the Fama-French global factor data from Kenneth French's website to control for global risk factors. Since this data is available from 1991 onward, our data range is from 1991 to 2015. (Anberd updates its data on a lagged but continuous basis. In the most recent update 2016 data were available, but only for a few countries). The stock price data are available for individual firms with particular industry designations in the various OECD countries. Table 10 in the Data Appendix presents a summary of the stock returns of the available firms by OECD country and by year (from 1992 until 2015) for all available firm returns in a country for that year. The average return differences by country are substantial. We focus on industries i in countries c and treat equal-weighted portfolios of all available firms for each country-industry with at least two such firms as our test assets represented by index ic. [5] To deal with potential data errors, individual stock returns are winsorized at 5%. Table 11 in the Data Appendix provides an overview of the firms available over the sample period for the set of industries and countries. The same countries and industries are included as in Anand and Balvers (2020) .

4.3 Measuring Variables

The model predicts that the expected return is a function of the technology gap, R&D intensity, and absorption capacity. All three of these variables as relevant for individual country-industries can be defined at either the country and the country-industry level. The technology gap (TG) is defined in terms of relative R&D stocks: $TG_t = log\left(\frac{z_t^*}{z_t}\right)$.

The technology gap at the country level (TGC_t^{ic}) represents the log difference between the aggregate R&D stock of the leading country (USA in the sample) with the aggregate R&D stock of the country. Anand and Balvers (2020) have shown that the country-level technology gap represents a systematic risk.

$$TGC_t^{ic} = log\left(\frac{z_t^{c^*}}{z_t^c}\right) \ \forall i \tag{19}$$

The model further predicts that the expected return is a function of R&D intensity. The R&D intensity is defined in the model as a ratio of the R&D stock to the capital stock. It is defined at the country level ($rndic_t^{ic}$)

$$rndic_t^{ic} = \frac{z_t^c}{K_t^c} \ \forall i \tag{20}$$

The proxy for γ is the imports in USD from the leading country, which is normalized by the GDP of the importing country (the STAN VALU field). The γ is defined at the country level ($absc_t^{ic}$)[6]

$$absc_t^{ic} = \frac{import_t^c}{VALU_t^c} \ \forall i \tag{21}$$

λ is the loading on z_{t+1} the R&D stock of the country. A scaled R&D stock variable (in 10 Billion units) of a country is represented by $sRnDs_t^c$.

[5]The number of firms in a portfolio is quite variable across portfolios and across time. However, we find that our main results do not change significantly if we exclude all industry-country portfolios with five of fewer firms.

[6]Other Variables are capturing the absorption capacity are tariffs, taxes, membership to EU / OECD, legal system, treaties etc. It is difficult to find proxies for them.

5 Empirical Model

5.1 Hypotheses 1, 2 , 3 & 4

To test Hypotheses 1, 2 & 3 with our panel data set, we perform a standard Fama-MacBeth two-stage regression procedure on the industry portfolios in each of the different countries at a monthly frequency. Equally-weighted industry portfolios are constructed from the Compustat data, where the portfolios consist of all firms in a particular industry of a particular country.

In the first stage, a time series regression is performed for each country-industry portfolio (denoted by ic, representing the industry index i and country index c) as in equation 22 to obtain the loadings of the portfolio returns on a set of standard systematic risk factors:

$$r_t^{ic} - r_t^f = \alpha^{ic} + \boldsymbol{\beta_t^{ic}}(\boldsymbol{F_t}) + \epsilon_t^{ic} \tag{22}$$

Here$\boldsymbol{F_t}$ is the vector of risk factors $\begin{bmatrix} F_{1t} \\ F_{2t} \\ \vdots \\ F_{nt} \end{bmatrix}$, and $\boldsymbol{\beta_t^{ic}}$ is the vector of estimated factor loadings $\begin{bmatrix} \beta_{1t}^{ic} \\ \beta_{2t}^{ic} \\ \vdots \\ \beta_{nt}^{ic} \end{bmatrix}$.

The risk factors represent those of the standard models: CAPM, Fama-French global three-factor (FF3), Fama-French global four-factor, including also the global Carhart momentum factor (FF3+MOM), Fama-French global five-factor (FF5), and the Fama-French global five-factors plus the global momentum factor (FF5+MOM). The excess annual returns of the industry portfolios are regressed on the different sets of factors. These factors act as controls for known factor risk.

In the second stage cross-sectional regressions are performed for each (monthly) time period in which the excess monthly returns for each country/industry portfolio are regressed on the technology gap, R&D intensity, imports and present R&D stock variables and the beta coefficients of the risk factors determined in the first stage.

$$r_{t+1}^{ic} - r_{t+1}^f = a_t + \boldsymbol{b_t}(\boldsymbol{\beta_t^{ic}}) + \boldsymbol{c_t}(\boldsymbol{X_t^{ic}}) + \eta_t^{ic} \tag{23}$$

In equations $23 X_t^{ic}$ is the vector of production-based variables which are a subset of the following variables $[TGC_t^{ic}, rndic_t^{ic}, absc_t^{ic}]$, where all variables are at the country level associated with each individual country/industry portfolio ic, $\boldsymbol{\beta_t^{ic}}$ is the vector of factor loadings for each country-industry portfolio obtained from the first stage. In the first stage a rolling regression is used to determine the set of betas for each model, with a window of 24 months. The coefficient (row) vectors $a_t, \boldsymbol{b_t}$, and $\boldsymbol{c_t}$ are estimated separately for each time period based on betas determined from prior data. Our productivity data start in January 1970 (for some countries). However, we use the global Fama-French risk factors which start in July 1990. Losing a minimum of 24 months for beta estimation, our effective sample period starts in July 1992. Thus, we employ monthly data from July 1992 until December 2015. This amounts to 282 monthly sample observations.

The mean of 282 monthly cross-sectional regressions, $[c_1 \ c_2] = \frac{\mathbf{1}}{\mathbf{282}} \sum_{\boldsymbol{t}=\mathbf{1992,7}}^{\mathbf{2015,12}} \boldsymbol{c_t}$, represents the estimated mean of the cross-sectional coefficients and the standard deviation of each element of $\boldsymbol{c}$ represents its standard error. The null hypothesis is that coefficients are 0, and a standard t-test is performed separately for each coefficient to check for statistical significance.

Note that empirically it is important to simultaneously control for all parameters that vary across countries, because these parameters may be correlated. We find that the correlation between R&D intensity and technology gap is negatively correlated and the correlation is significant at 1% and is -0.599. From the theoretical perspective, larger the technology gap the smaller the in house R&D and R&D intensity (likely because lower R&D leads to larger gap). As such, when we do cross-sectional regression we will need to include both Technology gap and R&D intensity together.

6 Results

Table 4 contains the mean coefficients of the 282 cross-sectional regressions. It is evident from the table that the technology gap at the country level, TGC, monotonically affects the stock returns. We also observe that R&D intensity is significant when combined with TGC and the absorption proxy at the country level. The absorption capacity is not significant when combined with TGC and *R&D Intensity*. The absorption capacity has a negative sign and the scaled R&D stock is also not significant, though it has the predicted positive sign. As we control for the global risk factors namely: CAPM, FF3 , Carhart, FF5 and FF5 + Momentum, we observe the same relationship.

The standard deviation of TGC in the sample of 26,157 country-industry portfolio months is 1.60. Thus a coefficient of 0.367 means that a one standard deviation increase in TGC increases excess return by 0.58% on a monthly basis. We observe that the standard deviation of $rndic$ is 0.0124 and the coefficient of 44.38. An increase in one standard deviation of $rndic$ causes an increase in excess return by 0.55% on a monthly basis.

We see the sign of γ, represented by total import is negative, which is consistent with the model prediction (ambiguous). Similarly, we find that the sign for R&D Stock representing λz is positive as predicted by the model. We don't find these factors significant. These could be due to the choice of γ that does not capture the spillover perfectly. The spillover may happen through trade of intermediate goods, FDI, and the use of patents and trademarks. We devise an alternate procedure, using factors to test the model predictions, as detailed below.

6.1 Factors from US TFP growth and US NAICS Sector 54

The US TFP growth rate can be converted into a factor which proxies the technology gap. The US NAICS sector 54 represents the Professional, Scientific, and Technical Services. It is the R&D intensive sector of the economy. The returns of this sector are related to the absorption capacity of the firms. Data about the US TFP growth rate is available from OECD Productivity (Growth in GDP per capita, productivity and ULC) database. The NAICS sector 54 returns are available from the CRSP database.

The TFP growth rate is converted into a mimicking portfolio by utilizing the method of Balvers and Luo (2018) and Balduzzi and Robotti (2008) to generate a "characteristic mimicking factor" with the property that the loadings of each test asset i (all countries) on this factor equals the asset characteristic – in this case, the $TFPgrowthUS_t^i$, at each time t. For monthly return data, the loading estimate on this factor for a particular month therefore is at the same time an estimate of the $TFPgrowthUS_t$ (observable only at the annual frequency) for the month. The mimicking factor allows a more comprehensive look at the systematic risk represented by the $TFPgrowthUS_t$.

The mimicking factor is obtained as

$$r_t^i = (\boldsymbol{r_t^i})' \left(\boldsymbol{\hat{\Sigma}_{t-1}^{ic}}\right)^{\boldsymbol{-1}} \boldsymbol{TFPgrowthUS_{t-1}^i},$$

where $\boldsymbol{r_t^i}$ is the vector of returns in month t for the firm. $\boldsymbol{\hat{\Sigma}_{t-1}^i}$is the estimated covariance matrix for the firm returns using information prior to month t. We use 24 prior months to estimate this covariance matrix on a rolling basis. $\boldsymbol{TFPgrowthUS_{t-1}^i}$ is the vector of the aggregate TFP growth rate for the US for all country-industry portfolios using the most recent annual observation preceding month t. The return of the characteristic mimicking portfolio is the $TFPgrowthUS_t$ mimicking factor ($r_t^i \equiv r_t^{TFPgrowthUS}$) .

Using the mimicking factor obtained from the US TFP growth rate and the US NAICS 54 return. The mimicking factor is obtained using the country-industry portfolios as the test assets. The Barillas-Shanken test (Barillas and Shanken (2017)) is performed to check whether the inclusion of this factor to the standard global factor models add any value.

We can make a nested unconditional (assuming constant factor loadings over the full sample) model comparison that is valid for any group of test assets. Essentially, any group of factors that has a larger maximum Sharpe ratio than a competing group of factors, will explain any group of test assets better (as long as this group of test assets includes both groups of factors). A model that consists of the union of the factors from two contesting models is the "large" model. We can test if the large model explains assets significantly better than either one of the "small" component models. The test is equivalent to the GRS test but with the small model serving as the factor model and the large model serving as the test assets. The test finds whether the maximum Sharpe Ratio of the large model is significantly larger than the Sharpe Ratio of the small model; or, equivalently, whether the factors excluded from the small model have significantly positive alphas as a group when explained by the factors from the small model. If they have significantly larger alphas, it follows that the large model when set to explain any group of test assets will have smaller alphas than the small model (when weighted by the inverse return covariance matrix).

When the larger model is the global FF5 + Momentum $+r_t^{TFPgrowthUS}+r_t^{NAICS54US}$ and the smaller model is the global FF5 + momentum, we find the GRS test statistics is 7.64 and is significant at 1% (p-value of 3.25*10^-9). This indicates that the model that includes the global FF5 + Momentum $+r_t^{TFPgrowthUS}+r_t^{NAICS54US}$ will explain the country-industry portfolio test assets results significantly better compared to the global FF5 + momentum model. Similarly when the larger model is the global FF5 $+r_t^{TFPgrowthUS}+r_t^{NAICS54US}$ and the smaller model is the global FF5 , we find the GRS test statistics is 9.06 and is significant at 1% (pvalue of 4.746*10^-10). This indicates that the model that includes the global FF5 $+r_t^{TFPgrowthUS}+r_t^{NAICS54US}$ will explain the country-industry portfolio test assets results better compared to the global FF5 model.

7 Conclusion

A series of empirical papers in the literature demonstrates that R&D intensity can predict stock returns, and risk-based explanations have been forwarded. The literature lacks a comprehensive perspective of the relation to systematic risk, which this paper provides using the PBAP framework in a global context. We find that theoretically the technology gap needs to be included with the R&D intensity and absorption capacity in a global context.

References

Anand, P. and Balvers, R. J. (2020). Productivity gaps and global systematic risk exposure: Pricing country-industry portfolios. *Available at SSRN 3663430*.

Balduzzi, P. and Robotti, C. (2008). Mimicking portfolios, economic risk premia, and tests of multi-beta models. *Journal of Business & Economic Statistics*, 26(3):354–368.

Balvers, R. and Luo, A. H. (2018). Distinguishing factors and characteristics with characteristic-mimicking portfolios.

Balvers, R. J. and Huang, D. (2007). Productivity-based asset pricing: Theory and evidence. *Journal of Financial Economics*, 86(2):405–445.

Barillas, F. and Shanken, J. (2017). Which alpha? *The Review of Financial Studies*, 30(4):1316–1338.

Berk, J. B., Green, R. C., and Naik, V. (1999). Optimal investment, growth options, and security returns. *The Journal of Finance*, 54(5):1553–1607.

Braconier, H., Ekholm, K., and Knarvik, K. H. M. (2001). In search of fdi-transmitted r&d spillovers: A study based on swedish data. *Review of World Economics*, 137(4):644–665.

Brock, W. A. (1982). Asset prices in a production economy. In *The economics of information and uncertainty*, pages 1–46. University of Chicago Press.

Campbell, J. Y. and Shiller, R. J. (1988). The dividend-price ratio and expectations of future dividends and discount factors. *The Review of Financial Studies*, 1(3):195–228.

Chan, L. K., Lakonishok, J., and Sougiannis, T. (2001). The stock market valuation of research and development expenditures. *The Journal of Finance*, 56(6):2431–2456.

Chen, S.-S., Chen, Y.-S., Liang, W.-l., and Wang, Y. (2013). R&d spillover effects and firm performance following r&d increases. *Journal of Financial and Quantitative Analysis*, 48(5):1607–1634.

Cochrane, J. H. (1991). Production-based asset pricing and the link between stock returns and economic fluctuations. *Journal of Finance*, 46(1):209–237.

Cochrane, J. H. (1996). A cross-sectional test of an investment-based asset pricing model. *Journal of Political Economy*, 104(3):572–621.

Coe, D. T. and Helpman, E. (1995). International r&d spillovers. *European economic review*, 39(5):859–887.

Cox, J., Ingersoll, J., and Ross, S. (1985). An intertemporal general equilibrium model of asset prices. *Econometrica*, 53(2):363–384.

Eberhart, A. C., Maxwell, W. F., and Siddique, A. R. (2004). An examination of long-term abnormal stock returns and operating performance following r&d increases. *The Journal of Finance*, 59(2):623–650.

Gavazzoni, F. and Santacreu, A. M. (2020). International r&d spillovers and asset prices. *Journal of Financial Economics*, 136(2):330 – 354.

Gu, L. (2016). Product market competition, r&d investment, and stock returns. *Journal of Financial Economics*, 119(2):441–455.

Ho, Y. K., Xu, Z., and Yap, C. M. (2004). R&d investment and systematic risk. *Accounting & Finance*, 44(3):393–418.

Hou, K., Hsu, P.-H., Watanabe, A., and Xu, Y. (2016). Corporate r&d and stock returns: International evidence. *Recuperado de http://www. cicfconf. org/sites/default/files/paper_413. pdf.*

Hsu, P.-H. (2009). Technological innovations and aggregate risk premiums. *Journal of Financial Economics*, 94(2):264–279.

Jiang, Y., Qian, Y., and Yao, T. (2016). R&d spillover and predictable returns. *Review of Finance*, 20(5):1769–1797.

Lev, B. and Sougiannis, T. (1996). The capitalization, amortization, and value-relevance of r&d. *Journal of accounting and economics*, 21(1):107–138.

Lin, X. (2012). Endogenous technological progress and the cross-section of stock returns. *Journal of Financial Economics*, 103(2):411–427.

Mead, C. I. et al. (2007). R&d depreciation rates in the 2007 r&d satellite account. *Bureau of Economic Analysis/National Science Foundation.*

Papanikolaou, D. (2011). Investment shocks and asset prices. *Journal of Political Economy*, 119(4):639–685.

Tseng, K. (2020). Learning from the joneses: Technology spillover, innovation externality, and stock returns. *Innovation Externality, and Stock Returns (April 28, 2020).*

Zhang, L. (2005). The value premium. *The Journal of Finance*, 60(1):67–103.

Table 1: Country Level R&D Stock in Billion USD

This Table presents the Mean, Standard Deviation (SD), Maximum, and Minimum of the R&D Stock . In calculating R&D stock, real purchasing power parity corrected R&D expenditure is capitalized with a depreciation rate of approximately 15%. Count is the number of years for which the country has the appropriate data in the 1990-2015 sample period. The countries are Austria (AUT), Belgium (BEL), Canada (CAN), the Czech Republic (CZE), Germany (DEU), Denmark (DMK), Estonia (EST), Finland (FIN), France (FRA), Great Britain (GBR), Greece (GRC), Hungary (HUN), Ireland (IRL), Italy (ITA), Japan (JPN), Lithuania (LTU), Luxemburg (LUX), Latvia (LVA), the Netherlands (NLD), Norway (NOR), Poland (POL), Portugal (PRT), the Slovak Republic (SVK), Slovenia (SVN), Sweden (SWE), and the United States of America (USA).

Country Level R&D Stock					
Country	Mean	SD	Max	Min	Count
AUT	29	10	48	16	16
BEL	32	9	48	23	16
CAN	57	24	91	25	26
CZE	6	2	11	3	23
DEU	262	77	421	182	23
DNK	32	0	33	32	5
EST	1	0	2	1	9
FIN	17	10	31	5	26
FRA	149	42	240	95	24
GBR	103	28	155	69	26
GRC	5	0	5	4	3
HUN	2	2	6	1	19
IRL	15	1	16	14	5
ITA	59	16	93	45	23
JPN	616	164	869	339	26
NLD	52	3	55	48	6
NOR	14	6	25	6	23
POL	9	5	18	4	12
SVK	2	0	3	2	17
SVN	2	1	5	1	17
SWE	80	1	81	79	7
USA	1187	430	1997	644	26

Table 2: Country Level R&D Stock Leaders

USA is the R&D stock leader in the sample. R&D Stock is quoted in billions of USD.

Year	Maximum R&D Stock	Max R&D Stock Country
1990	644	USA
1991	664	USA
1992	684	USA
1993	699	USA
1994	713	USA
1995	739	USA
1996	772	USA
1997	820	USA
1998	873	USA
1999	936	USA
2000	1007	USA
2001	1061	USA
2002	1094	USA
2003	1133	USA
2004	1188	USA
2005	1252	USA
2006	1329	USA
2007	1414	USA
2008	1512	USA
2009	1591	USA
2010	1632	USA
2011	1670	USA
2012	1731	USA
2013	1804	USA
2014	1897	USA
2015	1997	USA

Table 3: Correlation among variables

Pairwise correlation among two variables are determined using pair of variables $\{(x_1, y_1), (x_2, y_2), \cdots (x_n, y_n)\}$two variables

Pairwise Correlation				
	TGC	$rndic$	$absc$	$sRnDs$
TGC	1.0000			
$rndic$	-0.5993	1.0000		
$absc$	-0.1296	0.0872	1.0000	
$sRnDs$	-0.7304	0.5666	-0.0030	1.0000

Correlation among variables using the sets of data that exists. It is determined using variables$\{(x_1, y_1, z_1, a_1, b_1, c_1), (x_2, y_2, z_2, a_2, b_2, c_2), \cdots (x_m, y_m, z_m, a_m, b_m, c_m)\}$

Correlation				
	TGC	$rndic$	$absc$	$sRnDs$
TGC	1.0000			
$rndic$	-0.5993	1.0000		
$absc$	-0.1297	0.0872	1.0000	
$sRnDs$	-0.7394	0.5666	-0.0015	1.0000

Table 4: Second Stage Fama-MacBeth Regressions with Technology Gap, R&D Intensity and Absorption Capacity

The returns of the equal-weighted country-industry portfolios are regressed at a monthly frequency for the period July 1992-December 2015 on the various productivity gaps relevant for each country-industry portfolio and controlling for the global CAPM beta of the country-industry portfolio. The computation of the technology gap measures uses $R\&D$ Stock in current PPP terms. . The cross-sectional regression is a specific case of equation 23:

$$r_{t+1}^{ic} - r_{t+1}^{f} = a_t + c_t^{TGC} * TGC_t^{ic} + c_t^{rndic} * rndic_t^{ic} + c_t^{absc} * absc_t^{ic} + c_t^{sRnDs} * sRnDs_t^{ic} + \eta_t^{ic}$$

The coefficients and the standard errors in this table are the means and standard deviations of the elements of $\boldsymbol{c_t} = [c_t^{TGC}, c_t^{rndic}, c_t^{absc}, c_t^{sRnDs}]$ based on the 282 monthly regression from July 1992 until December 2015.

