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Growth Opportunities, Technology Shocks, and Asset Prices

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ABSTRACT

We explore the impact of investment-specific technology (IST) shocks on the cross-section of stock returns. Using a structural model, we show that IST shocks have a differential effect on the value of assets in place and the value of growth opportunities. This differential sensitivity to IST shocks has two main implications. First, firm risk premia depend on the contribution of growth opportunities to firm value. Second, firms with similar levels of growth opportunities comove with each other, giving rise to the value factor in stock returns and the the failure of the conditional CAPM. Our empirical tests confirm the model's predictions.

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Technological innovation is a key determinant of economic growth. In many cases, technological innovation affects aggregate output and consumption only to the extent that it is implemented through the formation of new capital stock. Since this type of innovation is embodied in new capital goods, it is termed *investment-specific*. The magnitude of investment-specific technical progress can be inferred from the decline in the quality-adjusted price of investment goods.[1] Recent literature on real determinants of economic growth emphasizes the role of capital-embodied shocks as an important driver of long-run growth and business cycle fluctuations.[2] In this paper, we argue that investment-specific technology (IST) shocks are helpful in understanding the patterns of risk premia and comovement in the cross-section of firms.

We start with the standard decomposition of firm value into the value of assets in place and the value of growth opportunities. Firms that are relatively rich in growth opportunities have higher demand for new capital goods. As a result, a positive IST shock, manifesting as a reduction in the quality-adjusted price of new capital goods, has a larger positive impact on the market value of such firms. This mechanism produces two important patterns in asset returns. First, firms with a higher ratio of growth opportunities to their market value (high growth firms) earn different risk premia than firms with fewer growth opportunities (low growth firms). Second, returns on high growth firms comove with each other, which creates a systematic factor in stock returns distinct from the market portfolio. Both of these patterns replicate the well-documented properties of value and growth stocks (e.g., Fama and French (1993)), because in our model firms' market-to-book ratios are positively correlated with firms' growth opportunities.

The premise that IST shocks affect assets in place and growth opportunities differently is at the heart of our argument, and distinguishes our theory from other proposed explanations of return comovement and the value premium in stock returns. We test two main implications of this core mechanism. First, a firm's stock return exposure to IST shocks is increasing in the share of growth opportunities in firm value. Second, since firms must invest to realize their growth opportunities, high growth firms increase investment relatively more following a positive IST shock. Since growth opportunities are not directly observable, we test these implications jointly using the firm's stock return beta on the IST shock as a measure of its growth opportunities. As an alternative strategy, we test both predictions using the market-to-book ratio as an approximate measure of growth opportunities.

Firms' growth opportunities change over time, thus we need to estimate time-varying stock return sensitivities to IST shocks. The macroeconomic literature typically measures IST shocks using the quality-adjusted price of equipment. However, this price series is available only at low frequencies. Our model suggests a natural mimicking portfolio for IST shocks: the difference between stock returns of investment good producers and consumption good producers (IMC). The key benefit of this stock-return-based measure of IST shocks is that it is available at high frequency. In our tests, we use the IMC portfolio to estimate the conditional stock return betas with respect to the IST shocks. We find that firms with high IST betas tend to have higher Tobin's Q, have higher investment rates in physical capital, hold more cash, pay less in dividends, and invest more in R&D. Tests of the model's mechanism show that, following a positive IST shock, firms with higher IST betas increase their investment relative to firms with low IST betas. The same pattern holds for high and low book-to-market firms. This pattern is both statistically and economically significant. The difference in IST shock sensitivity between the investment of high growth and low growth firms is in most cases substantially larger than the sensitivity of investment of an average firm. These results show that cross-sectional differences in IST risk exposures are linked to differences in growth opportunities among firms.

Sorting firms on their IST betas results in a declining profile of average stock returns and an increasing profile of market betas. Hence, the CAPM significantly misprices these portfolios. The difference in average annualized returns and CAPM alphas between the high and low IST beta decile portfolios is -2.2% and -6.2%, respectively. This finding implies that IST shocks are a systematic risk factor that carries a negative risk premium. In addition, we find that firms with higher market-to-book ratios are more exposed to IST shocks. This confirms that heterogeneous exposure to IST shocks generates comovement among stocks with similar book-to-market ratios.

Our model replicates the dispersion in risk premia and comovement associated with differences in growth opportunities, and the failure of the CAPM to price the cross-section of expected returns. The model generates lower average returns for high IMC beta and high market-to-book firms, assuming a negative price of risk for IST shocks. We verify that our calibration is consistent with the data by estimating the stochastic discount factor implied by the model using three different cross-sections of assets: portfolios of firms sorted on IMC beta, book-to-market portfolios, and industry portfolios. We find that a higher exposure to IST shocks is associated with lower risk premia across the discount factor specifications and test assets. Furthermore, differences in IST shock exposure account for a significant fraction of the heterogeneity in risk premia among the test assets.

Our model also replicates the dynamics of cash flows and profitability of value and growth firms documented by Fama and French (1995). In the year of portfolio formation, growth firms have higher average profitability than value firms. In the years following portfolio formation, the average profitability of growth firms declines, whereas the average profitability of value firms rises. Despite the reduction in average profitability, the earnings of growth firms grow faster than the earnings of value firms. In the model, this pattern of mean reversion in profitability is driven in part by the fact that growth firms invest relatively more on average. As growth firms accumulate capital, they become similar to value firms.

In summary, our analysis highlights that IST shocks are an important source of systematic risk. IST shocks naturally lead to patterns of stock return comovement among firms with different growth opportunities, and thus give rise to the value factor. Heterogenous exposure to IST shocks is an important source of cross-sectional heterogeneity in risk premia. Our mechanism has a number of implications for stock returns and firm investment behavior, which we confirm empirically. We verify that a parsimonious structural model is able to account for several key empirical patterns quantitatively, providing additional support for our theory.

The rest of the paper is organized as follows. In Section I we relate our work to existing literature. In Section II we develop our theoretical model. In Section III, we discuss the data construction and the calibration of our model. In Section IV we test the model's empirical predictions. We conclude in Section V.

I. Related Research

Our paper bridges and complements two distinct strands of the finance and macroeconomic literature. The first argues for the importance of investment-specific shocks for aggregate growth and fluctuations, and the second argues that differences in a firm's mix between growth opportunities and assets in place are important for understanding the cross-section of expected stock returns.

IST shocks capture the idea that technical change is embodied in new equipment. Starting with Solow (1960), a number of economists have proposed embodied technical change as an alternative to the unrealistic disembodied technology shocks in most macroeconomic models.[3] Cummins and Violante (2002) document significant instances of IST change in numerous industries. In macroeconomics, a number of studies have shown that IST shocks can account for a large fraction of the variability of output and employment, both in the long run and at business cycle frequencies (see, for example Greenwood, Hercowitz, and Krusell (1997, 2000), Christiano and Fisher (2003), Fisher (2006), Justiniano, Primiceri, and Tambalotti (2010), Fisher (2009), Justiniano, Primiceri, and Tambalotti (2011)). Given that IST advances lead to improvements in the real investment opportunity set in the economy, they naturally have a differential impact on growth opportunities of firms and their assets in place. Papanikolaou (2011) considers a general equilibrium model with a representative agent, and finds that IST shocks are positively correlated with the stochastic discount factor

– implying a negative price of risk for IST shocks – if households have time-separable utility or Epstein-Zin utility with preference for late resolution of uncertainty. Kogan, Papanikolaou, and Stoffman (2012) extend the model to allow for limited risk sharing, in which case the premium can be negative irrespective of whether households have preference for early or late resolution of uncertainty.

In financial economics, the idea that growth opportunities may have different risk characteristics than assets in place is not new (e.g., Berk, Green, and Naik (1999), Gomes, Kogan, and Zhang (2003), Carlson, Fisher, and Giammarino (2004)). In these studies, assets in place and growth opportunities have different exposures to systematic risk, which is summarized by firms' market betas. Our work complements this literature by illustrating how investment-specific shocks affect both differences in risk premia and return comovement between assets in place and growth opportunities. Most existing models focus on the risk premia but not on return comovement, and thus feature a single aggregate shock. In models with a single systematic shock, risk premia of firms are closely aligned with their conditional market betas. As a result, such models have limited ability to account for the empirical failures of the conditional CAPM (e.g., Lewellen and Nagel (2006)). The model of Berk, Green, and Naik (1999) is one of the few exceptions, as it incorporates shocks to both aggregate productivity and discount rates.

Our work is also connected to the literature relating asset prices and firm investment. In this literature, Tobin's Q is commonly used as a stock-market based predictor of investment (e.g., Hayashi (1982), Abel (1985), Abel and Eberly (1994, 1996), Eberly, Rebelo, and Vincent (2008)). Tobin's Q measures the valuation of capital installed in the firm relative to its replacement cost. Thus, Tobin's Q is commonly considered an observable proxy for growth opportunities. We use an alternative empirical measure of growth opportunities that is a unique implication of our model, that is, the stock return beta with respect to IST shocks. Our tests demonstrate that our measure is incrementally informative when controlling for Tobin's Q and other standard empirical predictors of investment.

A growing branch of asset pricing literature in finance relates Q-based theories of investment to stock returns (e.g., Cochrane (1991, 1996), Zhang (2005), Liu, Whited, and Zhang (2009)). This literature focuses on the relation between expected stock returns and firms' investment decisions, which follows from firms' optimizing behavior. Our focus is instead on the mechanism behind the joint determination of investment behavior and risk premia. Thus, our work complements the existing studies and offers a potentially fruitful way of improving our understanding of the links between real investment and stock returns.

II. The Model

In this section we develop a structural model of investment. We show that the value of assets in place and the value of growth opportunities have different sensitivity to IST shocks. As a result, the relative weight of growth opportunities in a firm's value can be identified by measuring the exposure of its stock returns to IST shocks.

There are two sectors in our model: the consumption good sector, and the investment good sector. IST shocks manifest as changes in the cost of new capital goods. We focus on heterogeneity in growth opportunities among consumption good producers.

A. *Consumption Good Producers*

There is a continuum of measure one of infinitely lived firms producing a homogeneous consumption good. Firms behave competitively, and there is no explicit entry or exit in this sector. Firms are financed only by equity, and hence firm value is equal to the market value of its equity.

A.1. Assets in Place

Each firm owns a finite number of individual projects. Firms create projects over time through investment, and projects expire randomly.[4] Let $\mathcal{F}$ denote the set of firms and $\mathcal{J}_t^f$ the set of projects owned by firm f at time t.

Project j managed by firm f produces a flow of output equal to

$$y_{fjt} = \varepsilon_{ft}\, u_{jt}\, x_t\, K_j^{\alpha}, \tag{1}$$

where K_j is physical capital chosen irreversibly at project j's inception date, u_{jt} is the project-specific component of productivity, ε_{ft} is the firm-specific component of productivity, such as managerial skill of the parent firm, and x_t a disembodied productivity shock affecting the output of all existing projects. We assume decreasing returns to scale at the project level, $\alpha \in (0, 1)$. Projects expire independently at rate δ.

The three components of projects' productivity evolve according to

$$d\varepsilon_{ft} = -\theta_{\varepsilon}(\varepsilon_{ft} - 1)\, dt + \sigma_{\varepsilon}\sqrt{\varepsilon_{ft}}\, dB_{ft} \tag{2}$$

$$du_{jt} = -\theta_{u}(u_{jt} - 1)\, dt + \sigma_{u}\sqrt{u_{jt}}\, dB_{jt} \tag{3}$$

$$dx_t = \mu_x\, x_t\, dt + \sigma_x x_t\, dB_{xt}, \tag{4}$$

where dB_{ft}, dB_{jt}, and dB_{xt} are independent standard Brownian motions. All idiosyncratic shocks are independent of the aggregate shock: $dB_{ft} \cdot dB_{xt} = 0$ and $dB_{jt} \cdot dB_{xt} = 0$. The firm and project-specific components of productivity are stationary processes, while the process for aggregate productivity follows a Geometric Brownian motion, generating long-run growth.

A.2. Investment

Firms acquire new projects exogenously according to a Poisson process with a firm-specific arrival rate λ_{ft}. At the time of investment, the project-specific component of productivity is at its long-run average value, $u_{jt} = 1$.

The firm-specific arrival rate of new projects is

$$\lambda_{ft} = \lambda_f \cdot \tilde{\lambda}_{ft}, \tag{5}$$

where $\tilde{\lambda}_{ft}$ follows a two-state continuous-time Markov process with transition probability matrix between time t and $t + dt$ given by

$$P = \begin{pmatrix} 1 - \mu_L \, dt & \mu_L \, dt \\ \mu_H \, dt & 1 - \mu_H \, dt \end{pmatrix}. \tag{6}$$

We label the two states as $[\lambda_H, \lambda_L]$, with $\lambda_H > \lambda_L$. Thus, at any point in time, a firm can be either in the high growth $(\lambda_f \cdot \lambda_H)$ state or the low growth state $(\lambda_f \cdot \lambda_L)$, and $\mu_H \, dt$ and $\mu_L \, dt$ denote the instantaneous probability of entering each state, respectively. Without loss of generality, we impose $E[\tilde{\lambda}_{ft}] = 1$, which translates to the restriction

$$1 = \lambda_L + \frac{\mu_H}{\mu_H + \mu_L}(\lambda_H - \lambda_L). \tag{7}$$

When presented with a new project at time t, a firm must make a take-it-or-leave-it decision. If the firm decides to invest in a project, it chooses the associated amount of capital K_j and pays the investment cost $z_t^{-1} x_t K_j$. The cost of capital relative to its average productivity depends on the stochastic process z_t, which follows a Geometric Brownian motion

$$dz_t = \mu_z z_t \, dt + \sigma_z z_t \, dB_{zt}, \tag{8}$$

where $dB_{zt} \cdot dB_{xt} = 0$. The z shock is the embodied, IST shock in our model, representing the component of the price of capital that is unrelated to its current level of average productivity x. A positive realization of z reduces the cost of new capital goods and thus leads to an improvement in investment opportunities.

A.3. *Valuation*

Let π_t denote the stochastic discount factor. For simplicity, we assume that the aggregate productivity shocks x_t and z_t have constant prices of risk, γ_x and γ_z respectively, and the risk-free interest rate r is also constant. Then,

$$\frac{d\pi_t}{\pi_t} = -r\,dt - \gamma_x\,dB_{xt} - \gamma_z\,dB_{zt}. \tag{9}$$

This form of the stochastic discount factor is motivated by a general equilibrium model with IST shocks in Papanikolaou (2011). IST shocks endogenously affect the representative household's consumption stream, and hence they are priced in equilibrium.