Coef	**Standalone Model**							
c^{TGC}	0.189				0.353	0.367	0.650	0.738
T-STAT	(3.08)***				(3.84)***	(3.78)***	(2.06)**	(2.14)**
P-VALUE	[0.00]				[0.00]	[0.00]	[0.04]	[0.03]
c^{rndic}		-6.121			39.318	44.379	18.570	19.824
T-STAT		(-0.55)			(2.07)**	(2.19)**	(1.76)*	(1.86)*
P-VALUE		[0.58]			[0.04]	[0.03]	[0.08]	[0.06]
c^{absc}			-0.101			-0.051		-0.065
T-STAT			(-1.06)			(-0.55)		(-0.71)
P-VALUE			[0.29]			[0.58]		[0.48]
c^{sRnDs}				-0.012			0.107	0.133
T-STAT				(-1.22)			(1.27)	(1.46)
P-VALUE				[0.23]			[0.20]	[0.15]
R^2	0.08	0.08	0.02	0.10	0.14	0.16	0.19	0.21
N	26,157	26,157	26,157	26,157	26,157	26,157	26,157	26,157

* p<0.10; ** p<0.05; *** p<0.01

Table 5: Second Stage Fama-MacBeth Regressions with Technology Gap, R&D Intensity and Absorption Capacity With Global Capm factors

The returns of the equal-weighted country-industry portfolios are regressed at a monthly frequency for the period July 1992-December 2015 on the various productivity gaps relevant for each country-industry portfolio and controlling for the global CAPM beta of the country-industry portfolio. The computation of the technology gap measures uses $R\&D$ Stock in current PPP terms. The global market factor is taken from Kenneth French's website. The cross-sectional regression is a specific case of equation 23:

$$r_{t+1}^{ic} - r_{t+1}^{f} = a_t + b_t^{MKT}\beta_{MKT}^{ic} + c_t^{TGC} * TGC_t^{ic} + c_t^{rndic} * rndic_t^{ic} + c_t^{absc} * absc_t^{ic} + c_t^{sRnDs} * sRnDs_t^{ic} + \eta_t^{ic}$$

The coefficients and the standard errors in this table are the means and standard deviations of the elements of $\boldsymbol{c_t} = [c_t^{TGC}, c_t^{rndic}, c_t^{absc}, c_t^{sRnDs}]$ based on the 282 monthly regression from July 1992 until December 2015.

Coef	CAPM Global Model								
b^{MKT}	-0.673	-0.664	-0.660	-0.726	-0.540	-0.491	-0.526	-0.424	-0.438
T-STAT	(-2.21)**	(-2.27)**	(-2.28)**	(-2.39)**	(-1.85)*	(-1.70)*	(-1.83)*	(-1.45)	(-1.52)
P-VALUE	[0.03]	[0.02]	[0.02]	[0.02]	[0.07]	[0.09]	[0.07]	[0.15]	[0.13]
c^{TGC}		0.181				0.332	0.342	0.638	0.724
T-STAT		(3.07)***				(3.52)***	(3.46)***	(2.09)**	(2.17)**
P-VALUE		[0.00]				[0.00]	[0.00]	[0.04]	[0.03]
c^{rndic}			-8.224			35.121	39.858	13.718	15.103
T-STAT			(-0.76)			(1.92)*	(2.04)**	(1.30)	(1.42)
P-VALUE			[0.45]			[0.06]	[0.04]	[0.20]	[0.16]
c^{absc}				-0.110			-0.076		-0.072
T-STAT				(-1.20)			(-0.85)		(-0.84)
P-VALUE				[0.23]			[0.39]		[0.40]
c^{sRnDs}					-0.011			0.106	0.132
T-STAT					(-1.11)			(1.32)	(1.51)
P-VALUE					[0.27]			[0.19]	[0.13]
R^2	0.08	0.15	0.15	0.11	0.16	0.20	0.22	0.24	0.26
N	26,157	26,157	26,157	26,157	26,157	26,157	26,157	26,157	26,157

* p<0.10; ** p<0.05; *** p<0.01

Table 6: Second Stage Fama-MacBeth Regressions with Technology Gap, R&D Intensity and Absorption Capacity With Global FF3 factors

The returns of the equal-weighted country-industry portfolios are regressed at a monthly frequency for the period July 1992-December 2015 on the various productivity gaps relevant for each country-industry portfolio and controlling for the global FF3 beta of the country-industry portfolio. The computation of the technology gap measures uses *R&D* Stock in current PPP terms. The global market factor is taken from Kenneth French's website. The cross-sectional regression is a specific case of equation 23:

$$r^{ic}_{t+1} - r^{f}_{t+1} = a_t + b^{MKT}_t \beta^{ic}_{MKT} + b^{SMB}_t \beta^{ic}_{SMB} + b^{HML}_t \beta^{ic}_{HML} + c^{TGC}_t * TGC^{ic}_t + c^{rndic}_t * rndic^{ic}_t + c^{absc}_t * absc^{ic}_t + c^{sRnDs}_t * sRnDs^{ic}_t + \eta^{ic}_t$$

The coefficients and the standard errors in this table are the means and standard deviations of the elements of $\boldsymbol{c_t} = [c^{TGC}_t, c^{rndic}_t, c^{absc}_t, c^{sRnDs}_t]$ based on the 282 monthly regression from July 1992 until December 2015.

Coef	FF 3 Factor Global Model								
b^{MKT}	-0.661	-0.637	-0.646	-0.726	-0.523	-0.425	-0.468	-0.340	-0.358
T-STAT	(-2.29)**	(-2.28)**	(-2.32)**	(-2.52)**	(-1.89)*	(-1.54)	(-1.70)*	(-1.23)	(-1.30)
P-VALUE	[0.02]	[0.02]	[0.02]	[0.01]	[0.06]	[0.12]	[0.09]	[0.22]	[0.19]
b^{SMB}	0.063	0.084	0.138	0.030	0.168	0.076	0.045	0.114	0.081
T-STAT	(0.46)	(0.65)	(1.07)	(0.22)	(1.35)	(0.59)	(0.35)	(0.94)	(0.66)
P-VALUE	[0.64]	[0.51]	[0.29]	[0.83]	[0.18]	[0.55]	[0.73]	[0.35]	[0.51]
b^{HML}	0.415	0.397	0.441	0.425	0.356	0.374	0.376	0.346	0.347
T-STAT	(3.00)***	(2.88)***	(3.25)***	(3.06)***	(2.57)**	(2.79)***	(2.79)***	(2.55)**	(2.55)**
P-VALUE	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
c^{TGC}		0.192				0.349	0.365	0.712	0.798
T-STAT		(3.30)***				(4.07)***	(4.22)***	(2.47)**	(2.66)***
P-VALUE		[0.00]				[0.00]	[0.00]	[0.01]	[0.01]
c^{rndic}			-7.600			37.320	42.491	12.525	14.695
T-STAT			(-0.74)			(2.10)**	(2.31)**	(1.23)	(1.44)
P-VALUE			[0.46]			[0.04]	[0.02]	[0.22]	[0.15]
c^{absc}				-0.166			-0.113		-0.120
T-STAT				(-1.89)*			(-1.29)		(-1.41)
P-VALUE				[0.06]			[0.20]		[0.16]
c^{sRnDs}					-0.012			0.127	0.152
T-STAT					(-1.33)			(1.66)*	(1.88)*
P-VALUE					[0.18]			[0.10]	[0.06]
R^2	0.15	0.21	0.21	0.17	0.22	0.25	0.27	0.29	0.31
N	26,157	26,157	26,157	26,157	26,157	26,157	26,157	26,157	26,157

* p<0.10; ** p<0.05; *** p<0.01

Table 7: Second Stage Fama-MacBeth Regressions with Technology Gap, R&D Intensity and Absorption Capacity With Global Carhart factors

The returns of the equal-weighted country-industry portfolios are regressed at a monthly frequency for the period July 1992-December 2015 on the various productivity gaps relevant for each country-industry portfolio and controlling for the global Cahart beta of the country-industry portfolio. The computation of the technology gap measures uses $R\&D$ Stock in current PPP terms. The global market factor is taken from Kenneth French's website. The cross-sectional regression is a specific case of equation 23:

$$r_{t+1}^{ic} - r_{t+1}^{f} = a_t + b_t^{MKT}\beta_{MKT}^{ic} + b_t^{SMB}\beta_{SMB}^{ic} + b_t^{HML}\beta_{HML}^{ic} + b_t^{WML}\beta_{WML}^{ic} + +c_t^{TGC} * TGC_t^{ic} + c_t^{rndic} * rndic_t^{ic} + c_t^{absc} * absc_t^{ic} + c_t^{sRnDs} * sRnDs_t^{ic} + \eta_t^{ic}$$

The coefficients and the standard errors in this table are the means and standard deviations of the elements of $\boldsymbol{c_t} = [c_t^{TGC}, c_t^{rndic}, c_t^{absc}, c_t^{sRnDs}]$ based on the 282 monthly regression from July 1992 until December 2015.

Coef	FF 3 Factor Global Model								
b^{MKT}	-0.356	-0.463	-0.422	-0.415	-0.343	-0.251	-0.318	-0.168	-0.220
T-STAT	(-1.30)	(-1.71)*	(-1.54)	(-1.51)	(-1.27)	(-0.94)	(-1.19)	(-0.61)	(-0.81)
P-VALUE	[0.20]	[0.09]	[0.12]	[0.13]	[0.21]	[0.35]	[0.24]	[0.54]	[0.42]
b^{SMB}	-0.025	0.016	0.046	-0.048	0.081	-0.031	-0.037	0.011	0.003
T-STAT	(-0.20)	(0.13)	(0.38)	(-0.38)	(0.68)	(-0.25)	(-0.30)	(0.09)	(0.03)
P-VALUE	[0.84]	[0.90]	[0.70]	[0.70]	[0.50]	[0.80]	[0.76]	[0.93]	[0.98]
b^{HML}	0.326	0.353	0.392	0.345	0.322	0.317	0.334	0.301	0.320
T-STAT	(2.33)**	(2.52)**	(2.84)***	(2.45)**	(2.29)**	(2.30)**	(2.41)**	(2.16)**	(2.28)**
P-VALUE	[0.02]	[0.01]	[0.00]	[0.01]	[0.02]	[0.02]	[0.02]	[0.03]	[0.02]
b^{WML}	0.314	0.195	0.463	0.369	0.371	0.038	0.128	-0.019	0.077
T-STAT	(1.38)	(0.86)	(2.07)**	(1.61)	(1.65)	(0.17)	(0.57)	(-0.09)	(0.34)
P-VALUE	[0.17]	[0.39]	[0.04]	[0.11]	[0.10]	[0.86]	[0.57]	[0.93]	[0.73]
c^{TGC}		0.186				0.346	0.330	0.643	0.634
T-STAT		(3.25)***				(4.31)***	(4.15)***	(2.54)**	(2.51)**
P-VALUE		[0.00]				[0.00]	[0.00]	[0.01]	[0.01]
c^{rndic}			-7.663			37.866	37.877	16.540	17.730
T-STAT			(-0.81)			(2.21)**	(2.21)**	(1.44)	(1.55)
P-VALUE			[0.42]			[0.03]	[0.03]	[0.15]	[0.12]
c^{absc}				-0.218			-0.134		-0.136
T-STAT				(-2.47)**			(-1.57)		(-1.66)*
P-VALUE				[0.01]			[0.12]		[0.10]
c^{sRnDs}					-0.012			0.107	0.109
T-STAT					(-1.57)			(1.55)	(1.58)
P-VALUE					[0.12]			[0.12]	[0.12]
R^2	0.18	0.23	0.23	0.20	0.23	0.27	0.29	0.31	0.32
N	26,108	26,108	26,108	26,108	26,108	26,108	26,108	26,108	26,108

* p<0.10; ** p<0.05; *** p<0.01

Table 8: Second Stage Fama-MacBeth Regressions with Technology Gap, R&D Intensity and Absorption Capacity With Global FF5 factors

The returns of the equal-weighted country-industry portfolios are regressed at a monthly frequency for the period July 1992-December 2015 on the various productivity gaps relevant for each country-industry portfolio and controlling for the global FF5 beta of the country-industry portfolio. The computation of the technology gap measures uses $R\&D$ Stock in current PPP terms. The global market factor is taken from Kenneth French's website. The cross-sectional regression is a specific case of equation 23:

$$r_{t+1}^{ic} - r_{t+1}^{f} = a_t + b_t^{MKT}\beta_{MKT}^{ic} + b_t^{SMB}\beta_{SMB}^{ic} + b_t^{HML}\beta_{HML}^{ic} + b_t^{RMW}\beta_{RMW}^{ic} + b_t^{CMA}\beta_{CMA}^{ic} + + c_t^{TGC} * TGC_t^{ic} + c_t^{rndic} * rndic_t^{ic} + c_t^{absc} * absc_t^{ic} + c_t^{sRnDs} * sRnDs_t^{ic} + \eta_t^{ic}$$

The coefficients and the standard errors in this table are the means and standard deviations of the elements of $\boldsymbol{c_t} = [c_t^{TGC}, c_t^{rndic}, c_t^{absc}, c_t^{sRnDs}]$ based on the 282 monthly regression from July 1992 until December 2015.

Coef	FF5 Global Model								
b^{MKT}	-0.650	-0.560	-0.593	-0.735	-0.620	-0.183	-0.278	-0.145	-0.222
T-STAT	(-2.25)**	(-1.89)*	(-2.08)**	(-2.52)**	(-2.11)**	(-0.61)	(-0.89)	(-0.48)	(-0.71)
P-VALUE	[0.03]	[0.06]	[0.04]	[0.01]	[0.04]	[0.54]	[0.38]	[0.63]	[0.48]
b^{SMB}	0.197	0.258	0.264	0.159	0.295	0.132	0.111	0.122	0.105
T-STAT	(1.45)	(2.07)**	(2.17)**	(1.17)	(2.39)**	(1.06)	(0.88)	(0.98)	(0.84)
P-VALUE	[0.15]	[0.04]	[0.03]	[0.24]	[0.02]	[0.29]	[0.38]	[0.33]	[0.40]
b^{HML}	0.402	0.395	0.416	0.414	0.433	0.347	0.366	0.331	0.348
T-STAT	(2.92)***	(2.84)***	(3.06)***	(2.99)***	(3.05)***	(2.53)**	(2.62)***	(2.37)**	(2.47)**
P-VALUE	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.02]	[0.01]
b^{RMW}	0.063	0.106	0.068	0.129	0.048	0.042	0.083	0.036	0.070
T-STAT	(0.69)	(1.17)	(0.73)	(1.42)	(0.53)	(0.45)	(0.87)	(0.38)	(0.74)
P-VALUE	[0.49]	[0.24]	[0.46]	[0.16]	[0.60]	[0.65]	[0.38]	[0.70]	[0.46]
b^{CMA}	0.090	0.090	0.039	0.096	0.055	0.088	0.084	0.105	0.098
T-STAT	(0.68)	(0.68)	(0.31)	(0.72)	(0.44)	(0.68)	(0.64)	(0.83)	(0.77)
P-VALUE	[0.50]	[0.50]	[0.76]	[0.47]	[0.66]	[0.50]	[0.52]	[0.41]	[0.44]
c^{TGC}		0.122				0.347	0.338	0.926	0.928
T-STAT		(1.91)*				(3.29)***	(3.17)***	(2.58)**	(2.56)**
P-VALUE		[0.06]				[0.00]	[0.00]	[0.01]	[0.01]
c^{rndic}			9.934			54.632	56.305	15.781	17.687
T-STAT			(0.85)			(2.65)***	(2.71)***	(1.38)	(1.53)
P-VALUE			[0.40]			[0.01]	[0.01]	[0.17]	[0.13]
c^{absc}				-0.209			-0.163		-0.150
T-STAT				(-2.35)**			(-1.83)*		(-1.70)*
P-VALUE				[0.02]			[0.07]		[0.09]
c^{sRnDs}					-0.000			0.194	0.199
T-STAT					(-0.01)			(2.08)**	(2.12)**
P-VALUE					[0.99]			[0.04]	[0.04]
R^2	0.22	0.26	0.27	0.24	0.26	0.30	0.32	0.33	0.35
N	26,157	26,157	26,157	26,157	26,157	26,157	26,157	26,157	26,157

* $p<0.10$; ** $p<0.05$; *** $p<0.01$

Table 9: Second Stage Fama-MacBeth Regressions with Technology Gap, R&D Intensity and Absorption Capacity With Global FF5 and Momentum factors

The returns of the equal-weighted country-industry portfolios are regressed at a monthly frequency for the period July 1992-December 2015 on the various productivity gaps relevant for each country-industry portfolio and controlling for the global FF5 beta of the country-industry portfolio. The computation of the technology gap measures uses $R\&D$ Stock in current PPP terms. The global market factor is taken from Kenneth French's website. The cross-sectional regression is a specific case of equation 23:

$$r_{t+1}^{ic} - r_{t+1}^{f} = a_t + b_t^{MKT}\beta_{MKT}^{ic} + b_t^{SMB}\beta_{SMB}^{ic} + b_t^{HML}\beta_{HML}^{ic} + b_t^{RMW}\beta_{RMW}^{ic} + b_t^{CMA}\beta_{CMA}^{ic} + b_t^{WML}\beta_{WML}^{ic} + + c_t^{TGC} * TGC_t^{ic} + c_t^{rndic} * rndic_t^{ic} + c_t^{absc} * absc_t^{ic} + c_t^{sRnDs} * sRnDs_t^{ic} + \eta_t^{ic}$$

The coefficients and the standard errors in this table are the means and standard deviations of the elements of $\boldsymbol{c_t} = [c_t^{TGC}, c_t^{rndic}, c_t^{absc}, c_t^{sRnDs}]$ based on the 282 monthly regression from July 1992 until December 2015.

Coef	FF5 + Momentum Global Model								
b^{MKT}	-0.393	-0.390	-0.407	-0.476	-0.399	-0.248	-0.388	-0.200	-0.335
T-STAT	(-1.47)	(-1.43)	(-1.49)	(-1.77)*	(-1.44)	(-0.92)	(-1.45)	(-0.74)	(-1.24)
P-VALUE	[0.14]	[0.15]	[0.14]	[0.08]	[0.15]	[0.36]	[0.15]	[0.46]	[0.22]
b^{SMB}	0.086	0.118	0.163	0.069	0.155	0.057	0.052	0.051	0.049
T-STAT	(0.70)	(0.99)	(1.37)	(0.55)	(1.32)	(0.47)	(0.43)	(0.43)	(0.41)
P-VALUE	[0.49]	[0.32]	[0.17]	[0.58]	[0.19]	[0.64]	[0.67]	[0.67]	[0.68]
b^{HML}	0.343	0.338	0.398	0.366	0.346	0.325	0.364	0.302	0.342
T-STAT	(2.46)**	(2.41)**	(2.84)***	(2.60)***	(2.42)**	(2.33)**	(2.59)**	(2.13)**	(2.40)**
P-VALUE	[0.01]	[0.02]	[0.00]	[0.01]	[0.02]	[0.02]	[0.01]	[0.03]	[0.02]
b^{RMW}	0.066	0.131	0.108	0.132	0.074	0.123	0.173	0.111	0.156
T-STAT	(0.72)	(1.46)	(1.17)	(1.44)	(0.81)	(1.37)	(1.89)*	(1.23)	(1.71)*
P-VALUE	[0.47]	[0.15]	[0.24]	[0.15]	[0.42]	[0.17]	[0.06]	[0.22]	[0.09]
b^{CMA}	0.119	0.141	0.150	0.127	0.130	0.142	0.137	0.152	0.145
T-STAT	(0.90)	(1.05)	(1.15)	(0.96)	(1.02)	(1.08)	(1.04)	(1.17)	(1.12)
P-VALUE	[0.37]	[0.29]	[0.25]	[0.34]	[0.31]	[0.28]	[0.30]	[0.24]	[0.26]
b^{WML}	0.273	0.089	0.369	0.357	0.290	-0.025	0.099	-0.069	0.069
T-STAT	(1.20)	(0.38)	(1.62)	(1.55)	(1.25)	(-0.11)	(0.42)	(-0.30)	(0.30)
P-VALUE	[0.23]	[0.71]	[0.11]	[0.12]	[0.21]	[0.91]	[0.67]	[0.76]	[0.77]
c^{TGC}		0.152				0.296	0.270	0.564	0.531
T-STAT		(2.58)**				(3.80)***	(3.61)***	(2.54)**	(2.41)**
P-VALUE		[0.01]				[0.00]	[0.00]	[0.01]	[0.02]
c^{rndic}			-0.726			32.922	33.793	14.330	16.085
T-STAT			(-0.07)			(2.05)**	(2.08)**	(1.13)	(1.26)
P-VALUE			[0.95]			[0.04]	[0.04]	[0.26]	[0.21]
c^{absc}				-0.237			-0.148		-0.140
T-STAT				(-2.76)***			(-1.75)*		(-1.69)*
P-VALUE				[0.01]			[0.08]		[0.09]
c^{sRnDs}					-0.009			0.091	0.091
T-STAT					(-1.02)			(1.51)	(1.48)
P-VALUE					[0.31]			[0.13]	[0.14]
R^2	0.24	0.28	0.28	0.26	0.28	0.32	0.33	0.35	0.36
N	26,108	26,108	26,108	26,108	26,108	26,108	26,108	26,108	26,108

* $p<0.10$; ** $p<0.05$; *** $p<0.01$

Table 10: Excess Returns of Equally Weighted Country Portfolios by Year

Equal-weighted portfolio returns for the OECD countries available in Compustat Global by Country and Year for the period 1992-2015. The excess returns are monthly means (aritmetic) and are in USD percentage terms obtained after local prices are converted to USD. The risk free rate used to compute the excess return is the USA risk free rate.The countries include Austria (AUT), Belgium (BEL), the Czech Republic (CZE), Germany (DEU), Denmark (DMK), Estonia (EST), Finland (FIN), France (FRA), Great Britain (GBR), Greece (GRC), Hungary (HUN), Ireland (IRL), Italy (ITA), Japan (JPN), Lithuania (LTU), Luxembourg (LUX), Latvia (LVA), Netherlands (NLD), Norway (NOR), Poland (POL), Portugal (PRT), Slovak Republic(SVK), Slovenia (SVN), Sweden (SWE), and the United States of America (USA).