Firms' investment decisions are based on a tradeoff between the market value of a new project and the cost of physical capital. Given (9), the time-t market value of an existing project j, $p(\varepsilon_{ft}, u_{jt}, x_t, K_j)$, is equal to the present value of its cash flows

$$p(\varepsilon_{ft}, u_{jt}, x_t, K_j) = \mathrm{E}_t\left[\int_t^\infty e^{-\delta(s-t)}\frac{\pi_s}{\pi_t}\varepsilon_{fs}u_{js}x_s K_j^\alpha\,ds\right] = A(\varepsilon_{ft}, u_{jt})\,x_t\,K_j^\alpha, \tag{10}$$

where

$$\begin{aligned} A(\varepsilon, u) = {} & \frac{1}{r+\gamma_x\,\sigma_x+\delta-\mu_X} + \frac{1}{r+\gamma_x\,\sigma_x+\delta-\mu_x+\theta_\varepsilon}(\varepsilon-1) + \frac{1}{r+\gamma_x\,\sigma_x+\delta-\mu_x+\theta_u}(u-1) \\ & + \frac{1}{r+\gamma_x\,\sigma_x+\delta-\mu_x+\theta_\varepsilon+\theta_u}(\varepsilon-1)(u-1). \end{aligned} \tag{11}$$

Firms' investment decisions are straightforward because the arrival rate of new projects is exogenous and does not depend on their previous decisions. Thus, optimal investment decisions are based on the NPV rule. Firm f chooses the amount of capital K_j to invest in project j to maximize

$$p(\varepsilon_{ft}, 1, x_t, K_j) - z_t^{-1}x_t K_j. \tag{12}$$

PROPOSITION 1: *The optimal investment K_j in project j undertaken by firm f at time t is*

$$K^*(\varepsilon_{ft}, z_t) = \left(\alpha z_t A(\varepsilon_{ft}, 1)\right)^{\frac{1}{1-\alpha}}. \tag{13}$$

The scale of the firm's new projects, that is, its new investment, depends on firm-specific productivity ε_{ft} and the IST shock z_t. Because the marginal productivity of capital in (1) is infinite at zero, it is always optimal to invest a positive and finite amount.

The value of the firm can be computed as the sum of market values of its existing projects and the present value of its growth opportunities. The former equals the present value of cash flows generated by existing projects. The latter equals the expected discounted NPV of future investments. Following the standard convention, we call the first component of firm value *the value of assets in place*, VAP_{ft}, and the second component *the present value of growth opportunities*, $PVGO_{ft}$.

The value of a firm's assets in place is the value of its existing projects:

$$VAP_{ft} = \sum_{j \in \mathcal{J}_t^f} p(\varepsilon_{ft}, u_{jt}, x_t, K_j) = x_t \sum_{j \in \mathcal{J}_t^f} A(\varepsilon_{ft}, u_{j,t}) K_j^\alpha. \tag{14}$$

The present value of growth opportunities is the NPV of all future projects, which is given by the following proposition.

PROPOSITION 2: *The value of growth opportunities for firm f is*

$$PVGO_{ft} = z_t^{\frac{\alpha}{1-\alpha}} \, x_t \, G(\varepsilon_{ft}, \lambda_{ft}), \tag{15}$$

where

$$\begin{aligned} G(\varepsilon_{ft}, \lambda_{ft}) &= C \cdot E_t \left[\int_t^\infty e^{-\rho(s-t)} \, \lambda_{fs} \, A(\varepsilon_{fs})^{\frac{1}{1-\alpha}} \, ds \right] \\ &= \begin{cases} \lambda_f \left(G_1(\varepsilon_{ft}) + \frac{\mu_L}{\mu_L + \mu_H} (\lambda_H - \lambda_L) \, G_2(\varepsilon_{ft}) \right), & \tilde{\lambda}_{ft} = \lambda_H \\ \lambda_f \left(G_1(\varepsilon_{ft}) - \frac{\mu_H}{\mu_L + \mu_H} (\lambda_H - \lambda_L) \, G_2(\varepsilon_{ft}) \right), & \tilde{\lambda}_{ft} = \lambda_L, \end{cases} \end{aligned} \tag{16}$$

and

$$\rho = r + \gamma_x \, \sigma_x - \mu_x - \frac{\alpha}{1-\alpha} \left(\mu_z - \gamma_z \, \sigma_z - \frac{1}{2} \sigma_z^2 \right) - \frac{1}{2} \left(\frac{\alpha}{1-\alpha} \right)^2 \sigma_z^2, \tag{17}$$

and

$$C = \alpha^{\frac{1}{1-\alpha}} \left(\alpha^{-1} - 1 \right). \tag{18}$$

The functions $G_1(\varepsilon)$ and $G_2(\varepsilon)$ solve the following differential equations

$$C \cdot A(\varepsilon, 1)^{\frac{1}{1-\alpha}} - \rho \, G_1(\varepsilon) - \theta_\varepsilon (\varepsilon - 1) \frac{d}{d\varepsilon} \, G_1(\varepsilon) + \frac{1}{2} \sigma_\varepsilon^2 \, \varepsilon \, \frac{d^2}{d\varepsilon^2} \, G_1(\varepsilon) = 0, \tag{19}$$

$$C \cdot A(\varepsilon, 1)^{\frac{1}{1-\alpha}} - (\rho + \mu_H + \mu_L) \, G_2(\varepsilon) - \theta_\varepsilon (\varepsilon - 1) \frac{d}{d\varepsilon} \, G_2(\varepsilon) + \frac{1}{2} \sigma_\varepsilon^2 \, \varepsilon \, \frac{d^2}{d\varepsilon^2} \, G_2(\varepsilon) = 0. \tag{20}$$

Examining equation (15), the value of growth opportunities depends on two systematic sources of risk. In addition to aggregate productivity x, the present value of growth opportunities depends on the IST shock, z, because the NPV of future projects depends on the cost of new investment.

Putting the two pieces together, the total value of the firm is equal to

$$V_{ft} = x_t \sum_{j \in \mathcal{J}_{ft}} A(\varepsilon_{ft}, u_{jt}) K_j^{\alpha} + z_t^{\frac{\alpha}{1-\alpha}} x_t \, G(\varepsilon_{ft}, \lambda_{ft}). \tag{21}$$

A.4. Risk and Risk Premia

Both assets in place and growth opportunities have constant exposure to the systematic shocks dB_{xt} and dB_{zt}. However, their betas with respect to the IST shock z are different. In particular, the value of assets in place is independent of the IST shock z and loads only on the aggregate productivity shock x. In contrast, the present value of growth option depends positively on aggregate productivity x and the IST shock z. Thus, the firm's stock return beta with respect to the IST shock is time-varying, and depends linearly on the fraction of firm value accounted for by growth opportunities:

$$\beta^z_{ft} = \frac{\partial \ln V_{ft}}{\partial \ln z_t} = \frac{\alpha}{1-\alpha} \frac{PVGO_{ft}}{V_{ft}}. \tag{22}$$

Since, by assumption, the price of risk of aggregate shocks is constant, the expected excess return of a firm is an affine function of the weight of growth opportunities in firm value, as shown in the following proposition.

PROPOSITION 3: *The expected excess return on firm f is*

$$\frac{1}{dt} \mathrm{E}\left[R_{ft}\right] - r_f = \gamma_x \sigma_x + \frac{\alpha}{1-\alpha} \gamma_z \sigma_z \frac{PVGO_{ft}}{V_{ft}}. \tag{23}$$

Many existing models of the cross-section of stock returns generate an affine relation between expected stock returns and firms' asset composition similar to (23) (e.g., Berk, Green, and Naik (1999), Gomes, Kogan, and Zhang (2003)). The distinguishing feature of our model is the presence of two aggregate shocks x and z. Thus, realized returns have a conditional two-factor structure, and as a result the conditional CAPM fails to price the cross-section of stock returns.

Whether the relation (23) gives rise to a value (or growth) premium depends on the risk premia attached to the two aggregate shocks, γ_x and γ_z. Most equilibrium models imply a positive price of risk for disembodied technology shocks, so $\gamma_x > 0$. The price of risk of the IST shock γ_z depends on preferences. In the models of Papanikolaou (2011) and Kogan, Papanikolaou, and Stoffman (2012), states with low cost of new capital (high z) are high marginal valuation states, which is analogous to a negative value of γ_z.[5]

We infer the price of risk of IST shocks from the cross-section of stock returns. In particular, firms' market-to-book (M/B) ratios are positively correlated with the share of growth opportunities to firm value, $PVGO_f/V_f$. Empirically, growth firms have relatively high exposure to IST shocks and relatively low expected excess returns. This suggests that the market price of IST shocks is negative.

B. Investment Good Producers

There is a continuum of firms producing new capital goods. We assume that these firms produce the demanded quantity of capital goods at the current unit price z_t. Furthermore, profits of investment firms are a fraction ϕ of total sales of new capital goods.[6] Consequently, profits accrue to investment firms at a rate $\Pi_t = \phi\, z_t\, x_t\, \overline{\lambda} \int_{\mathcal{F}} K_{ft}\, df$, where $\overline{\lambda} = \int_{\mathcal{F}} \lambda_{ft}\, df$ is the average arrival rate of new projects among consumption good producers.[7]

PROPOSITION 4: *The price of the investment firm satisfies*

$$V_{It} = \Gamma\, x_t\, z_t^{\frac{\alpha}{1-\alpha}}, \tag{24}$$

where the constant Γ *equals*

$$\Gamma \equiv \phi\, \overline{\lambda}\, \alpha^{\frac{1}{1-\alpha}}\, \rho^{-1} \left(\int_{\mathcal{F}} A(\varepsilon_f, 1)^{\frac{1}{1-\alpha}}\, df \right). \tag{25}$$

A positive IST shock z benefits the investment good producers. Even though the price of their output declines, the elasticity of investment demand with respect to price is greater than one, so their profits increase. Hence, we can use the relative stock returns of the investment and consumption good producers to create a factor-mimicking portfolio for the IST shock.

We define the IMC portfolio in the model as the portfolio that is long the investment sector and short the consumption sector. The instantaneous return on the IMC portfolio $R_t^I - R_t^C$ is given by

$$R_t^I - R_t^C = E_t[R_t^I - R_t^C]\, dt + \frac{\alpha}{1-\alpha}\, \beta_{0t}\, \sigma_z\, dB_{zt}, \tag{26}$$

where $\beta_{0t} \equiv \left(\int_{\mathcal{F}} VAP_{ft}\, df\right)/\left(\int_{\mathcal{F}} V_{ft}\, df\right)$ is a term that depends on the fraction of aggregate value due to growth opportunities in the consumption sector, which affects the IMC portfolio's beta with respect to the z-shock. The beta of firm f with respect to the IMC portfolio return is given by

$$\beta_{ft}^{imc} \equiv \frac{cov_t(R_{ft}, R_t^I - R_t^C)}{var_t(R_t^I - R_t^C)} = \beta_{0t}^{-1} \left(\frac{PVGO_{ft}}{V_{ft}} \right). \tag{27}$$

Equation (27) is the basis of our empirical approach to measuring growth opportunities. The beta of firm f's return with respect to the IMC portfolio return is proportional to its beta with the investment shock defined in equation (22), and is thus proportional to the fraction of firm f's value represented by its growth opportunities. Firms that have few active projects but expect to create many projects in the future derive most of their value from their future growth opportunities. These firms are anticipated to increase their investment in the future, and their stock price reflects that.

III. Data and Calibration

Here, we describe the construction of our main variables and the calibration of our model.

A. Data

Following our theoretical analysis above, we exclude firms producing investment goods. We relegate the details to the Appendix.

A.1. Investment-Specific Shocks

We focus on four measures of capital-embodied technical change directly implied by the model. The first measure of IST shocks is based on the quality-adjusted price of new capital goods, as in Greenwood, Hercowitz, and Krusell (1997, 2000). Similar to real business cycle models with IST shocks, in our model the cost of capital goods relative to their productivity z^{-1} is directly related to the IST shock.

We use the quality-adjusted price series of new equipment constructed by Gordon (1990), and extended by Cummins and Violante (2002) and Israelsen (2010). We normalize the price of new equipment by the NIPA consumption deflator. As Fisher (2006) points out, the real equipment price experiences an abrupt increase in its average rate of decline in 1982, which could be due to the effect of more accurate quality adjustment in more recent data (see for example, Moulton (2001)). To address this issue, we remove the time trend from the series of equipment prices and define the IST shock as the negative of the change in the de-trended log relative price of new equipment goods. Specifically, we construct a de-trended equipment price series z^I_t by regressing the logarithm of the quality-adjusted price of new equipment p^I relative to the NIPA personal consumption deflator on a piece-wise linear time trend:

$$p^I_t = a_0 + b_0 \mathbf{1}_{1982} + (a_1 + b_1 \mathbf{1}_{1982}) \cdot t - z^I_t, \tag{28}$$

where $\mathbf{1}_{1982}$ is an indicator function that takes the value one post 1982. We measure IST shocks as Δz^I_t. Our results are similar when we use residuals from an AR(1) model or simple first differences of the relative price series.

Our second measure is based on the stock return spread between investment and consumption good producers (IMC portfolio). As we can see from equation (26), the IMC portfolio is spanned by the IST shock. Hence, we use returns to the IMC portfolio as a factor-mimicking portfolio for IST shocks. To construct the IMC portfolio, we first classify industries as producing either investment or consumption goods according to the NIPA Input-Output tables. We then match firms to industries according to their NAICS codes. Gomes, Kogan, and Yogo (2009) and Papanikolaou (2011) describe the details of this classification procedure.

As a robustness test, we also consider an additional proxy for IST shocks based on real variables, that is, the ratio of aggregate investment to consumption. In our model, a positive IST shock leads to an improvement in investment opportunities, and therefore to an increase in aggregate investment relative to the output of the consumption sector. As a result, the aggregate log investment-to-consumption ratio is positively correlated with the IST shock z:

$$\ln\left(\frac{I_t}{C_t}\right) = \chi_t + \frac{\alpha}{1-\alpha}\ln z_t, \tag{29}$$

$$\text{where} \quad \chi_t \equiv \ln\left(\overline{\lambda}\,\alpha^{\frac{1}{1-\alpha}}\,\rho^{-1}\int A(\varepsilon_{ft},1)^{\frac{1}{1-\alpha}}df \Big/ \int_{\mathcal{F}}\varepsilon_{ft}\left(\sum_{j\in\mathcal{J}^f_t}u_{jt}K_j^{\alpha}\right)df\right) =$$

$$a_0 + a_1\ln\left(\int_{\mathcal{J}_t}K_j^{\alpha}\,dj\right), \tag{30}$$

where a_0 and a_1 are constants, and $\mathcal{J}_t$ denotes the set of all existing projects at time t.

Since χ_t is a locally deterministic process, innovations in the investment-to-consumption ratio are driven by the IST shock z. Hence, we construct our alternative proxy for the IST shock z as the first difference of the log ratio of nonresidential private investment to consumption of nondurables plus services $\Delta ic \equiv \Delta\ln\left(\frac{I_t}{C_t}\right)$. Using residuals from an AR(1) model rather than first differences leads to similar results. The correlation between the two real proxies for the investment shock z^I and Δic is equal to 34%.

We verify that two series Δz^I and Δic are positively correlated with returns to the IMC portfolio, controlling for returns to the market and/or disembodied productivity shocks. We estimate

$$\Delta\hat{z}_t = a + bR^{imc}_t + c_1R^{mkt}_t + c_2\Delta x_t + u_t, \tag{31}$$

where $\Delta\hat{z} = [\Delta z^I, \Delta ic]$. We adjust the standard errors using the Newey-West procedure with three lags. The coefficient b is always positive and statistically significant across all specifications, ranging from 1.80 to 2.48.

Last, to illustrate the connection in our model between the value factor and IST shocks, we construct the equivalent of the HML portfolio as in Fama and French (1993). To be consistent with our model, we focus on firms producing consumption goods.[8] Our HML portfolio excluding investment sector firms has a correlation of 92% with the Fama and French (1993) HML factor.

In Panel A of Table I we show the moments of the two portfolios, IMC and HML, constructed using consumption firms only. The IMC portfolio has a negative average return of -1.4% and a standard deviation of 11%, while our version of the value factor has an average return of 3.4% and a standard deviation of 9.3%. In our model, reported in Panel B of Table I, the value factor is negatively correlated with the IST shock z, because firms' market-to-book ratios are positively correlated with the ratio of growth opportunities to firm value. In the data, the correlation between IMC and HML is -56%.

[**Insert Table I here**]

The IMC and HML portfolios are both mispriced by the CAPM, having alphas of -3.0% and 4.1%, respectively. Importantly, even though both portfolios are diversified, they have low correlation with the market portfolio (R^2 of 6.3% to 9.8%). Hence, these two portfolios are correlated with a source of systematic risk distinct from the market portfolio. Investment firms tend to be on average smaller than consumption firms, and thus the IMC portfolio has a positive size tilt. Its alpha with the market portfolio and the size (SMB) factor is -3.9%. Finally, consistent with our model, the Fama and French (1993) model prices both portfolios.[9]

A.2. Growth Opportunities

Here, we construct measures of growth opportunities that are motivated by our model. The firm's asset composition between growth opportunities and assets in place changes over time, as new projects are acquired, old projects expire, or investment opportunities change. Thus, it is important that our empirical proxies for growth opportunities capture these fluctuations.

Our first empirical measure of growth opportunities is directly implied by our model. Equation (22) shows that the firm's ratio of the value of growth opportunities to total firm value is proportional to the sensitivity of its stock return to the IST shock z. Thus, given our high frequency proxy for the IST shock (IMC portfolio), we estimate time-varying IST betas for each firm,

$$r_{ftw} = \alpha_{ft} + \beta_{ft}^{imc} r_{tw}^{imc} + \varepsilon_{ftw}, \qquad w = 1 \dots 52. \tag{32}$$

Here r_{ftw} refers to the log return of firm f in week w of year t, and r_{ftw}^{imc} refers to the log return of the IMC portfolio in week w of year t. Thus, β_{ft}^{imc} is constructed using information only in year t. The slope estimate of equation (32) is the direct counterpart of equation (27) in the model. To evaluate the accuracy of a firm's estimated IMC beta as a measure of growth opportunities, we also use equation (32) to estimate β^{imc} in simulated data. Our estimates β_{ft}^{imc} contain estimation noise, but display significant persistence at the firm level: the serial correlation of β_{ft}^{imc} is 0.27 with a t-statistic of 6.6 computed using standard errors clustered by both firm and year.[10]

Our second measure of growth opportunities is the firm's market-to-book ratio. The value of growth opportunities enters the market value of the firm but not the book value of capital. Hence, a firm's market-to-book ratio is positively correlated with the ratio of growth opportunities to firm value in our model. We construct the firm's market-to-book ratio as the ratio of the market value equity to the book value of equity.[11]

Both of these measures of growth opportunities are noisy measures of $PVGO/V$. The firm's IMC beta contains estimation noise. The firm's market-to-book ratio is a noisy measure of growth opportunities because it is influenced by the productivity u of existing projects.[12] Hence, in our empirical analysis we report results using both measures.

B. *Calibration*

We calibrate our model to approximately match moments of aggregate dividend growth and investment growth, accounting ratios, and asset returns. Thus, most of the parameters are chosen jointly based on the behavior of financial and real variables. Table II summarizes our parameter choices.

[Insert Table II here]

We model the distribution of mean project arrival rates $\lambda_f = E[\lambda_{ft}]$ across firms as

$$\lambda_f = \mu_\lambda \delta - \sigma_\lambda \delta \log(X_f), \quad X_f \sim U[0,1]. \tag{33}$$

We choose the project decreasing returns-to-scale parameter $\alpha = 0.85$, the parameters governing the projects' cash flows ($\sigma_\varepsilon = 0.2$; $\theta_\varepsilon = 0.35$; $\sigma_u = 1.5$; and $\theta_u = 0.5$), and the parameters of the distribution of λ_f ($\sigma_\lambda = 2$; $\mu_\lambda = 2$) in order to match the average values and the cross-sectional distribution of the investment rate, the market-to-book ratio, and the return to capital. We select the dynamics of the stochastic component of the firm-specific arrival rate ($\mu_H = 0.075$; $\mu_L = 0.16$; and $\lambda_H = 2.35$) to ensure that the firm grows at about twice the average rate in its high growth phase and at about a third of the average rate in the low growth phase. We set the project expiration rate δ to 10%, to be consistent with commonly used values for the depreciation rate.

We choose the parameters governing the dynamics of the shocks x_t and z_t to match the first two moments of aggregate dividend growth and investment growth. We choose $\phi = 0.07$ to match the relative size of the consumption and investment sectors in the data. The parameters of the pricing kernel, $\gamma_x = 0.69$ and $\gamma_z = -0.35$, are picked to approximately match the average excess returns on the market portfolio and the HML portfolio. We set the interest rate r to 2.5%, which is close to the historical average real risk-free rate (see, for example Campbell and Cochrane (1999)).

We simulate the model at a weekly frequency ($dt = 1/52$) and time-aggregate the data to form annual observations. We simulate 1,000 samples of 2,500 firms over a period of 100 years. We drop the first half of each simulated sample to eliminate the dependence on initial values. Unless noted otherwise, we report median moment estimates and t-statistics across simulations.

[**Insert Table III here**]

In Table III, we compare the estimated moment in the data to the median moment estimate and the 5th and 95th percentiles in simulated data. In most cases, the median moment estimate of the model is close to the empirical estimate. The model matches the moments of aggregate dividend and investment growth, the moments of the market portfolio and the mean and dispersion of most firm characteristics.

In some cases, the model generates median point estimates that are different than the empirical estimates. First, the model produces a somewhat lower average return on the IMC portfolio, -3.9% versus -1.4% in the data, though the empirical estimates lie within the 90% confidence intervals implied by the model.[13] Second, the distribution of firm size produced by the model is somewhat less skewed than in the data. The ratio of median to average firm size is higher than in the data (0.70 versus 0.20), since the model does not generate a sufficient number of large firms. Similarly, the dispersion of estimated IMC beta is higher in the data (0.99) than in the model, but this is may be partly due to higher measurement error in the data than in the model. Third, the median value of Tobin's Q in the data is a bit smaller than in the model (1.41 versus 1.98). The average level of Tobin's Q in the model depends on a number of simplifying assumptions, such as the absence of labor costs, financial leverage, or fixed costs of production. Last, the joint distribution of Tobin's Q and firm size is somewhat different in the model and the data. In the data, firm size and Q are weakly positively correlated (16.2%); in the model, the correlation is negative (-36.9%). We conjecture that introducing a small level of fixed costs in our model is sufficient to match the empirical correlation between Q and size, while leaving our main quantitative predictions unaffected.

IV. Empirical Implications

In this section, we explore the empirical predictions of our model.

A. *Inspecting the Mechanism*

Here, we explore direct tests of the mechanism. In particular, there are two main predictions of our model. First, growth opportunities are proportional to firms' stock return betas with the IMC portfolio. Second, firms with more growth opportunities increase their investment more following a positive IST shock. Since growth opportunities are not directly observable, we take two approaches. In the first approach, we test both predictions jointly using firms' IMC betas as a measure of growth opportunities. In the second approach, we use firms' market-to-book ratios as an approximate measure of growth opportunities. In both cases, we compare our empirical findings to the output of the calibrated model.

A.1. Growth Opportunities and IMC Beta

Here, we show that our measure of growth opportunities (IMC beta) is related to firm characteristics commonly associated with growth opportunities. In Table IV, we report the time-series average of firm characteristics in each of the 10 portfolios sorted on IMC beta. The top panel shows results in the historical data, and the bottom panel shows results in simulated data from the model. As we see Panel A of Table IV, our portfolio sorting procedure is successful in generating ex-post dispersion in loadings to three out of the four measures of IST shocks. The difference in sensitivities between the highest and lowest portfolio with respect to Δz^I, IMC and HML, is statistically significant at the 5% level. The difference in Δic loadings between the extreme decile portfolios is not significant, but this is driven in part by the lowest decile portfolio. See the Internet Appendix for more details.

[Insert Table IV here]

The pattern of firm characteristics across the portfolio deciles is consistent with our interpretation of IMC beta as measuring heterogeneity in growth opportunities. Within the consumption sector, firms in the highest IMC beta portfolio invest more (14.8% investment rate) than firms in the lowest IMC beta portfolio (10.7%). Moreover, the highest IMC beta firms tend to have higher Tobin's Q (2.39), and higher R&D expenditures (6.0% as a fraction of sales) than lowest IMC beta firms (1.49 and 1.4%, respectively). In addition, high IMC beta firms seem to exhibit higher preference for liquidity, since they hold more cash (11.4% versus 6.6%) and pay lower dividends (2.8% versus 9.0%) than the lowest IMC beta firms.

High IMC beta firms tend to be smaller, in terms of both their market capitalization as well as their book value of capital. The highest IMC beta portfolio accounts for 3.9% (2.8%) of the total market capitalization (book value) of capital, versus 8.8% (9.8%) for the lowest IMC beta portfolio. Finally, there is little difference in the ratio of debt to assets across these portfolios, suggesting that these differences in beta are not due to differences in financial leverage.

As we see in Panel B of Table IV, the model mimics most of the empirical patterns above. Firms in the highest IMC beta portfolio have higher investment rates (14.0%) and higher Tobin's Q (3.30) relative to the firms in the lowest IMC beta portfolio (7% and 1.05, respectively). In addition, as in the data, high IMC beta firms tend to have smaller size, measured either by their market capitalization or by their capital stock.

One dimension in which the model and the data are different is in the sign of portfolio loadings with the real measures of IST shocks. In both the data and the model, Δz loadings are increasing in the IMC beta sort across the four proxies. However, the sign of these loadings is not always consistent. In the data, Δz^I and Δic loadings are mostly negative while in the model these loadings are positive; loadings to IMC and (minus) HML are mostly positive both in the data and in the model. One potential culprit for this discrepancy is the partial equilibrium nature of our model. Specifically, in the general equilibrium model of Papanikolaou (2011), the value of assets in place declines following a positive IST shock. This decline occurs because a positive IST shock predicts higher aggregate capital stock and consumption in the future, and thus affects the equilibrium stochastic discount factor, lowering the market value of installed capital. The net effect of IST shocks on total firm values – and hence the sign of the Δz loadings – is ambiguous and depends on whether most of the stock market value comes from growth opportunities (PVGO) or assets in place (VAP). Given that the focus of our paper is on the cross-sectional rather than the level implications of IST shocks, that is, we are interested in the dispersion in Δz loadings, this mechanism is absent in our model. We leave the analysis of the effect of IST shocks on the *level* of equity prices to future research.[14]

A.2. Investment

The main mechanism of our model is that firms with higher growth opportunities, being better positioned to take advantage of positive IST shocks, should increase their investment more in response to a positive IST shock than firms with lower growth opportunities. Since growth opportunities are not observable directly, our empirical tests rely on the observable proxies for growth opportunities motivated by the model. Thus, we jointly evaluate the validity of the main mechanism of our model and the model-based empirical proxies for the IST shocks and the market value of firms' growth opportunities.

We compare the investment response of firms with different measures of growth opportunities (IMC beta or market-to-book) to a positive IST shock. We use the following specification:

$$i_{ft} = a_1 + \sum_{d=2}^{5} a_d\, D(G_{f,t-1})_d + b_1\, \Delta z_{t-1} + \sum_{d=2}^{5} b_d\, D(G_{f,t-1})_d \Delta z_{t-1} + c\, X_{f,t-1} + u_t, \tag{34}$$

where i_t is the firm's investment rate, Δz_t refers to measures of the IST shock, $D(G_f)_d$ is a dummy variable that takes the value one if the firm's growth opportunity measure $G_f \in \{\beta_f^{imc}, M_f/B_f\}$ belongs to quintile d in year $t-1$, and X is a vector of controls which includes the firm's Tobin's Q, leverage, cash flows, log of the firm's capital stock relative to the aggregate capital stock, and firm fixed effects. Definitions of these variables are standard and are summarized in the Appendix. Including lagged investment and lags of the disembodied shock Δx interacted with the dummy variables $D(G_f)_d$ leads to quantitatively similar results. We standardize all variables to zero mean and unit standard deviation. We cluster standard errors by firm and year, following Petersen (2009). To evaluate the ability of the model to quantitatively replicate the data, we also estimate (34) using simulated data from the model.

We estimate equation (34) using four proxies for the IST shock implied by the model: i) returns to the IMC portfolio, R^{imc}; ii) our measure based on the price of equipment, Δz^I; iii) the first difference of the aggregate log investment-to-consumption ratio, Δic; and iv) minus the returns to the value factor (using consumption firms only), $-R^{hml}$. To account for time-to-build, we use two lags of each measure as regressors in (34), so for instance $\Delta z_t = R_t^{imc} + R_{t-1}^{imc}$.

We focus on the coefficients $(b_1, \ldots, b_5)$ on the dummy variables, which measure differences in the response of investment to IST shocks. We report the results in Tables V and VI. Panel A of Table V compares the response of investment to IMC portfolio returns for firms with different measures of growth opportunities. The first column shows that a one-standard-deviation IMC return shock is associated with an increase in firm-level investment of 0.09 standard deviations on average. Columns (2) and (3) show how this investment response varies with the firm's IMC beta. Specifically, the sensitivity of the investment rate to our measure of IST shocks varies between 0.048 for the low β^{imc} firms and 0.179 for the high β^{imc} firms. When we include firm-level controls, the difference in investment sensitivity drops somewhat to 0.08, but is still statistically significant at the 1% level. Columns (4) and (5) show that results are similar if we proxy for growth opportunities using market-to-book ratios.

[**Insert Table V here**]

Our results are similar using the other three measures of IST shocks, as we show in Table VI. Panel A shows that a positive one-standard-deviation IST shock constructed using the price of equipment Δz^I is associated with a 0.031 standard deviation increase in investment for the average firm. However, this response varies dramatically in the cross-section, ranging from -0.01 to 0.093 between firms in the low and high IMC beta quintiles. Panel B shows that using the investment-to-consumption ratio Δic to measure IST shocks leads to comparable results. Following a positive one-standard-deviation shock, high IMC beta firms increase investment by 0.17 standard deviations, while low IMC beta firms increase investment by 0.04 standard deviations. Using the market-to-book ratio as a measure of growth opportunities leads to comparable, but often quantitatively smaller effects.

[**Insert Table VI here**]

Panel C of Table VI shows that the common factor in firms' investment rates is related to the value factor in returns. Following a one-standard-deviation negative change in the value factor, firms with high IMC beta (market-to-book) increase investment by 0.071 (0.086) standard deviations, while firms with low IMC beta (market-to-book) exhibit no statistically significant response.

The magnitude of this investment comovement is economically significant. Our point estimates imply that a positive one-standard-deviation shock to Δz_t increases the level of investment rate of high growth firms relative to low growth firms by 0.4% to 3.1%, depending on the specification. Fluctuations in the investment rate of this magnitude are substantial relative to the median level of the investment rate (11%) in the population of firms. Moreover, these fluctuations are not diversified across firms. Hence, these fluctuations are also large relative to the unconditional volatility of the aggregate investment rate changes in our sample, which is 2.4%.