Year	AUT	BEL	CZE	DEU	DMK	EST	FIN	FRA	GBR	GRC	HUN	IRL	ITA	JPN	LTU	LUX	LVA	NLD	NOR	POL	PRT	SVK	SVN	SWE	USA
1992	-2.24	-0.61		-1.56	-2.40		-0.75	-0.94	-1.58	-2.77	-11.99		-3.55	-2.48		-2.93		-0.29	-3.72					-3.35	0.51
1993	1.25	1.53		1.99	1.15		3.12	1.86	2.33	3.71	1.63		-0.64	1.48		2.73		1.84	4.60					3.85	0.66
1994	-0.05	0.47		0.80	1.05		0.77	-0.02	-0.08	0.53	0.89		0.01	0.51		2.06		1.47	0.82					0.94	-0.30
1995	-1.07	0.82	-0.29	0.01	0.25		-0.29	-0.24	0.59	-0.31	-2.17	-0.07	-1.14	-1.24		0.11		1.04	1.67	0.22	-1.23	-1.32	1.11	1.68	2.20
1996	-1.60	0.31	2.57	-1.32	1.71	7.62	3.12	0.62	1.51	-0.90	2.08	2.36	-0.41	-1.68		0.97		2.17	2.36	3.09	1.24	5.46	-0.01	2.22	1.24
1997	-0.74	0.25	-2.39	0.22	-0.40	0.44	0.23	-0.53	0.24	2.23	0.89	0.47	1.19	-4.45		-0.55	1.70	0.28	0.22	-0.18	0.60	-3.69	-0.03	0.28	1.95
1998	0.90	1.84	0.24	0.83	-0.98	-4.20	0.42	1.49	-0.33	4.66	-1.70	-0.04	2.10	0.06		0.09	-3.36	0.76	-3.25	-0.05	1.55	-2.84	1.61	-0.20	1.65
1999	-2.60	-1.49	0.63	-1.33	-0.09	1.81	0.30	0.36	1.38	8.88	-0.52	-0.51	0.38	3.06		1.96	0.47	-0.93	2.21	0.96	-1.02	-1.92	-0.69	1.39	1.59
2000	-3.02	-1.63	-1.31	-2.48	-0.89	2.31	-2.35	-0.57	-1.31	-7.03	-2.31	-0.63	-0.88	-2.34		-1.39	1.17	-0.89	-2.21	-0.57	-1.14	-2.83	-0.80	-0.92	-1.37
2001	-1.37	-0.75	1.13	-2.81	-1.44	-0.20	-0.28	-1.06	-1.01	-1.04	-0.87	-1.63	-2.53	-1.12		-1.30	0.27	-1.50	-1.67	-2.29	-1.75	3.28	0.64	-1.34	-1.14
2002	0.72	0.76	5.21	-1.97	0.47	3.61	0.63	0.51	-1.09	-1.36	1.91	1.17	-0.56	-0.26		-1.87	0.31	-0.73	0.02	-1.62	0.31	1.33	4.78	-0.20	-1.94
2003	2.52	3.00	6.29	2.74	4.06	4.58	4.49	2.66	2.87	3.76	1.48	4.78	2.66	2.60		4.57	7.41	3.23	3.42	3.47	2.52	5.83	2.97	4.16	2.29
2004	2.29	2.63	5.99	0.84	2.37	3.00	2.39	1.60	1.65	-0.51	3.84	2.40	1.31	1.61		3.32	3.68	2.31	3.18	3.82	2.09	4.34	2.62	3.09	0.87
2005	0.34	0.93	1.50	0.65	2.21	3.07	1.21	0.71	-0.20	0.95	0.78	1.23	0.52	1.45		1.52	5.68	1.84	2.52	0.92	0.00	-1.03	-1.92	1.44	0.28
2006	1.77	1.68	3.02	0.61	1.65	3.52	2.67	1.83	1.65	3.30	3.88	2.40	1.72	-2.11		2.42	0.81	2.68	2.86	5.15	2.41	3.05	2.18	1.62	0.83
2007	0.75	0.77	3.55	-0.06	0.63	-0.31	1.07	0.99	-1.05	1.92	2.19	-1.29	-0.26	-1.48		0.17	0.67	0.47	1.36	1.24	1.24	0.86	4.64	-0.51	0.12
2008	-3.81	-2.02	-1.64	-2.94	-4.72	-6.09	-3.76	-3.24	-5.65	-4.94	-3.99	-6.07	-3.67	-1.29		-4.04	-4.93	-4.25	-6.54	-5.34	-2.72	-3.20	-5.92	-5.12	-3.68
2009	2.13	1.71	2.63	0.80	0.44	1.53	3.29	2.05	2.51	1.25	2.47	1.72	1.01	0.65		1.95	3.05	2.91	3.36	3.04	1.92	0.57	0.10	3.72	2.28
2010	0.86	0.02	0.78	0.31	-0.88	3.37	0.94	-0.03	0.27	-3.52	-0.33	-0.93	-0.69	1.44	1.57	-0.12	2.92	0.85	0.97	0.56	-1.74	-1.21	-1.44	1.28	1.49
2011	-2.09	-0.99	0.50	-0.93	-1.73	-2.66	-2.36	-1.47	-1.38	-3.62	-2.39	-1.96	-2.43	0.26	-2.41	-2.08	-0.91	-1.97	-1.55	-4.78	-2.67	-1.11	-3.88	-2.19	0.14
2012	0.82	0.63	0.64	0.18	0.05	2.00	0.50	0.74	1.18	3.35	0.76	1.13	-0.11	0.60	1.05	-0.09	0.75	1.18	1.12	-0.12	-0.17	0.65	0.42	0.73	1.31
2013	1.30	1.57	-0.27	0.99	1.54	0.96	1.96	1.51	1.58	1.86	0.93	2.83	2.07	1.33	1.21	0.02	0.23	1.98	0.21	0.63	2.40	1.17	-0.36	1.30	2.57
2014	-0.46	-0.43	-0.18	-0.76	-1.14	-1.90	-1.20	-0.33	-0.56	-2.00	-1.14	-0.97	-1.35	-0.40	-0.67	-2.33	0.32	-1.06	-1.69	-2.00	-0.89	-0.90	1.95	-1.26	0.96
2015	0.09	0.51	0.97	-0.46	0.19	0.76	1.31	-0.11	-0.29	-1.00	0.93	0.75	-0.61	0.66	-0.56	-1.25	0.14	0.03	-1.00	-0.64	-0.80	0.69	-2.02	0.49	0.07
Mean	-0.14	0.48	1.41	-0.24	0.13	1.16	0.73	0.35	0.13	0.31	-0.12	0.34	-0.24	-0.13	0.03	0.16	1.07	0.56	0.39	0.26	0.10	0.34	0.28	0.55	0.61

Appendix A: Derivations

Lagging Country-Industry Firm Investment Decisions and Market Valuation

For the Bellman equation 1, the first order condition for equation [7] are given by equation 11 & 12. The envelop conditions [8],[9] are given by 13 & 14

Moving one time period ahead 13 & 14, and using the FOCs 11 & defining $\alpha+\beta=1$ and utilizing equations 6, 7, 8, 9, and 10.

$$K_{t+1}^{1-\alpha}=\left(\frac{\alpha\theta\widehat{\eta}_{\beta}}{r+\delta}\right)\widehat{z}_{t+1}^{1-\alpha} \tag{A.1}$$

$$K_{t+1}^{\alpha}=\left(\frac{(r+\gamma)+(2\lambda\widehat{\eta}_2\widehat{z}_{t+1})-\lambda(\frac{1+r}{1+\kappa})\widehat{z}_{t+1}^{*}}{(1-\alpha)\theta\widehat{\eta}_{\beta}}\right)\widehat{z}_{t+1}^{\alpha} \tag{A.2}$$

using equation A.1 and A.2

$$K_{t+1}=\frac{\alpha}{1-\alpha}\left(\frac{(r+\gamma)+(2\lambda\widehat{\eta}_2\widehat{z}_{t+1})-\lambda(\frac{1+r}{1+\kappa})\widehat{z}_{t+1}^{*}}{r+\delta}\right)\widehat{z}_{t+1} \tag{A.3}$$

$$\widehat{z}_{t+1}=\frac{1}{2\widehat{\eta}_2}(\frac{1+r}{1+\kappa})\widehat{z}_{t+1}^{*}+\frac{(1-\alpha)}{2\lambda\widehat{\eta}_2}\left(\frac{\alpha}{r+\delta}\right)^{\frac{\alpha}{1-\alpha}}(\widehat{\eta}_{\beta}\theta)^{\frac{1}{1-\alpha}}-\frac{(r+\gamma)}{2\lambda\widehat{\eta}_2} \tag{A.4}$$

Flow variable in 1 is $Y_t-i_t-h_t=\theta K_t^{\alpha}z_t^{1-\alpha}-K_{t+1}+(1-\delta)K_t-\frac{z_{t+1}}{\eta_{t+1}}+z_t+(\gamma+\lambda z_t)(z_t^{*}-z_t)$. Assuming that the optimal i_t and h_t is used:

$$V(t)=Y_t+(1-\delta)K_t+(1-\gamma)z_t+\gamma z_t^{*}+\lambda z_t z_t^{*}-\lambda z_t^2-K_{t+1}-\widehat{z}_{t+1}+E_t[m_{t+1}V(t+1)] \tag{A.5}$$

Using Guess and Verify Method of V_t

$$V(t)=Y_t+(1-\delta)K_t+(1-\gamma)z_t+\gamma z_t^{*}+\lambda z_t z_t^{*}-\lambda z_t^2+C \tag{A.6}$$

$$\therefore E_t[m_{t+1}V(t+1)]=C+K_{t+1}+\widehat{z}_{t+1} \tag{A.7}$$

Defining

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[7] Flow variable in 1 is $Y_t-i_t-h_t=\theta K_t^{\alpha}z_t^{1-\alpha}-K_{t+1}+(1-\delta)K_t-\frac{z_{t+1}}{\eta_{t+1}}+z_t+(\gamma+\lambda z_t)(z_t^{*}-z_t)$
FOC involves differentiating w.r.t to SV_{t+1} where SV are the state variables.

[8] Envelop Condition involves differentiating w.r.t to SV_t where SV are the state variables. If it is to be compared with FOC then we move envelop condition by one time period ahead.

[9] $Y_t-i_t-h_t=\theta K_t^{\alpha}z_t^{1-\alpha}-K_{t+1}+(1-\delta)K_t-\frac{z_{t+1}}{\eta_{t+1}}+z_t+(\gamma+\lambda z_t)(z_t^{*}-z_t)$ 1 can be expressed as $V(X_t)=F(X_t,X_{t+1})+E_t\left[m_{t+1}V(X_{t+1})\right]$
Envelop Condition can be written as $V_{X_t}(X_t)=F_{X_t}(X_t,X_{t+1})+F_{X_{t+1}}(X_t,X_{t+1})\frac{dX_{t+1}}{dX_t}+E_t\left[m_{t+1}V(X_{t+1})\right]\frac{dX_{t+1}}{dX_t}$
$V_{X_t}(X_t)=F_{X_t}(X_t,X_{t+1})+\left[F_{X_{t+1}}(X_t,X_{t+1})+E_t\left[m_{t+1}V_{X_{t+1}}(X_{t+1})\right]\right]\frac{dX_{t+1}}{dX_t}$

$$x = \left(\frac{\alpha\theta\widehat{\eta}_\beta}{r+\delta}\right)^{\frac{1}{\beta}} \tag{A.8}$$

using equation A.1

$$K_{t+1} + \widehat{z}_{t+1} = (1 + \left(\frac{\alpha\theta\widehat{\eta}_\beta}{r+\delta}\right)^{\frac{1}{\beta}})\widehat{z}_{t+1} = (1+x)\widehat{z}_{t+1} \tag{A.9}$$

Using equations A.6,6, 7, 8, 9, and 10.

$$E_t[m_{t+1}V(t+1)] = E_t\left[m_{t+1}\left[Y_{t+1} + (1-\delta)K_{t+1} + (1-\gamma)z_{t+1} + \gamma z^*_{t+1} + \lambda z_{t+1}z^*_{t+1} - \lambda z^2_{t+1}\right]\right] + \frac{C}{1+r} \tag{A.10}$$

$$E_t(m_{t+1}Y_{t+1}) = x^\alpha\theta\widehat{\eta}_\beta\widehat{z}_{t+1}\frac{1}{1+r} \tag{A.11}$$

$$E_t\left[m_{t+1}(1-\delta)K_{t+1}\right] = (1-\delta)x\widehat{z}_{t+1}\frac{1}{1+r} \tag{A.12}$$

$$E_t\left[m_{t+1}(1-\gamma)z_{t+1}\right] = (1-\gamma)\widehat{z}_{t+1}\frac{1}{1+r} \tag{A.13}$$

$$E_t[m_{t+1}\gamma z^*_{t+1}] = \gamma\widehat{z}^*_{t+1}\frac{1}{1+\kappa} \tag{A.14}$$

$$E_t[m_{t+1}\lambda z_{t+1}z^*_{t+1}] = \lambda\widehat{z}_{t+1}\widehat{z}^*_{t+1}\frac{1}{1+\kappa} \tag{A.15}$$

$$E_t[m_{t+1}(-\lambda z^2_{t+1})] = -\lambda\widehat{\eta}_2\widehat{z}^2_{t+1}\frac{1}{1+r} \tag{A.16}$$

Using equations A.10, A.11, A.12, A.13, A.14, A.15,A.16, A.7, and A.9

$$C+(1+x)\widehat{z}_{t+1} = \frac{1}{1+\kappa}(\gamma+\lambda\widehat{z}_{t+1})\widehat{z}^*_{t+1} + \frac{C}{1+r} + \frac{1}{1+r}\left(\left(\frac{r+\delta}{\alpha} + (1-\delta)\right)x\widehat{z}_{t+1} + (1-\gamma)\widehat{z}_{t+1} - \lambda\widehat{\eta}_2\widehat{z}^2_{t+1}\right) \tag{A.17}$$

Defining

$$\gamma + \lambda\widehat{z}_{t+1} = \widehat{\gamma}_t \tag{A.18}$$

$$rC = \widehat{\gamma}_t\left(\frac{1+r}{1+\kappa}\right)\widehat{z}^*_{t+1} + \frac{1-\alpha}{\alpha}(r+\delta)x\widehat{z}_{t+1} - (r+\gamma)\widehat{z}_{t+1} - \lambda\widehat{\eta}_2\widehat{z}^2_{t+1} \tag{A.19}$$

The ex-dividend stock price is given by $P_t = E_t\left[m_{t+1}V_{t+1}\right]$, The value function, equal to the stock-market value of the firm with dividend included. $V(t+1)$ is the value of the stock including dividends. Hence, the gross stock returns equals $1 + r^s_{t+1} = \frac{V(t+1)}{E_t[m_{t+1}V(t+1)]}$. And, therefore: $r^s_{t+1} - r = \frac{V(t+1)-(1+r)E_t[m_{t+1}V(t+1)]}{E_t[m_{t+1}V(t+1)]}$

From equations A.10, A.11, A.12, A.13, A.14, A.15,A.16, A.7, A.18, A.19

$$E_t(r^s_{t+1}-r)=\frac{\frac{1}{1+\kappa}\widehat{\gamma}_t\widehat{z}^*_{t+1}(\kappa-r)}{\frac{1}{1+\kappa}\widehat{\gamma}_t\widehat{z}^*_{t+1}+\frac{C+\left(\frac{r+\delta}{\alpha}+(1-\delta)\right)x\widehat{z}_{t+1}+(1-\gamma)\widehat{z}_{t+1}-\lambda\widehat{\eta}_2\widehat{z}^2_{t+1}}{1+r}} \tag{A.20}$$

Eliminating C

$$E_t(r^s_{t+1}-r)=\frac{\frac{1}{1+\kappa}\widehat{\gamma}_t\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}(\kappa-r)}{\frac{1}{1+\kappa}\widehat{\gamma}_t\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}+\frac{1}{r}\widehat{\gamma}_t\frac{1}{1+\kappa}\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}+\frac{1}{r}\left(\frac{r+\delta}{\alpha}-\delta\right)x-\frac{1}{r}\gamma-\frac{1}{r}\lambda\widehat{\eta}_2\widehat{z}_{t+1}}$$

Dividing by $\widehat{z}_{t+1}$

$$E_t(r^s_{t+1}-r)=\frac{\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}(\kappa-r)}{\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}+\frac{1}{r}\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}+\frac{1+\kappa}{r}\left(\frac{r+\delta}{\alpha}-\delta\right)\frac{x}{\widehat{\gamma}_t}-\frac{1+\kappa}{\widehat{\gamma}_t}\frac{1}{r}\gamma-\frac{1}{r}\frac{1+\kappa}{\widehat{\gamma}_t}\lambda\widehat{\eta}_2\widehat{z}_{t+1}}$$

$$E_t(r^s_{t+1}-r)=\frac{\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}(\kappa-r)}{\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}+\frac{1}{r}\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}+\frac{1+\kappa}{r}\left[\left(\frac{r+\delta}{\alpha}-\delta\right)\frac{x}{\widehat{\gamma}_t}-\frac{\gamma}{\widehat{\gamma}_t}-\lambda\widehat{\eta}_2\frac{\widehat{z}_{t+1}}{\widehat{\gamma}_t}\right]}$$

$$\because \gamma+\lambda\widehat{z}_{t+1}=\widehat{\gamma}_t;\ \frac{\gamma}{\widehat{\gamma}_t}=\frac{\widehat{\gamma}_t-\lambda\widehat{z}_{t+1}}{\widehat{\gamma}_t}=1-\frac{\lambda\widehat{z}_{t+1}}{\widehat{\gamma}_t}$$

$$E_t(r^s_{t+1}-r)=\frac{\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}(\kappa-r)}{\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}+\frac{1}{r}\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}+\frac{1+\kappa}{r}\left[\left(\frac{r+\delta}{\alpha}-\delta\right)\frac{x}{\widehat{\gamma}_t}-1+\frac{\lambda\widehat{z}_{t+1}}{\widehat{\gamma}_t}-\lambda\widehat{\eta}_2\frac{\widehat{z}_{t+1}}{\widehat{\gamma}_t}\right]}$$

$$E_t(r^s_{t+1}-r)=\frac{\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}(\kappa-r)}{\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}+\frac{1}{r}\frac{\widehat{z}^*_{t+1}}{\widehat{z}_{t+1}}+\frac{1+\kappa}{r}\left[\left(\frac{r+\delta}{\alpha}-\delta\right)\frac{x}{\widehat{\gamma}_t}-1+(1-\widehat{\eta}_2)\lambda\frac{\widehat{z}_{t+1}}{\widehat{\gamma}_t}\right]} \tag{A.21}$$

Appendix B: Productivity Measures

Compustat Global Database

Return are computed in local currency using the following Compustat fields: prccd, trfd and ajexdi. The returns are computed as $prccd * trfd/ajexdi$ and converted to USD using exchange rates from Bloomberg.