Panel B of Table V shows that our model generates comovement in investment rates across firms that is quantitatively similar to the data. To conserve space, we only report results using returns to the IMC portfolio to proxy for IST shocks. Results are very similar using the other three measures, since all measures are highly correlated in the model. In simulated data, a positive one-standard-deviation IST shock leads to an increase in firm-level investment of 0.053 standard deviations. The impact of investment shocks varies in the cross-section of firms from 0.08 to 0.10 depending on the measure of growth opportunities. Similar to the data, including firm-level controls reduces the difference in investment responses among high and low growth firms to 0.03-0.04.

Our empirical results confirm that the firms we identify as rich in growth opportunities increase their investment more following a positive IST shock relative to firms identified as poor in growth opportunities. Furthermore, consistent with the prediction of our model, the common factor in firms' investment rates is related to the value factor.

A.3. Alternative Interpretations

Here we explore alternative interpretations of our empirical findings. To conserve space, we briefly summarize the results of additional tests and refer the reader to the Internet Appendix for details.

First, our results could be consistent with a Q-theory model, under the assumption that stock returns have a multifactor structure. Under this alternative, a multifactor structure in returns implies a multifactor structure of changes in Tobin's Q, generating a similar factor structure in investment rates. We explore this alternative by estimating a modified version of (34), replacing G_f with the firm's market beta and Δz with returns to the market portfolio. The market portfolio is a major source of comovement in the cross-section of stock returns, and thus under this alternative it should lead to a high degree of comovement in investment rates. We find no evidence to support this alternative. The investment of high and low market-beta firms has roughly the same response to the market portfolio, even though the stock returns of these firms respond very differently.

Second, IMC betas may capture firms' financial constraints and not differences in their real production opportunities. If financial constraints limit firms' ability to take advantage of new investment opportunities, the market value of such growth opportunities may be relatively low. To sharpen the interpretation of our empirical results, we replicate our empirical analysis on a sample of firms that have been assigned a credit rating by Standard and Poor's. Such firms are relatively less likely to be financially constrained, as they have access to the public debt markets. We find that our results are stronger in this subsample, indicating that our findings are unlikely to be explained by financial constraints.

Third, we estimate IMC betas using stock return data, while the theory suggests using returns on total firm value. To address this concern, we approximate firm-level IMC betas by de-levering the equity-based estimates under the assumption that firm debt is risk-free. We find that our results remain similar, regardless of whether we use book or market leverage.

Fourth, we consider whether IMC betas capture inter-industry linkages rather than differences in growth opportunities. We construct IMC beta quintiles based on the firm's intra-industry IMC beta ranking, using the 30-industry classification of Fama and French (1997). We find that the intra-industry dispersion in investment responses is comparable to our baseline estimates, suggesting that our findings are not driven by inter-industry variation.

B. Asset Prices

Our model implies that heterogeneity in stock return exposure to IST shocks leads to cross-sectional differences in equity risk premia. Here, we evaluate the ability of our model to jointly reproduce the cross-section of risk premia and the patterns of return comovement in the data.

B.1. Risk Premia and Return Comovement

We first explore how growth opportunities are related to average returns and CAPM alphas, in both the model and the data. We focus on portfolios of firms sorted on our two measures of growth opportunities, IMC beta and book-to-market. We report the results in Tables VII and VIII, respectively.

Panel A of Table VII replicates the findings of Papanikolaou (2011), who shows that sorting firms into portfolios based on IMC betas results in a declining pattern of average returns. However, as we see in the fourth row of Table VII, there is a strongly increasing pattern in market betas. As a result, the CAPM misprices the IMC beta portfolios. The difference in average returns and CAPM alphas between the highest and lowest IMC beta portfolios is −2.2% and −6.2%, respectively.[15]

[Insert Table VII here]

There is also substantial return comovement within the IMC beta sorted portfolios. The portfolio long the top IMC beta decile and short the bottom IMC beta decile has a standard deviation of 25.3%, yet the market captures only a small fraction of this variation ($R^2 =$ 26.7%). Thus, the long-short portfolio has exposure to a systematic risk factor that is not captured by the market portfolio. Including the IMC portfolio captures most of this comovement, increasing the R^2 to 74.4%.

Panel B of Table VII shows that our calibrated model reproduces these findings. The model replicates the declining pattern of risk premia across the IMC beta deciles accompanied by the increasing pattern of market betas. Hence, the model reproduces the failure of the CAPM. The difference in average returns and CAPM alphas between the high and low IMC beta portfolios is -3.6% and -5.7%, respectively. In the model, firms with more growth opportunities have higher market exposure because the market portfolio is a linear combination of the disembodied shock x and the IST shock z. Since all firms have the same exposure to disembodied shocks x, firms with higher growth opportunities have higher market betas.

Our simulation results illustrate that the presence of two aggregate shocks generates magnitudes of return comovement comparable to the data. The long-short portfolio of high versus low IMC beta deciles has a standard deviation of 10.5%, yet it is not spanned by the market portfolio ($R^2 = 34.6\%$).

Next, we assess the ability of our model to replicate the empirical relation between stock returns and the book-to-market ratio (B/M). Panel A of Table VIII replicates the well-known value premium in our sample (see, for example Fama and French (1992, 1993)). Sorting firms on their ratio of book-to-market equity generates large differences in average returns, but virtually no differences in market betas. As a result, the difference in average returns and CAPM alphas between value firms and growth firms is 5.4% and 5.2%, respectively. Our model produces significant dispersion in risk premia between value and growth firms, and the failure of the CAPM. In simulated data, the difference in average returns and CAPM alphas between the two extreme book-to-market portfolios is 4.3% and 6.3%, respectively.

[**Insert Table VIII here**]

An important piece of the value puzzle is the presence of the value factor. In particular, the long-short portfolio of high versus low B/M deciles has a standard deviation of 14.8% and low correlation with the market portfolio. Motivated by this pattern, Fama and French (1993) argue that value and growth firms have differential exposure to a systematic source of risk that is not captured by the market portfolio. Our model replicates this pattern in return comovement, as we see in Panel B of Table VIII. The high minus low B/M portfolio has a standard deviation of 10.6% and is not spanned by the market portfolio ($R^2 = 31.2\%$). Thus, our model replicates the existence of the value factor, as well as the failure of the CAPM to account for the value premium in stock returns.

The model mechanism behind the dispersion in risk premia and comovement among high and low growth firms is that firms with different growth opportunities have different exposures to IST shocks. We verify that the market-adjusted risk premia (CAPM alphas) of firms with different growth opportunities are related to the heterogeneous exposures of these portfolios to the IST shock. Figure 1 plots the portfolio CAPM alphas versus their betas with respect to our two benchmark measures of the IST shock – changes in the relative price of equipment Δz^I (top), and returns of the IMC portfolio R^{imc} (bottom). As we see in the left panel of Figure 1, there is a strong and negative relation between the CAPM alphas of the IMC beta portfolios and their exposures to both measures of the IST shock z.

The right panel of Figure 1 shows that the corresponding relation between CAPM alphas and IST shock exposure is similar for the cross-section of book-to-market portfolios. The two extreme book-to-market portfolios have statistically different loadings on the IMC portfolio (t-statistic of -3.2), but not on the changes in the price of equipment Δz^I (t-statistic of -1.66). However, the difference in the exposure to Δz^I between decile portfolios 9 and 2 is statistically significant at the 10% level with a t-statistic of -1.88.

[Insert Figure 1 here]

Our results of this section qualitatively support the view that the observed differences in risk premia and comovement across high and low growth portfolios can be attributed to heterogeneous exposure to IST shocks. Next, we explore whether this observed difference in IST shock sensitivity can account for the observed differences in risk premia for empirically plausible values of the price of risk of IST shocks γ_z.

B.2. Market Price of IST Shocks

Consistent with our model, firms with different growth opportunities differ in their exposures to IST shocks and their risk premia. In this section, we estimate empirically the market prices of the IST and the disembodied technology shocks and compare the estimates to their calibrated model counterparts. Moreover, we evaluate the extent to which the observed differences in IST-risk exposures contribute to the observed differences in risk premia among stocks with different growth opportunities.

We estimate the empirical equivalent of the SDF (9) in our model,

$$m = a - \gamma_x \, \Delta x - \gamma_z \, \Delta z, \tag{35}$$

using generalized method of moments (GMM). We use the model pricing errors as moment restrictions, that is, we impose that the SDF in equation (35) should price the cross-section of asset returns. The resulting moment restrictions are

$$E[R_i^e] = -cov(m, R_i^e), \tag{36}$$

where R_i^e denotes the excess return of portfolio i over the risk-free rate.[16] We report first-stage GMM estimates using the identity matrix to weigh moment restrictions, and adjust the standard errors using the Newey-West procedure with a maximum of three lags. As a measure of fit, we report the sum of squared errors from the Euler equations (36).

We proxy for IST shocks with the relative price of new equipment, Δz^I. As a robustness test, we also use the change in the log investment-to-consumption ratio, Δic. For the neutral technology shock x, we use the change in the (log) total factor productivity in the consumption sector from Basu, Fernald, and Kimball (2006). We also consider specifications of the SDF based on portfolio returns. In particular, we use a linear combination of the market portfolio with either the IMC portfolio, or the HML portfolio, both of which span the same linear subspace as the two technology shocks x and z in the model.[17] We normalize all shocks to unit standard deviation.

[**Insert Table IX here**]

Table IX shows the estimation results for the 10 IMC beta portfolios in the data (Panel A) and in the model (Panel B). The market price of the IST shock in columns (M1) and (M2) is negative and statistically significant. Depending on whether we approximate the IST shock using equipment prices or the investment-to-consumption ratio, the point estimate of the price of risk ranges between -0.68 and -0.91. The model produces comparable but somewhat smaller estimates ranging between -0.40 and -0.65, respectively. Thus, our calibrated price of risk γ_z is conservative relative to the data.

In addition, the cross-sectional differences in IST risk among the IMC beta portfolios account for a sizable portion of the differences in their average returns. Column (CAPM) shows that the unconditional CAPM produces large pricing errors – the sum of squared errors (SSQE) is equal to 0.37%. This number is similar to the model in column (TFP) with only a disembodied productivity shock (SSQE of 0.41%). In contrast, adding the real proxies for the IST shock to the SDF results in a substantial reduction in pricing errors to 0.07% and 0.13% in specifications M1 and M2, respectively. For comparison, adding IMC or HML portfolio returns to the market return in columns (M3) and (M4) results in SSQE values of 0.02% and 0.04% respectively. Figure 2 compares the pricing errors generated across different specifications.

[**Insert Figure 2 here**]

Table X shows similar results for the cross-section of 10 B/M portfolios. The point estimates of the market price of IST shocks are negative and significant, and somewhat larger than those resulting from the model: the empirical estimates based on equipment prices and the investment-to-consumption ratio are -0.98% and -1.09%, respectively, compared to -0.43% and -0.70% in the model. Furthermore, the pricing errors are substantially reduced by the addition of the IST shock to the SDF. The CAPM results in a sum of squared pricing errors of 0.33%, while the two real proxies for the IST shocks above, together with the disembodied shocks, result in a SSQE of 0.12% and 0.19%, respectively. For comparison, the combinations of the market portfolio with the IMC or HML portfolio returns (specifications M3 and M4) produce SSQE values of 0.16% and 0.06%, respectively. Last, the J-test rejects all specifications at the 5% level.[18] However, the J-test often rejects the correctly specified model even in simulated data. The J test rejects models M1 to M4 at the 5% level in 10% to 17.1% of the simulations.

[**Insert Table X here**]

Our findings suggest that differential exposure to IST shocks generates sizable differences in expected stock returns. However, we should be careful when interpreting these findings. In our analysis above, we treat the estimated prices of risk as free parameters. We consider two alternative strategies. First, we constrain the prices of risk to equal their calibrated values $\gamma_x = 0.69$ and $\gamma_z = 0.35$ in the baseline specification. In this case, the pricing errors are substantially larger in the data (0.3%). However, the same is true in simulated data from the model. Fixing γ_x and γ_z across simulations results in large pricing errors of 0.24% to 0.30%. Further, the J tests rejects the model at the 5% level in 34.2% of the simulations. Second, in the case in which the factors are portfolio returns, we constrain the risk premium to equal the in-sample Sharpe ratio of each portfolio. In this case, we find that the IMC portfolio does substantially worse in pricing the book-to-market cross-section. The two factor model with the market portfolio and IMC results in a SSQE that is only moderately smaller than the CAPM (0.43% versus 0.65%).[19] See the Internet Appendix for more details.

One important limitation of estimating the price of IST shocks using the portfolios formed on the book-to-market ratios is that such portfolios have a strong factor structure. As discussed in Lewellen, Nagel, and Shanken (2010) and Daniel and Titman (2012), this may result in spurious empirical estimates of the market prices of shocks correlated with the common factors among such portfolios. Both papers advocate the use of industry portfolios as a pragmatic solution, since returns on these portfolios do not exhibit a strong low dimensional factor structure. We report the estimates of the SDF using the 30 Fama-French industry portfolios (Fama and French (1997)) in Table XI. The point estimates of the market price of IST shocks, when using the equipment price or the investment-to-consumption ratio as empirical proxies (columns (2) and (3)) are -0.52 and -0.70, respectively, which are comparable to the estimates in Tables IX and X. As before, we find that the pricing errors of the SDF using real proxies for the systematic risk factors are comparable to those obtained when using portfolio returns – market, and IMC or HML.

[**Insert Table XI here**]

Last, the results of this section shed some light on why the average return spread between investment and consumption producers is substantially smaller in the data than in the model. We find that, contrary to the model, the IMC portfolio has a positive correlation (13%) with the disembodied shock. Even though the magnitude is small, correlations between stock returns and macroeconomic variables are small in general, and this positive correlation may contaminate the IMC portfolio with the x-shock exposure. To explore the extent to which this x-shock exposure affects average returns on the IMC portfolio, we use the model (M1 and M2) to compute what the risk premium of the IMC portfolio would have been if its x-shock exposure were equal to zero. Depending on the cross-section used to estimate the price of risk of the IST shock, the implied risk premium on the IMC portfolio ranges from -1.6% to -4.4%.[20]

We conclude that the market price of IST risk is negative, and the empirical estimates are consistent in magnitude with the values we use in our calibration. Moreover, the cross-sectional dispersion in average stock returns resulting from their heterogeneous exposures to IST shocks captures a sizable portion of the return spread among the portfolios sorted on either IMC betas or the book-to-market ratio.

C. Cash Flows

Here, we show that our model closely replicates the empirical patterns of earnings and profitability of value and growth firms. In particular, Fama and French (1995) document that the cash flows of value and growth firms display a mean-reverting pattern. At the time of portfolio formation, growth firms are more profitable in terms of return on equity (ROE) than value firms. In the years following portfolio formation, the profitability of growth firms declines whereas the profitability of value firms increases. In contrast, earnings of growth firms grow faster than those of value firms in the years after portfolio formation.

Panel A of Table XII replicates the findings of Fama and French (1995) for the subset of firms producing consumption goods. As we see in Panel B of Table XII, our model reproduces these empirical patterns. In the model, growth firms have higher earnings-to-book than value firms at the time of portfolio formation. Similar to the data, over the next five years the average profitability of growth firms declines and the average profitability of value firms rises. This pattern arises because firm (and project) productivity is mean-reverting, and hence this productivity gap dissipates over time. However, even though the average profitability of growth firms declines, growth firms accumulate capital at a faster rate than value firms. Hence, the earnings of growth firms grow faster than those of value firms of similar size.

[**Insert Table XII here**]

V. Conclusion

In the last few years we have seen significant developments in structural models of the cross-sectional differences in risk premia. However, there has been far less progress in theoretical analysis of the key sources of systematic risk in stock returns. In contrast, the empirical literature has put forward a number of portfolio-based factor pricing models. However, the economic sources of return comovement behind many of these factors are not well understood.

In this paper we show that investment-specific technology shocks are an important source of systematic risk in the cross-section of stock returns. The key theoretical insight behind our analysis is that firms with abundant growth opportunities benefit more from positive IST shocks than firms with limited growth opportunities, and therefore stock returns of high growth firms have higher exposure to IST shocks. Thus, cross-sectional differences in growth opportunities generate differences in risk premia and comovement among stock returns and firm investment. In particular, our results suggest that the value factor in returns is driven in part by heterogeneous exposures of firms with different growth opportunities to the IST shocks. Our empirical findings support the model's predictions.

More generally, our analysis in this paper focuses on one type of embodied technology shock, that is, investment-specific technical change. Embodied shocks, by definition, do not automatically benefit all firms uniformly. Thus, embodied shocks offer a promising avenue for understanding the empirical patterns of comovement and dispersion in risk premia in the cross-section of stock returns. A recent example of this line of research is Eisfeldt and Papanikolaou (2013), who consider technology shocks embodied in the human capital of firms' key employees.

Appendix

A. *Data*

A.1. Macroeconomic Variables

Data on the consumption deflator, consumption of nondurables and servicesn and nonresidential investment are from the Bureau of Economic Analysis. Data on the relative price of equipment are from Israelsen (2010). We construct the investment-consumption ratio as the ratio of nonresidential fixed investment expenditures (row 9 of NIPA table 1.1.5) divided by the sum of consumption expenditures in nondurables (row 5) plus services (row 6). We measure the disembodied shock x using the total factor productivity series in the consumption sector from Basu, Fernald, and Kimball (2006).

A.2. Sample

We omit firms with fewer than 50 weekly stock return observations per year, firms producing investment goods, financial firms (SIC codes 6000-6799), and utilities (SIC codes 4900-4949). In our investment regressions we also exclude firms with missing values of CAPEX (Compustat item capx), PPE (Compustat item ppent), Tobin's Q, and firms with negative book values. Our sample covers the 1964 to 2008 period.

A.3. Firm Level Variables

Firm-level variables are from Compustat, unless otherwise noted. Investment is measured using capital expenditures (capx); in the model, investment is computed as $x\, z^{-1} K_f^*$. Book value of capital is PPE (ppegt); in the model, replacement value of capital is computed as $K = z^{-1}\, x \sum_{j \in \mathcal{J}^f} K_j$. Operating cash flows is operating income (ib) plus depreciation (dp); in the model, cash flows equals $\sum_{j \in \mathcal{J}^f} y_j$. Payout equals dividends (dvc + dvp) plus repurchases (prstkc); in the model, payout equals earnings minus investment expenses $\sum_{j \in \mathcal{J}_t^f} y_{jt} - x\, z^{-1}\, K_f^*$. Market-to-book equity equals market value of equity (CRSP December market cap) divided by book value of equity (ceq); in the model, market-to-book equity equals market value V_f divided by replacement value of capital K. Tobin's Q equals market value of equity plus book value of debt (dltt) plus book value of preferred equity (pstkrv) minus inventories (invt) and deferred taxes (txdb) divided by book value of capital (ppegt); in the model, Q equals market value V_f divided by replacement value of capital K. In addition, we use R&D expenditures (xrd), cash holdings (che), and firm sales (sale).

A.4. Portfolio construction

HML portfolio We construct a 2×3 sort, sorting firms first on their market value of equity (CRSP December market capitalization) and then on their ratio of book-to-market (see above for more details). We construct the value factor (HML) as $1/2(SV - SG) + 1/2(LV - LG)$, where SG, SV, LG, and LV refer to the corner portfolios. Portfolios are value-weighted.

IMC portfolio We follow Gomes, Kogan, and Yogo (2009) and Papanikolaou (2011) and classify firms as investment or consumption producers based on the U.S. Department of Commerce's National Income and Product Account (NIPA) tables. We classify industries based on the sector to which they contribute the most value. We use the 1997 Input-Output tables to classify NAICS industries into investment or consumption producers. We include common shares (shrcd=10,11) of all firms traded in NYSE, Amex, and NASDAQ (exchcd=1,2,3). Portfolios are value-weighted.

10 IMC beta portfolios We sort firms annually into 10 value-weighted portfolios based on the past value of β^{imc}. We estimate β^{imc} using weekly returns. We include common shares (shrcd=10,11) of all firms traded in NYSE, AMEX and NASDAQ (exchcd=1,2,3). We restrict the sample to firms producing consumption goods, and exclude financial firms (SIC6000-6799) and utilities (SIC4900-4949). We rebalance the portfolios at the end of every calendar year. Portfolios are value-weighted.

10 BE/ME portfolios We follow Fama and French (1993) and sort firms in the consumption industry on their ratio of book equity (Compustat item ceq) to market equity (CRSP December market capitalization) into 10 portfolios. We include common shares (shrcd=10,11) of all firms traded in NYSE, Amex and NASDAQ (exchcd=1,2,3). We use NYSE breakpoints. We restrict the sample to firms producing consumption goods, and exclude financial firms (SIC6000-6799) and utilities (SIC4900-4949). We rebalance the portfolios on June of every calendar year. Portfolios are value-weighted.

30 Industry portfolios Returns on these value-weighted portfolios are available from Kenneth French's website, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

B. Proofs and Derivations

Proof of Proposition 1. K_f is the solution to the problem

$$\max_{K_f} A(\varepsilon_{ft}, 1) x_t K_f^{\alpha} - z_t^{-1}\, x_t\, K_f. \tag{A1}$$

The first order condition is

$$\alpha\, A(\varepsilon_{ft},1)K_f^{\alpha-1} = z_t^{-1}. \tag{A2}$$

$\square$

Proof of Proposition 2. The value of growth opportunities depends on the NPV of future projects. When a project is financed, the value added net of investment costs is

$$\left[\alpha^{\frac{\alpha}{1-\alpha}} - \alpha^{\frac{1}{1-\alpha}}\right] z_t^{\frac{\alpha}{1-\alpha}} x_t\, A(\varepsilon_{ft},1)^{\frac{1}{1-\alpha}} = C z_t^{\frac{\alpha}{1-\alpha}} x_t\, A(\varepsilon_{ft},1)^{\frac{1}{1-\alpha}}. \tag{A3}$$

The value of growth opportunities for firm f equals the sum of the NPV of all future projects

$$\begin{aligned} PVGO_{ft} &= \mathrm{E}_t^{\mathcal{Q}}\left[\int_t^\infty e^{-r(s-t)}\lambda_{fs} C z_s^{\frac{\alpha}{1-\alpha}} x_s\, A(\varepsilon_{fs},1)^{\frac{1}{1-\alpha}}\, ds\right] \\ &= C z_t^{\frac{\alpha}{1-\alpha}} x_t\, \mathrm{E}_t\left[\int_t^\infty e^{-\rho(s-t)}\lambda_{fs}\, A(\varepsilon_{fs},1)^{\frac{1}{1-\alpha}}\, ds\right] \\ &= z_t^{\frac{\alpha}{1-\alpha}} x_t\, G(\varepsilon_{ft},\lambda_{ft}), \end{aligned}$$

where $\mathrm{E}_t^{\mathcal{Q}}$ denotes expectations under the risk-neutral measure $\mathcal{Q}$, and

$$\frac{d\mathcal{Q}}{d\mathcal{P}} = \exp\left(-\gamma_x B_{xt} - \gamma_z B_{zt} - \frac{1}{2}\gamma_x^2\, t - \frac{1}{2}\gamma_z^2\, t\right), \tag{A4}$$

where $\mathcal{P}$ being the physical probability measure. The second-to-last equality follows from the fact that λ_{ft} and ε_{ft} are idiosyncratic, and thus have the same dynamics under $\mathcal{P}$ and $\mathcal{Q}$.

Let $\mathbf{M}$ be the infinitesimal matrix associated with the transition density (Karlin and Taylor (1975)) of λ_{ft}:

$$\mathbf{M} = \begin{pmatrix} -\mu_L & \mu_L \\ \mu_H & -\mu_H \end{pmatrix}. \tag{A5}$$

The eigenvalues of $\mathbf{M}$ are zero and $-(\mu_L+\mu_H)$. Let $\mathbf{U}$ be the matrix of the associated eigenvectors, and define

$$\Lambda(u) = \begin{pmatrix} 1 & 0 \\ 0 & e^{(-\mu_L+\mu_H)\,u} \end{pmatrix} \tag{A6}$$

Then

$$\mathrm{E}_t[\lambda_{fs}] = \lambda_f \cdot \mathbf{U}\,\Lambda(s-t)\,\mathbf{U}^{-1}\begin{bmatrix} \lambda_H \\ \lambda_L \end{bmatrix} = \lambda_f \cdot \begin{bmatrix} 1 + \frac{\mu_L}{\mu_L+\mu_H}(\lambda_H-\lambda_L)e^{-(\mu_L+\mu_H)(s-t)} \\ 1 - \frac{\mu_H}{\mu_L+\mu_H}(\lambda_H-\lambda_L)e^{-(\mu_L+\mu_H)(s-t)} \end{bmatrix} \tag{A7}$$

and

$$
\begin{aligned}
G(\varepsilon_{ft}, \lambda_{ft}) &= C \cdot E_t \left[\int_t^\infty e^{-\rho(s-t)}\, \lambda_{fs}\, A(\varepsilon_{fs}, 1)^{\frac{1}{1-\alpha}}\, ds \right] \\
&= C \cdot E_t \left[\int_t^\infty e^{-\rho(s-t)}\, E_t[\lambda_{fs}]\, A(\varepsilon_{fs}, 1)^{\frac{1}{1-\alpha}}\, ds \right] \\
&= \begin{cases} \lambda_f \left(G_1(\varepsilon_{ft}) + \frac{\mu_L}{\mu_L+\mu_H}(\lambda_H - \lambda_L)\, G_2(\varepsilon_{ft}) \right), & \tilde{\lambda}_{ft} = \lambda_H, \\ \lambda_f \left(G_1(\varepsilon_{ft}) - \frac{\mu_H}{\mu_L+\mu_H}(\lambda_H - \lambda_L)\, G_2(\varepsilon_{ft}) \right), & \tilde{\lambda}_{ft} = \lambda_L, \end{cases}
\end{aligned} \tag{A8}
$$

The second equality uses the law of iterated expectations and the fact that λ_{ft} is independent across firms. The functions $G_1(\varepsilon)$ and $G_2(\varepsilon)$ are defined as

$$
G_1(\varepsilon_t) \quad = \quad C \cdot \mathrm{E}_t \left[\int_t^\infty e^{-\rho(s-t)}\, A(\varepsilon_s, 1)^{\frac{1}{1-\alpha}}\, ds \right], \tag{A9}
$$

$$
G_2(\varepsilon_t) \quad = \quad C \cdot \mathrm{E}_t \left[\int_t^\infty e^{-(\rho+\mu_L+\mu_H)(s-t)}\, A(\varepsilon_s, 1)^{\frac{1}{1-\alpha}}\, ds \right]. \tag{A10}
$$

$G_1(\varepsilon)$ and $G_1(\varepsilon)$ satisfy the ODEs:

$$
C \cdot A(\varepsilon, 1)^{\frac{1}{1-\alpha}} - \rho G_1(\varepsilon) - \theta_\varepsilon(\varepsilon - 1)\frac{d}{d\,\varepsilon}\, G_1(\varepsilon) + \frac{1}{2}\sigma_e^2\, \varepsilon\, \frac{d^2}{d\,\varepsilon^2}\, G_1(\varepsilon) \quad = \quad 0 \tag{A11}
$$

$$
C \cdot A(\varepsilon, 1)^{\frac{1}{1-\alpha}} - (\rho + \mu_H + \mu_L) G_2(\varepsilon) - \theta_\varepsilon(\varepsilon - 1)\frac{d}{d\,\varepsilon}\, G_2(\varepsilon) + \frac{1}{2}\sigma_e^2\, \varepsilon\, \frac{d^2}{d\,\varepsilon^2}\, G_2(\varepsilon) \quad = \quad 0. \tag{A12}
$$

□

Proof of Proposition 3. The risk premium on assets in place is determined by the covariance with the pricing kernel:

$$
\mathrm{E}_t \left[R_{ft}^{vap} \right] - r_f = -cov \left(\frac{dVAP_{ft}}{VAP_{ft}}, \frac{d\pi_t}{\pi_t} \right) = \gamma_x \sigma_x. \tag{A13}
$$

Similarly, for growth opportunities,

$$
\mathrm{E}_t \left[R_{ft}^{gro} \right] - r_f = -cov \left(\frac{dPVGO_{ft}}{PVGO_{ft}}, \frac{d\pi_t}{\pi_t} \right) = \gamma_x \sigma_x + \frac{\alpha}{1-\alpha} \gamma_z \sigma_z. \tag{A14}
$$

The risk premium on growth opportunities is lower than the risk premium on assets in place as long as $\gamma_z > 0$.

Expected excess returns of the firm are a weighted average of the risk premia of the two components of its value:

$$
\mathrm{E}_t \left[R_{ft} \right] - r_f = \frac{VAP_{ft}}{V_{ft}} (\mathrm{E}_t \left[R_{ft}^{vap} \right] - r_f) + \frac{PVGO_{ft}}{V_{ft}} (\mathrm{E}_t \left[R_{ft}^{gro} \right] - r_f). \tag{A15}
$$

$\square$

Proof of Proposition 4. Profits accruing to the investment sector are

$$\begin{aligned}\Pi_t &= \phi\, z_t\, x_t \int_{\mathcal{F}} K_{ft} df \\ &= \phi \left(\int_{\mathcal{F}} A(e_{ft}, 1)^{\frac{1}{1-\alpha}} df \right) \bar{\lambda} \alpha^{\frac{1}{1-\alpha}}\, x_t\, z_t^{\frac{\alpha}{1-\alpha}} = \Gamma \cdot x_t\, z_t^{\frac{\alpha}{1-\alpha}}\end{aligned}$$

where K_{ft} is the solution to the first order condition (A2). Because ε_{ft} has a stationary distribution, $\Gamma = \phi\, \bar{\lambda} \alpha^{\frac{1}{1-\alpha}} \left(\int_{\mathcal{F}} A(e_{ft}, 1)^{\frac{1}{1-\alpha}} df \right)$ is a constant.

The price of the representative investment-sector firm satisfies

$$\begin{aligned}V_{It} &= \Gamma\, \mathrm{E}_t^{\mathcal{Q}} \left[\int_t^\infty \exp\left\{ -r(s-t) \right\}\, x_s\, z_s^{\frac{\alpha}{1-\alpha}}\, ds \right] \\ &= \Gamma\, x_t\, z_t^{\frac{\alpha}{1-\alpha}} \frac{1}{\rho},\end{aligned}$$

where $\rho > 0$ is defined in equation (17).