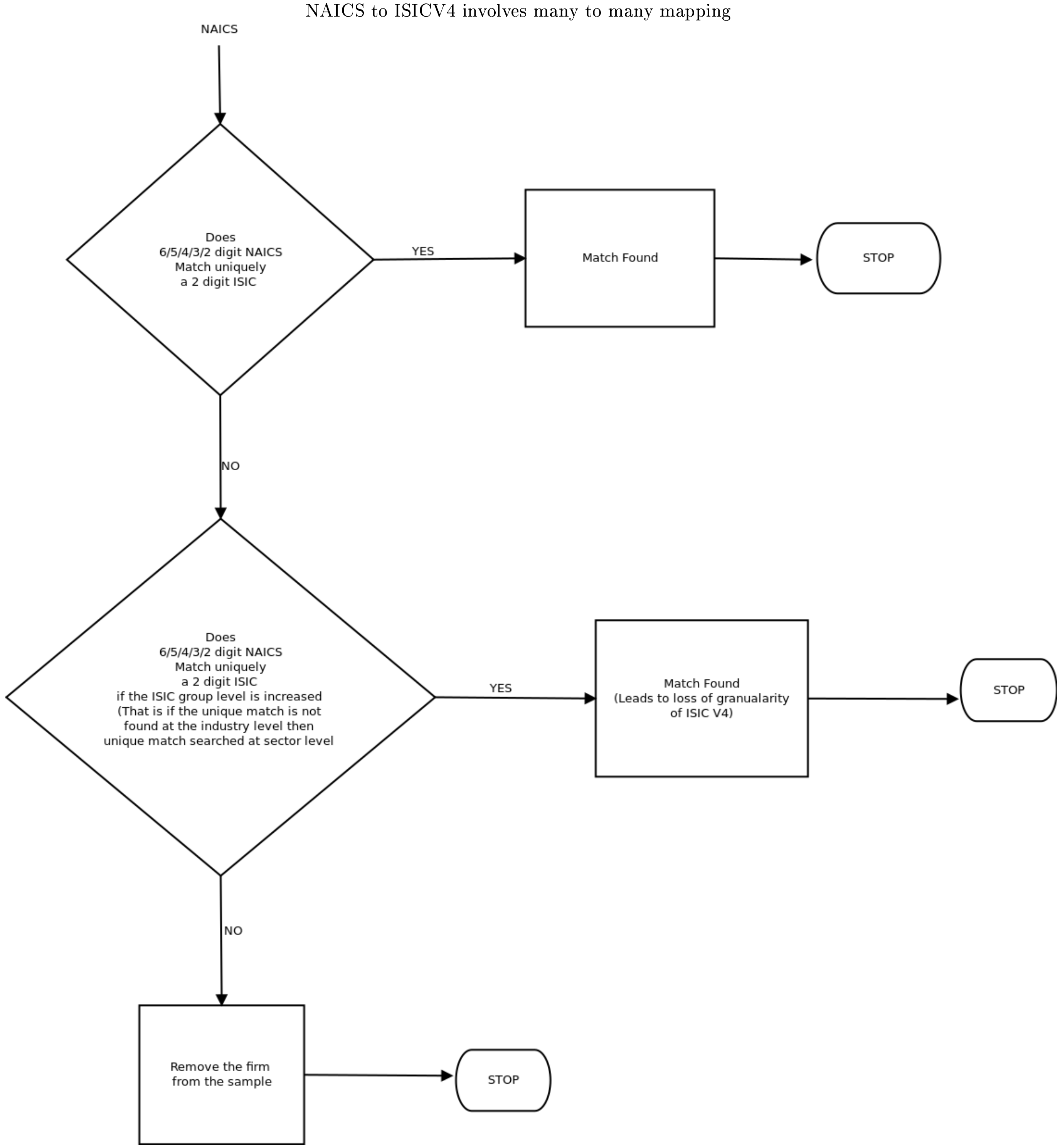
STAN

Mapping NAICS with ISICV4.0

One important point to note is that Compustat uses North American Industry classification system (NAICS) whereas STAN uses the version 4.0 of the International Standard Industrial Classification (ISIC). The standard correspondence table is utilized to map NAICS into ISIC V4. In the Compustat data, we observe that classification of all firms is not available in 6 digits of NAICS. There are firms with 2,3,4,5 or 6-digit NAICS which implies that classification is available at the sector, subsector, industry groups or industry level. We use a simple algorithm to map NAICS (2,3,4,5 or 6 digits) code to ISIC V4.0. Since the mapping of NACIS to ISICV4.0 is many to many mapping, we keep on expanding the ISIC matching industry so that the NAICS can map into a logical unit.

The flowchart of the algorithm used to map NAICS to ISICV4 is in figure 1. In the process of mapping we loose 10% of the firms as they map to multiple sectors.

Figure 1: Mapping NAICS To ISICV4
NAICS to ISICV4 involves many to many mapping



Appendix C: Details of Included Data

Table 11: Country/Industry Portfolios (Test Assets) Time Series Description

This table provides information about the available firm-level data by industry for each country. *Months* is the number of months for which the country industry portfilio data is available between July 1992 to December 2015. *Start Year* and the *End Year* is the data availability in years. *Firms* is the mean number of firms in the country industry portfilio; *Min* is the minimum number of firms in the portfolio and *Max* is the maximum number of firms in the portfolio. The Industry Portfolios are represented by MAN for Manufacturing, ELE for Electricity, Gas, Steam, and Air Conditioning, WAT is Water Supply, Sewage, Waste Management and Remediation Activities, CON is Construction, WHO is Wholesale Retail Trade, Repair of Motor Vehicles and Motorcycles, TRA is Transportation and Storage, FOO is Accomodation and Food Services, COM is Information and Communication, PRO is Professional Scientific and Technical Activities, EMP is Employment Activities, EDU is Education, HEA is Human Health Activities, ART is Arts, Entertainment and Recreation, and OTH is Other Services. The countries include Austria (AUT), Belgium (BEL), the Czech Republic (CZE), Germany (DEU), Denmark (DMK), Estonia (EST), Finland (FIN), France (FRA), Great Britain (GBR), Greece (GRC), Hungary (HUN), Ireland (IRL), Italy (ITA), Japan (JPN), Lithuania (LTU), Luxembourg (LUX), Latvia (LVA), and Netherlands (NLD), Norway (NOR), Poland (POL), Portugal (PRT), Slovak Republic(SVK), Slovenia (SVN), and Sweden (SWE).

	Industry	MAN	ELE	WAT	CON	WHO	TRA	FOO	COM	PRO	EMP	EDU	HEA	ART	OTH
Country															
AUT	Start Year	1992	1992		1992	1992	1992	1999	1998	2001	1994			2000	
	End Year	2015	2015		2015	2015	2015	2015	2015	2007	2001			2015	
	Months	282	282		277	269	272	193	205	62	51			179	
	Firms	47.4	4.0		2.8	2.1	1.5	2.3	8.7	1.0	1.0			2.2	
	Min	25	3		1	1	1	1	1	1	1			1	
	Max	57	5		5	4	2	4	13	1	1			4	
BEL	Start Year	1992	1992		1992	1992	1992	1992	1995	2005	1992			1997	
	End Year	2015	2015		2015	2015	2015	2007	2015	2015	2007			2015	
	Months	282	282		282	282	281	175	241	108	175			205	
	Firms	48.2	4.4		3.4	11.8	3.0	2.4	15.0	1.5	1.0			1.6	
	Min	16	2		2	8	2	1	1	1	1			1	
	Max	64	11		4	15	4	3	23	3	1			2	
CZE	Start Year	1995	1995	1997	1995		1995	1997	1995					1997	
	End Year	2015	2015	2015	2001		2013	2008	2015					2015	
	Months	251	251	94	78		175	55	241					94	
	Firms	8.7	6.5	1.0	1.0		1.9	1.0	2.2					1.0	
	Min	4	2	1	1		1	1	1					1	
	Max	18	12	1	1		3	1	3					1	
DEU	Start Year	1992	1992	1995	1992	1992	1992	1992	1992	1992	1992	2001	1992	1999	2001
	End Year	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2014

	Industry	MAN	ELE	WAT	CON	WHO	TRA	FOO	COM	PRO	EMP	EDU	HEA	ART	OTH
	Months	282	282	242	282	282	282	282	282	282	282	148	280	202	149
	Firms	270.1	22.3	3.4	14.7	39.5	9.1	1.8	116.0	15.0	12.8	1.3	8.2	7.4	1.4
	Min	113	16	1	8	12	2	1	4	1	4	1	1	1	1
	Max	337	30	5	19	50	14	2	183	27	22	2	12	11	2
DNK	Start Year	1992	1993	1993	1992	1992	1992		1993	1992	1992			1995	
	End Year	2015	2015	2007	2015	2015	2015		2015	2006	2005			2015	
	Months	282	239	130	281	282	282		267	159	150			241	
	Firms	59.3	1.4	1.0	7.0	11.2	8.6		13.2	1.0	1.6			5.4	
	Min	16	1	1	1	2	6		1	1	1			1	
	Max	75	2	1	8	17	13		25	1	2			8	
EST	Start Year	1997			1997	1997	2006		1999					2006	
	End Year	2015			2015	2015	2015		2015					2015	
	Months	227			218	211	111		192					98	
	Firms	5.8			3.1	1.0	1.0		1.4					1.2	
	Min	3			1	1	1		1					1	
	Max	8			6	1	1		3					2	
FIN	Start Year	1992	1994	1992	1992	1992	1993	2013	1992	1996	1996		1999		
	End Year	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015		2015		
	Months	282	254	273	251	282	268	25	280	240	224		163		
	Firms	59.7	2.6	1.0	2.6	7.5	6.7	1.2	22.6	3.3	2.5		1.1		
	Min	26	1	1	1	3	5	1	1	1	1		1		
	Max	74	4	1	4	10	9	2	37	5	3		2		
FRA	Start Year	1992	1992	1992	1992	1992	1992	1992	1992	1992	1992	2000	1994	1992	2000
	End Year	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015
	Months	282	282	282	282	282	282	282	282	282	282	168	253	280	156
	Firms	247.7	9.3	4.6	16.3	45.3	8.9	11.7	101.4	29.9	11.3	1.5	4.1	6.8	2.0
	Min	82	3	1	6	19	5	4	12	5	2	1	1	1	1
	Max	313	19	8	24	64	16	18	160	46	18	2	6	10	3
GBR	Start Year	1992	1992	1992	1992	1992	1992	1992	1992	1992	1992	1992	1992	1992	1992
	End Year	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015
	Months	282	282	282	282	282	282	282	282	282	282	282	282	282	282
	Firms	403.3	13.0	6.2	47.8	117.4	31.9	37.5	197.6	94.2	47.1	4.7	7.9	35.1	3.2
	Min	329	10	3	33	67	14	19	69	39	31	2	3	11	2

	Industry	MAN	ELE	WAT	CON	WHO	TRA	FOO	COM	PRO	EMP	EDU	HEA	ART	OTH
	Max	503	22	9	64	187	41	56	290	151	64	9	12	51	4
GRC	Start Year	1992	1998	2013	1994	1992	1996	1992	1995	1996	1992		1996	2000	
	End Year	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015		2015	2015	
	Months	282	204	32	257	281	229	278	243	232	272		228	182	
	Firms	67.2	1.9	1.0	15.3	17.9	6.8	4.0	22.0	2.3	1.3		4.2	3.5	
	Min	6	1	1	1	1	2	1	1	1	1		1	1	
	Max	98	3	1	21	31	9	6	32	3	2		5	4	
HUN	Start Year	1993	1995			1992		1993	1997	2012	1993				
	End Year	2015	2015			2015		2015	2015	2015	2015				
	Months	269	239			269		261	215	38	117				
	Firms	16.4	2.7			2.4		1.9	5.4	1.0	1.0				
	Min	1	1			1		1	1	1	1				
	Max	24	4			3		2	8	1	1				
IRL	Start Year	1992	2008		1992	1992	1992	1992	1992	1992	1998			1992	
	End Year	2015	2015		2015	2015	2015	2015	2015	2015	2015			2015	
	Months	282	64		281	281	281	184	282	281	199			269	
	Firms	25.1	1.0		3.9	6.4	4.2	3.8	7.1	5.6	2.3			3.5	
	Min	13	1		1	4	2	1	1	1	1			1	
	Max	31	1		6	9	7	6	15	9	4			6	
ITA	Start Year	1992	1992	1999	1992	1992	1992	1992	1992	1999	2001	1992	2006	1992	2007
	End Year	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015
	Months	282	282	187	282	282	282	272	282	193	179	245	87	282	99
	Firms	94.0	16.0	1.5	8.2	7.6	5.8	1.8	27.0	2.9	3.5	1.0	1.0	4.6	1.0
	Min	58	8	1	6	3	3	1	8	1	1	1	1	2	1
	Max	128	26	2	10	13	10	3	51	8	5	1	1	7	1
JPN	Start Year	1992	1992	1995	1992	1992	1992	1992	1992	1992	1992	1992	1992	1992	1992
	End Year	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015
	Months	282	282	236	282	282	282	282	282	282	282	274	280	282	282
	Firms	1480.9	22.2	3.6	208.0	492.7	99.0	86.5	244.9	82.0	55.7	22.4	10.5	13.6	7.9
	Min	961	16	1	126	158	61	20	27	17	5	1	1	2	1
	Max	1628	26	8	248	601	111	116	403	121	83	33	22	18	12
LTU	Start Year	2010	2010		2010	2010	2010		2010		2013				
	End Year	2015	2015		2015	2015	2015		2015		2015				

	Industry	MAN	ELE	WAT	CON	WHO	TRA	FOO	COM	PRO	EMP	EDU	HEA	ART	OTH
	Months	61	61		56	61	60		61		29				
	Firms	15.0	5.7		1.0	2.0	3.1		1.0		1.0				
	Min	14	4		1	2	2		1		1				
	Max	17	6		1	2	4		1		1				
LUX	Start Year	1992	1992		1998	1992	2007		1992	2000	2001			1992	
	End Year	2015	2015		2015	2015	2015		2015	2015	2015			2015	
	Months	282	248		175	144	100		282	146	158			216	
	Firms	14.8	1.3		1.5	1.5	2.1		4.8	1.0	2.6			1.3	
	Min	3	1		1	1	1		1	1	1			1	
	Max	31	2		3	2	3		7	1	4			3	
LVA	Start Year	1997			1998		2000						2007		
	End Year	2015			2015		2015						2015		
	Months	219			123		185						85		
	Firms	11.7			1.0		3.9						1.0		
	Min	1			1		1						1		
	Max	18			1		5						1		
NLD	Start Year	1992			1992	1992	1992	1992	1992	1992	1992			1992	
	End Year	2015			2015	2015	2015	2015	2015	2015	2015			2015	
	Months	282			282	282	282	203	282	282	282			282	
	Firms	68.6			7.8	17.9	4.2	1.0	26.3	8.5	5.3			4.5	
	Min	48			6	6	3	1	10	6	3			1	
	Max	83			9	29	6	1	49	11	7			9	
NOR	Start Year	1992	1992	2014	1992	1992	1992	1998	1992	1992	1998			1992	
	End Year	2015	2015	2015	2015	2015	2015	2006	2015	2015	2015			2015	
	Months	282	282	20	282	277	282	100	282	282	202			282	
	Firms	49.1	4.3	1.6	4.5	3.3	18.3	1.6	18.5	7.3	1.0			14.3	
	Min	20	3	1	1	1	10	1	2	3	1			3	
	Max	76	7	2	7	5	24	2	31	12	1			33	
POL	Start Year	1995	1995	2008	1995	1995	2004	1998	1996	1995	2003	2010	2006	2012	
	End Year	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	
	Months	251	247	95	251	243	132	204	238	244	145	52	115	41	
	Firms	97.4	6.6	3.9	17.5	22.2	3.5	3.9	39.8	9.8	5.9	1.6	4.9	1.5	
	Min	9	1	1	1	1	1	1	1	1	1	1	1	1	

	Industry	MAN	ELE	WAT	CON	WHO	TRA	FOO	COM	PRO	EMP	EDU	HEA	ART	OTH
	Max	236	19	7	48	68	10	8	134	37	13	3	12	2	
PRT	Start Year	1992	1997		1992	1992	1992	1992	1994	1998			2014	1992	
	End Year	2015	2015		2015	2015	2015	2015	2015	2001			2015	2015	
	Months	282	222		273	281	55	282	256	45			22	280	
	Firms	17.8	1.5		3.2	5.5	1.0	2.7	8.3	1.0			1.0	2.9	
	Min	12	1		1	2	1	2	1	1			1	1	
	Max	29	3		5	8	1	5	12	1			1	5	
SVK	Start Year	1995			1995		2005	2011	2007						
	End Year	2015			2011		2010	2015	2015						
	Months	244			73		42	54	104						
	Firms	4.7			1.0		1.8	1.0	1.0						
	Min	2			1		1	1	1						
	Max	6			1		2	1	1						
SVN	Start Year	1995				1995	1998	1995	2005	1999					
	End Year	2015				2015	2015	2015	2015	2015					
	Months	241				238	196	224	124	170					
	Firms	8.5				2.9	1.0	1.0	2.1	1.0					
	Min	1				1	1	1	1	1					
	Max	12				4	1	1	3	1					
SWE	Start Year	1992	1992	2001	1992	1992	1992	1997	1992	1992	1993	2001	2000	2001	
	End Year	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	2015	
	Months	282	282	171	282	282	282	227	282	282	268	150	181	163	
	Firms	137.9	3.2	1.7	9.4	20.2	9.1	2.5	48.8	12.2	8.3	1.0	2.8	5.8	
	Min	40	1	1	6	7	5	1	2	1	1	1	1	1	
	Max	281	6	5	16	34	15	4	81	23	17	1	5	10	

Part IV

Political Risk and Cross-Sectional Variation in Equity Returns

Political Risk and Cross-Sectional Variation in Equity Returns

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Abstract

We find that the changes in the Hassan et al. (2019) political Risk proxy derived from text processing of analyst transcripts can price cross-sectional returns after controlling for standard factor risks. A mimicking factor for the political risk measure, when added to the standard Fama French 5 factor model or the Q5 model, explains the test asset returns better than these models. In our limited sample, changes in the PRisk measure captures more information about political risk than the traditional measures from Baker et al. (2016), which suggests that one can start using changes in PRisk as a sysematic political risk proxy.

Keywords Political Risk, Text Processing based Measure, Analyst Transcript

1 Introduction

Hassan et al. (2019) construct a firm-based political risk (PRisk) characteristic measure using text processing of transcripts. The authors further demonstrate that their measure captures political risk as a) it varies during elections, b) it varies across sectors that are more exposed to political policy (ex: Finance, Insurance, Real Estate, Construction), c) the measure correlates with stock volatility (implied and realized), d) its increases, at the firm level, decrease investment and employment growth, and e) its increases raise lobbying and donations to politicians to manage political risk.

We show that the PRisk characteristic can explain the cross-sectional variation in stock returns and subsumes the political risk uncertainty index of Baker et al. (2016). If the sensitivity of different firms and sectors to the political risk is different across firms then the PRisk characteristics may explain differences in cross-sectional expected returns. We find evidence that the political risk characteristic indeed can explain cross-sectional variation in stock returns.

The Pastor and Veronesi (2012) general equilibrium model builds on the premise that a firm's profitability is impacted by government policy. Profitability is assumed to be stochastic with its mean affected by government policy. A cash flow effect occurs because a policy change can lead to an increase in a firm's expected profits. A discount factor effect is due to the uncertainty of the policy. On average the discount factor effect dominates over the cash flow effect and on the date of a policy announcement stock prices tend to decrease.

Pástor and Veronesi (2013) further develop their 2012 general equilibrium model by allowing investors to learn in a Bayesian fashion about the political cost through political news. Moreover they also allow for the government to choose from a set of heterogeneous policies. Investors believe that governments often intervene in times of trouble and provide put protection on asset prices. As there is uncertainty about which of potential policies will be adopted, there is a reduction in the value of the put protection. According to Pástor and Veronesi (2013), the policy decision has economic and political cost dimensions. A policy is more likely to be adopted if the political cost is low and the impact on profitability is high. It is the political cost of a policy decision that leads to uncertainty and gives rise to a political risk premium. The risk premium is smaller under weaker economic conditions, when the implicit put decreases the premium, but increases with political uncertainty. The authors decompose the risk premium into three categories: capital, impact and political. In a weak economic environment the equity premium is mainly political, whereas in a strong economic environment the equity premium is mainly impact.

Brogaard and Detzel (2015) study cross-sectional returns and empirically demonstrate that policy uncertainty has a significant negative risk premium. The authors anchor their results to the Merton (1973) ICAPM theoretical framework. Economic Policy Uncertainty (EPU) is a state variable in the ICAPM framework, measured using Baker et al. (2016), which is distinct from general economic uncertainty. EPU is largely driven by news-based shocks and can predict stock returns after controlling for general uncertainty and economic distress. The EPU represents a deterioration of the investment opportunity set and should command a negative risk premium. The authors find that the EPU is correlated to the VIX Index, VXO and monthly variance of daily VaR (value at risk) on the S&P100 index. In the contemporaneous setting EPU has a negative risk premium. We also find that changes in PRisk has a) a negative risk premium, b) is systematic in nature, & c) is correlated to the investment factor

The Baker et al. (2016) economic policy uncertainty index is the most used index in the market to refer to political uncertainty. This index is derived from text processing of articles from the 10 leading US newspapers that contains three terms namely: 1) economic or economy; 2) uncertain or uncertainty; and 3) congress, deficit, Federal reserve, legislation, regulation or White House. Ludvigson et al. (2015) and Jurado et al. (2015) measure macroeconomic uncertainty using volatility of the surprise, where the surprise is the difference between realization and forecast. The authors use a number of macro-economic series to construct their economic uncertainty index.

We show in our limited sample from 2000 to 2019 that the Hassan et al. (2019) changes in PRisk characteristic is significant after controlling for the Baker et al. (2016) and the Ludvigson et al. (2015) measures, representing policy uncertainty and general uncertainty, respectively.

Hassan et al. (2019) show that individual firm level variation accounts for 91.69% of the changes in the aggregate political risk as measured by PRisk. They suggest that firm-level idiosyncratic variations capture the political risk measure, whereas sector level and time variations do not account for much. They suggest "interactions between firms and governments are broad and complex, including crafting, revision, litigation of laws and regulations as well as budgeting and procurement decisions with highly heterogeneous and granular impact". Moreover, the authors suggest that the conventional models of Pastor and Veronesi (2012); Baker et al. (2016) do not account for the real world economic impact of political risk, as the firms care about the cross-sectional distribution of political risk more than the time-series variation. Thus one expects, PRisk to contain more information than EPU which is a news driven proxy.