$\square$

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Table I
Time-Series Moments of IST Shock Mimicking Portfolios

The table shows time-series moments for the two IST-shock mimicking portfolios: IMC, and HML constructed excluding investment firms. We show mean returns μ, the matrix of standard deviations and correlations Σ, and alphas from the CAPM (columns (1) to (2)), market and size (columns (3) to (4)) and Fama-French three-factor model (columns (5) to (6)). Columns (7) and (8) show the corresponding moments in simulated data. The sample period is 1963 to 2008. We use monthly data and report annualized estimates of mean returns and CAPM alphas by multiplying the monthly estimates by 12. The market portfolio and the Fama-French factors include the investment and consumption sectors. The Fama-French factors are from Kenneth French's website.

	Panel A. Data						Panel B. Model	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	R^{imc}	R^{hml} (C only)	R^{imc}	R^{hml} (C only)	R^{imc}	R^{hml} (C only)	R^{imc}	R^{hml} (C only)
μ	-0.014	0.034					-0.039	0.029
Σ	0.112	-0.559					0.115	-0.978
	-0.559	0.093					-0.978	0.061
α	-0.030	0.041	-0.039	0.042	-0.005	-0.004	-0.056	0.039
	(-1.67)	(2.47)	(-2.48)	(2.59)	(-0.28)	(-0.79)	(-4.01)	(5.58)
β^{mkt}	0.223	-0.148	0.134	-0.130	0.041	0.065	0.319	-0.203
	(4.62)	(-4.11)	(2.97)	(-3.21)	(1.08)	(4.02)	(4.40)	(4.38)
β^{smb}			0.407	-0.082	0.344	0.044		
			(5.69)	(-0.84)	(7.00)	(1.30)		
β^{hml}					-0.430	0.888		
					(-4.73)	(33.52)		
R^2	0.098	0.063	0.250	0.072	0.375	0.864	0.285	0.297

Table II
Parameter values used in model calibration

The table summarizes the calibrated parameter values.

Parameter	Symbol	Value
Technology, aggregate shocks		
Mean growth rate of the disembodied technology shock	μ_x	0.02
Volatility of the disembodied technology shock	σ_x	0.17
Mean growth rate of the IST shock	μ_z	0.002
Volatility of the IST shock	σ_z	0.035
Technology, idiosyncratic shocks		
Persistence of the firm-specific shock	θ_ε	0.35
Volatility of the firm-specific shock	σ_ε	0.15
Persistence of the project-specific shock	θ_u	0.50
Volatility of the project-specific shock	σ_u	2
Project arrival and depreciation		
Project depreciation rate	δ	0.10
Arrival rate parameter 1	μ_λ	2.00
Arrival rate parameter 2	σ_λ	2.00
Transition probability into high-growth state	μ_H	0.075
Transition probability into low-growth state	μ_L	0.160
Project arrival rate in the high-growth state	λ_H	2.35
Stochastic discount factor		
Risk-free rate	r	0.03
Price of risk of the disembodied shock	γ_x	0.59
Price of risk of the IST shock	γ_z	-0.45
Other		
Project-level returns-to-scale parameter	α	0.85
Profit margin of the investment sector	ϕ	0.06

Table III
Calibration Moments

The table compares sample moments to moments in simulated data. Stock return moments are estimated over the 1963 to 2008 period. The moments of investment growth are estimated using the series on real private nonresidential investment in equipment and software. Moments of firm-specific variables are estimated using Compustat data, where we report time series averages of the median and interquintile range (IQR) of the investment rate, cash flows over capital, the market-to-book ratio, IMC beta, and the ratio of firm size to average firm size. Moments of dividend growth are from Campbell and Cochrane (1999).

Moment	Data	Model		
		Median	5%	95%
Aggregate moments: quantities				
Aggregate dividend growth, mean	0.025	0.017	-0.054	0.072
Aggregate dividend growth, volatility	0.118	0.150	0.104	0.477
Aggregate investment growth, mean	0.047	0.041	-0.041	0.068
Aggregate investment growth, volatility	0.157	0.171	0.129	0.273
Aggregate moments: asset prices				
Mean excess return of market portfolio	0.059	0.056	0.037	0.127
Volatility of market portfolio return	0.161	0.164	0.122	0.215
Mean return of IMC portfolio	-0.014	-0.039	-0.091	-0.012
Volatility of IMC portfolio return	0.112	0.115	0.089	0.157
Relative market capitalization of I and C sectors	0.149	0.140	0.088	0.197
Cross-sectional moments				
Firm investment rate, median	0.112	0.121	0.074	0.251
Firm investment rate, IQR	0.157	0.168	0.074	0.200
Cash flows-to-Capital, median	0.160	0.249	0.186	0.283
Cash flows-to-Capital, IQR	0.234	0.222	0.161	0.252
Tobin's Q, median	1.412	1.988	1.268	2.627
Tobin's Q, IQR	2.981	1.563	0.721	1.937
IMC beta, median	0.683	0.731	0.456	1.074
IMC beta, IQR	0.990	0.636	0.377	0.841
Relative firm size, median	0.201	0.701	0.679	0.721
Relative firm size, IQR	0.830	0.882	0.851	0.942
Correlation between Tobin's Q and relative firm size	0.162	-0.369	-0.446	-0.325

Table IV
Summary Statistics: Portfolios Sorted on IMC Beta

The table shows summary statistics for 10 portfolios of firms sorted by β^{imc}_{t-1}. β^{imc}_t refers to the firm's beta with the investment minus consumption portfolio (IMC) in year t, estimated using non-overlapping weekly returns within year t. We report time-series averages of the following firm characteristics: median Tobin's Q; total firm investment in the portfolio divided by the total capital stock in the portfolio ($I/K = \sum_{i\in P} I_i / \sum_{i\in P} K_i$), the median cash holdings over assets ($CASH/A$), the median ratio of dividends plus share repurchases over cash flows (DIV/CF), the median ratio of research and development over sales ($R\&D/A$), the sum of firms' PPE in each portfolio scaled by total PPE (k/K), cumulative market capitalization of firms in each portfolio scaled by aggregate market capitalization (m/M), and the median β^{imc} on which firms are sorted into portfolios. Rows 3 through 6 contain median full-sample betas of each portfolio with respect to four alternative proxies for IST shocks: β^z, the beta with respect to quality-adjusted equipment price shocks, Δz^I; β^{ic}, the beta with respect to changes in the log aggregate investment-to-consumption ratio, Δic; β^{imc}, the beta with respect to the IMC portfolio; and β^{-hml}, the negative of the beta with respect to HML portfolio, constructed excluding investment sector firms. See main text and the Appendix for more details and sample selection.

Panel A. Data										
β^{imc} decile	Lo	2	3	4	5	6	7	8	9	Hi
Formation β^{imc}	-0.53	-0.08	0.19	0.40	0.61	0.82	1.04	1.32	1.74	2.59
β^z	-3.41	-2.80	-2.60	-2.37	-2.77	-3.18	-1.67	-2.47	-1.38	-0.51
β^{ic}	0.23	-0.45	-0.39	-0.37	-0.32	-0.37	-0.18	-0.41	0.15	0.38
β^{imc}	-0.06	-0.01	-0.01	0.00	0.22	0.27	0.55	0.60	1.11	1.51
β^{-hml}	-0.31	-0.01	-0.06	-0.02	0.14	0.07	0.45	0.45	0.84	1.17
$I/K(\%)$	10.7	10.5	10.5	10.6	11.1	11.6	11.6	12.3	13.2	14.8
Tobin's Q	1.49	1.29	1.31	1.32	1.33	1.42	1.51	1.73	2.00	2.39
$k/K(\%)$	9.3	15.9	15.7	13.5	12.1	10.1	9.1	6.9	4.7	2.7
$m/M(\%)$	8.8	15.7	14.4	12.6	10.8	11.0	9.2	7.6	6.0	3.9
CASH/ASSETS (%)	6.6	6.0	6.0	6.1	6.0	6.3	6.6	7.3	8.9	11.4
DEBT/ASSETS (%)	16.1	17.2	17.5	17.5	17.6	17.7	17.7	17.3	17.2	14.6
R&D/SALES (%)	1.4	1.2	1.2	1.3	1.5	1.5	1.8	2.4	3.7	6.0
DIV/CF (%)	9.0	16.6	18.4	18.1	17.4	16.9	13.7	10.3	7.3	2.8
Panel B. Model										
β^{imc} decile	Lo	2	3	4	5	6	7	8	9	Hi
Formation β^{imc}	0.10	0.32	0.51	0.57	0.63	0.70	0.87	0.96	1.16	1.32
β^z	1.32	1.59	1.80	2.00	2.24	2.48	2.73	3.08	3.50	4.14
β^{ic}	0.17	0.21	0.23	0.26	0.29	0.32	0.36	0.40	0.45	0.53
β^{imc}	0.21	0.40	0.45	0.50	0.56	0.62	0.69	0.78	0.92	1.14
β^{-hml}	0.67	0.81	0.92	1.03	1.16	1.27	1.44	1.61	1.82	2.19
$I/K(\%)$	7.0	7.5	7.8	8.1	8.4	8.8	9.2	9.8	10.8	14.0
Tobin's Q	1.05	1.09	1.15	1.21	1.30	1.40	1.54	1.74	2.11	3.30
$k/K(\%)$	18.2	17.2	14.9	12.7	10.6	8.7	7.0	5.3	3.6	1.7
$m/M(\%)$	14.3	14.6	13.5	12.1	10.8	9.5	8.3	7.1	5.8	3.9

Table V
Response of Firm Investment to IST Shocks

The table shows the response of investment i_t to returns on the IMC portfolio for firms with different levels of growth opportunities G_f. We consider two measures of growth opportunities G_f: the firm stock return beta with the IMC portfolio (β^{imc}), and the firm's ratio of market-to-book equity (M/B). $D(G_f)_i$ is a dummy quintile variable equal to one if firm f belongs in quintile i in year $t-1$ and zero otherwise. We show results with and without a vector of controls that includes firm fixed effects and lagged values of log Tobin's Q, cash flows over lagged capital, log book equity over book assets, and log capital stock. See equation (34) for more details on the specification, and the Appendix for more details on data construction and sample selection. We compute standard errors using two-way clustering by firm and by year. Panel A shows results in historical data. Panel B shows results in data simulated from the model. We report the average values of the estimated coefficients and t-statistics (in parentheses) across simulations. We simulate 1,000 samples. Each simulation sample contains 2,500 firms for 50 years. In each simulation, we exclude firms with no active projects.

Panel A. Data

	(1)	(2)	(3)	(4)	(5)
R^{imc}_{t-1}	0.089	0.048	0.048	0.051	0.046
	(4.30)	(3.44)	(2.95)	(4.30)	(2.66)
$D(G_f)_3 \times (R^{imc}_{t-1})$		0.019	0.014	0.023	0.020
		(1.23)	(1.15)	(2.05)	(1.83)
$D(G_f)_H \times (R^{imc}_{t-1})$		0.131	0.084	0.091	0.055
		(5.53)	(5.50)	(3.06)	(2.11)
$R^2(\%)$	0.7	2.3	45.1	8.1	45.3
Growth opportunities (G_f)	-	β^{imc}	β^{imc}	M/B	M/B
Controls	N	N	Y	N	Y

Panel B. Model

	(1)	(2)	(3)	(4)	(5)
R^{imc}_{t-1}	0.053	0.026	-0.022	0.020	-0.047
	(4.40)	(4.07)	(-3.02)	(3.63)	(-3.60)
$D(G_f)_3 \times (R^{imc}_{t-1})$		0.014	-0.008	0.018	-0.002
		(3.16)	(-1.48)	(4.36)	(-1.27)
$D(G_f)_H \times (R^{imc}_{t-1})$		0.084	0.029	0.102	0.041
		(3.74)	(1.91)	(4.00)	(2.35)
$R^2(\%)$	0.3	2.5	7.4	3.5	7.9
Growth opportunities (G_f)	-	β^{imc}	β^{imc}	M/B	M/B
Controls	N	N	Y	N	Y

Table VI
Response of Firm Investment to IST shocks, Alternative Measures

The table shows the response of investment i_t to measures of the IST shocks for firms with different levels of growth opportunities G_f. We report results using three empirical proxies for the investment shock: (a) the first difference of the de-trended log quality-adjusted relative price of investment goods from Israelsen (2010); (b) changes in the log aggregate investment-to-consumption ratio; and (c) the negative of the returns on the HML portfolio, constructed excluding firms producing investment goods. See equation (34) in the text and notes to Table V for more details on the specification, and the Appendix for more details on data construction and sample selection.

Panel A. Price of equipment					
	(1)	(2)	(3)	(4)	(5)
Δz^I_{t-1}	0.031	-0.01	0.017	0.027	0.028
	(1.05)	(-0.43)	(0.61)	(2.10)	(1.37)
$D(G_f)_3 \times (\Delta z^I_{t-1})$		0.031	0.017	0.009	0.011
		(2.63)	(1.62)	(0.65)	(0.86)
$D(G_f)_H \times (\Delta z^I_{t-1})$		0.103	0.048	0.067	0.038
		(4.43)	(2.52)	(1.92)	(2.30)
$R^2(\%)$	0.1	1.5	44.7	8.3	45.7
Panel B. Investment-consumption ratio					
	(1)	(2)	(3)	(4)	(5)
Δic_{t-1}	0.088	0.039	0.067	0.054	0.065
	(3.85)	(1.91)	(3.20)	(3.53)	(3.39)
$D(G_f)_3 \times (\Delta ic_{t-1})$		0.038	0.02	0.006	0.006
		(3.03)	(1.57)	(0.49)	(0.41)
$D(G_f)_H \times (\Delta ic_{t-1})$		0.128	0.063	0.064	0.043
		(5.29)	(3.01)	(1.92)	(1.95)
$R^2(\%)$	0.8	2.2	45.3	7.7	43.9
Panel C. Returns to the value factor					
	(1)	(2)	(3)	(4)	(5)
$-R^{hml}_{t-1}$	0.019	-0.014	-0.002	0.005	-0.009
	(0.77)	(-0.68)	(-0.11)	(0.28)	(-0.47)
$D(G_f)_3 \times (-R^{hml}_{t-1})$		0.029	0.012	0.023	0.037
		(1.67)	(0.97)	(1.81)	(4.40)
$D(G_f)_H \times (-R^{hml}_{t-1})$		0.085	0.054	0.081	0.064
		(2.84)	(2.45)	(2.34)	(1.93)
$R^2(\%)$	0.8	2.2	45.3	7.7	43.9
Growth opportunities (G_f)	-	β^{imc}	β^{imc}	M/B	M/B
Controls	N	N	Y	N	Y

Table VII
Decile Portfolios Sorted on IMC Beta

Panel A reports return moments of decile portfolios sorted on IMC beta. IMC beta is the firm's beta with the investment-minus-consumption portfolio (IMC) in year t, estimated using non-overlapping weekly returns within year t. See the Appendix for more details on data construction and sample selection. Standard errors are computed using Newey-West with three lags to adjust for autocorrelation in returns. t-statistics are reported in parentheses. All portfolios are value-weighted. We exclude firms producing investment goods, financial firms, and utilities. We use monthly data and report annualized estimates of mean returns and CAPM alphas by multiplying the monthly estimates by 12. Panel B reports the corresponding median estimates in simulated data.

Panel A. Data											
β^{imc}-decile	Lo	2	3	4	5	6	7	8	9	Hi	Hi - Lo
$E(R) - r_f$ (%)	5.82	5.33	6.31	6.36	5.67	5.38	5.18	5.39	4.82	3.63	-2.20
	(2.58)	(2.61)	(3.07)	(3.01)	(2.54)	(2.22)	(2.02)	(1.83)	(1.38)	(0.85)	(-0.59)
σ (%)	15.33	13.86	13.94	14.34	15.14	16.40	17.38	20.01	23.65	28.99	25.29
β^{mkt}	0.75	0.77	0.80	0.85	0.92	1.02	1.07	1.20	1.40	1.60	0.85
	(18.38)	(28.65)	(30.95)	(37.45)	(42.08)	(60.78)	(56.13)	(52.15)	(35.52)	(28.17)	(10.00)
α(%)	2.30	1.71	2.58	2.38	1.37	0.61	0.20	-0.25	-1.71	-3.88	-6.18
	(1.57)	(1.58)	(2.55)	(2.60)	(1.69)	(0.81)	(0.23)	(-0.23)	(-1.13)	(-1.74)	(-1.97)
R^2(%)	57.20	73.65	77.29	83.17	87.28	91.46	88.88	85.71	82.32	72.44	26.74
Panel B. Model											
β^{imc}-decile	Lo	2	3	4	5	6	7	8	9	Hi	Hi - Lo
$E(R) - r_f$(%)	7.52	7.30	7.04	6.78	6.50	6.20	5.83	5.40	4.84	3.97	-3.55
	(3.72)	(3.51)	(3.30)	(3.10)	(2.89)	(2.67)	(2.42)	(2.14)	(1.81)	(1.34)	(-2.50)
σ(%)	14.36	14.81	15.16	15.55	15.99	16.47	17.04	17.75	18.72	20.39	10.53
β^{mkt}	0.83	0.87	0.89	0.92	0.95	0.98	1.02	1.06	1.11	1.19	0.36
	(23.51)	(30.68)	(38.90)	(49.83)	(68.62)	(94.21)	(105.80)	(77.51)	(49.93)	(31.73)	(5.15)
α(%)	2.71	2.25	1.82	1.38	0.93	0.44	-0.13	-0.79	-1.65	-2.99	-5.70
	(4.82)	(5.00)	(4.93)	(4.65)	(4.07)	(2.49)	(-0.85)	(-3.46)	(-4.57)	(-4.89)	(-5.05)
R^2(%)	91.27	94.69	96.56	97.81	98.70	99.21	99.30	98.91	97.63	94.49	34.59

Table VIII
Decile Portfolios Sorted on BE/ME

Panel *A* reports return moments of decile portfolios sorted on book-to-market equity. We exclude firms producing investment goods, financial firms, and utilities. We use NYSE breakpoints for portfolio assignments, following Fama and French (1993). Standard errors are computed using the Newey-West procedure with three lags to adjust for autocorrelation in returns. *t*-statistics are reported in parentheses. All portfolios are value-weighted. We use monthly data and report annualized estimates of mean returns and CAPM alphas by multiplying the monthly estimates by 12. The market portfolio includes the investment and the consumption sector. Panel B reports the corresponding median estimates in simulated data.

Panel A. Data											
BE/ME decile	Lo	2	3	4	5	6	7	8	9	Hi	Hi - Lo
$E(R) - r_f$ (%)	3.37	5.48	4.22	5.29	5.40	5.85	5.55	7.98	7.75	8.78	5.41
	(1.35)	(2.33)	(1.79)	(2.43)	(2.40)	(2.64)	(2.42)	(3.25)	(3.02)	(3.05)	(2.47)
σ (%)	16.90	15.90	15.93	14.72	15.17	14.96	15.52	16.57	17.30	19.44	14.79
β^{mkt}	1.01	0.97	0.97	0.87	0.89	0.85	0.87	0.92	0.96	1.05	0.04
	(43.78)	(48.30)	(50.44)	(34.65)	(34.02)	(26.84)	(24.11)	(25.00)	(24.13)	(23.14)	(0.72)
α(%)	-1.13	1.14	-0.10	1.41	1.44	2.06	1.66	3.89	3.49	4.08	5.22
	(-1.11)	(1.42)	(-0.12)	(1.46)	(1.48)	(1.91)	(1.35)	(2.86)	(2.44)	(2.43)	(2.26)
R^2(%)	84.83	89.04	87.53	83.07	80.93	76.76	74.81	72.67	72.36	69.64	0.20
Panel B. Model											
BE/ME decile	Lo	2	3	4	5	6	7	8	9	Hi	Hi - Lo
$E(R) - r_f$(%)	3.62	4.65	5.26	5.72	6.12	6.46	6.78	7.06	7.40	7.90	4.28
	(1.21)	(1.76)	(2.12)	(2.40)	(2.66)	(2.89)	(3.11)	(3.31)	(3.53)	(3.83)	(2.98)
σ(%)	20.49	18.49	17.48	16.83	16.30	15.87	15.50	15.18	14.91	14.67	10.65
β^{mkt}	1.19	1.09	1.04	1.00	0.97	0.94	0.92	0.90	0.87	0.84	-0.34
	(29.75)	(48.67)	(75.39)	(98.94)	(87.67)	(64.14)	(48.75)	(38.70)	(31.12)	(24.01)	(-4.71)
α(%)	-3.35	-1.76	-0.85	-0.17	0.42	0.92	1.40	1.83	2.31	2.98	6.34
	(-5.16)	(-4.88)	(-3.70)	(-1.01)	(2.22)	(3.85)	(4.60)	(4.94)	(5.18)	(5.33)	(5.41)
R^2(%)	93.81	97.65	98.93	99.29	99.14	98.59	97.71	96.56	94.90	91.60	31.02

Table IX
Asset Pricing - IMC Beta Sorted Portfolios

The table reports GMM estimates of the model SDF (9) using the 10 value-weighted portfolios sorted on IMC beta. Δx is the disembodied productivity shock, R^{mkt} is the market return, and $\Delta Z = [\Delta z^I, \Delta ic, R^{imc}, -R^{hml}]$ are proxies for the IST shock; see the main text for more details. Panel A presents parameter estimates using annual data over the 1964 to 2008 period, along with 90% confidence intervals computed using the Newey-West procedure with three lags, sum of squared errors (SSQE), mean absolute pricing errors (MAPE), and the p values of the J over-identification test. Panel B presents median point estimates from 1,000 simulations of 50 years, and the 5% and 95% percentiles.

Panel A. Data						
	(TFP)	(M1)	(M2)	(CAPM)	(M3)	(M4)
Δx	1.47	0.48	1.32			
	[0.41, 2.52]	[-1.03, 1.99]	[0.26, 2.39]			
R^{mkt}				0.29	0.41	0.39
				[0.08, 0.51]	[0.19, 0.62]	[0.17, 0.60]
Δz^I		-0.69				
		[-1.36, -0.02]				
Δic			-0.91			
			[-1.58, -0.24]			
R^{imc}					-0.27	
					[-0.53, -0.01]	
$-R^{hml}$						-0.42
						[-0.81, -0.02]
SSQE (%)	0.41	0.10	0.13	0.37	0.02	0.04
MAPE (%)	1.62	0.82	0.96	1.59	0.40	0.50
p(J) (%)	0.01	6.71	0.07	7.08	81.83	18.08

Panel B. Model						
	(TFP)	(M1)	(M2)	(CAPM)	(M3)	(M4)
Δx	0.45	0.70	0.70			
	$[0.15, 0.80]$	$[0.40, 1.05]$	$[0.36, 1.13]$			
R^{mkt}				0.36	0.81	0.82
				$[0.12, 0.61]$	$[0.41, 1.37]$	$[0.39, 1.45]$
Δz^I		-0.40				
		$[-0.78, -0.08]$				
Δic			-0.65			
			$[-1.46, -0.12]$			
R^{imc}					-0.87	
					$[-1.36, -0.54]$	
$-R^{hml}$						-0.87
						$[-1.39, -0.54]$
SSQE (%)	0.13	0.00	0.00	0.30	0.00	0.00
	$[0.01, 0.31]$	$[0.00, 0.02]$	$[0.00, 0.04]$	$[0.13, 0.55]$	$[0.00, 0.03]$	$[0.00, 0.03]$
MAPE (%)	0.96	0.15	0.16	1.47	0.16	0.15
	$[0.29, 1.48]$	$[0.07, 0.42]$	$[0.08, 0.49]$	$[1.00, 1.99]$	$[0.08, 0.44]$	$[0.08, 0.43]$
p(J) (%)	2.11	49.91	29.49	0.00	35.96	45.30
	$[0.00, 93.35]$	$[0.00, 99.82]$	$[0.00, 99.73]$	$[0.00, 8.62]$	$[0.00, 99.61]$	$[0.00, 99.82]$

Table X
Asset Pricing - BE/ME-Sorted Portfolios

The table reports GMM estimates of the model SDF (9) using the 10 value-weighted BE/ME portfolios. Δx is the disembodied productivity shock, R^{mkt} is the market return, and $\Delta Z = [\Delta z^I, \Delta ic, R^{imc}, -R^{hml}]$ are proxies for the IST shock; see the main text for more details. Panel A presents parameter estimates using annual data over the 1964 to 2008 period, along with 90% confidence intervals computed using the Newey-West procedure with three lags, sum of squared errors (SSQE), mean absolute pricing errors (MAPE), and the p values of the J over-identification test. Panel B presents median point estimates from 1,000 simulations of 50 years, and the 5% and 95% percentiles.

Panel A. Data						
	(TFP)	(M1)	(M2)	(CAPM)	(M3)	(M4)
Δx	1.54 [0.76, 2.32]	0.27 [-0.77, 1.31]	1.13 [0.52, 1.74]			
R^{mkt}				0.40 [0.19, 0.62]	0.50 [0.25, 0.75]	0.38 [0.17, 0.59]
Δz^I		-0.94 [-1.93, 0.04]				
Δic			-1.09 [-2.17, -0.02]			
R^{imc}					-0.66 [-1.23, -0.08]	
$-R^{hml}$						-0.33 [-0.61, -0.06]
SSQE (%)	0.37	0.12	0.19	0.33	0.16	0.06
MAPE (%)	1.35	0.98	1.07	1.44	1.02	0.66
p(J) (%)	0.00	2.26	0.00	0.28	0.01	0.03

Panel B. Model						
	(TFP)	(M1)	(M2)	(CAPM)	(M3)	(M4)
Δx	0.45 $[0.15, 0.80]$	0.72 $[0.41, 1.07]$	0.72 $[0.37, 1.15]$			
R^{mkt}				0.36 $[0.12, 0.62]$	0.83 $[0.42, 1.41]$	0.82 $[0.38, 1.47]$
Δz^I		-0.43 $[-1.01, -0.10]$				
Δic			-0.70 $[-1.57, -0.15]$			
R^{imc}					-0.92 $[-1.46, -0.56]$	
$-R^{hml}$						-0.90 $[-1.43, -0.55]$
SSQE (%)	0.16 $[0.02, 0.37]$	0.00 $[0.00, 0.02]$	0.00 $[0.00, 0.03]$	0.36 $[0.16, 0.64]$	0.01 $[0.00, 0.03]$	0.00 $[0.00, 0.02]$
MAPE (%)	1.06 $[0.37, 1.54]$	0.16 $[0.08, 0.37]$	0.18 $[0.09, 0.45]$	1.59 $[1.07, 2.09]$	0.20 $[0.09, 0.45]$	0.16 $[0.07, 0.40]$
p(J) (%)	0.64 $[0.00, 86.81]$	30.67 $[0.00, 99.73]$	16.22 $[0.00, 99.36]$	0.00 $[0.00, 4.45]$	12.07 $[0.00, 98.83]$	33.75 $[0.00, 99.55]$

Table XI
Asset pricing - Industry portfolios

The table reports GMM estimates of b_x and b_z from the model SDF: $m = a - \gamma_x \; \Delta x - \gamma_z \; \Delta z$. We use the 30 Fama and French (1997) industry portfolios, excluding the 'Other' industry. See the Appendix and the main text for more details, and the caption to Table IX for variable definitions and details on the estimation procedure. Portfolio returns are value weighted and are from Kenneth French's website.

	(TFP)	(M1)	(M2)	(CAPM)	(M3)	(M4)
Δx	1.06	0.49	0.92			
	(3.48)	(2.02)	(3.27)			
R^{mkt}				0.37	0.42	0.37
				(3.68)	(3.93)	(3.67)
Δz^I		-0.52				
		(-3.17)				
Δic			-0.70			
			(-2.97)			
R^{imc}					-0.21	
					(-1.55)	
$-R^{hml}$						0.06
						(0.33)
SSQE	5.82	2.55	3.03	2.24	1.74	2.22
MAPE	3.41	2.18	2.54	1.93	1.81	1.89
p(J)	0.00	0.00	0.00	0.00	0.00	0.00

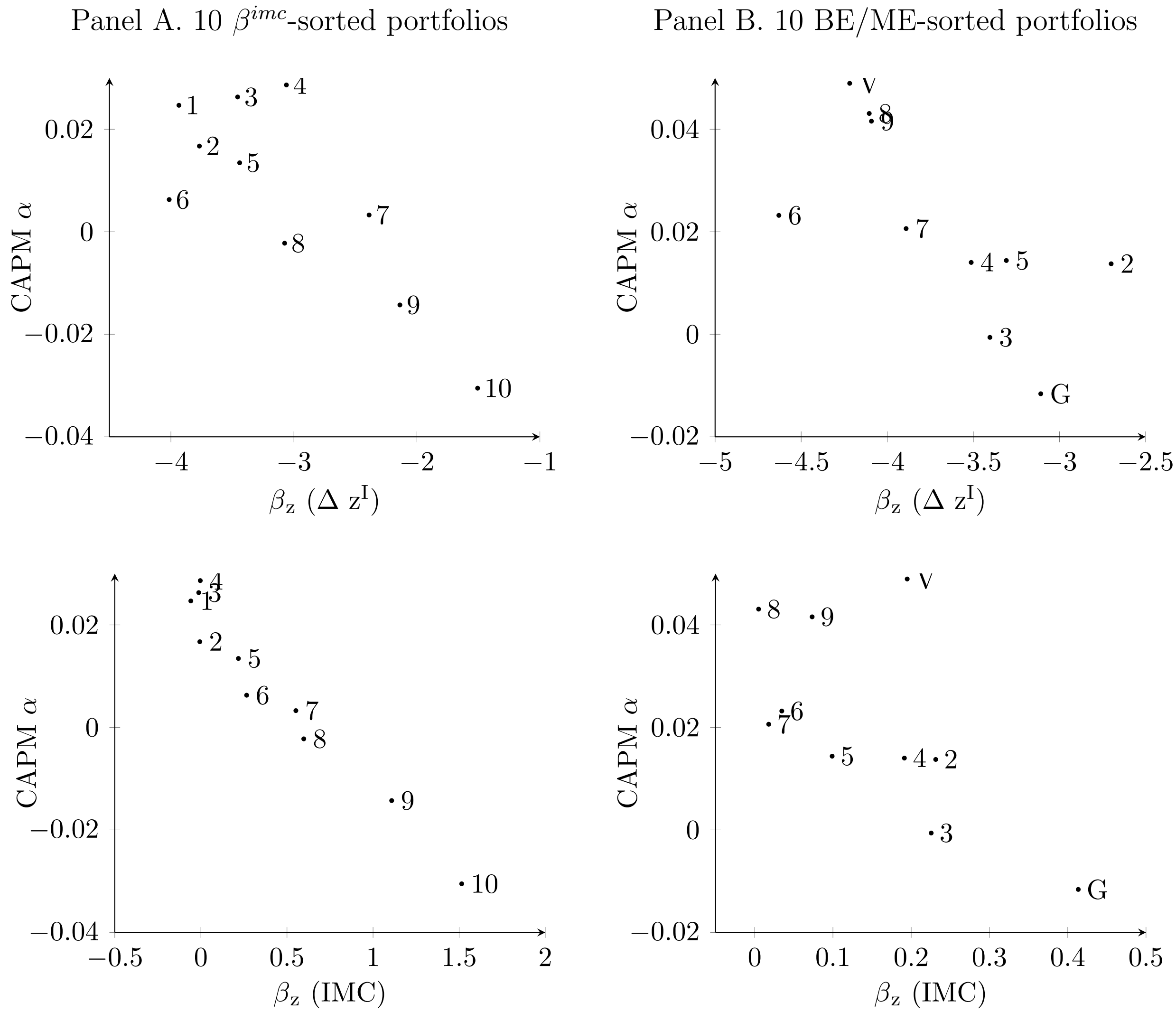
Table XII
Cash Flows Around Portfolio Formation

The table compares the empirical cash flow patterns of value and growth firms (Panel A) to the patterns in simulated data (Panel B). In the top part of each panel, we calculate post-formation changes in profitability, defined as cash flows over portfolio book equity ($\bar{E}^p_{t+i}/\bar{B}^p_{t+i-1}$), for size-BM portfolios formed in June of each year. Our procedure closely mimics the construction in Fama and French (1995). The four portfolios LV, LG, SV, and LG refer to the corner portfolios of a 2-by-3 sort on ME and BE/ME using consumption firms only and NYSE breakpoints. $\bar{E}^p_{t+i}$ equals the sum of earnings at time $t+i$ of firms assigned to portfolio p in year t. In the bottom part of each panel, earnings are measured relative to the total earnings of the market portfolio constructed using only consumption firms (E^m_t), and then standardized to one at the portfolio formation date. Hence, for portfolio p we compute $\bar{E}^p_{t+i}/\bar{E}^m_{t+i}$ and $\bar{E}^p_t/\bar{E}^m_t$ for each portfolio formation year t and lead/lag i using firms that have data in years t and $t+i$. The two ratios are then averaged separately across portfolio formation years. See the main text and the Appendix for variable definitions.