2 Research Question

Firm-level quarterly earnings conference calls have information.Hassan et al. (2019) construct a firm-based political risk (PRisk) characteristic measure using text processing of quarterly earning conference calls. The biagrams that are searched include: "economic policy & budget" "environment," "trade," "institutions & political process," "health care," "security & defense," "tax policy," and "technology & infrastructure." Moreover, the authors combine the aforementioned biagrams with political biagrams like "constitution", "president", etc. to come up with their PRisk measure. The PRisk is defined as:

$$PRisk_{it} = \frac{\sum_{b}^{B_{it}} \left(\mathbf{1}\left[b \in \mathbb{P} \backslash \mathbb{N}\right] \times \mathbf{1}\left[|b-r| < 10\right] \times \frac{f_{b,\mathbb{P}}}{B_{\mathbb{P}}} \right)}{B_{it}} \tag{1}$$

"where $\mathbf{1}[.]$ is an indicator function, $\mathbb{P}\backslash\mathbb{N}$is the set of biagrams contained in $\mathbb{P}$ (training library of political text) but not $\mathbb{N}$(training library of Non political topics), and r represents the nearest synonyms of risk or uncertainty. The first two terms in the numerator thus simply count the number of bigrams associated with discussions of political but not nonpolitical topics that occur in proximity to a synonym for risk or uncertainty (within 10 words) Hassan et al. (2019)." Each biagram is weighted, in which the weights reflect the strength of the biagram to political topics $\frac{f_{b,\mathbb{P}}}{B_{\mathbb{P}}}$. $f_{b,\mathbb{P}}$ is the frequency of biagram b in the political training library $\mathbb{P}$, and $B_{\mathbb{P}}$ is the total number of biagrams in the library.

Hassan et al. (2019) demonstrates that their PRisk characteristic measures political risk: the characteristic varies during elections and across sectors which are more exposed to political policy (ex: Finance, Insurance, Real

Estate, Construction) and the measure correlates with stock volatility (implied and realized). At the firm level an increase in PRisk decreases investment and employment growth. A measured increase in PRisk increases lobbying and donating to politicians to manage political risk. The authors demonstrate that as PRisk increases there is a decrease in investment, capital expenditure, and employment at the firm level. The authors suggest that there is a macro-economic effect of the measure. The PRisk characteristic may be viewed as a type of beta for an "Economy Wide Political Risk Factor".

The main objective of this paper is to see whether the firm-level political risk characteristic proposed by Hassan et al. (2019) can explain the cross-sectional variation in stock returns after controlling for standard factors. Specifically, the objectives of this paper are:

1. Is the PRisk characteristic able to explain/ predict mean stock returns after controlling for standard factor models, the Fama-French and q-factor models Hou et al. (2014)?

2. Does the PRisk characteristic explain more cross-sectional variation than the Economic Uncertainty Index Jurado et al. (2015); Ludvigson et al. (2015) and the Policy Uncertainty Index Baker et al. (2016)?

3. Does the PRisk factor explain the investment and profitability factors of Fama and French or the Investment factor of the Q factor model, or is it simply correlated with these factors?

4. Can PRisk be viewed as a systematic risk?

5. Does PRisk Explain TFP of the firms?

The answers allow us to evaluate the value of the political risk proxy measured by the PRisk characteristic.

3 Data

The following data sources are used:

- The URL https://www.firmlevelrisk.com/ to get the PRisk characteristic at the firm level.
- CRSP for returns and market capitalization of the US firms.
- COMPUSTAT for firm level data.
- Fama-French risk factors from Kenneth French's Website.
- The factor data for the Q-factor model Hou et al. (2014) are downloaded from the url http://global-q.org/index.html
- The Baker et al. (2016) economic policy uncertainty index data are obtained from https://www.policyuncertainty.com/

- The Ludvigson et al. (2015) uncertainty index data are taken from https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes.

The data to compute return and market capitalization of the US firms are obtained from CRSP. We limit our sample to the US firms for which PRisk data are available. Table 1 details the number of firms and our sample coverage in terms of market capitalization. We see that our coverage is steadily increasing in terms of market capitalization from 65.2% in 2002 to approximately 83.4%. Thus our sample in terms of market capitalization approximates the US domestic stock market. Moreover, the breakdown in terms of the NAICS industry classification (see table 2) clearly shows that the Information, Finance & Insurance, and Manufacturing sectors are the largest sectors today and are adequately represented in our sample. Table 3 details the number of firms by NAICS sector. Tables 4, 5 & 6detail the number of large cap, medium cap and small cap firms by NAICS sector in our sample.

The PRisk summary statistics are in table 7. We have PRisk data from January 2002 to June 2019 on a quarterly basis. Since our return data is on a monthly basis, PRisk is extrapolated on a monthly basis with the assumption that for months between subsequent quarters PRisk is equal to the last quarter's value. This is a common assumption used in asset pricing (e.g. most of the papers by Fama). The Table 8 summarizes PRisk by NAICS sector. The summary statistics of the excess returns on a monthly basis are in table 7. We observe that mean returns of the sample are positive and equal 0.752% per month which is approximately 9% per year.

4 Methodology

4.1 Does PRisk explain cross-sectional variation in stock Returns

Firm level cross sectional regression avoids some of the portfolio grouping methods that are shown to affect the results (Lewellen et al., 2010). Nevertheless firm-level cross-sectional regression suffers from the Error in variable problem (EIV). Fama and MacBeth (1973), Jensen et al. (1972) avoid this problem by using portfolios rather than individual assets. Fama and French (1992) uses individual stocks, but they compute factor loadings from test portfolios as an instrument. In accordance with the EIV issue we will also form portfolios and see whether the PRisk is statistically significant in the portfolios[1].

In order to test this research question, we perform a standard Fama-MacBeth two-stage regression procedure on ~~the firm level data~~ NAICS 2 digit sector portfolios (equal weighted) formed by the firms at a monthly frequency

In the first stage, a time series regression is performed for each portfolio (denoted by i, representing the sector)

[1] PRisk data contains 0 values, which relates to Hassan et al. (2019) reporting. Moreover, when we form portfolios, it will minimize errors due to the presence of zeros in the data

as in equation 2 to obtain the loadings of the portfolio returns on a set of standard systematic risk factors:

$$r_t^i - r_t^f = \alpha^i + \boldsymbol{\beta_t^i}(\boldsymbol{F_t}) + \epsilon_t^i \tag{2}$$

Here $\boldsymbol{F_t}$ is the vector of risk factors $\begin{bmatrix} F_{1t} \\ F_{2t} \\ \vdots \\ F_{nt} \end{bmatrix}$, and $\boldsymbol{\beta_t^i}$ is the vector of estimated factor loadings $\begin{bmatrix} \beta_{1t}^i \\ \beta_{2t}^i \\ \vdots \\ \beta_{nt}^i \end{bmatrix}$.

The risk factors represent those of the standard models: CAPM, Fama-French global three-factor (FF3), Fama-French global four-factor, including also the global Carhart momentum factor (FF3+MOM), Fama-French global five-factor (FF5), and Fama-French global five-factor including the global momentum factor (FF5+MOM), the Q factor model namely the Q4 & Q5 factors. The excess annual returns of the industry portfolio are regressed on the different sets of factors. These factors act as controls for known factor risk.

We look at the stationarity of PRisk and we find that the PRisk characteristic at the portfolio level (equally weighted) are not stationary. We perform the panel unit root test as proposed by Levin et al. (2002)[2]. We find that we cannot reject the null hyphothesis that there is a unit root in the panel data. Since there is a unit root in PRisk (portfolio level) we difference the PRisk data. At the quarterly frequency we define $dPRisk_{t^q} = PRisk_{t^q} - PRisk_{t^q-1}$. At the monthly frequency the definition is $dPRisk_t = PRisk_t - PRisk_{t-3}$

In the second stage, cross-sectional regressions are performed for each (monthly) time period in which the excess monthly returns for each firm are regressed on the dPRisk characteristic and the beta coefficients of the risk factors determined in the first stage.

$$r_{t+1}^i - r_{t+1}^f = a_t + \boldsymbol{b_t}(\boldsymbol{\beta_t^i}) + c_t(dPRisk_t^i) + \eta_t^i \tag{3}$$

In equation 3 $dPRisk_t^i$ is the change in the PRisk characteristic of each firm, $\boldsymbol{\beta_t^i}$ is the vector of factor loadings for each firm obtained from the first stage. In the first stage a rolling regression is used to determine the set of betas for each model, with a window of 60 months (minimum window of 24 months). The coefficient (row) vectors $a_t, \boldsymbol{b_t}$, and $\boldsymbol{c_t}$ are estimated separately for each time period based on betas determined from prior data. Our dPRisk starts in April 2002. So we start our second stage cross-sectional regression from April 2002. We have PRisk available until June 2019[3].

[2]The adjusted t* is 4.75 with a p-value of 1.00 with a lag of 4 quarters.
[3]It would be interesting to include election dummies to account for the political risk premium varying over time, However, this is difficult to implement due to the cross-sectional nature of the study.

The mean of 207 monthly cross-sectional regressions, $[c_1\ c_2]= \frac{\mathbf{1}}{\mathbf{207}} \sum_{\boldsymbol{t=2002,4}}^{\mathbf{2019,6}} \boldsymbol{c_t}$[4], represents the estimated mean of the cross-sectional coefficients and the standard deviation of each element of $\boldsymbol{c}$ represents its standard error. The null hypothesis is that coefficients are 0, and a standard t-test is performed separately for each coefficient to check for statistical significance. Rejecting the null hypothesis in favor of the alternative hypothesis that $c_1 > 0$ and $c_2 = 0$ tests our first research question.

4.2 Does dPRisk explain more cross-sectional variation than the Economic Uncertainty Index & Policy Uncertainty Index?

In order to test this research question, we include the Baker et al. (2016) economic policy uncertainty index (henceforth PUI) and the Ludvigson et al. (2015) Economic uncertainty index (henceforth EUI) in the first stage time series regression (Equation 2). The Betas for EUI and PUI are included as factors in the second stage regression together with the PRisk characteristics. If dPRisk is significant even after the inclusion of these two risk factors then dPRisk subsumes the two indices.

We need to perform a two-pass regression for EUI and PUI as these are not tradable factors. dPRisk is treated as a characteristic (which is a loading on a characteristic mimicking portfolio) and not a factor loading.

4.3 Does dPRisk explains the Investment and Profitability factors?

An increase in political risk, leads to a decrease in investment in firms (Hassan et al. (2019)). As such, one can expect that the investment factor in the standard factor models will be capturing some of the political risk component. Moreover, the profitability of the firms will be impacted by the political risk.

In order to test whether the investment and profitability factors of the standard factor models can be explained by dPRisk, we concentrate on the factor sensitivities β^i_{RMW}, β^i_{CMA} from the FF5 and FF5 + momentum models and the β_{ROE}, β_{IA} of the q-factor models. These betas are obtained in the first pass for the systematic profitability and investment factors.

The factor loadings for each portfolios are regressed cross-sectionally on the PRisk values pertaining to each firm in a cross-sectional regression as in equations 4, 5, 6, and 7below. The hypothesis is supported if the null hypothesis that a slope coefficient $h = 0$ can be rejected in favor of the alternative hypothesis that a slope coefficient is significantly positive, $h > 0$

[4]For PRisk it is the mean of 210 monthly cross-sectional regression $[c_1\ c_2]= \frac{\mathbf{1}}{\mathbf{210}} \sum_{\boldsymbol{t=2002,1}}^{\mathbf{2019,6}} \boldsymbol{c_t}$

$$\beta^i_{RMW} = g + h * dPRisk^i_t + \omega^i. \tag{4}$$

$$\beta^i_{CMA} = g + h * dPRisk^i_t + \omega^i. \tag{5}$$

$$\beta^i_{ROE} = g + h * dPRisk^i_t + \omega^i. \tag{6}$$

$$\beta^i_{IA} = g + h * dPRisk^i_t + \omega^i. \tag{7}$$

In addition, we check directly how much the risk premium on β^i_{RMW}, β^i_{CMA}, β_{ROE}, $\beta_{IA}$is attenuated when $dPRisk^i$ is added in the cross-sectional regressions, equation 3.

4.4 Can dPRisk be viewed as a systematic risk?

We convert the PRisk characteristic into a risk factor using the Fama-French Methodology Fama and French (1992). A hedge portfolio is formed from portfolio sorts based on PRisk. The hedge portfolio is long on the top quintile and short on the bottom quintile. The returns of the portfolio are the PRisk mimicking factor ($r^i_t \equiv r^{dPRisk}_t$) . Once we have the mimicking factor, we can perform the Barillas-Shanken test (Barillas and Shanken (2017)) to check whether the inclusion of this factor to the standard factor models adds value.

4.5 Does dPRisk impact TFP?

Hassan et al. (2019) shows that an increase in PRisk leads to a decrease in employment and a decrease in investment. This is a firm level regression as TFP is found at the firm level.

We want to check whether a firm's increase in sensitivity to political risk is directly related to the firm's productivity, whether the PRisk characteristic or changes in PRisk characteristic (dPRisk) and Total Factor Productivity (TFP) are related. We check this with a panel regression, including fixed effects for "sector", "year", and "sector*year". Here $dPRisk\_sc^i_t = dPRisk^i_t/1000$. We also check whether PRisk explains TFP.

$$dTFP^i_t = \alpha_0 + \beta * dPRisk\_sc^i_t + e_t \tag{8}$$

$$TFP_t^i = \alpha_0 + \beta * PRisk\_sc_t^i + e_t \tag{9}$$

We compute TFP at the firm level using İmrohoroğlu and Tüzel (2014). Firm level data are obtained from Compustat. Labor is estimated by the number of employees. Capital is estimated from gross property plant and equipment, which is deflated using the price index for private fixed investment (Hall (1990)). Following İmrohoroğlu and Tüzel (2014)'s web appendix, Value Added is computed using net sales - (total expenses - labor expense). The labor expense is estimated as average wage * number of employees. Average wage is derived from the national wage index from the US social security administration. Total expense is estimated using net sales - operating income before depreciation and amortization. The value added so obtained is deflated using the price index for GDP.

TFP is estimated from

$$y_t^i = \beta_0 + \beta_k k_t^i + \beta_l l_t^i + TFP_t^i + \eta_t^i \tag{10}$$

Equation 10 is estimated in semi-parametric manner using Olley and Pakes (1996).

5 Empirical Results

5.1 Does dPRisk explain cross-sectional variation in stock Returns?

Table 10 provides the second pass Fama-Macbeth cross-sectional results, standalone and with the CAPM factor. We observe that the scaled dPRisk (dPRisk_sc defined as dPRisk/1000) variable is significant at 1% and can explain the cross-sectional variation in stock returns. The scaled dPRisk characteristic alone has a coefficient of -4.57. Since the standard deviation of scaled dPRisk is 0.057, an increase of one standard deviation of scaled dPRisk causes a decrease in return of 0.26% or, annualized, 3.15%. After controlling for the CAPM factor, FF3, Carhart, FF5 (Tables 11, 12, 13, and 14) , the scaled dPRisk coefficients are -4.27, -5.19, -4.09, & -3.80 respectively. All are significant at 1 or 5%[5]. The coefficient estimates imply that an increase of one standard deviation of the scaled dPRisk causes a decrease varying from 2.62% to 3.58% annually. We also observe that for FF5 + carhart momentum factor is not statistically significant at 10%. but economically significant.

In terms of the Q model, the coefficients of the scaled dPRisk charateristic are -3.32 (Q4), and -3.33 (Q5) and significant at 5%. The details are in tables 15, and 16.

It is clear that dPRisk is significant at 5% and that a one standard deviation change in dPRisk explains a change of approximately 3% in annual mean returns after controlling for the standard model risk factors.

[5] We find similar results for value-weighted portfolio.

The dPRisk risk premium is negative supporting the Brogaard and Detzel (2015) prediction.

5.2 Does dPRisk explain more cross-sectional variation than the Economic Uncertainty Index & Policy Uncertainty Index?

Table 10 shows that on a standalone basis PUI (Baker et al. (2016)) and EUI (Ludvigson et al. (2015) have coefficients of 6.80 and 0.01. But these results are not significant in our sample. Moreover, we find that when scaled dPRisk is combined with PUI, EUI or both scaled dPRisk remains significant at 5% and has a coefficient of -4.24, -3.74 and -4.57 respectively. After controlling for the CAPM factor, scaled dPRisk when combined with PUI, EUI is significant at 1% and has a coefficient of -4.94 & -4.27. When dPRisk is combined with both PUI and EUI after controlling for CAPM risk factor, the coefficient is -4.06 and significant at 5%.

From tables 11, 12, 13 we observe that, after controlling for the FF3, Carhart, FF5 , scaled dPRisk is still significant at 1% to 5% significance. The scaled dPRisk coefficient ranges from -3.78 to -5.34 when combined with PUI. Its coefficient ranges from -3.64 to -5.05 when combined with EUI and its coefficient ranges from -3.73 to -5.07 when combined with PUI and EUI. For FF5 + momentum factor (table 14) we don't see any statistical significance though there is economic significance.

From the table 15, we see that for Q4 model scaled dPRisk is significant at 5% and 10% when controlling for PUI and EUI. But when we control for both then it is not significant. From the table 16, we see that after controlling for the Q5 model scaled dPRisk is not staitistically significant.

In our sample, we see that the dPRisk characteristic is able to explain cross-sectional variation after controlling for standard factor models and EUI and PUI for most cases. We can conclude from our sample that dPRisk is a better measure of political risk compared to PUI.

5.3 Does dPRisk explain the investment and profitability factors of FF or the investment factor of the Q factor model?

Table 17 shows the results when the factor loadings on the profitability and the investment factors are regressed cross-sectionally on the scaled dPRisk values according to equations 4, 5, 6, and 7. We observe that the Investment factor of FF5 and FF5 + momentum and the IA factor of Q4 and Q5 can be explained by the scaled dPRisk factor. The average of 207 cross-sectional regressions is significant at 1% for the Q4 & Q5 models and significant at 10% for the FF5 & FF5+momentum models. We also observe that the sign of the coefficient is negative for both profitability and investment factors. We observe that dPRisk cannot explain the profitability factor[6].

5.4 Can dPRisk be viewed as a systematic risk?

The mimicking factor r_t^{dPRisk}derived from an equal weighted portfolio, can be tested with standard factor models using Barillas and Shanken (2017). We can conduct a nested unconditional (assuming constant factor loadings over the full sample) model comparison that is valid for any group of test assets. Essentially, any group of factors that has a larger maximum Sharpe ratio than a competing group of factors, will explain any group of test assets better (as long as this group of test assets includes both groups of factors). A model that consists of the union of the factors from two contesting models is the "large" model. We can test if the large model explains assets significantly better than either one of the "small" component models. The test is equivalent to the GRS test but with the small model serving as the factor model and the large model serving as the test assets. The test finds whether the maximum Sharpe Ratio of the large model is significantly larger than the Sharpe Ratio of the small model; or, equivalently, whether the factors excluded from the small model have significantly positive alphas as a group when explained by the factors from the small model. If they have significantly larger alphas, it follows that the large model when set to explain any group of test assets will have smaller alphas than the small model (when weighted by the inverse return covariance matrix).

From the table 19, we observe that when the larger model is CAPM + r_t^{dPRisk}, FF3 + r_t^{dPRisk}, Carhart + r_t^{dPRisk}, FF5 + r_t^{dPRisk}, FF5 +momentum +r_t^{dPRisk}, Q4 + r_t^{dPRisk}, and Q5 + r_t^{dPRisk} and the smaller model are CAPM, FF3. Carhart, FF5, FF5+ momentum, Q4 and Q5 respectively. The alpha are large and significant. The absolute mean alpha ranges from 0.038% per month to 0.14% per month and is significant at 1%. This evidence suggest that adding the characteristic mimicking portfolio returns r_t^{dPRisk} to the standard models can explain the test assets results better than the standard model.

The Barillas and Shanken (2017) test supports the fact that dPRisk is capturing systematic risk component.

Other industry level characteristics may affect returns, but are not considered since they are unlikely to affect average returns because they are not associated with a systematic risk.

5.5 Does dPRisk Impact TFP?

From table 20, we observe that dPRisk is not able to explain $dTFP$. Whereas PRisk is able to explain TFP.

[6]When we use PRisk (we have to interpret the result with caution, as there is a unit root in the panel data) instead of dPrisk as in table 18, we observe that both systematic profitability and investment factor can be explained by PRisk.

Table 21 details the results for the fixed panel regression for equation 9. This panel regression is at the firm level. We see that an increase in scaled PRisk causes a decrease in firm level TFP. The scaled PRisk has a standard deviation of 0.23. Thus a one standard deviation increase in PRisk will lead to a decrease in TFP by 7.22% (coefficient -0.018 multiplied by 0.23 the standard deviation of scaled PRisk and divided by standard deviation of TFP 0.58). Thus political risk as represented by PRisk appears to be an important retardant of productivity at the firm level.

6 Conclusion

In our limited sample, we are able to show that the Hassan et al. (2019) dPRisk characteristic can explain cross-sectional variation in returns after controlling for standard risk measures. We also show that this measure is significant even after controlling for the policy uncertainty index and the economic uncertainty index. Further, we see that a mimicking portfolio obtained from the characteristic is able to explain returns better when combined with the standard models. All this suggests that the dPRisk measure derived from PRisk is a superior alternative measure for political systematic risk.

Differences in PRisk measure (dPRisk) are correlated to the investment risk factor which suggest that the investment risk factor in the standard models can be explained to some extend by dPRisk. Though PRisk is correlated to TFP, we don't find any evidence that dTFP is correlated to dPRisk.

PRisk characteristic is available at the firm level, whereas PUI is a macro non-tradable political risk index. These two indexes are constructed differently and just on the basis of construction PRisk will capture firm specific sensisitivity to political risk. The Difference in PRisk is built from bottom up and we find that it can price portfolios in the cross-section after controlling for PUI. Moreover, with the help of a mimicking portfolio, we can create a tradable political risk factor at the frequency of our choice.

References

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The quarterly journal of economics*, 131(4):1593–1636.

Barillas, F. and Shanken, J. (2017). Which alpha? *The Review of Financial Studies*, 30(4):1316–1338.

Brogaard, J. and Detzel, A. (2015). The asset-pricing implications of government economic policy uncertainty. *Management Science*, 61(1):3–18.

Fama, E. F. and French, K. R. (1992). The cross-section of expected stock returns. *the Journal of Finance*, 47(2):427–465.

Fama, E. F. and MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3):607–636.

Hall, B. H. (1990). The manufacturing sector master file: 1959-1987. Technical report, National Bureau of Economic Research.

Hassan, T. A., Hollander, S., van Lent, L., and Tahoun, A. (2019). Firm-level political risk: Measurement and effects. *The Quarterly Journal of Economics*, 134(4):2135–2202.

Hou, K., Xue, C., and Zhang, L. (2014). Digesting Anomalies: An Investment Approach. *The Review of Financial Studies*, 28(3):650–705.

İmrohoroğlu, A. and Tüzel, Ş. (2014). Firm-level productivity, risk, and return. *Management Science*, 60(8):2073–2090.

Jensen, M. C., Black, F., and Scholes, M. S. (1972). The capital asset pricing model: Some empirical tests.

Jurado, K., Ludvigson, S. C., and Ng, S. (2015). Measuring uncertainty. *American Economic Review*, 105(3):1177–1216.

Levin, A., Lin, C.-F., and Chu, C.-S. J. (2002). Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of econometrics*, 108(1):1–24.

Lewellen, J., Nagel, S., and Shanken, J. (2010). A skeptical appraisal of asset pricing tests. *Journal of Financial economics*, 96(2):175–194.

Ludvigson, S. C., Ma, S., and Ng, S. (2015). Uncertainty and business cycles: exogenous impulse or endogenous response? Technical report, National Bureau of Economic Research.

Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica: Journal of the Econometric Society*, pages 867–887.

Olley, G. S. and Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64(6):1263.

Pastor, L. and Veronesi, P. (2012). Uncertainty about government policy and stock prices. *The journal of Finance*, 67(4):1219–1264.

Pástor, L. and Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of financial Economics*, 110(3):520–545.

Table 1: Details of PRisk Data For US Firms in terms of number & market Capitalization

The table summarizes the sample for which PRisk is available in terms of number of firms and market capitalization. The data is for June of every year. The total Market Cap in Trillions of USD is from World Bank.

Year	# of firms	Market Cap in Trillions of USD (June)	Market Cap in Trillions of USD (Dec)	Total Market Cap in Trillions of USD	Coverage
2002	1,325	7.06	7.2	11.05	65.2%
2003	1,705	8.34	9.93	14.27	69.6%
2004	2,261	10.5	11.1	16.32	68.0%
2005	2,405	11.3	12.4	17	72.9%
2006	2,529	13	14.3	19.57	73.1%
2007	2,584	15	14.8	19.92	74.3%
2008	2,770	13.4	9.02	11	82.0%
2009	2,689	9.42	11.7	15.08	77.6%
2010	2,593	10.9	13.1	17.28	75.8%
2011	2,744	15.3	14	15.64	89.5%
2012	2,780	15.1	15.8	18.67	84.6%
2013	2,452	17.6	20.6	24.03	85.7%
2014	2,768	21.9	22.2	26.33	84.3%
2015	2,696	22.5	21.4	25.07	85.4%
2016	2,585	22.1	22.9	27.35	83.7%
2017	2,814	25.7	28.4	32.12	88.4%
2018	2,890	28.4	25.4	30.44	83.4%
2019	2,932	29.7			NA

Table 2: Market Cap of US Firms in USD Billions by Sector

The table summarizes the sample in terms of NAICS sectors for which PRisk is available in terms of market capitalization. In order to arrive at the sector market capitalization the market cap of firms are added together for the month of June of every year.

Sector	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Agriculture, Forestry, Fishing and Hunti	3.3	3.4	2.4	19.6	24.5	39.0	71.8	44.3	27.9	44.3	47.6	56.8	68.0	52.2	48.3	54.9	2.7	1.8
Mining, Quarrying, and Oil and Gas Extra	163.0	203.0	292.0	462.0	676.0	773.0	1250.0	637.0	737.0	1190.0	986.0	1030.0	1440.0	880.0	805.0	886.0	1150.0	810.0
Utilities	221.0	237.0	293.0	410.0	464.0	525.0	539.0	386.0	426.0	512.0	562.0	637.0	765.0	708.0	869.0	803.0	810.0	1050.0
Construction	29.3	42.6	112.0	168.0	168.0	187.0	213.0	114.0	115.0	66.3	65.4	92.4	103.0	87.4	83.6	118.0	132.0	131.0
Manufacturing	3040.0	3470.0	4730.0	4930.0	5610.0	6700.0	6250.0	4310.0	4900.0	6850.0	6760.0	7710.0	9600.0	9780.0	9540.0	10600.0	11500.0	11800.0
Wholesale Trade	81.5	103.0	135.0	144.0	165.0	172.0	137.0	102.0	130.0	168.0	168.0	210.0	280.0	293.0	292.0	320.0	321.0	315.0
Retail Trade	602.0	601.0	713.0	737.0	740.0	805.0	665.0	581.0	655.0	726.0	807.0	969.0	1040.0	1370.0	1620.0	1670.0	1880.0	2010.0
Transportation and Warehousing	83.7	163.0	209.0	248.0	334.0	357.0	352.0	244.0	285.0	393.0	381.0	462.0	640.0	699.0	600.0	796.0	815.0	874.0
Information	770.0	1050.0	1240.0	1190.0	1200.0	1410.0	1110.0	898.0	1010.0	1760.0	1840.0	2180.0	2800.0	3030.0	3460.0	4130.0	4880.0	5570.0
Finance and Insurance	1320.0	1640.0	2070.0	2250.0	2720.0	3130.0	2010.0	1470.0	1850.0	2470.0	2320.0	3000.0	3600.0	3910.0	3430.0	4580.0	4980.0	5110.0
Real Estate and Rental and Leasing	11.4	14.0	53.6	54.5	62.0	97.5	73.4	51.2	70.3	110.0	105.0	136.0	198.0	196.0	179.0	230.0	317.0	300.0
Professional, Scientific, and Technical	237.0	278.0	312.0	308.0	324.0	356.0	365.0	283.0	332.0	481.0	471.0	497.0	523.0	530.0	355.0	447.0	523.0	575.0
Administrative and Support and Waste Man	50.6	60.2	83.7	87.8	113.0	121.0	94.8	75.0	75.5	116.0	119.0	154.0	190.0	216.0	217.0	278.0	333.0	348.0
Educational Services	6.9	10.9	16.1	15.7	12.6	14.3	12.4	15.9	17.3	25.4	15.6	11.0	15.7	11.3	8.4	15.3	13.8	18.7
Health Care and Social Assistance	64.7	60.7	83.2	109.0	105.0	93.2	68.2	54.6	68.3	96.9	88.1	113.0	142.0	199.0	140.0	180.0	196.0	197.0
Arts, Entertainment, and Recreation	9.6	14.8	9.4	13.7	17.0	32.4	15.4	12.5	14.0	21.6	22.9	31.8	33.3	32.1	33.3	45.4	64.3	62.7
Accommodation and Food Services	74.3	88.9	106.0	146.0	201.0	222.0	166.0	137.0	183.0	273.0	300.0	334.0	447.0	453.0	423.0	509.0	526.0	605.0
Other Services (except Public Administra	1.8	8.6	11.7	13.2	12.3	12.8	8.8	6.3	7.7	15.0	11.3	11.5	10.5	12.2	11.0	11.4	15.3	11.5
Undefined	289.0	287.0							0.1									
Sum (Trillion $)	**7.06**	**8.34**	**10.47**	**11.31**	**12.95**	**15.05**	**13.40**	**9.42**	**10.90**	**15.32**	**15.07**	**17.64**	**21.90**	**22.46**	**22.11**	**25.67**	**28.46**	**29.79**

Table 3: Number of US Firms by Sector

The table summarizes the sample in terms of NAICS sectors for which PRisk is available in terms of number of firms. In order to arrive at the sector market capitalization the market cap of firms are added together for the month of June of every year.

Sector	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Agriculture, Forestry, Fishing and Hunti	3	3	3	4	4	3	4	4	4	5	5	5	5	4	4	3	3	3
Mining, Quarrying, and Oil and Gas Extra	53	58	86	92	107	122	141	151	141	156	173	154	175	163	131	165	177	172
Utilities	48	52	66	70	73	77	81	80	83	82	74	72	78	77	74	76	70	75
Construction	22	21	29	31	35	37	40	39	35	40	41	44	46	37	39	44	45	48
Manufacturing	594	718	954	1,018	1,085	1,127	1,200	1,149	1,104	1,153	1,150	997	1,121	1,088	1,009	1,129	1,169	1,217
Wholesale Trade	34	44	65	70	73	73	71	66	67	71	73	70	73	70	70	84	84	81
Retail Trade	83	117	138	133	133	139	140	134	131	142	144	138	137	136	129	128	133	126
Transportation and Warehousing	30	39	54	57	66	65	72	74	71	73	76	73	74	73	70	75	78	84
Information	151	226	280	293	295	284	299	293	275	281	305	277	329	325	329	337	356	355
Finance and Insurance	127	173	251	274	284	293	326	312	311	336	345	277	350	363	387	390	404	406
Real Estate and Rental and Leasing	19	14	27	30	34	39	43	41	41	48	51	46	51	50	49	58	59	61
Professional, Scientific, and Technical	61	97	121	136	129	124	138	131	124	133	130	109	120	107	96	104	94	94
Administrative and Support and Waste Man	34	43	59	60	61	57	62	61	50	62	59	54	59	55	54	63	69	66
Educational Services	9	8	11	12	12	11	13	15	17	21	18	16	19	15	12	15	13	13
Health Care and Social Assistance	21	34	44	48	53	55	58	57	59	53	54	42	45	45	44	49	48	46
Arts, Entertainment, and Recreation	9	13	15	17	17	17	17	18	18	19	19	18	20	17	16	21	19	21
Accommodation and Food Services	22	37	46	48	54	50	54	53	50	56	52	51	58	63	65	67	64	59
Other Services (except Public Administra	4	7	12	12	14	11	11	11	11	13	11	9	8	8	7	6	5	5
Undefined	1	1							1									
Sum	**1325**	**1705**	**2261**	**2405**	**2529**	**2584**	**2770**	**2689**	**2593**	**2744**	**2780**	**2452**	**2768**	**2696**	**2585**	**2814**	**2890**	**2932**

Table 4: Number of Large-Cap US Firms by Sector

The table summarizes the sample in terms of NAICS sectors for which PRisk is available in terms of number of Large Cap firms. Large Cap firms are defined as one with market cap > $10 Billion USD. The data is for the month of June for a given year.

Sector	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Agriculture, Forestry, Fishing and Hunti	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
Mining, Quarrying, and Oil and Gas Extra	4	7	8	13	23	24	35	21	20	32	27	31	36	22	25	25	31	26
Utilities	7	8	9	14	16	17	18	14	15	15	18	20	26	21	26	25	26	31
Construction	0	1	2	4	2	1	3	1	1	1	0	0	1	1	1	3	3	4
Manufacturing	50	59	80	86	98	114	99	78	85	117	109	136	162	167	156	170	187	180
Wholesale Trade	2	3	3	3	3	3	3	3	3	4	3	6	7	7	7	9	11	10
Retail Trade	11	10	14	15	15	15	14	13	13	22	22	23	24	28	22	23	24	21
Transportation and Warehousing	3	5	7	9	10	11	10	8	7	10	8	11	15	17	16	19	21	20
Information	11	18	20	19	22	26	19	17	21	32	31	37	48	50	48	55	66	72
Finance and Insurance	33	37	41	43	53	59	47	36	36	51	50	57	59	65	63	80	83	86
Real Estate and Rental and Leasing	0	0	1	1	1	2	2	0	2	3	2	3	5	3	3	4	3	3
Professional, Scientific, and Technical	3	4	4	5	6	6	5	2	4	9	8	7	7	9	6	10	15	14
Administrative and Support and Waste Man	1	1	1	2	2	2	1	1	2	2	2	4	5	7	6	7	9	9
Educational Services	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Health Care and Social Assistance	2	1	1	2	2	1	0	1	0	2	2	3	3	6	5	6	5	5
Arts, Entertainment, and Recreation	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	2	1
Accommodation and Food Services	1	1	3	5	6	6	4	3	5	7	8	7	10	10	8	14	13	13
Other Services (except Public Administra	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Undefined	1	1							0									
Sum	**129**	**156**	**194**	**222**	**260**	**289**	**261**	**199**	**215**	**308**	**291**	**346**	**409**	**414**	**393**	**451**	**499**	**495**

Table 5: Number of Medium-Cap US Firms by Sector

The table summarizes the sample in terms of NAICS sectors for which PRisk is available in terms of number of Medium Cap firms. Medium Cap firms are defined as one with market cap between 2 Billion and $10 Billion USD. The data is for the month of June for a given year.

Sector	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Agriculture, Forestry, Fishing and Hunti	0	0	0	0	0	0	0	1	0	1	0	0	0	1	1	1	1	0
Mining, Quarrying, and Oil and Gas Extra	17	22	29	32	34	40	50	32	39	55	54	53	69	56	45	50	57	28
Utilities	18	21	27	34	34	34	33	34	36	37	33	33	35	39	33	32	29	29
Construction	5	6	10	13	12	15	8	8	9	10	9	13	13	12	10	13	15	14
Manufacturing	103	136	165	177	192	223	201	156	185	250	229	250	282	288	250	279	301	301
Wholesale Trade	4	4	11	11	17	16	14	10	12	19	18	21	24	25	24	25	22	24
Retail Trade	13	19	29	27	29	35	24	21	28	29	31	37	43	40	31	30	26	25
Transportation and Warehousing	4	9	10	14	18	17	14	9	12	15	18	20	18	15	16	15	15	16
Information	18	29	35	36	39	55	50	46	48	55	66	75	79	85	79	90	106	102
Finance and Insurance	25	57	75	78	74	82	65	52	66	79	82	94	114	113	107	108	122	114
Real Estate and Rental and Leasing	0	1	4	4	8	11	7	7	8	8	9	14	21	17	15	22	23	20
Professional, Scientific, and Technical	11	13	16	19	19	23	22	21	19	25	15	27	33	31	33	31	29	30
Administrative and Support and Waste Man	4	9	10	10	12	14	11	9	7	15	16	16	19	18	16	19	23	19
Educational Services	1	2	3	4	3	2	2	3	3	4	2	0	3	1	1	3	2	3
Health Care and Social Assistance	3	8	11	10	12	12	11	6	9	11	11	11	14	12	10	11	12	14
Arts, Entertainment, and Recreation	1	1	0	1	1	2	1	2	1	4	4	8	6	6	7	7	8	10
Accommodation and Food Services	3	7	8	10	10	6	5	6	6	6	6	11	17	18	17	11	13	14
Other Services (except Public Administra	0	1	2	2	2	2	2	0	0	2	2	2	1	1	2	2	2	1
Undefined	0	0							0									
Sum	**230**	**345**	**445**	**482**	**516**	**589**	**520**	**423**	**488**	**625**	**605**	**685**	**791**	**778**	**697**	**749**	**806**	**764**

Table 6: Number of Small-Cap US Firms by Sector

The table summarizes the sample in terms of NAICS sectors for which PRisk is available in terms of number of Small Cap firms. Small Cap firms are defined as one with market cap $<$ \$2 Billion USD. The data is for the month of June for a given year.

Sector	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Agriculture, Forestry, Fishing and Hunti	3	3	3	3	3	2	3	2	3	3	4	4	4	2	2	1	2	3
Mining, Quarrying, and Oil and Gas Extra	32	29	49	47	50	58	56	98	82	69	92	70	70	85	61	90	89	118
Utilities	23	23	30	22	23	26	30	32	32	30	23	19	17	17	15	19	15	15
Construction	17	14	17	14	21	21	29	30	25	29	32	31	32	24	28	28	27	30
Manufacturing	441	523	709	755	795	790	900	915	834	786	812	611	677	633	603	680	681	736
Wholesale Trade	28	37	51	56	53	54	54	53	52	48	52	43	42	38	39	50	51	47
Retail Trade	59	88	95	91	89	89	102	100	90	91	91	78	70	68	76	75	83	80
Transportation and Warehousing	23	25	37	34	38	37	48	57	52	48	50	42	41	41	38	41	42	48
Information	122	179	225	238	234	203	230	230	206	194	208	165	202	190	202	192	184	181
Finance and Insurance	69	79	135	153	157	152	214	224	209	206	213	126	177	185	217	202	199	206
Real Estate and Rental and Leasing	19	13	22	25	25	26	34	34	31	37	40	29	25	30	31	32	33	38
Professional, Scientific, and Technical	47	80	101	112	104	95	111	108	101	99	107	75	80	67	57	63	50	50
Administrative and Support and Waste Man	29	33	48	48	47	41	50	51	41	45	41	34	35	30	32	37	37	38
Educational Services	8	6	8	8	9	9	11	12	14	17	16	16	16	14	11	12	11	10
Health Care and Social Assistance	16	25	32	36	39	42	47	50	50	40	41	28	28	27	29	32	31	27
Arts, Entertainment, and Recreation	8	12	15	16	16	14	16	16	17	15	15	10	14	11	9	14	9	10
Accommodation and Food Services	18	29	35	33	38	38	45	44	39	43	38	33	31	35	40	42	38	32
Other Services (except Public Administra	4	6	10	10	12	9	9	11	11	11	9	7	7	7	5	4	3	4
Undefined	0	0							1									
Sum	**966**	**1204**	**1622**	**1701**	**1753**	**1706**	**1989**	**2067**	**1890**	**1811**	**1884**	**1421**	**1568**	**1504**	**1495**	**1614**	**1585**	**1673**

Table 7: PRisk Summary Statistics

The table finds summary statistics of PRisk and excess stock returns on a monthly basis.

PRisk				
# of firm Months	Mean	Std. Deviation	Min	Max
530,263	122.1467	229.1574	0	11056.95

$scalePRisk = PRisk/1000$				
# of firm Months	Mean	Std. Deviation	Min	Max
530,263	.1221467	.2291574	0	11.05695

$r_t^i - r_t^f$ (in percentage)				
# of firm Months	Mean	Std. Deviation	Min	Max
530,263	.7517944	13.47603	-43.69586	60.19606

Table 8: Summary Statistics of PRisk by Sector

The table summarizes the sample in terms of NAICS sectors for which PRisk is available.

Sector	**Mean**	**SD**	**Min**	**Max**
Agriculture, Forestry, Fishing and Hunti	97.8	160.1	0	1526.8
Mining, Quarrying, and Oil and Gas Extra	120.2	195.9	0	4644.2
Utilities	171.6	265.0	0	5883.4
Construction	134.2	208.0	0	3076.7
Manufacturing	110.9	218.6	0	11056.9
Wholesale Trade	87.0	175.7	0	4239.7
Retail Trade	69.1	135.2	0	4455.6
Transportation and Warehousing	107.6	169.0	0	2571.1
Information	96.5	170.1	0	5421.9
Finance and Insurance	194.6	303.5	0	8330.1
Real Estate and Rental and Leasing	113.6	187.6	0	2646.6
Professional, Scientific, and Technical	139.9	274.0	0	6363.4
Administrative and Support and Waste Man	146.2	279.5	0	6032.0
Educational Services	142.8	232.8	0	2947.0
Health Care and Social Assistance	171.9	333.6	0	5264.4
Arts, Entertainment, and Recreation	128.0	298.8	0	7524.2
Accommodation and Food Services	85.1	173.6	0	2977.3
Other Services (except Public Administra	70.3	102.0	0	1385.0
Undefined	165.4	135.4	40.3	516.6

Table 9: PRisk portfolio level (equal weighted) Summary Statistics

The table finds summary statistics of PRisk for a equal weighted portfolio and excess stock returns of an equal weighted portfolio on a monthly basis.