Panel A. Data											
	-5	-4	-3	-2	-1	0	1	2	3	4	5
					Profitability E_t/B_{t-1}						
SG	0.213	0.212	0.217	0.229	0.240	0.250	0.221	0.231	0.226	0.225	0.226
SV	0.158	0.151	0.144	0.131	0.116	0.112	0.127	0.153	0.162	0.170	0.171
LG	0.318	0.324	0.326	0.332	0.341	0.345	0.317	0.318	0.311	0.307	0.305
LV	0.200	0.201	0.199	0.194	0.188	0.182	0.183	0.201	0.204	0.209	0.215
					Earnings E_t/E^m_t						
SG	0.620	0.626	0.658	0.717	0.780	1.000	1.042	1.076	1.118	1.125	1.177
SV	1.534	1.492	1.443	1.335	1.071	1.000	1.106	1.144	1.159	1.140	1.162
LG	0.895	0.895	0.919	0.926	0.968	1.000	1.007	1.019	1.060	1.081	1.101
LV	1.103	1.116	1.151	1.066	1.022	1.000	1.007	1.008	0.955	0.947	0.955

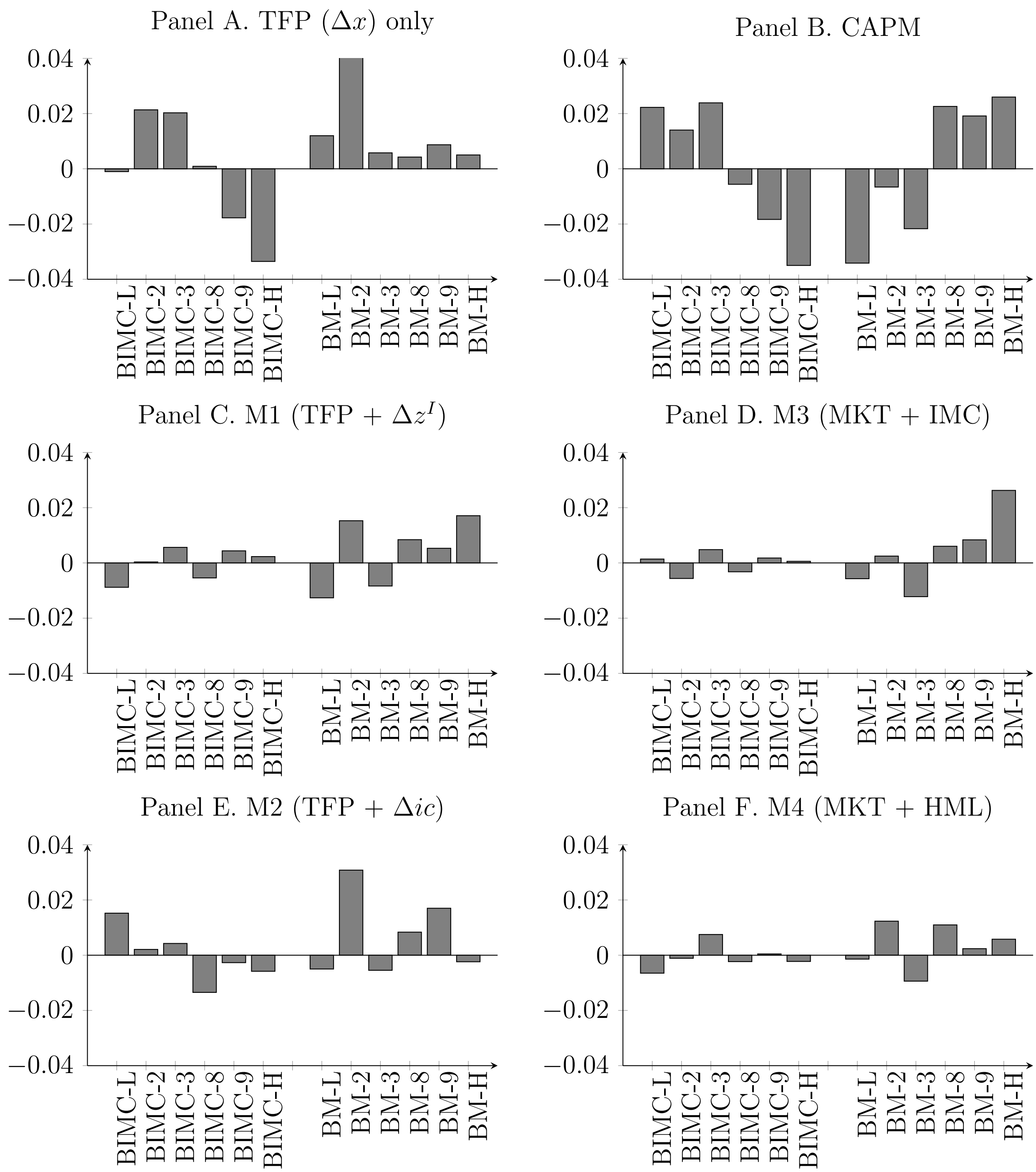
Panel B. Model											
	-5	-4	-3	-2	-1	0	1	2	3	4	5
					Profitability E_t/B_{t-1}						
SG	0.226	0.230	0.237	0.251	0.280	0.324	0.298	0.285	0.277	0.271	0.267
SV	0.229	0.223	0.214	0.197	0.168	0.166	0.194	0.211	0.221	0.227	0.231
LG	0.234	0.239	0.250	0.268	0.301	0.313	0.286	0.271	0.263	0.258	0.255
LV	0.243	0.239	0.233	0.223	0.206	0.199	0.210	0.216	0.220	0.222	0.223
					Earnings E_t/E^m_t						
SG	1.193	1.109	1.037	0.988	0.979	1.000	1.052	1.145	1.255	1.379	1.509
SV	1.388	1.359	1.305	1.205	1.023	1.000	1.138	1.206	1.236	1.246	1.246
LG	0.819	0.815	0.827	0.869	0.967	1.000	0.957	0.951	0.965	0.987	1.014
LV	1.133	1.144	1.140	1.109	1.034	1.000	1.018	1.013	0.996	0.975	0.951

Figure 1. CAPM alphas versus IST betas.



The figure plots CAPM alphas versus IST-shock betas for two sets of portfolios. Panel A uses 10 portfolios sorted on their univariate betas with respect to the IMC portfolio, β^{imc}. Panel B uses 10 portfolios sorted on their book-to-market ratio. We use two proxies for the IST shock z: (i) the negative of the changes in the de-trended log relative price of investment goods Δz^I (see the definition in Section III.A), and (ii) returns on the IMC portfolio.

Figure 2. GMM pricing errors.



The figure plots pricing errors for the decile portfolios sorted on IMC beta and book-to-market ratios, for the various specifications considered in Tables IX and X.

Notes

[1] A classic example of IST change is computers. In 2011, a typical computer server costs \$5,000. In 1960, a state of the art computer server (e.g., the Burroughs 205), cost \$5.1 million in 2011 dollars. Furthermore, adjusting for quality is important: a modern computer server would cost \$160.8 million in 1960, using the quality-adjusted NIPA deflator for computers and software. Greenwood (1999) offers numerous additional examples of IST change since the industrial revolution: Watt's steam engine, Crompton's spinning mule, and the dynamo. These innovations were embodied in new vintages of capital goods, and hence they required substantial new investments before they could affect the production of consumption goods.

[2] See, for example Greenwood, Hercowitz, and Krusell (1997), Fisher (2006)

[3] Solow (1960, p. 91) is sceptical of disembodied technology shocks: "...This conflicts with the casual observation that many, if not most, innovations need to be embodied in new kinds of durable equipment before they can be made effective. Improvements in technology affect output only to the extent that they are carried into practice either by net capital formation or by the replacement of old-fashioned equipment by the latest models..."

[4] Firms with no current projects can be viewed as firms that temporarily left the sector. Likewise, idle firms that begin operating a new project can be viewed as new entrants. Thus, our model implicitly captures entry and exit by firms.

[5] In Papanikolaou (2011), households attach higher marginal valuations to states with a positive IST shock because in those states households substitute resources away from consumption and into investment. In Kogan, Papanikolaou, and Stoffman (2012), future generations capture the rents from capital embodied shocks, while existing households are displaced.

[6] These assumptions are made for simplicity. Alternatively, we could specify z as the productivity shock to the investment sector, which produces capital goods using a fixed factor of production. The two formulations are equivalent.

[7] The firm-level arrival rate λ_{ft} has a stationary distribution, so $\overline{\lambda}$ is a constant.

[8] We construct a 2×3 sort, sorting firms first on their market value of equity (CRSP December market capitalization) and then on their ratio of book-to-market (Compustat item ceq). We construct the breakpoints using NYSE firms only. We construct our value factor excluding investment firms as $1/2(SV - SG) + 1/2(LV - LG)$, where SG, SV, LG, and LV refer to the corner portfolios.

[9] The size factor is redundant in the model; since there are only two aggregate shocks, the stochastic discount factor is spanned by the market portfolio and HML.

[10] See the Internet Appendix for a comparison of the firm transition probabilities across β^{imc}-quintiles,

in the data and in the model. The Internet Appendix is available in the online version of the article on the Journal of Finance website.

[11]In our model firms are financed entirely by equity. Hence, the ratio of market-to-book equity and Tobin's Q are the same. In our empirical work, we use the ratio of market-to-book equity to sort firms into portfolios in order to be close to the literature on the value premium. Using Tobin's Q instead of book-to-market equity produces very similar results.

[12]The firm's market-to-book ratio is $\frac{V}{K} = \frac{1}{1-\frac{PVGO}{V}} \times \frac{VAP}{K}$, where K is the value of installed capital $K_{ft} = z_t^{-1} x_t \int_{\mathcal{J}_{ft}} k_j$. Firms with more profitable existing projects have higher ratios VAP/K, and hence higher market-to-book ratios.

[13]Investment firms tend to be quite a bit smaller than consumption firms, so the size effect may bias the estimated return of the IMC portfolio upwards. Two pieces of evidence support this conjecture: when excluding the month of January, which is when the size effect is strongest, the average return on the IMC portfolio is -2.7%; in addition, its alpha with respect to the small-minus-big (SMB) portfolio of Fama and French (1993) is -3.9%, as we see in Table I.

[14]Even though a general equilibrium model is likely to be successful in replicating the negative sign of Δz loadings, it cannot replicate the difference in sign between the Δz^I and IMC loadings without additional assumptions. One way to replicate this pattern in general equilibrium is to relax the assumption that IMC is a pure proxy for IST shocks. Allowing investment firms to have a higher loading on the disembodied TFP shock x than consumption firms – in line with the evidence for higher cyclicality of investment firms – could be sufficient to resolve this discrepancy between the data and the model.

[15]Our theory treats the consumption good sector as a homogeneous industry. We therefore implicitly assume that cross-sectional variation in IMC betas is determined entirely by firm-level differences in asset composition rather than unobservable cross-industry differences, for instance, differences in production technologies. To help interpret our empirical results on cross-sectional return differences, we consider whether average return differences are related mainly to between- or within-industry variation in IMC betas. We find that there exists some between-industry variation in CAPM alphas in relation to industry-level IMC betas, driven in part by the lowest IMC beta quintile. When we sort firms on their IMC betas within industries, we find that the relation between CAPM alphas and IMC betas is quantitatively similar to the one in the unconditional sort. We conclude that unobservable differences across industries are not the main driver behind our empirical results. See the Internet Appendix for details.

[16]Since we use portfolio returns in excess of the risk free rate, the mean of the SDF is not identified. Without loss of generality, we choose the normalization $E(m) = 1$, which leads to the moment restrictions (36). See Cochrane (2001), pages 256-258, for details.

[17]Note that the coefficients on the market and IMC portfolio returns are not equal to the market prices of x and z shocks, and depend on how the market portfolio loads on the primitive shocks.

[18]The J-test essentially tests whether the model correctly prices the in-sample minimum variance portfolio. See Cochrane (2001) for more details.

[19]Constraining the price of risk to equal the in-sample Sharpe ratio is equivalent to a time-series test, since it imposes that the SDF prices the market and IMC portfolio perfectly. See Cochrane (2001) for details.

[20]These findings raise a concern that when we sort on IMC betas we are sorting on the x-shock exposure in addition the z-shock exposure. However, this does not seem to be the case. The difference in x-shock exposures between the highest and lowest IMC beta portfolios is small and statistically insignificant, with a t-statistic of 0.19, whereas the difference in z-shock exposures has a t-statistic of 2.64. Hence, IMC betas are useful in creating dispersion in exposures to the IST shock. This pattern – IMC has some x exposure, while the x-exposure of the β^{imc} portfolios is similar across portfolios – may explain why the high minus low β^{imc} portfolio has a significant CAPM alpha with the market, while the IMC portfolio has an alpha not statistically different from zero (t-statistic of -1.67). One possible reason why β^{imc} portfolios have similar x-exposures is that firm-level x-shock exposures among the consumption-sector firms may be similar. The x-exposure of the IMC portfolio in the data arises because investment sector firms have higher exposure to x-shocks than consumption-sector firms. The latter pattern could arise for several reasons. Aggregate investment is more cyclical than aggregate consumption. Moreover, investment sector firms are smaller than consumption sector firms, and small firms have higher exposure to the neutral TFP shock, potentially due to operating leverage.