PRisk				
# of portfilo Months	Mean	Std. Deviation	Min	Max
3809	121.996	58.06	0	530.57

$scalePRisk = PRisk/1000$				
# of portfilo Months	Mean	Std. Deviation	Min	Max
3809	.121996	.05806	0	0.5305

dPRisk				
# of portfilo Months	Mean	Std. Deviation	Min	Max
3,749	-.40833	57.47169	-527.0787	771.7422

$scaledPRisk = dPRisk/1000$				
# of portfilo Months	Mean	Std. Deviation	Min	Max
3,749	-.0004083	.0574717	-.5270787	.7717422

$r_t^i - r_t^f$ (in percentage)				
# of Portfolio Months	Mean	Std. Deviation	Min	Max
4489	.7061	6.4492	-17.04	22.77

Table 10: Second Stage Fama-MacBeth Regressions with PRisk and the Fama-French CAPM Risk Factor

The excess returns of equally weighted portfolios are regressed at a monthly frequency for the period January 2002-June 2019 on dPRisk controlling for the CAPM beta, Economic Uncertainty Index Beta Ludvigson et al. (2015) and Policy Uncertainty Index Beta Baker et al. (2016) . The US market factor is taken from Kenneth French's website. The cross-sectional regression is :

$$r_t^i - r_t^f = a_t + b_t^{MKT}\beta_{MKT}^i + b_t^{EUI}\beta_{EUI}^i + b_t^{PUI}\beta_{PUI}^i + c_t^{dPRisk\_sc} dPRisk\_sc_t^i + \eta_t^i$$

where i is representing a sector level portfolio and $dPRisk\_sc = dPRisk/1000$. The coefficients and the standard errors in this table are the means and standard deviations of a_t, $b_t^{MKT}, b_t^{EUI}, b_t^{PUI}$, $c_t^{dPRisk\_sc}$ based on the 207 monthly regression from April 2002-June 2019.

	dPRisk_sc	eui	eui+	pui	pui+	puieui	puieui+	CAPM	CAPM+	CAPMunc	CAPMunc+	CAPMpui	CAPMpui+	CAPMup	CAPMup
c^{dPRisk_sc}	-4.5713		-3.7403		-4.2474		-4.5713		-4.4488		-4.2797		-4.9497		-4.0634
T-STAT	(-2.31)**		(-2.02)**		(-2.13)**		(-2.31)**		(-2.45)**		(-2.62)***		(-2.67)***		(-2.27)**
P-VALUE	[0.02]		[0.04]		[0.03]		[0.02]		[0.02]		[0.01]		[0.01]		[0.02]
b^{EUI}		0.0148	0.0113							-0.0003	-0.0005			0.0057	0.0032
T-STAT		(1.14)	(0.89)							(-0.02)	(-0.03)			(0.38)	(0.22)
P-VALUE		[0.26]	[0.37]							[0.99]	[0.98]			[0.70]	[0.83]
b^{PUI}				6.8012	5.6850							4.1010	4.1069	0.3852	-0.0723
T-STAT				(1.18)	(0.95)							(0.68)	(0.66)	(0.07)	(-0.01)
P-VALUE				[0.24]	[0.34]							[0.49]	[0.51]	[0.95]	[0.99]
b^{MKT}								-0.1070	-0.2388	0.1519	-0.0196	-0.0790	-0.1302	0.0277	-0.0081
T-STAT								(-0.26)	(-0.58)	(0.35)	(-0.05)	(-0.18)	(-0.29)	(0.06)	(-0.02)
P-VALUE								[0.80]	[0.56]	[0.73]	[0.96]	[0.86]	[0.77]	[0.95]	[0.99]
R^2	0.08	0.11	0.18	0.12	0.20	0.00	0.08	0.15	0.22	0.26	0.32	0.26	0.33	0.36	0.42
N	3,749	3,749	3,749	3,749	3,749	3,749	3,749	3,749	3,749	3,749	3,749	3,749	3,749	3,749	3,749

* $p<0.10$; ** $p<0.05$; *** $p<0.01$

Table 11: Second Stage Fama-MacBeth Regressions with PRisk and the Fama-French FF3 Risk Factor

The excess returns of equally weighted portfolios are regressed at a monthly frequency for the period January 2002-June 2019 on dPRisk controlling for the FF 3 factor betas, Economic Uncertainty Index Beta Ludvigson et al. (2015) and Policy Uncertainty Index Beta Baker et al. (2016). The US market factor is taken from Kenneth French's website. The cross-sectional regression is :

$$r_t^i - r_t^f = a_t + b_t^{MKT}\beta_{MKT}^i + b_t^{SMB}\beta_{SMB}^i + b_t^{HML}\beta_{HML}^i + b_t^{EUI}\beta_{EUI}^i + b_t^{PUI}\beta_{PUI}^i + c_t^{dPRisk\_sc} dPRisk\_sc_t^i + \eta_t^i$$

where i is representing a sector level portfolio and $dPRisk\_sc = dPRisk/1000$. The coefficients and the standard errors in this table are the means and standard deviations of a_t, $b_t^{MKT}, b_t^{SMB}, b_t^{HML}, b_t^{EUI}, b_t^{PUI}$, $c_t^{dPRisk\_sc}$ based on the 207 monthly regression from April 2002-June 2019.

Coeff	FF3	FF3+	FF3unc	FF3unc+	FF3pui	FF3pui+	FF3up	FF3up
b^{MKT}	-0.5774	-0.7588	-0.2049	-0.2949	-0.3548	-0.4680	-0.3988	-0.3721
T-STAT	(-1.07)	(-1.40)	(-0.39)	(-0.55)	(-0.65)	(-0.85)	(-0.77)	(-0.71)
P-VALUE	[0.29]	[0.16]	[0.70]	[0.58]	[0.52]	[0.39]	[0.44]	[0.48]
b^{SMB}	0.5577	0.6586	0.7325	0.7915	0.2747	0.3248	0.4792	0.5053
T-STAT	(1.71)*	(2.02)**	(2.28)**	(2.44)**	(0.82)	(0.97)	(1.49)	(1.56)
P-VALUE	[0.09]	[0.05]	[0.02]	[0.02]	[0.41]	[0.33]	[0.14]	[0.12]
b^{HML}	0.2974	0.3390	0.2519	0.3389	0.1164	0.1540	0.1388	0.2426
T-STAT	(1.10)	(1.25)	(0.94)	(1.27)	(0.41)	(0.54)	(0.50)	(0.88)
P-VALUE	[0.27]	[0.21]	[0.35]	[0.21]	[0.68]	[0.59]	[0.62]	[0.38]
c^{dPRisk_sc}		-5.1936		-5.0526		-5.3401		-5.0761
T-STAT		(-2.93)***		(-3.04)***		(-2.92)***		(-2.77)***
P-VALUE		[0.00]		[0.00]		[0.00]		[0.01]
b^{EUI}			-0.0052	-0.0076			0.0057	0.0031
T-STAT			(-0.35)	(-0.52)			(0.39)	(0.22)
P-VALUE			[0.73]	[0.60]			[0.69]	[0.83]
b^{PUI}					0.8554	-0.5841	-2.8616	-4.6582
T-STAT					(0.15)	(-0.09)	(-0.51)	(-0.76)
P-VALUE					[0.88]	[0.93]	[0.61]	[0.45]
R^2	0.35	0.42	0.44	0.49	0.44	0.50	0.52	0.57
N	3,749	3,749	3,749	3,749	3,749	3,749	3,749	3,749

* p<0.10; ** p<0.05; *** p<0.01

Table 12: Second Stage Fama-MacBeth Regressions with PRisk and the Carhart Model (Fama-French FF3 + Momentum Factor) Risk Factor

The excess returns of equally weighted portfolios are regressed at a monthly frequency for the period January 2002-June 2019 on dPRisk controlling for the Carhart betas, Economic Uncertainty Index Beta Ludvigson et al. (2015) and Policy Uncertainty Index Beta Baker et al. (2016) . The US market factor is taken from Kenneth French's website. The cross-sectional regression is :

$$r_t^i - r_t^f = a_t + b_t^{MKT}\beta^i_{MKT} + b_t^{SMB}\beta^i_{SMB} + b_t^{HML}\beta^i_{HML} + b_t^{WML}\beta^i_{WML} + b_t^{EUI}\beta^i_{EUI} + b_t^{PUI}\beta^i_{PUI} + c_t^{dPRisk\_sc} dPRisk\_sc_t^i + \eta_t^i$$

where i is representing a sector level portfolio and $dPRisk\_sc = dPRisk/1000$. The coefficients and the standard errors in this table are the means and standard deviations of a_t, $b_t^{MKT}, b_t^{SMB}, b_t^{HML}, b_t^{WML}, b_t^{EUI}, b_t^{PUI}$, $c_t^{dPRisk\_sc}$ based on the 207 monthly regression from April 2002-June 2019.

Coeff	CARHART	CARHART+	CARHARTunc	CARHARTunc+	CARHARTpui	CARHARTpui+	CARHARTup	CARHARTup
b^{MKT}	-0.7152	-0.8230	-0.1994	-0.2554	-0.4104	-0.4061	-0.5361	-0.5128
T-STAT	(-1.13)	(-1.30)	(-0.31)	(-0.40)	(-0.66)	(-0.65)	(-0.88)	(-0.85)
P-VALUE	[0.26]	[0.20]	[0.75]	[0.69]	[0.51]	[0.52]	[0.38]	[0.40]
b^{SMB}	0.6546	0.7974	0.7131	0.8029	0.4213	0.5169	0.4763	0.5259
T-STAT	(1.97)*	(2.43)**	(2.18)**	(2.45)**	(1.24)	(1.53)	(1.43)	(1.57)
P-VALUE	[0.05]	[0.02]	[0.03]	[0.02]	[0.22]	[0.13]	[0.16]	[0.12]
b^{HML}	-0.0104	0.1019	0.0733	0.1959	-0.1333	-0.0040	-0.1565	-0.0258
T-STAT	(-0.04)	(0.38)	(0.27)	(0.72)	(-0.47)	(-0.01)	(-0.55)	(-0.09)
P-VALUE	[0.97]	[0.71]	[0.79]	[0.47]	[0.64]	[0.99]	[0.58]	[0.93]
b^{WML}	0.1660	0.2630	0.4884	0.4397	0.1590	0.3543	0.4259	0.3553
T-STAT	(0.27)	(0.43)	(0.82)	(0.72)	(0.27)	(0.59)	(0.72)	(0.59)
P-VALUE	[0.79]	[0.67]	[0.41]	[0.47]	[0.79]	[0.55]	[0.47]	[0.55]
c^{dPRisk_sc}		-4.0982		-3.9381		-3.7846		-3.7348
T-STAT		(-2.34)**		(-2.31)**		(-2.08)**		(-2.07)**
P-VALUE		[0.02]		[0.02]		[0.04]		[0.04]
b^{EUI}			0.0006	-0.0023			0.0084	0.0062
T-STAT			(0.04)	(-0.14)			(0.55)	(0.41)
P-VALUE			[0.97]	[0.89]			[0.58]	[0.68]
b^{PUI}					2.4130	-1.0866	2.5020	-1.6380
T-STAT					(0.40)	(-0.16)	(0.43)	(-0.26)
P-VALUE					[0.69]	[0.87]	[0.67]	[0.79]
R^2	0.46	0.52	0.53	0.57	0.53	0.58	0.60	0.64
N	3,749	3,749	3,749	3,749	3,749	3,749	3,749	3,749

* p<0.10; ** p<0.05; *** p<0.01

Table 13: Second Stage Fama-MacBeth Regressions with PRisk and the Fama-French FF5 Risk Factor

The excess returns of equally weighted portfolios are regressed at a monthly frequency for the period January 2002-June 2019 on dPRisk controlling for the FF5 betas, Economic Uncertainty Index Beta Ludvigson et al. (2015) and Policy Uncertainty Index Beta Baker et al. (2016) . The US market factor is taken from Kenneth French's website. The cross-sectional regression is :

$$r_t^i - r_t^f = a_t + b_t^{MKT}\beta_{MKT}^i + b_t^{SMB}\beta_{SMB}^i + b_t^{HML}\beta_{HML}^i + b_t^{RMW}\beta_{RMW}^i + b_t^{CMA}\beta_{CMA}^i + b_t^{EUI}\beta_{EUI}^i + b_t^{PUI}\beta_{PUI}^i + c_t^{dPRisk\_sc} dPRisk\_sc_t^i + \eta_t^i$$

where i is representing a sector level portfolio and $dPRisk\_sc = dPRisk/1000$. The coefficients and the standard errors in this table are the means and standard deviations of a_t, $b_t^{MKT}, b_t^{SMB}, b_t^{HML}, b_t^{RMW}, b_t^{CMA}, b_t^{EUI}, b_t^{PUI}$, $c_t^{dPRisk\_sc}$ based on the 207 monthly regression from April 2002-June 2019.

Coeff	FF5	FF5+	FF5unc	FF5unc+	FF5pui	FF5pui+	FF5up	FF5up
b^{MKT}	-0.5172	-0.7049	-0.1172	-0.1982	-0.2776	-0.3778	-0.0348	0.0828
T-STAT	(-0.97)	(-1.32)	(-0.22)	(-0.37)	(-0.51)	(-0.69)	(-0.07)	(0.15)
P-VALUE	[0.33]	[0.19]	[0.82]	[0.71]	[0.61]	[0.49]	[0.95]	[0.88]
b^{SMB}	0.4806	0.5546	0.4623	0.4895	0.3105	0.3746	0.2785	0.2917
T-STAT	(1.42)	(1.64)	(1.41)	(1.49)	(0.90)	(1.09)	(0.84)	(0.88)
P-VALUE	[0.16]	[0.10]	[0.16]	[0.14]	[0.37]	[0.28]	[0.40]	[0.38]
b^{HML}	0.3314	0.3756	0.3259	0.4204	0.2489	0.3210	0.3839	0.4996
T-STAT	(1.18)	(1.35)	(1.19)	(1.55)	(0.85)	(1.10)	(1.34)	(1.78)*
P-VALUE	[0.24]	[0.18]	[0.23]	[0.12]	[0.40]	[0.27]	[0.18]	[0.08]
b^{RMW}	-0.1629	-0.2339	-0.3952	-0.4512	-0.1163	-0.1880	-0.4193	-0.5361
T-STAT	(-0.68)	(-0.98)	(-1.66)*	(-1.88)*	(-0.48)	(-0.78)	(-1.80)*	(-2.25)**
P-VALUE	[0.50]	[0.33]	[0.10]	[0.06]	[0.63]	[0.43]	[0.07]	[0.03]
b^{CMA}	-0.2576	-0.2626	-0.3018	-0.2979	-0.1534	-0.1230	-0.0181	0.0317
T-STAT	(-0.90)	(-0.91)	(-1.08)	(-1.04)	(-0.54)	(-0.44)	(-0.06)	(0.11)
P-VALUE	[0.37]	[0.36]	[0.28]	[0.30]	[0.59]	[0.66]	[0.95]	[0.91]
c^{dPRisk_sc}		-3.8015		-3.6488		-4.3344		-4.3357
T-STAT		(-2.29)**		(-2.24)**		(-2.55)**		(-2.38)**
P-VALUE		[0.02]		[0.03]		[0.01]		[0.02]
b^{EUI}			-0.0023	-0.0076			-0.0040	-0.0131
T-STAT			(-0.16)	(-0.52)			(-0.28)	(-0.87)
P-VALUE			[0.87]	[0.61]			[0.78]	[0.39]
b^{PUI}					2.1115	-0.5158	-0.8103	-2.7856
T-STAT					(0.35)	(-0.08)	(-0.14)	(-0.44)
P-VALUE					[0.73]	[0.94]	[0.89]	[0.66]
R^2	0.51	0.56	0.58	0.62	0.58	0.63	0.64	0.68
N	3,749	3,749	3,749	3,749	3,749	3,749	3,749	3,749

* p<0.10; ** p<0.05; *** p<0.01

Table 14: Second Stage Fama-MacBeth Regressions with PRisk and the Fama-French FF5 Risk Factor & Momentum Risk Factor

The excess returns of equally weighted portfolios are regressed at a monthly frequency for the period January 2002-June 2019 on dPRisk controlling for the FF 5 factor and carhart momentum betas, Economic Uncertainty Index Beta Ludvigson et al. (2015) and Policy Uncertainty Index Beta Baker et al. (2016) . The US market factor is taken from Kenneth French's website. The cross-sectional regression is :

$$r_t^i - r_t^f = a_t + b_t^{MKT}\beta_{MKT}^i + b_t^{SMB}\beta_{SMB}^i + b_t^{HML}\beta_{HML}^i + b_t^{RMW}\beta_{RMW}^i + b_t^{CMA}\beta_{CMA}^i + b_t^{WML}\beta_{WML}^i + b_t^{EUI}\beta_{EUI}^i + b_t^{PUI}\beta_{PUI}^i + c_t^{dPRisk\_sc} dPRisk\_sc_t^i + \eta_t^i$$

where i is representing a sector level portfolio and $dPRisk\_sc = dPRisk/1000$. The coefficients and the standard errors in this table are the means and standard deviations of a_t, $b_t^{MKT}, b_t^{SMB}, b_t^{HML}, b_t^{RMW}, b_t^{CMA}, b_t^{WML}, b_t^{EUI}, b_t^{PUI}$, $c_t^{dPRisk\_sc}$ based on the 207 monthly regression from April 2002-June 2019.

Coeff	FF5MoM	FF5MoM+	FF5MoMunc	FF5MoMunc+	FF5MoMpui	FF5MoMpui+	FF5MoMup	FF5MoMup
b^{MKT}	-0.7343	-0.8205	-0.2522	-0.2944	-0.5260	-0.5088	-0.3292	-0.2143
T-STAT	(-1.24)	(-1.37)	(-0.41)	(-0.47)	(-0.87)	(-0.83)	(-0.54)	(-0.35)
P-VALUE	[0.22]	[0.17]	[0.68]	[0.64]	[0.38]	[0.41]	[0.59]	[0.73]
b^{SMB}	0.3964	0.5098	0.4541	0.4987	0.2693	0.3741	0.2017	0.2410
T-STAT	(1.15)	(1.47)	(1.33)	(1.45)	(0.77)	(1.07)	(0.58)	(0.69)
P-VALUE	[0.25]	[0.14]	[0.18]	[0.15]	[0.44]	[0.28]	[0.56]	[0.49]
b^{HML}	-0.0108	0.0668	0.0573	0.1775	-0.1260	-0.0021	-0.0880	0.1087
T-STAT	(-0.04)	(0.25)	(0.21)	(0.66)	(-0.44)	(-0.01)	(-0.31)	(0.38)
P-VALUE	[0.97]	[0.81]	[0.83]	[0.51]	[0.66]	[0.99]	[0.76]	[0.70]
b^{RMW}	-0.0845	-0.1561	-0.2965	-0.3517	-0.0472	-0.1175	-0.2894	-0.3803
T-STAT	(-0.33)	(-0.61)	(-1.17)	(-1.36)	(-0.18)	(-0.46)	(-1.15)	(-1.47)
P-VALUE	[0.74]	[0.54]	[0.24]	[0.17]	[0.85]	[0.65]	[0.25]	[0.14]
b^{CMA}	-0.3958	-0.4008	-0.3575	-0.3238	-0.2881	-0.2414	0.0223	0.0705
T-STAT	(-1.32)	(-1.35)	(-1.27)	(-1.15)	(-0.96)	(-0.81)	(0.07)	(0.22)
P-VALUE	[0.19]	[0.18]	[0.21]	[0.25]	[0.34]	[0.42]	[0.94]	[0.82]
b^{WML}	-0.0515	0.0309	0.3457	0.3686	-0.1445	0.0156	0.1161	0.1912
T-STAT	(-0.08)	(0.05)	(0.54)	(0.56)	(-0.22)	(0.02)	(0.18)	(0.29)
P-VALUE	[0.94]	[0.96]	[0.59]	[0.58]	[0.82]	[0.98]	[0.86]	[0.77]
c^{dPRisk_sc}		-2.5654		-2.3852		-2.6424		-3.0021
T-STAT		(-1.50)		(-1.41)		(-1.55)		(-1.68)*
P-VALUE		[0.13]		[0.16]		[0.12]		[0.09]
b^{EUI}			0.0117	0.0082			0.0174	0.0116
T-STAT			(0.70)	(0.47)			(1.10)	(0.66)
P-VALUE			[0.49]	[0.64]			[0.27]	[0.51]
b^{PUI}					6.5195	2.0805	6.6474	2.5516
T-STAT					(1.07)	(0.32)	(1.15)	(0.40)
P-VALUE					[0.29]	[0.75]	[0.25]	[0.69]
R^2	0.60	0.64	0.65	0.69	0.66	0.70	0.70	0.74
N	3,749	3,749	3,749	3,749	3,749	3,749	3,749	3,749

* p<0.10; ** p<0.05; *** p<0.01

Table 15: Second Stage Fama-MacBeth Regressions with PRisk and the Q4 factor model

The excess returns of equally weighted portfolios are regressed at a monthly frequency for the period January 2002-June 2019 on dPRisk controlling for the Q 4 factor betas, Economic Uncertainty Index Beta Ludvigson et al. (2015) and Policy Uncertainty Index Beta Baker et al. (2016) . The US market factor is taken from Kenneth French's website. The cross-sectional regression is :

$$r_t^i - r_t^f = a_t + b_t^{MKT}\beta_{t,MKT}^i + b_t^{ME}\beta_{t,ME}^i + b_t^{IA}\beta_{t,IA}^i + b_t^{ROE}\beta_{t,ROE}^i + b_t^{EUI}\beta_{t,EUI}^i + b_t^{PUI}\beta_{t,PUI}^i + c_t^{dPRisk\_sc} dPRisk\_sc_t^i + \eta_t^i$$

where i is representing a sector level portfolio and $dPRisk\_sc = dPRisk/1000$. The coefficients and the standard errors in this table are the means and standard deviations of a_t, $b_t^{MKT}, b_t^{ME}, b_t^{IA}, b_t^{ROE}, b_t^{EUI}, b_t^{PUI}$, $c_t^{dPRisk\_sc}$ based on the 207 monthly regression from April 2002-June 2019.

Coeff	Q4	Q4+	Q4unc	Q4unc+	Q4pui	Q4pui+	Q4up	Q4up
b^{MKT}	-0.6196	-0.7608	-0.2692	-0.3668	-0.4401	-0.5621	-0.1707	-0.2170
T-STAT	(-1.06)	(-1.30)	(-0.45)	(-0.61)	(-0.74)	(-0.94)	(-0.29)	(-0.36)
P-VALUE	[0.29]	[0.20]	[0.66]	[0.54]	[0.46]	[0.35]	[0.78]	[0.72]
b^{ME}	0.3962	0.5027	0.5207	0.5269	0.3041	0.3825	0.4114	0.3876
T-STAT	(1.19)	(1.52)	(1.50)	(1.51)	(0.90)	(1.14)	(1.19)	(1.12)
P-VALUE	[0.24]	[0.13]	[0.13]	[0.13]	[0.37]	[0.26]	[0.24]	[0.27]
b^{IA}	-0.2569	-0.2959	0.0124	-0.0381	-0.4312	-0.4640	-0.1565	-0.2026
T-STAT	(-1.04)	(-1.19)	(0.05)	(-0.14)	(-1.72)*	(-1.85)*	(-0.60)	(-0.75)
P-VALUE	[0.30]	[0.24]	[0.96]	[0.89]	[0.09]	[0.07]	[0.55]	[0.45]
b^{ROE}	-0.3075	-0.3358	-0.1837	-0.2635	-0.2917	-0.3131	-0.1054	-0.1973
T-STAT	(-1.05)	(-1.13)	(-0.56)	(-0.79)	(-0.99)	(-1.05)	(-0.32)	(-0.59)
P-VALUE	[0.29]	[0.26]	[0.58]	[0.43]	[0.32]	[0.29]	[0.75]	[0.56]
c^{dPRisk_sc}		-3.3242		-3.3481		-2.8887		-2.2340
T-STAT		(-1.99)**		(-2.02)**		(-1.70)*		(-1.26)
P-VALUE		[0.05]		[0.05]		[0.09]		[0.21]
b^{EUI}			0.0083	0.0078			0.0087	0.0086
T-STAT			(0.46)	(0.45)			(0.51)	(0.50)
P-VALUE			[0.64]	[0.65]			[0.61]	[0.62]
b^{PUI}					6.6871	5.7022	4.4107	1.9648
T-STAT					(1.21)	(1.00)	(0.78)	(0.33)
P-VALUE					[0.23]	[0.32]	[0.44]	[0.74]
R^2	0.48	0.53	0.54	0.59	0.55	0.60	0.61	0.66
N	3,749	3,749	3,749	3,749	3,749	3,749	3,749	3,749

* p<0.10; ** p<0.05; *** p<0.01

Table 16: Second Stage Fama-MacBeth Regressions with PRisk and the Q5 factor model

The excess returns of equally weighted portfolios are regressed at a monthly frequency for the period January 2002-June 2019 on dPRisk controlling for the Q 5 factor betas, Economic Uncertainty Index Beta Ludvigson et al. (2015) and Policy Uncertainty Index Beta Baker et al. (2016) . The US market factor is taken from Kenneth French's website. The cross-sectional regression is :

$$r_t^i - r_t^f = a_t + b_t^{MKT}\beta_{MKT}^i + b_t^{ME}\beta_{ME}^i + b_t^{IA}\beta_{IA}^i + b_t^{ROE}\beta_{ROE}^i + b_t^{EG}\beta_{EG}^i + b_t^{EUI}\beta_{EUI}^i + b_t^{PUI}\beta_{PUI}^i + c_t^{dPRisk\_sc} dPRisk\_sc_t^i + \eta_t^i$$

where i is representing a sector level portfolio and $dPRisk\_sc = dPRisk/1000$. The coefficients and the standard errors in this table are the means and standard deviations of a_t, $b_t^{MKT}, b_t^{ME}, b_t^{IA}, b_t^{ROE}, b_t^{EUI}, b_t^{PUI}$, $c_t^{dPRisk\_sc}$ based on the 207 monthly regression from April 2002-June 2019.

Coeff	**Q5**	**Q5+**	**Q5unc**	**Q5unc+**	**Q5pui**	**Q5pui+**	**Q5up**	**Q5up**
b^{MKT}	-0.4157	-0.5967	-0.0723	-0.1978	-0.1518	-0.3297	0.0017	-0.2075
T-STAT	(-0.72)	(-0.99)	(-0.12)	(-0.31)	(-0.26)	(-0.54)	(0.00)	(-0.32)
P-VALUE	[0.47]	[0.32]	[0.90]	[0.76]	[0.80]	[0.59]	[1.00]	[0.75]
b^{ME}	0.3785	0.4471	0.4870	0.4471	0.2832	0.3268	0.3815	0.3445
T-STAT	(1.14)	(1.34)	(1.43)	(1.31)	(0.83)	(0.96)	(1.11)	(1.01)
P-VALUE	[0.26]	[0.18]	[0.15]	[0.19]	[0.41]	[0.34]	[0.27]	[0.32]
b^{IA}	-0.0885	-0.1720	0.0356	-0.0681	-0.2430	-0.3143	-0.0928	-0.1671
T-STAT	(-0.38)	(-0.71)	(0.13)	(-0.25)	(-1.03)	(-1.31)	(-0.34)	(-0.61)
P-VALUE	[0.71]	[0.48]	[0.89]	[0.80]	[0.30]	[0.19]	[0.73]	[0.54]
b^{ROE}	-0.3303	-0.3560	-0.1658	-0.2046	-0.2916	-0.3467	-0.1216	-0.1712
T-STAT	(-1.14)	(-1.21)	(-0.51)	(-0.63)	(-1.02)	(-1.19)	(-0.38)	(-0.51)
P-VALUE	[0.26]	[0.23]	[0.61]	[0.53]	[0.31]	[0.24]	[0.71]	[0.61]
b^{EG}	0.1505	0.0373	0.1659	0.0209	0.0566	-0.0340	0.1147	-0.0411
T-STAT	(0.63)	(0.16)	(0.67)	(0.08)	(0.22)	(-0.13)	(0.43)	(-0.15)
P-VALUE	[0.53]	[0.88]	[0.50]	[0.93]	[0.83]	[0.90]	[0.67]	[0.88]
c^{dPRisk_sc}		-3.3396		-2.8604		-2.2522		-1.0840
T-STAT		(-1.99)**		(-1.65)		(-1.31)		(-0.57)
P-VALUE		[0.05]		[0.10]		[0.19]		[0.57]
b^{EUI}			0.0037	0.0032			0.0053	0.0100
T-STAT			(0.21)	(0.18)			(0.30)	(0.53)
P-VALUE			[0.84]	[0.86]			[0.77]	[0.59]
b^{PUI}					9.4375	8.8806	8.0234	3.4185
T-STAT					(1.62)	(1.46)	(1.33)	(0.57)
P-VALUE					[0.11]	[0.15]	[0.19]	[0.57]
R^2	0.54	0.59	0.60	0.64	0.61	0.65	0.66	0.71
N	3,749	3,749	3,749	3,749	3,749	3,749	3,749	3,749

* p<0.10; ** p<0.05; *** p<0.01

Table 17: Cross-Sectional Regression of Profitability and Investment Factor Loadings from the FF Five- Factor, FF Five-Factor plus Momentum Model, Q4 and Q5 Models on the dPRisk Measures

The Profitability betas are based on the Fama-French Five-Factor Model(Panel A) and the largest risk model we used, the Fama-French Five-Factor Model plus Momentum (Panel B) of each country-industry portfolio are regressed at a monthly frequency for the period from April 2002 to June 2019 on $dPRisk\_sc_t^i$ relevant for each sector level portfolio (equal weighted). The computation of the productivity gap measures uses TFP based on capital measured as the Net Capital Stock in current PPP terms and labor measured in Employee Hours. The global risk factors are from Kenneth French's website.

$$\beta_{RMW}^i = g + h * dPRisk\_sc_t^i + \omega^i \tag{11}$$

$$\beta_{CMA}^i = g + h * dPRisk\_sc_t^i + \omega^i \tag{12}$$

$$\beta_{ROE}^i = g + h * dPRisk\_sc_t^i + \omega^i \tag{13}$$

$$\beta_{IA}^i = g + h * dPRisk\_sc_t^i + \omega^i \tag{14}$$

The coefficients and the standard errors in this table are the means and standard deviations of scaled PRisk based on the 217 monthly regression from April 2002-June 2019. Please note that the R^2 in the regression is for cross-sectional regression.

Profitability Factors from Standard Models				
	β_{RMW}FF5	β_{RMW}FF5+MoM	β_{ROE} Q4	β_{ROE}Q5
h	-0.0386	-0.0304	-0.0904	-0.1878
t-stat	(-0.28)	(-0.21)	(-0.41)	(-0.82)
p-value	[0.78]	[0.84]	[0.68]	[0.41]
R^2	0.03	0.04	0.09	0.09
N	3,749	3,749	3,749	3,749
Investment Factors from Standard Models				
	β_{CMA}FF5	β_{CMA}FF5+MoM	β_{IA} Q4	β_{IA}Q5
h	-0.2990	-0.3245	-0.4204	-0.3760
t-stat	(-1.71)*	(-1.82)*	(-2.84)***	(-2.93)***
p-value	[0.09]	[0.07]	[0.00]	[0.00]
R^2	0.07	0.07	0.04	0.04
N	3,749	3,749	3,749	3,749

* p<0.10; ** p<0.05; *** p<0.01

Table 18: Cross-Sectional Regression of Profitability and Investment Factor Loadings from the FF Five- Factor, FF Five-Factor plus Momentum Model, Q4 and Q5 Models on the PRisk Measures

The Profitability betas are based on the Fama-French Five-Factor Model(Panel A) and the largest risk model we used, the Fama-French Five-Factor Model plus Momentum (Panel B) of each country-industry portfolio are regressed at a monthly frequency for the period from January 2002 to June 2019 on $PRisk\_sc_t^i$ relevant for each sector level portfolio (equal weighted).. The computation of the productivity gap measures uses TFP based on capital measured as the Net Capital Stock in current PPP terms and labor measured in Employee Hours. The global risk factors are from Kenneth French's website.

$$\beta^i_{RMW} = g + h * PRisk\_sc_t^i + \omega^i \tag{15}$$

$$\beta^i_{CMA} = g + h * PRisk\_sc_t^i + \omega^i \tag{16}$$

$$\beta^i_{ROE} = g + h * PRisk\_sc_t^i + \omega^i \tag{17}$$

$$\beta^i_{IA} = g + h * PRisk\_sc_t^i + \omega^i \tag{18}$$

The coefficients and the standard errors in this table are the means and standard deviations of scaled PRisk based on the 210 monthly regression from January 2002-June 2019. Please note that the R^2 in the regression is for cross-sectional regression.

Profitability Factors from Standard Models				
	β_{RMW}FF5	β_{RMW}FF5+MoM	β_{ROE} Q4	β_{ROE}Q5
h	-0.2648	-0.4502	1.3829	1.2046
t-stat	(-2.14)**	(-3.98)***	(10.60)***	(9.35)***
p-value	[0.03]	[0.00]	[0.00]	[0.00]
R^2	0.05	0.05	0.08	0.08
N	3,809	3,809	3,809	3,809
Investment Factors from Standard Models				
	β_{CMA}FF5	β_{CMA}FF5+MoM	β_{IA} Q4	β_{IA}Q5
h	0.6872	0.4922	0.8820	0.9464
t-stat	(5.45)***	(4.18)***	(8.53)***	(8.82)***
p-value	[0.00]	[0.00]	[0.00]	[0.00]
R^2	0.06	0.06	0.04	0.05
N	3,809	3,809	3,809	3,809

* p<0.10; ** p<0.05; *** p<0.01

Table 19: Details of Barillias Shanken Test

The table summarizes the Barillias-Shanken test result. The test is equivalent to the GRS test but with the small model serving as the factor model and the large model serving as the test assets. If the test have significantly larger alphas, it follows that the large model when set to explain any group of test assets will have smaller alphas than the small model (when weighted by the inverse return covariance matrix).

Larger Model	**Smaller Model**	**Absolute mean Return per month (%)**	**GRS test Statistics**	**Pvalue**
$CAPM + r_t^{dPRisk}$	$CAPM$	0.14	11.70***	0.000015
$FF3 + r_t^{dPRisk}$	$FF3$	0.071	6.06***	0.0001
$Carhart + r_t^{dPRisk}$	$Carhart$	0.057	4.93***	0.0003
$FF5 + r_t^{dPRisk}$	$FF5$	0.044	3.22***	0.0049
$FF5 + Momentum + r_t^{dPRisk}$	$FF5 + Momentum$	0.038	2.78***	0.0089
$Q4 + r_t^{dPRisk}$	$Q4$	0.056	4.52***	0.0006
$Q5 + r_t^{dPRisk}$	$Q5$	0.041	2.66***	0.0167

* p<0.10; ** p<0.05; *** p<0.01

Table 20: Panel Regression between dPRisk and $dTFP$

The PRisk is regressed with The TFP computed using İmrohoroğlu and Tüzel (2014) in a fixed panel regression at the firm level.

$$dTFP_t^i = \alpha_0 + \beta * dPRisk\_sc_t^i + \omega^i \tag{19}$$

The coefficients and the standard errors in this table are the means and standard deviations of scaled dPRisk based on quarterly regression from April 2002-June 2019.

ΔTFP with $dPRisk$					
	model 1	model 2	model 3	model 4	model 5
β	-.0009039	-.0010987	-.0015446	-.001764	-.0016679
t-stat	(0.66)	(-0.71)	(-0.94)	(-1.07)	(-1.01)
p-value	[0.511]	[0.479]	[0.349]	[0.284]	[0.311]
year Fixed effect		✓		✓	✓
sector Fixed effect			✓	✓	✓
Year*Sector Fixed effect					✓
R^2 (Within)	0.0000	0.0019	0.0001	0.0023	0.0073
N	124,451	124,451	103,643	103,643	103,643

* p<0.10; ** p<0.05; *** p<0.01

Table 21: Panel Regression between PRisk and TFP

The PRisk is regressed with The TFP computed using İmrohoroğlu and Tüzel (2014) in a fixed panel regression at the firm level.

$$TFP_t^i = \alpha_0 + \beta * PRisk\_sc_t^i + \omega^i \tag{20}$$

The coefficients and the standard errors in this table are the means and standard deviations of scaled PRisk based on quarterly regression from January 2002-June 2019.

TFP with PRisk					
	model 1	model 2	model 3	model 4	model 5
β	-0.01826	-0.01692	-0.0200	-0.1789	-0.01837
t-stat	(-4.16)***	(-3.86)***	(-4.26)***	(-3.82)***	(-3.95)***
p-value	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
year Fixed effect		✓		✓	✓
sector Fixed effect			✓	✓	✓
Year*Sector Fixed effect					✓
R^2 (Within)	0.0061	0.0040	0.0055	0.0136	0.0399
N	135,004	135,004	111,293	111,293	111,293

* $p<0.10$; ** $p<0.05$; *** $p<0.01$

Part V
Conclusion

In this thesis we deal with three distinct paper which are related to the asset pricing literature. All the three papers deal with total factor productivity shocks and their impact on asset returns. The first paper develops a stylized model of asset pricing using the dynamics of knowledge and technology diffusion process in a production-based framework. The productivity shocks from leading countries to trailing countries are systematic sources of risk, and in the first paper we find that productivity gaps determine the level of exposure to the productivity shock. For OECD panel data, a country-industry's productivity gap significantly predicts the stock returns of the country-industry: holding the quintile of country- industry portfolios with the largest gaps and shorting the quintile with the smallest gaps generates annual returns of 9.8% (6.7% after risk adjustment with standard factors). A factor associated with the productivity gap explains country-industry portfolio returns substantially better than standard factor models.

In the second paper we further develop the model of the first paper. The productivity shocks are in turn determined by the technology shocks. The technology gap, R&D intensity and the absorption capacity determines the level of exposure to the technology shock. For the OECD panel data, one standard deviation increase in technology gap leads to increase in excess return by 0.58% per month. and one standard deviation increase in R&D intensity leads to an increase of 0.55% per month. The result for absorption capacity is mixed.

The first two paper lays the foundation of a production based asset pricing model in an international context. Moreover, we find empirical evidence for the model in 24 OECD countries. This is a significant contribution to advance production based asset pricing models to price international assets. Some of the empirical results like R&D intensity is explained in a theoretical context.

The third paper, though empirical in nature shows that political shocks due to the political uncertainty of a policy change leads to a productivity shock in the economy. Moreover, a recent political risk proxy derived from text processing of Analyst transcripts has more information than Bakers' policy uncertainty index that is used in the literature

References

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The quarterly journal of economics*, 131(4):1593–1636.

Balvers, R. and Luo, A. H. (2018). Distinguishing factors and characteristics with characteristic-mimicking portfolios.

Barillas, F. and Shanken, J. (2017). Which alpha? *The Review of Financial Studies*, 30(4):1316–1338.

Breeden, D. (1979). An intertemporal asset pricing model with stochastic consumption and investment opportunities. *Journal of Financial Economics*, 7(3):265–296.

Brogaard, J. and Detzel, A. (2015). The asset-pricing implications of government economic policy uncertainty. *Management Science*, 61(1):3–18.

Chan, L. K., Lakonishok, J., and Sougiannis, T. (2001). The stock market valuation of research and development expenditures. *The Journal of Finance*, 56(6):2431–2456.

Chen, S.-S., Chen, Y.-S., Liang, W.-l., and Wang, Y. (2013). R&d spillover effects and firm performance following r&d increases. *Journal of Financial and Quantitative Analysis*, 48(5):1607–1634.

Cochrane, J. H. (1991). Production-based asset pricing and the link between stock returns and economic fluctuations. *Journal of Finance*, 46(1):209–237.

Comin, D. and Hobijn, B. (2004). Cross-country technology adoption: making the theories face the facts. *Journal of Monetary Economics*, 51(1):39–83.

Comin, D. and Hobijn, B. (2010). An exploration of technology diffusion. *American Economic Review*, 100(5):2031–59.

Comin, D. and Mestieri, M. (2018). If technology has arrived everywhere, why has income diverged? *American Economic Journal: Macroeconomics*, 10(3):137–78.

Eberhart, A. C., Maxwell, W. F., and Siddique, A. R. (2004). An examination of long-term abnormal stock returns and operating performance following r&d increases. *The Journal of Finance*, 59(2):623–650.

Fama, E. F. and French, K. R. (1992). The cross-section of expected stock returns. *the Journal of Finance*, 47(2):427–465.

Hassan, T. A., Hollander, S., van Lent, L., and Tahoun, A. (2019). Firm-level political risk: Measurement and effects. *The Quarterly Journal of Economics*, 134(4):2135–2202.

Ho, Y. K., Xu, Z., and Yap, C. M. (2004). R&d investment and systematic risk. *Accounting & Finance*, 44(3):393–418.

Hou, K., Hsu, P.-H., Watanabe, A., and Xu, Y. (2016). Corporate r&d and stock returns: International evidence. *Recuperado de http://www. cicfconf. org/sites/default/files/paper_413. pdf.*

Hsu, P.-H. (2009). Technological innovations and aggregate risk premiums. *Journal of Financial Economics*, 94(2):264–279.

Jiang, Y., Qian, Y., and Yao, T. (2016). R&d spillover and predictable returns. *Review of Finance*, 20(5):1769–1797.

Lin, X. (2012). Endogenous technological progress and the cross-section of stock returns. *Journal of Financial Economics*, 103(2):411–427.

Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica: Journal of the Econometric Society*, pages 867–887.

Parente, S. L. and Prescott, E. C. (1994). Barriers to technology adoption and development. *Journal of Political Economy*, 102(2):298–321.

Pastor, L. and Veronesi, P. (2012). Uncertainty about government policy and stock prices. *The journal of Finance*, 67(4):1219–1264.

Pástor, L. and Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of financial Economics*, 110(3):520–545.

Solnik, B. (1974). An equilibrium model of the international capital market. *Journal of Economic Theory*, 8(4):500–524.

Zhang, L. (2005). The value premium. *The Journal of Finance*, 60(1):67–103.